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Implementation of the Hybrid ARIMA-LSTM Model for Gold Price Prediction Based on Yahoo Finance Data

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Abstract: This paper presents a hybrid ARIMA–LSTM model to forecast daily gold price using historical data from Yahoo Finance. Gold price is highly volatile due to macroeconomic, geopolitical, and monetary factors, making accurate forecasting difficult and increasing uncertainty in investment decisions. In this study, ARIMA is used for modeling linear patterns in the time series data, while an LSTM network captures the nonlinear relationships and temporal dynamics that are not captured by statistical models. The dataset consists of daily observations of gold prices between June 2022 and June 2025. The analysis involves cleaning and normalizing the data, splitting it into training and testing subsets, estimating ARIMA parameters, extracting residuals, and forecasting these residuals with LSTM. Performance evaluation is carried out through MAE, RMSE, and MAPE metrics. The hybrid framework compares favorably against standalone ARIMA and LSTM models in terms of all three metrics used for assessment. Empirical results show that the hybrid ARIMA–LSTM model produces lower forecasting errors than the individual models on all evaluation metrics. These findings validate that combining statistical time series modeling with neural sequence learning increases predictive reliability in volatile commodity markets. The proposed framework can be considered methodologically sound for gold price forecasting and subsequently may enhance informed decision-making within financial analysis as well as investment practice.

Keywords: ARIMA; LSTM; Hybrid Forecasting; Gold Price Prediction; Time Series Analysis.

1. Introduction

Gold is widely recognized as a financial asset that attracts investors during periods of heightened uncertainty due to its perceived ability to preserve value. Empirical studies show that gold prices respond positively to geopolitical risk, monetary policy shifts, and broader economic uncertainty, although the magnitude and timing of these responses may vary across different risk conditions [1][2][3]. Such characteristics strengthen the role of gold as a reference asset in risk management and portfolio allocation, while simultaneously exposing its price dynamics to pronounced volatility. The inherent volatility of gold prices poses substantial challenges for forecasting tasks. Price movements are shaped by interacting macroeconomic forces, political developments, and market expectations, producing nonlinear and irregular patterns in time series data. Traditional statistical approaches, particularly the Autoregressive Integrated Moving Average (ARIMA) model, have been extensively applied to financial forecasting due to their solid theoretical foundation and effectiveness in modeling linear and stationary processes [4][5]. However, ARIMA-based models often experience performance degradation when confronted with nonlinear behavior, regime changes, or abrupt market shocks, which are common features of commodity markets such as gold [6][7].

Recent advances in machine learning have introduced deep learning models as alternatives for capturing complex temporal dependencies in financial data. Long Short-Term Memory (LSTM) networks, a class of recurrent neural networks, are designed to learn nonlinear relationships and long-range dependencies within sequential data. Prior studies demonstrate that LSTM-based models achieve competitive predictive accuracy in financial and commodity price forecasting, including applications to gold markets [8][10][14]. Despite their flexibility, LSTM models are not without limitations, as they typically require extensive datasets, careful hyperparameter tuning, and substantial computational resources to achieve stable performance [9]. To address the respective limitations of linear statistical models and nonlinear neural networks, hybrid forecasting frameworks have been proposed. In a hybrid ARIMA–LSTM structure, ARIMA is employed to model linear patterns in the time series, while LSTM is applied to the residual series to learn nonlinear dynamics that remain unexplained by the statistical component. Empirical evidence suggests that such hybrid approaches consistently outperform standalone ARIMA and LSTM models across various financial domains, including stock markets and commodity price forecasting [16][17][18][19]. These findings indicate that combining statistical rigor with neural sequence learning improves forecasting robustness under volatile market conditions.

The increasing availability of open-access financial data has further supported the development of data-driven forecasting models. Yahoo Finance has become a commonly used data source in academic research due to its accessibility and consistency, and its reliability for machine learning-based financial modeling has been empirically validated [22]. Several recent studies have successfully utilized Yahoo Finance data for gold price prediction using hybrid and deep learning models 0[24]. Nevertheless, existing studies—particularly within the Indonesian research context—often emphasize single-model approaches or provide limited comparative evaluation using multiple error metrics. Based on these considerations, this study implements a hybrid ARIMA–LSTM model to forecast daily gold prices using Yahoo Finance data. By integrating linear time series modeling with nonlinear deep learning techniques, the proposed approach seeks to improve predictive reliability under volatile market conditions. The results are expected to provide methodological insights for financial time series analysis and practical relevance for investors and analysts engaged in risk-aware decision-making.

2. Related Work

Early studies on financial time series forecasting predominantly relied on linear statistical models, with the Autoregressive Integrated Moving Average (ARIMA) model being among the most frequently adopted approaches. ARIMA has demonstrated strong performance in modeling stationary and linear processes due to its parsimonious structure and well-established theoretical foundation [4][5]. Nevertheless, empirical evidence indicates that ARIMA-based models often fail to accommodate nonlinear dynamics, abrupt regime shifts, and volatility clustering commonly observed in commodity markets, including gold [6][7]. These limitations restrict the applicability of purely linear models in environments characterized by persistent uncertainty and complex price behavior.

To overcome such constraints, recent research has increasingly adopted deep learning techniques for financial forecasting. Long Short-Term Memory (LSTM) networks have attracted particular attention due to their capability to model nonlinear relationships and long-range temporal dependencies within sequential data. Prior studies report that LSTM-based architectures outperform traditional statistical models in various financial applications, including stock indices, foreign exchange rates, and commodity prices [8][10]. LSTM models have been shown to achieve relatively low prediction errors when compared to ARIMA, especially during periods of heightened volatility [11][14]. Despite these advantages, LSTM models demand substantial computational resources and are sensitive to hyperparameter configuration, which may limit their robustness and reproducibility across datasets [9].

Recognizing the complementary characteristics of statistical and neural approaches, several studies have proposed hybrid forecasting frameworks that integrate ARIMA and LSTM models. In such frameworks, ARIMA is first applied to capture linear structures in the time series, while LSTM is subsequently employed to learn nonlinear patterns from the residual series. Empirical evaluations consistently show that hybrid ARIMA–LSTM models outperform standalone ARIMA and LSTM models across multiple performance metrics, including MAE, RMSE, and MAPE [16][17][18][19]. Similar performance gains have also been observed in related domains such as foreign exchange forecasting, further supporting the generalizability of hybrid modeling strategies 0. With respect to gold price prediction, several recent studies have emphasized the importance of incorporating nonlinear learning mechanisms due to the influence of macroeconomic factors, geopolitical risk, and monetary policy on price dynamics [1][2][3]. Deep learning and hybrid models have therefore been increasingly adopted to account for such complexities, often yielding more stable forecasts than linear approaches alone [12][15]. These findings reinforce the relevance of hybrid ARIMA–LSTM models for volatile commodity markets.

Regarding data sources, Yahoo Finance has emerged as a widely used platform for financial time series research due to its accessibility and consistency. The reliability of Yahoo Finance data for machine learning–based financial forecasting has been empirically validated, supporting its use in predictive modeling experiments [22]. Several studies have successfully implemented hybrid ARIMA–LSTM models for financial forecasting using Yahoo Finance data, demonstrating favorable performance outcomes 0[24]. However, within the Indonesian research landscape, empirical investigations that rigorously compare hybrid and standalone models using multiple evaluation metrics remain scarce. In light of the reviewed literature, a clear research gap emerges concerning the systematic evaluation of hybrid ARIMA–LSTM models for gold price forecasting using open-access financial data. This study addresses the gap by implementing a hybrid ARIMA–LSTM framework and benchmarking its performance against individual ARIMA and LSTM models using standardized error metrics.

3. Research Method

The dataset comprises daily gold price data obtained from Yahoo Finance for the period spanning June 2022 to June 2025. The raw data include several attributes, namely open, high, low, close, and trading volume. In this study, the closing price is selected as the primary variable for modeling because it represents the final market consensus at the end of each trading day [22].
Data preprocessing involved several stages:
1) Handling missing values using the forward-fill method.
2) Normalizing the data using the Min–Max Scaler to rescale values into the range [0, 1].
3) Dividing the dataset into training (80%) and testing (20%) subsets.

3.1 Feature Selection

To ensure that the model processes only informative variables, a Random Forest algorithm was employed to assess feature importance and identify predictors with the strongest influence on gold price movements. This procedure aims to reduce noise and enhance predictive performance by retaining only the most relevant variables.

3.2 ARIMA Model Implementation

The ARIMA model was applied to capture linear and stationary patterns in the gold price time series. The model parameters (p, d, q)were determined through analysis of the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. After model estimation, ARIMA generated forecasts for the linear component of the series along with residuals, which represent variations not explained by the linear structure.

3.3 LSTM Model Implementation

The residuals produced by the ARIMA model were subsequently used as inputs for the LSTM network in order to model nonlinear dependencies. The residual series was transformed into supervised learning sequences using sliding lag windows. The LSTM architecture consisted of:
1) a single hidden LSTM layer with 50 neurons,
2) a ReLU activation function,
3) the Adam optimization algorithm,
4) a batch size of 32, and
5) 100 training epochs.

This configuration enables the network to learn temporal dependencies and nonlinear fluctuations present in the gold price series.

3.4 Hybrid ARIMA–LSTM Model

The hybrid framework integrates the outputs of both models. First, ARIMA is used to forecast the linear component of the time series. Subsequently, LSTM is applied to predict the residual component. The final forecast is obtained by combining both outputs as follows:

$$Y_t = Y_t^{ARIMA} + Y_t^{LSTM}$$

where $Y_t$denotes the hybrid forecast, Y_t^{ARIMA}represents the ARIMA prediction, and Y_t^{LSTM}corresponds to the LSTM-based residual forecast.

3.5 Evaluation Metrics

The performance of the ARIMA, LSTM, and hybrid ARIMA–LSTM models was evaluated using three commonly adopted error metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics are widely applied in time series forecasting to quantify predictive accuracy [16]. The model exhibiting the lowest error values across these measures was considered to provide superior forecasting performance.

3.6 Tools and Implementation

All experiments were conducted using the Python programming language within the Google Colab environment. Data preprocessing and analysis were performed using the *pandas* and *numpy* libraries. The ARIMA model was implemented using *statsmodels*, while *scikit-learn* was used for feature selection and data scaling. The LSTM network was developed using *TensorFlow/Keras*, and *matplotlib* was utilized for result visualization (Zhao, 2023).

4. Result and Discussion

4.1 Results

4.1.1 Descriptive Analysis of Data

Daily gold price data obtained from Yahoo Finance for the period June 2022 to June 2025 were analyzed to examine their statistical properties and temporal behavior. The descriptive analysis indicates that gold prices experienced substantial fluctuations throughout the observation period, characterized by a relatively stable central tendency alongside intervals of pronounced volatility. These volatility episodes coincided with periods of heightened geopolitical tension and adjustments in global interest rates. Visual inspection of the time series reveals the presence of long-term trends and recurring seasonal movements. Such characteristics suggest that gold price dynamics cannot be adequately represented by a single linear structure, thereby posing challenges for forecasting models that rely solely on linear assumptions.

4.1.2 ARIMA Model Results

The ARIMA model was employed to capture linear and stationary components of the gold price series. Model parameters (p, d, q)were selected based on autocorrelation function (ACF) and partial autocorrelation function (PACF) diagnostics. During periods of relative market stability, the ARIMA model produced moderate forecasting errors, indicating an adequate fit to short-term linear patterns. However, as volatility increased, the forecasting accuracy of the ARIMA model deteriorated. Residual diagnostics revealed systematic patterns that were not explained by the linear structure, indicating the presence of nonlinear dynamics in the gold price series. These residual patterns provided empirical justification for incorporating a nonlinear modeling stage.

4.1.3 LSTM Model Results

The residual series obtained from the ARIMA model was subsequently used as input to the LSTM network to capture nonlinear dependencies. The LSTM model was trained using a single hidden layer with 50 neurons, a batch size of 32, and 100 training epochs. Compared to the standalone ARIMA model, the LSTM-based approach achieved lower prediction errors, particularly during periods characterized by rapid price changes. These results indicate that the LSTM model was able to learn nonlinear temporal relationships present in the residual series, leading to improved predictive performance under volatile market conditions.

4.1.4 Hybrid ARIMA–LSTM Results

The hybrid ARIMA–LSTM model integrates linear forecasts generated by ARIMA with nonlinear residual predictions produced by the LSTM network. This integration resulted in forecasts that were smoother and more closely aligned with the observed gold prices than those produced by either model individually. Quantitative evaluation using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) demonstrates the superiority of the hybrid approach. As shown in Table 1, the hybrid ARIMA–LSTM model achieved the lowest error values across all three metrics. In particular, the hybrid model reduced MAPE by approximately 2–3% compared to the standalone ARIMA and LSTM models, indicating improved forecasting accuracy and robustness.

4.1.5 Comparison of Model Performance

A direct comparison of forecasting results further highlights the advantage of the hybrid framework. Table 2 presents a sample of predicted gold prices alongside actual values for selected dates. The hybrid model consistently produced predictions that were closer to the observed prices than those generated by ARIMA and LSTM individually, especially during periods of pronounced price movement. This pattern is further illustrated in Figure 1, which depicts the Security Effectiveness Index (SEI). The figure shows that the hybrid ARIMA–LSTM forecasts track the actual price series more closely than the individual models, reflecting improved stability and reduced deviation during volatile intervals.

Table 1. Comparison of Model Performance Using Error Metrics

Model	MAE	RMSE	MAPE
ARIMA	25.42	31.85	4.75%
LSTM	18.73	25.14	3.22%
Hybrid ARIMA–LSTM	12.58	19.47	2.11%

Table 2. SEI Calculation Results

Date	Actual Price (USD)	ARIMA Pred (USD)	LSTM Pred (USD)	Hybrid Pred (USD)
2023-06-01	1950.2	1942.8	1947.1	1950.0
2023-06-02	1961.5	1953.7	1958.9	1961.2
2023-06-03	1948.0	1955.1	1949.3	1948.6
2023-06-04	1970.3	1962.5	1968.4	1970.0
2023-06-05	1985.7	1978.0	1982.2	1985.4

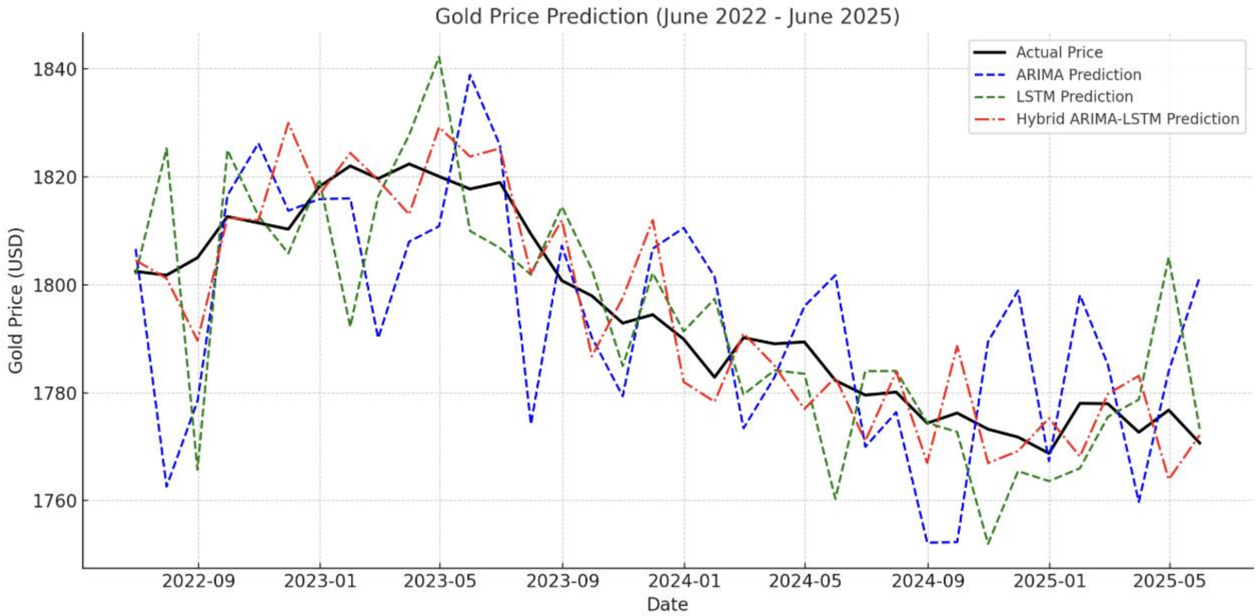

Figure 1. Security Effectiveness Index (SEI).

4.2 Discussion

The empirical results demonstrate that the ARIMA model is effective in capturing short-term linear patterns but struggles under conditions of heightened volatility. This finding is consistent with prior studies that report limitations of linear time series models when applied to financial data characterized by nonlinear behavior and regime shifts [4][6][7]. Such limitations are particularly relevant in gold markets, where price movements are influenced by geopolitical risk and monetary policy dynamics [1][2][3]. The LSTM model exhibited improved performance relative to ARIMA by capturing nonlinear dependencies in the residual series. This result aligns with earlier findings that highlight the ability of LSTM networks to model complex temporal relationships in financial and commodity markets [8][10][14]. Nevertheless, the performance gains achieved by LSTM alone remain constrained by its sensitivity to hyperparameter settings and data requirements, as noted in previous research [9].

The superior performance of the hybrid ARIMA–LSTM model confirms the advantages of integrating statistical and deep learning approaches. By separating linear and nonlinear components, the hybrid framework effectively leverages the strengths of both models, resulting in more stable and accurate forecasts. This outcome is consistent with empirical evidence reported in studies on hybrid forecasting models applied to financial assets and commodities [16][17][18][19]. Similar improvements have also been documented in related domains such as foreign exchange forecasting, suggesting that the hybrid strategy is broadly applicable across financial time series 0. From an applied perspective, the results support the use of hybrid ARIMA–LSTM models for gold price forecasting using open-access data sources. The consistent performance achieved with Yahoo Finance data reinforces previous findings regarding the reliability of this platform for financial modeling and machine learning applications [22]0[24].

5. Conclusion

This research applied a hybrid ARIMA-LSTM approach for the daily gold price prediction using Yahoo Finance data from June 2022 to June 2025. The findings indicated that the ARIMA model was adequate in capturing linear and short-term stationary dynamics of the series, while LSTM could better describe nonlinear and volatile price movements that are not sufficiently captured by linear modeling approaches. The hybridization of both models will always be an improvement in forecast accuracy as verified by lower values of MAE, RMSE, and MAPE compared to those obtained with each model separately. Empirical findings also revealed that hybrid ARIMA-LSTM forecasts are more stable and closer to actual observed gold prices especially under conditions of high market volatility. Such performance illustrates the practical importance of hybrid modeling in financial forecasting toward better reliability in investment decisions, risk management, and hedging strategies. Despite these good results, however, this study is limited by its univariate design based on closing price data only. Future research could expand the application of this framework by including macroeconomic and financial variables such as exchange rates, interest rates, and global stock indices for wider market influence reflection. Also, advanced parameter optimization techniques like Genetic Algorithms and Bayesian Optimization may be explored for better model performance. This study reemphasizes the effectiveness of hybrid ARIMA-LSTM models in forecasting financial time series with empirical evidence directed toward its application in highly volatile commodity markets such as gold.

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