DYNAMES
Dynamics in Engineering Systems: Innovations and Applications
DYNAMES 3(1): 1–19
ISSN 3048-2666

A hybrid machine learning and long short-term memory approach for gold price prediction to support strategic decision-making in the bullion business

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Received Date: November 12, 2025 Revised Date: January 28, 2026 Accepted Date: February 28, 2026

ABSTRACT

Background: Gold price volatility presents a strategic challenge for the bullion business, particularly for institutions such as Pegadaian, where pricing accuracy directly affects gold savings products, pawn valuation, inventory planning, and risk exposure. Previous studies indicate that traditional forecasting models struggle to capture long-term temporal dependencies, while deep learning models often lack interpretability. This study aims to address this gap by developing a forecasting framework that balances predictive accuracy with business-oriented interpretability. **Methods**: This study applies a quantitative experimental design using 5,391 daily gold price observations from 2004 onward. Feature engineering incorporates lagged prices, moving averages, and rolling volatility indicators. Random Forest and Extreme Gradient Boosting models are employed to model nonlinear relationships and extract feature importance, while a Long Short-Term Memory (LSTM) network captures long-term temporal dependencies through sequential learning. Model performance is evaluated using Mean Absolute Error, Root Mean Squared Error, and Mean Absolute Percentage Error. **Findings**: The results demonstrate that the LSTM model significantly outperforms ensemble-based machine learning models, achieving the lowest forecasting error with a Mean Absolute Percentage Error of 2.27%. Feature importance analysis identifies recent price ranges and moving averages as dominant predictors, confirming trend-based behavior in gold price movements. **Conclusion**: The proposed hybrid framework delivers accurate and interpretable gold price forecasts applicable to business-oriented decision support in the bullion industry. Within this framework, LSTM serves as the primary forecasting engine for capturing temporal dependencies, while Random Forest and XGBoost provide interpretable insights through feature importance analysis. **Novelty/Originality of this article**: This study introduces a decision-oriented hybrid framework integrating deep learning-based temporal modeling with interpretable machine learning for strategic applications in bullion-based financial institutions.

KEYWORDS: bullion business; decision-support system; gold price forecasting; hybrid machine learning; long short-term memory

1. Introduction

Gold has long played a central role in the global financial system due to its dual function as both a physical commodity and a strategic financial asset (Maryati & Paramita, 2023). Beyond its intrinsic value, gold is widely recognized as a store of wealth, an inflation hedge, and a safe-haven instrument during periods of economic uncertainty (Maryati & Paramita, 2023; Shafiee & Topal, 2010). In recent decades, its strategic relevance has intensified as

Cite This Article:
Ikasatya, R. A., Apriliani, C., & Firdaus, F. J. (2026). A hybrid machine learning and long short-term memory approach for gold price prediction to support strategic decision-making in the bullion business. *Dynamics in Engineering Systems: Innovations and Applications, 3*(1), 1-19. https://doi.org/10.61511/dynames.v3i1.3458

global financial markets experience heightened volatility driven by macroeconomic shocks, geopolitical tensions, and fluctuating monetary policies (Ogundu, 2025; Rejeb et al., 2023). These conditions have amplified gold price uncertainty across global financial markets. Consequently, institutions operating within the bullion business—particularly state-owned entities such as Pegadaian—require accurate price forecasting, as gold-related products form a core component of business operations and pricing accuracy is closely linked to institutional risk exposure and managerial decision-making (Fadillah et al., 2025; Maryati & Paramita, 2023; Shafiee & Topal, 2010).

Within the bullion industry, gold price movements directly influence a wide range of strategic and operational decisions. Procurement timing, inventory allocation, pawn valuation, pricing formulation for gold savings products, and risk management policies are all highly sensitive to short-term and medium-term price dynamics (Changani, 2024; Fadillah et al., 2025; Shafiee & Topal, 2010). Inaccurate forecasts may result in mispriced products, inefficient inventory levels, increased exposure to market risk, and suboptimal capital utilization. Despite their intuitive appeal, these approaches lack the capacity to model the rapidly evolving and nonlinear dynamics of contemporary gold markets (Sasikala & Bhuvana, 2024; Xie, 2025). Traditional statistical forecasting models have historically been applied to financial time series analysis due to their interpretability and methodological simplicity. Linear regression, autoregressive integrated moving average models, and related techniques remain commonly used in practice. However, these models rely on restrictive assumptions such as linearity, stationarity, and limited interaction effects (Vuong & Phu, 2024). In real-world financial environments, gold price dynamics are influenced by intertwined nonlinear factors, including global economic conditions, interest rate movements, exchange rate fluctuations, and market sentiment (Pandit & Luo, 2025). These characteristics frequently violate the assumptions underlying classical statistical approaches, thereby limiting their predictive accuracy and adaptability.

The advancement of data-driven analytics has led to the growing adoption of Machine Learning techniques in financial forecasting including equity prices, foreign exchange rates, and commodity markets, particularly gold price forecasting (Sasikala & Bhuvana, 2024; Shafiee & Topal, 2010). Unlike traditional models, Machine Learning algorithms are capable of learning complex nonlinear relationships directly from historical data without predefined functional forms (Kyriazos & Poga, 2024). Their ability to process large datasets and capture intricate feature interactions has resulted in improved forecasting performance across various financial applications, including equity prices, foreign exchange rates, and commodity markets (Pala, 2023). As a result, Machine Learning approaches have become increasingly attractive for modeling gold price volatility (Gadage & Baporikar, 2025; Pennacchio et al., 2024).

Among Machine Learning methods, ensemble-based tree algorithms such as Random Forest and Extreme Gradient Boosting have demonstrated strong predictive capability in gold price forecasting (Sasikala & Bhuvana, 2024). Random Forest reduces overfitting by aggregating multiple decision trees, while Extreme Gradient Boosting iteratively refines predictions through gradient-based optimization. Beyond accuracy, a key advantage of these models lies in their interpretability through feature importance analysis, which enables the identification of dominant price-driving factors. This characteristic is particularly valuable for business-oriented applications, where understanding the drivers of price movements is essential for strategic decision-making rather than prediction alone (Barreñada et al., 2024; Jakobs & Saadallah, 2023).

Despite their strengths, conventional Machine Learning models primarily establish static relationships between input features and output values. While effective in capturing nonlinear dependencies, these models do not explicitly account for long-term temporal dependencies inherent in sequential financial data (Ahmad et al., 2025; Sezer et al., 2020). Gold prices exhibit strong temporal characteristics, where historical price patterns influence future movements over extended horizons. Forecasting frameworks that fail to incorporate temporal dynamics may therefore provide an incomplete representation of underlying market behavior (Yang, 2025).

To address this limitation, Deep Learning techniques—particularly Long Short-Term Memory networks—have gained prominence in time series forecasting. Long Short-Term Memory models are designed to capture long-range temporal dependencies through memory cells and gating mechanisms that regulate information flow over time (Hochreiter & Schmidhuber, 1997; Krichen & Mihoub, 2025). This architecture enables the model to retain relevant historical information while filtering noise, making it well suited for complex financial time series (Song, 2024). Empirical studies have shown that Long Short-Term Memory models outperform traditional Machine Learning and statistical approaches in various financial forecasting tasks, including commodity price forecasting (Amryliana et al., 2025).

However, despite their superior predictive performance, Long Short-Term Memory models are often criticized for their limited interpretability. The internal representations learned by deep neural networks are difficult to translate into transparent decision rules, posing challenges for practical adoption in business environments (Amryliana et al., 2025). In the context of the bullion business, high forecasting accuracy alone is insufficient if decision-makers cannot understand the underlying drivers of predictions. This creates a trade-off between accuracy and interpretability that remains insufficiently addressed in existing gold price forecasting literature (Majumdar, 2025; Nazir et al., 2022; Quang & Thang, 2025).

This observation highlights a critical research gap. While numerous studies focus on improving predictive accuracy, relatively few propose integrated frameworks that balance temporal modeling capability with interpretability and direct business relevance (Elebe et al., 2022; Fozap, 2025). In particular, gold price forecasting research rarely adopts hybrid approaches that combine the explanatory strengths of Machine Learning with the temporal learning capacity of Deep Learning models. Moreover, limited attention has been given to translating forecasting outputs into actionable insights for strategic decision-making in bullion institutions such as Pegadaian. In response to this gap, this study proposes a hybrid forecasting framework that integrates Machine Learning models and Long Short-Term Memory networks for gold price prediction. The framework combines Random Forest and Extreme Gradient Boosting to model nonlinear relationships and extract interpretable feature importance, alongside a Long Short-Term Memory model to capture long-term temporal dependencies. Using daily gold price data spanning multiple market cycles, this research develops a comprehensive prediction system that emphasizes both forecasting accuracy and decision-oriented insight generation.

The originality of this study lies in its explicit alignment of advanced predictive modeling with strategic business needs in the bullion industry. Rather than evaluating models solely on statistical performance, this research positions forecasting outcomes within the context of pricing strategy, pawn valuation consistency, inventory planning, and risk management (Fadillah et al., 2025). By integrating Machine Learning interpretability with Deep Learning accuracy, this study contributes a decision-focused framework that enhances the practical value of gold price forecasting. Accordingly, the primary objective of this research is to develop and evaluate a hybrid Machine Learning and Long Short-Term Memory-based framework for gold price prediction to support strategic decision-making in the bullion business. Specifically, this study aims to engineer relevant price-based features, compare the predictive performance of Random Forest, Extreme Gradient Boosting, and Long Short-Term Memory models, analyze feature importance to identify dominant price drivers, and assess the implications of forecasting results for business-oriented decision support.

Based on these objectives, this study formulates directional hypotheses. First, the proposed hybrid framework is expected to achieve higher predictive accuracy than standalone Machine Learning models. Second, the Long Short-Term Memory model is hypothesized to outperform ensemble-based Machine Learning models in capturing temporal patterns in gold price movements. Third, tree-based Machine Learning models are expected to provide interpretable insights that enhance strategic decision-making in the bullion business. The remainder of this manuscript is organized as follows. Section 2 describes the materials and methods, including data sources, preprocessing procedures, feature engineering, and modeling techniques. Section 3 presents the experimental results and performance evaluation. Section 4 discusses the findings and their implications for strategic decision-making in the bullion industry. Finally, Section 5 concludes the study and outlines limitations and directions for future research.

2. Methods

2.1 Research design

This study adopts a quantitative, experimental research design grounded in data-driven modeling to develop a decision-oriented gold price forecasting framework for the bullion business. This framework is formulated as a time-series forecasting problem, where historical price information is utilized to predict future gold price movements over short-term horizons. The forecasting task is defined as a one-step-ahead prediction, where each model estimates the next day's gold closing price based on historical observations. The research integrates Machine Learning and Deep Learning approaches to systematically evaluate their complementary strengths in predictive accuracy and interpretability. Rather than focusing solely on statistical performance, the methodological design emphasizes the relevance of forecasting outputs for strategic decision-making, particularly in contexts such as procurement planning, pricing formulation, inventory management, and risk mitigation (Gamage, 2025).

An experimental modeling framework is employed, in which multiple predictive models are developed, trained, evaluated, and compared using historical gold price time series data. The methodological structure ensures transparency, reproducibility, and empirical rigor by explicitly defining data sources, preprocessing steps, feature engineering procedures, model architectures, hyperparameter settings, and evaluation metrics. This design enables objective comparison across modeling approaches and facilitates replication in future research (Zangana & Obeyd, 2024). From an epistemological perspective, this study follows a positivist paradigm, where knowledge is derived from observable numerical data and validated through quantitative performance indicators. Ontologically, gold price movements are conceptualized as a dynamic, nonlinear, and temporally dependent phenomenon that can be effectively modeled using computational learning algorithms capable of capturing both structural patterns and sequential dependencies (Gbadamosi et al., 2024).

2.2 Data source and research context

This study utilizes secondary data consisting of historical daily gold price records obtained from a publicly available financial dataset. The dataset comprises 5,391 observations spanning from June 2004 to recent years, allowing the models to learn from diverse market conditions, including long-term structural trends, short-term volatility, and multiple economic cycles. The dataset was obtained from a publicly accessible financial data provider that aggregates historical gold price information from global commodity markets (Novandraanugrah, 2024).

Each observation includes six core variables (Date, Open price, High price, Low price, Close price, and Trading Volume). These variables reflect daily market activity and are widely adopted in financial forecasting literature due to their relevance in capturing price behavior and trading dynamics. As the research relies exclusively on secondary financial time series data, it does not involve a specific physical research location. Instead, the research context is situated within the global bullion market. The findings are interpreted with a particular emphasis on their applicability to bullion-based financial institutions, such as Pegadaian, where gold price dynamics directly affect operational and strategic decision-making.

2.3 Data preprocessing

Data preprocessing was conducted to ensure data quality, temporal consistency, and suitability for both Machine Learning and Deep Learning models. First, the Date variable was converted into a datetime format and set as the dataset index. The data were subsequently sorted chronologically to preserve the sequential order required for time series forecasting (Li et al., 2025). Initial data inspection confirmed the absence of missing values. Duplicate records, where applicable, were removed to prevent redundancy and potential bias during model training. To avoid data leakage—a critical issue in time series modeling—dataset partitioning was performed using a chronological split rather than random sampling. Specifically, 80% of the data were allocated for model training and 20% for testing, ensuring that future information was not used to predict past values (Bichri et al., 2024; Rosenblatt et al., 2024).

For models requiring feature scaling, Min–Max normalization was applied to rescale numerical variables into the [0, 1] interval. The scaler was fitted exclusively on the training data and then applied to the testing data, maintaining strict separation between training and evaluation phases (Safriandono et al., 2024). From the training dataset, a subset was further allocated as a validation set to support hyperparameter tuning and early stopping in the Deep Learning model. This validation set was derived exclusively from the training portion to preserve the integrity of the chronological testing data.

2.4 Feature engineering

Feature engineering was conducted to enhance predictive performance while preserving interpretability for business-oriented analysis. In addition to the original market variables (Open, High, Low, and Volume), several derived features were constructed from the Close price based on financial theory and empirical evidence from prior forecasting studies. These engineered features reflect commonly used indicators in bullion market operations, where short-term momentum, trend direction, and price volatility are critical inputs for pricing and risk assessment. These features were selected to balance predictive strength with interpretability, ensuring relevance for operational decision-making in the bullion business (Laska & Yolanda, 2024; Santoso et al., 2025).

Lagged features were generated to represent historical price dependence, including one-day, three-day, and seven-day lag values. To capture short-term and medium-term trend behavior, moving averages with window sizes of seven and fourteen days were calculated. Market uncertainty and price fluctuation intensity were approximated using a seven-day rolling standard deviation as a volatility indicator (Salim & Djunaidy, 2024). Observations affected by undefined values due to lag and rolling computations were removed to ensure data completeness. The final feature set consisted of ten explanatory variables, which served as inputs for the Machine Learning models. Across all experiments, the Close price was consistently defined as the target variable, aligning the modeling objective with practical pricing and valuation needs in the bullion business (Laska & Yolanda, 2024).

2.5 Machine learning model development

Two ensemble-based Machine Learning models were developed: Random Forest Regression and Extreme Gradient Boosting (XGBoost) Regression. These models were selected due to their strong capability in modeling nonlinear relationships, robustness against multicollinearity, and ability to provide feature importance measures for interpretability (Barreñada et al., 2024; Chen & Guestrin, 2016). The Random Forest model was configured using 200 decision trees with a maximum tree depth of 10, enabling balanced learning between bias and variance while maintaining computational efficiency through parallel processing. The XGBoost model was implemented with 300 boosting iterations, a learning rate of 0.05, a maximum tree depth of 6, and subsampling strategies to reduce overfitting. Both models were trained using the engineered feature set and evaluated on the held-out test dataset. Hyperparameter values were selected based on preliminary tuning experiments and guided by configurations commonly adopted in prior gold price forecasting studies (Quang & Thang, 2025; Sasikala & Bhuvana, 2024). Beyond predictive accuracy, these models were explicitly employed to extract explanatory insights regarding key drivers of gold price movements, supporting transparent and interpretable decision-making. These configurations were selected based on preliminary experimentation and prior studies (Quang & Thang, 2025).

Table 1. Feature engineering variables

Feature	Description
Open	Opening gold price
High	Highest daily gold price
Low	Lowest daily gold price
Volume	Daily trading volume
Lag_1	Closing price one day before
Lag_3	Closing price three days before
Lag_7	Closing price seven days before
MA_7	7-day moving average
MA_14	14-day moving average
Volatility_7	7-day rolling standard deviation

2.6 Deep learning model development

To capture long-term temporal dependencies inherent in gold price movements, a Long Short-Term Memory (LSTM) neural network was developed. Prior to training, the Close price series was normalized using Min–Max scaling. The LSTM model utilizes only the historical closing price sequence as input, enabling a focused evaluation of temporal dependency learning without additional engineered features. Sequential input samples were generated using a sliding window approach with a window size of 30 days, where each sequence was used to predict the subsequent day's closing price.

The use of only historical closing prices was intentionally designed to evaluate the capability of LSTM in learning temporal dependencies directly from sequential market data without relying on manually engineered predictors. Unlike tree-based Machine Learning models that utilize multiple explanatory variables, LSTM architectures are inherently capable of extracting temporal patterns through sequential learning. This design enables a clearer comparison between feature-based learning and sequence-based learning approaches while maintaining model interpretability within the proposed hybrid framework.

The LSTM architecture comprises two stacked LSTM layers with 64 and 32 units, respectively, allowing the model to learn hierarchical temporal representations. Dropout regularization with a rate of 0.2 was applied after each LSTM layer to mitigate overfitting. A fully connected dense layer with a single neuron produced the final output. The model was optimized using the Adam optimizer with mean squared error as the loss function (Ma & Fan, 2024). To improve generalization performance and prevent excessive training, early stopping was implemented based on validation loss with a patience threshold of ten epochs. These configurations were selected based on preliminary experimentation and prior studies (Kong et al., 2025).

2.7 Model training and evaluation

All models were trained using the training dataset and evaluated on the testing dataset. The use of multiple evaluation metrics allows for consistent and fair performance comparison across models with different learning mechanisms. Predictive performance was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics were selected to provide complementary perspectives on forecast accuracy and robustness, particularly in financial time series contexts where relative and absolute errors are both relevant. For the LSTM model, predicted values were inverse-transformed to their original scale prior to evaluation to ensure consistency and comparability with the outputs of the Machine Learning models (Bareth et al., 2024).

2.8 Feature importance and interpretability analysis

To translate predictive outputs into actionable business insights, feature importance analysis was conducted for both Random Forest and XGBoost models. Importance scores were extracted from each model and ranked to identify dominant predictors influencing gold price forecasts. Comparative analysis across models enabled the identification of consistently influential features, such as price range indicators and moving average variables. These insights form a critical bridge between model performance and strategic applications, allowing decision-makers in the bullion business to better understand market drivers underlying forecasted price movements (Barreñada et al., 2024; Little et al., 2023).

2.9 Implementation environment

All experiments were implemented using Python in a cloud-based computational environment. The study utilized established open-source libraries, including pandas and NumPy for data processing, scikit-learn for Machine Learning algorithms and evaluation, XGBoost for gradient boosting implementation, and TensorFlow/Keras for Deep Learning model development. Data visualization was performed using Matplotlib. The use of standardized and widely adopted libraries enhances methodological transparency, reproducibility, and accessibility. To enhance reproducibility, all preprocessing procedures, model configurations, and evaluation protocols were applied consistently across experiments and documented to support replication in future studies.

3. Results and Discussion

3.1 Descriptive analysis of gold price dynamics

Gold price movements exhibit distinctive characteristics that make them both attractive and challenging for financial forecasting, particularly in the context of bullion-based business operations such as Pegadaian. As a globally traded commodity, gold functions simultaneously as an investment asset, a hedge against inflation, and a store of value, causing its price to respond sensitively to macroeconomic conditions, market sentiment, and short-term speculative activity. Understanding these dynamics is therefore a critical preliminary step before the application of predictive modeling techniques. An exploratory analysis of the historical gold price dataset reveals pronounced price variability over time, marked by alternating phases of relative stability and heightened volatility. Periods of sharp price increases are often followed by corrective movements, indicating non-linear and temporally dependent behavior rather than purely random fluctuations. This pattern suggests that gold prices are influenced by both immediate market reactions and accumulated historical effects, reinforcing the importance of time-aware modeling approaches. From a business perspective, such volatility directly affects Pegadaian’s core activities, including gold-based lending, inventory valuation, pricing of gold products, and risk exposure management. Sudden price declines may increase collateral risk, while rapid price increases can create procurement and liquidity challenges. Consequently, descriptive insights into price behavior are not merely statistical observations but form the foundation for operational risk mitigation and strategic planning.

Statistical inspection of daily Open, High, Low, and Close prices indicates that intraday price ranges vary considerably across the observation period. Wider price spreads tend to emerge during turbulent market phases, reflecting increased uncertainty and intensified trading activity. These intraday variations are particularly relevant for Pegadaian, as valuation decisions are often made on a daily basis, and even small pricing inaccuracies can accumulate into significant financial implications at scale. Volume dynamics further complement the price analysis. Fluctuations in trading volume often coincide with periods of heightened price movement, suggesting stronger market participation during uncertain or opportunistic conditions. For Pegadaian, this relationship implies that increased market activity may signal upcoming shifts in customer behavior, such as higher gold pawn transactions or increased interest in gold investment products.

Overall, the descriptive analysis confirms that gold prices demonstrate complex temporal structures, characterized by volatility clustering, trend persistence, and short-term reversals. These properties validate the need for advanced predictive models capable of capturing nonlinear relationships and temporal dependencies. More importantly, the findings establish a clear linkage between gold price dynamics and Pegadaian's business environment, emphasizing that accurate forecasting is not solely an academic exercise but a strategic necessity for enhancing pricing accuracy, safeguarding asset value, and supporting data-driven decision-making. These characteristics are consistent with prior empirical findings that identify gold prices as volatile, trend-persistent, and sensitive to macroeconomic uncertainty, reinforcing the suitability of time-aware forecasting models (Maryati & Paramita, 2023; Shafiee & Topal, 2010).

3.2 Comparative performance of forecasting models

This subsection evaluates and compares the predictive performance of the proposed forecasting models, namely Random Forest, Extreme Gradient Boosting (XGBoost), and Long Short-Term Memory (LSTM). The comparison is conducted using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) to ensure a comprehensive assessment of model accuracy from both absolute and relative perspectives. The empirical results demonstrate a clear distinction between the forecasting capabilities of Machine Learning models and the Deep Learning approach. Among the evaluated models, the LSTM network consistently outperforms both Random Forest and XGBoost across all evaluation metrics. The LSTM model achieves the lowest MAE, RMSE, and MAPE values, indicating its superior ability to generate accurate and stable gold price forecasts.

Table 2. Forecasting performance results on the testing dataset

Model	MAE	RMSE	MAPE (*%)*
Random Forest	192.15	385.54	6.97
XGBoost	210.34	411.34	7.69
LSTM	55.20	89.60	2.27

In quantitative terms, the LSTM model reduces prediction error by more than two-thirds compared to the ensemble-based Machine Learning models. This substantial performance gap confirms that gold price movements are strongly influenced by temporal dependencies that cannot be fully captured through static regression-based learning alone. While Random Forest and XGBoost rely on engineered lag features and moving averages, these representations remain limited in expressing long-term sequential relationships inherent in financial time series. This finding reinforces the necessity of integrating sequence-aware models into gold price forecasting frameworks intended for strategic business use. Between the two Machine Learning models, Random Forest exhibits better overall performance than XGBoost. The lower error values achieved by Random Forest suggest that its bagging-based ensemble structure provides stronger generalization under volatile market conditions. In contrast, XGBoost, which emphasizes residual correction through boosting, appears more sensitive to short-term noise in daily gold prices, resulting in relatively higher forecasting errors.

From a methodological standpoint, these findings support the hypothesis that models explicitly designed for sequence learning are more effective for gold price prediction, as they are capable of capturing long-term temporal dependencies inherent in financial time series (Amryliana et al., 2025; Hochreiter & Schmidhuber, 1997). Gold markets are characterized by trend persistence, delayed reactions to macroeconomic signals, and volatility clustering. The LSTM architecture, with its memory cells and gating mechanisms, is better suited to model such characteristics, enabling it to retain relevant historical information while filtering out short-term disturbances. Importantly, the implications of these results extend beyond technical accuracy. For Pegadaian, improved forecasting precision directly translates into reduced pricing uncertainty and better risk control. A lower MAPE value indicates that forecast deviations are relatively small in proportion to actual prices, which is critical when gold prices are used as a reference for collateral valuation, loan pricing, and inventory accounting. Even minor forecasting improvements can significantly affect financial outcomes when applied to large-scale gold-backed transactions.

Moreover, the comparative analysis highlights that although LSTM delivers the highest predictive accuracy, Machine Learning models still play a complementary role within the proposed framework. While their forecasting errors are higher, they remain valuable for providing transparent and explainable insights, which are essential for operational decision-making and regulatory accountability in financial institutions such as Pegadaian. Overall, the results in this subsection confirm that the proposed hybrid approach—combining temporal deep learning with interpretable Machine Learning—offers a balanced solution. The LSTM model serves as the primary forecasting engine, while Random Forest and XGBoost function as supporting analytical tools that enhance understanding of market behavior. This complementary structure strengthens the practical applicability of the forecasting system for gold-backed financial institutions.

3.3 Temporal forecasting behavior of the LSTM Model

This subsection analyzes the temporal forecasting behavior of the Long Short-Term Memory (LSTM) model to further understand its superior predictive performance. Beyond numerical accuracy metrics, examining how the model tracks actual gold price movements over time is essential to assess its reliability for real-world decision support in the bullion business. Fig. 1 illustrates the comparison between actual gold prices and LSTM-generated forecasts over the testing period. The visual inspection reveals a strong alignment between the predicted and actual price trajectories. The LSTM model successfully captures both long-term price trends and short-term fluctuations, producing forecasts that closely follow market movements with minimal lag.

One notable characteristic of the LSTM predictions is their ability to maintain smooth transitions while remaining responsive to directional changes in gold prices. This behavior indicates that the model effectively filters market noise without oversmoothing critical price signals. During periods of relative market stability, the LSTM forecasts exhibit high consistency with actual prices, reinforcing confidence in its short-term predictive reliability.

Deviations between predicted and actual values are primarily observed during periods of heightened volatility, such as sudden price spikes or sharp corrections. These deviations are expected, as extreme price movements are often driven by exogenous shocks, including geopolitical events, global monetary policy announcements, or abrupt changes in investor sentiment. Nevertheless, even in such conditions, the LSTM model demonstrates a rapid recovery, quickly realigning its predictions with subsequent price movements.

From a technical perspective, this performance can be attributed to the internal memory structure of the LSTM architecture. The use of memory cells and gating mechanisms enables the model to selectively retain relevant historical information while discarding irrelevant fluctuations. As a result, the LSTM is capable of learning long-term temporal dependencies that span multiple market cycles, which are difficult to encode using fixed-length lag features alone.

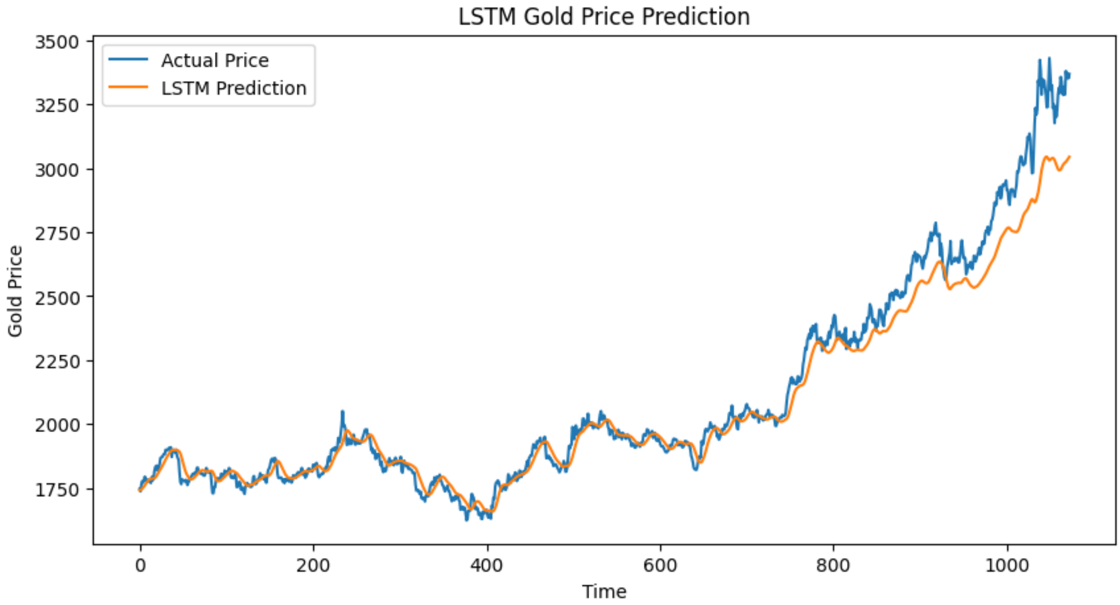

Fig. 1. Comparison of actual gold prices and LSTM-based predicted prices

The ability to capture temporal dependencies is particularly important for gold price forecasting, where current price behavior is often influenced by historical trends, momentum effects, and delayed market reactions. Unlike static Machine Learning models, which treat each observation independently, the LSTM processes gold price data as a continuous sequence. This sequential learning process allows the model to adapt to evolving market conditions more effectively. From the perspective of Pegadaian's bullion business, the temporal reliability demonstrated by the LSTM model has direct strategic implications. Consistent and smooth price forecasts support more accurate valuation of gold-backed assets, which is critical for determining loan-to-value ratios and managing collateral risk. Additionally, the model's ability to anticipate short-term directional changes can assist in optimizing procurement timing and adjusting pricing strategies in response to emerging market trends.

Furthermore, the reduced forecast lag observed in the LSTM predictions is particularly valuable for operational decision-making. In rapidly changing market environments, delayed signals may lead to suboptimal decisions, such as overstocking during price peaks or underestimating risk during downward corrections. The LSTM's responsiveness helps mitigate such risks by providing timely and forward-looking price estimates. Overall, the temporal forecasting behavior of the LSTM model confirms its suitability as the core predictive component within the proposed hybrid framework. Its capacity to learn sequential patterns, adapt to market dynamics, and maintain stability under volatile conditions strengthens the robustness of gold price forecasting. When combined with interpretable Machine Learning models, the LSTM enables a forecasting system that is not only accurate but also strategically actionable for the bullion business.

3.4 Feature importance and interpretability

While the Long Short-Term Memory model demonstrates superior predictive accuracy, its internal decision-making process remains largely opaque. To address the need for transparency and actionable insight in business applications, feature importance analysis was conducted using the Random Forest and Extreme Gradient Boosting (XGBoost) models. This analysis provides an interpretable perspective on the key factors driving gold price predictions, which is essential for strategic decision-making in the bullion business. Fig. 2 presents the ranked feature importance scores generated by the Random Forest model. The results indicate that price-based variables dominate the forecasting process. Specifically, the daily High price and Low price emerge as the most influential predictors, followed closely by the 14-day moving average and the one-day lag of the Close price. These findings suggest that short-term price ranges and recent historical trends play a central role in determining daily gold price movements.

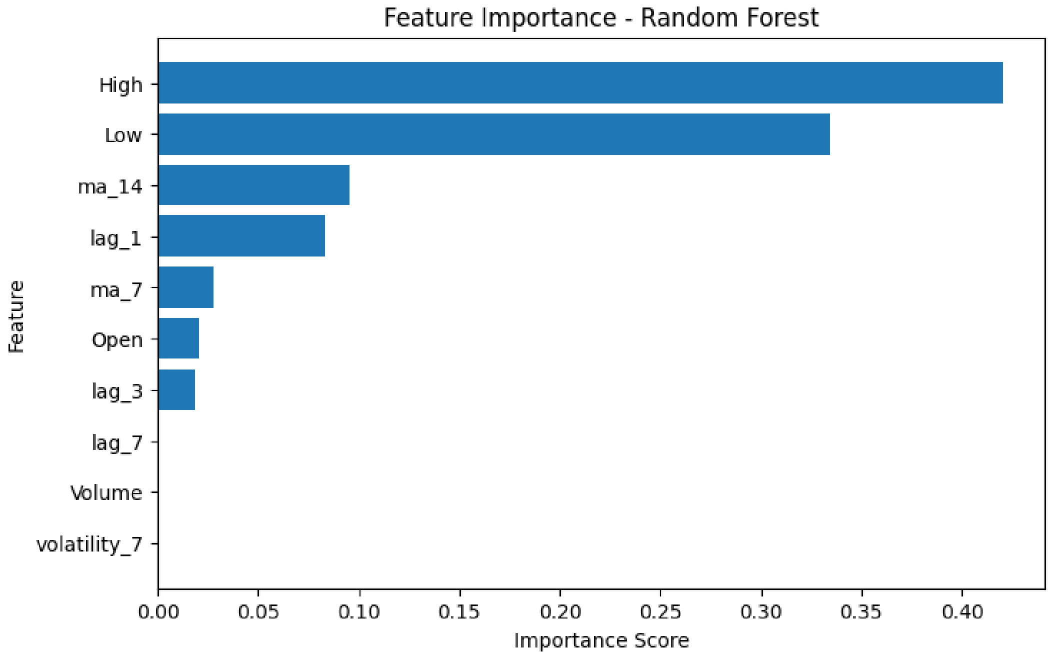

Fig. 2. Feature importance ranking generated by the random forest model

The prominence of High and Low prices reflects the importance of intraday price dispersion as a signal of market sentiment and short-term volatility. A wider price range often indicates heightened market activity and uncertainty, which tends to influence subsequent price adjustments. For bullion businesses, this insight underscores the importance of monitoring daily trading ranges when evaluating short-term price risks and opportunities. In contrast, volume-related and long-horizon lag features exhibit relatively low importance scores. This suggests that, within the studied forecasting horizon, gold price movements are more strongly driven by price dynamics than by trading volume fluctuations. This outcome is consistent with prior empirical findings in commodity markets, where short-term price momentum and trend persistence often dominate volume effects in forecasting models (Barreñada et al., 2024; Sasikala & Bhuvana, 2024).

Fig. 3 illustrates the feature importance ranking produced by the XGBoost model. Although the exact ordering differs slightly from that of Random Forest, the overall pattern remains consistent. The 7-day moving average is identified as the most influential predictor, followed by the Low and High prices. This consistency across models reinforces the robustness of the identified key drivers and reduces the likelihood that the results are model-specific artifacts. The convergence of feature importance findings across two distinct ensemble algorithms strengthens the interpretability of the forecasting framework. It indicates that short-term trend indicators and recent price ranges consistently influence gold price behavior, regardless of the specific modeling technique employed. This stability is particularly valuable for decision-makers, as it provides confidence that the identified signals are reliable and not dependent on a single algorithmic configuration.

From a strategic perspective, these interpretability results carry direct implications for Pegadaian's bullion business operations. The dominance of short-term moving averages suggests that procurement and pricing decisions should be closely aligned with recent market trends rather than relying solely on long-term price forecasts. For example, recognizing upward momentum in the 7-day or 14-day moving averages can inform decisions to accelerate procurement before prices rise further. Similarly, the significance of daily price ranges highlights the importance of incorporating intraday volatility indicators into risk management practices. For Pegadaian, which operates gold-backed financing and collateral valuation mechanisms, understanding periods of elevated price dispersion can support more prudent loan-to-value adjustments and buffer setting against short-term market risk.

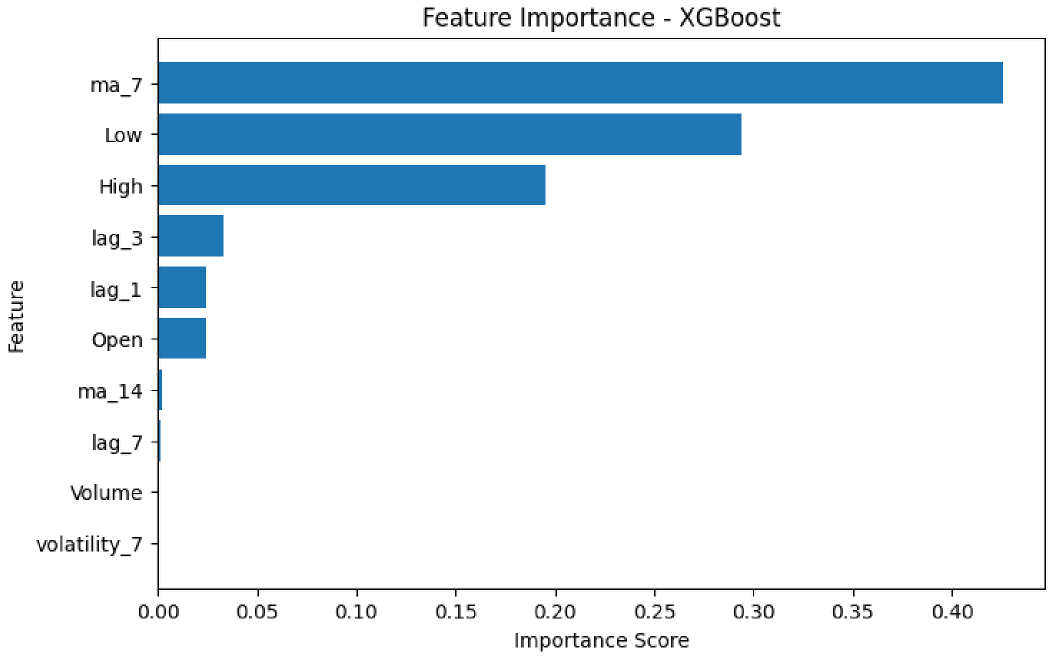

Fig. 3. Feature importance ranking generated by the XGBoost model

Importantly, the interpretability provided by Machine Learning models complements the predictive strength of the LSTM model. While LSTM serves as the primary engine for accurate price forecasting, Random Forest and XGBoost function as explanatory tools that translate complex market behavior into understandable signals. This dual-role structure ensures that the forecasting system does not operate as a “black box” but instead supports transparent and accountable decision-making. Overall, the feature importance analysis demonstrates that the proposed hybrid framework effectively balances accuracy and interpretability. By revealing the key market drivers underlying gold price predictions, this approach enables bullion businesses to align data-driven forecasts with practical operational strategies. This interpretability-driven insight represents a critical contribution of the study, positioning the proposed framework as a viable decision-support tool rather than a purely academic forecasting exercise.

3.5 Integrated discussion and research positioning

The results obtained in this study provide strong empirical support for the effectiveness of advanced learning-based approaches in gold price forecasting, particularly when temporal dependencies are explicitly modeled. The superior performance of the Long Short-Term Memory model is consistent with prior studies that emphasize the importance of temporal dependency modeling in financial time series forecasting (Amryliana et al., 2025; Sasikala & Bhuvana, 2024). Gold prices are influenced by historical patterns that unfold over time, and models capable of retaining and selectively updating memory are better suited to capture such dynamics. However, this study goes beyond confirming the predictive advantage of deep learning models. While previous research largely focuses on accuracy improvement, the present work adopts an integrated perspective by explicitly addressing the trade-off between predictive performance and interpretability. This distinction is critical, especially in business-oriented applications where forecasting outputs must support transparent and accountable decision-making. This finding aligns with concerns raised in previous studies regarding the trade-off between predictive accuracy and interpretability in deep learning-based financial models (Majumdar, 2025; Nazir et al., 2022).

The comparative results demonstrate that ensemble-based Machine Learning models, although less accurate than LSTM, remain valuable for their explanatory capabilities. Random Forest and XGBoost consistently identify short-term price trends and daily price ranges as dominant predictors. These findings reinforce theoretical assumptions in financial economics regarding trend persistence and market responsiveness, while also providing interpretable evidence that can be directly communicated to non-technical stakeholders. From a research positioning standpoint, the proposed hybrid framework occupies a distinct space between purely accuracy-driven deep learning studies and interpretability-focused machine learning research. Unlike studies that rely solely on LSTM or other recurrent architectures, this research intentionally integrates multiple modeling paradigms to achieve complementary objectives. The LSTM model functions as the core forecasting engine, capturing complex temporal patterns, while the Machine Learning models serve as explanatory instruments that reveal the structural drivers of gold price movements.

This integrated approach addresses a notable gap in the existing literature. Many gold price forecasting studies treat interpretability as a secondary concern or omit it entirely, thereby limiting their practical relevance. In contrast, this study positions interpretability as an essential component of forecasting performance, particularly within the context of strategic decision support for the bullion business. Furthermore, the findings of this study contribute to the growing body of evidence that hybrid modeling strategies outperform single-model approaches in complex financial environments. By demonstrating that accuracy and interpretability are not mutually exclusive, this research challenges the conventional dichotomy between "black-box" deep learning models and transparent but less powerful machine learning techniques.

In relation to the broader objectives of applied financial analytics, this study aligns closely with the need for decision-oriented modeling frameworks. Rather than producing forecasts in isolation, the proposed approach emphasizes the translation of predictive outputs into strategic insight. This orientation enhances the relevance of the research for practitioners in the bullion industry, including institutions such as Pegadaian, where forecasting tools must support operational planning, risk management, and pricing decisions. Overall, this study positions itself as a methodological and applied contribution to gold price forecasting research. By integrating temporal deep learning with interpretable machine learning, it advances existing knowledge while responding directly to the practical demands of real-world bullion businesses. This positioning strengthens the study's relevance within both academic and industry-oriented discourse, reinforcing its suitability for competitive research and applied analytics contexts.

3.6 Implications for managerial and operational decision support in the bullion business

The findings of this study provide direct and actionable implications for managerial and operational decision processes in the bullion business, particularly for institutions such as Pegadaian that operate at the intersection of gold trading, financing, and risk management. In highly volatile gold markets, the ability to anticipate short-term price movements with high accuracy is a critical determinant of operational efficiency and financial sustainability. First, the superior forecasting performance of the Long Short-Term Memory model offers significant value for procurement and inventory planning. Accurate short-term gold price predictions enable bullion institutions to optimize the timing of gold acquisition and release, reducing exposure to adverse price movements. For Pegadaian, this capability can support more precise planning of gold stock levels across branches, minimizing excess inventory during declining price trends while ensuring availability during periods of rising demand.

Second, the interpretability derived from the Machine Learning models enhances pricing strategy formulation. Feature importance analysis reveals that short-term price ranges and moving average indicators are dominant drivers of daily gold price changes. This insight allows decision-makers to align pricing adjustments with observable market signals rather than relying solely on reactive or heuristic-based approaches. In the context of Pegadaian's gold products, such as gold savings and gold-backed financing, transparent pricing mechanisms are essential for maintaining customer trust and regulatory compliance. Third, the proposed hybrid framework contributes to improved risk management practices. By combining accurate forecasts with explanatory indicators, bullion institutions can better assess downside and upside risks associated with gold price fluctuations. For Pegadaian, this supports more informed decisions related to hedging strategies, collateral valuation, and margin determination in gold-backed lending products. The ability to anticipate volatility-driven price shifts also strengthens institutional resilience against sudden market shocks.

Moreover, the integration of forecasting accuracy and interpretability facilitates organizational decision alignment. While advanced deep learning models often remain confined to technical units, the inclusion of interpretable Machine Learning components enables broader managerial adoption. Strategic insights derived from feature importance rankings can be communicated effectively across operational, financial, and risk management divisions, fostering data-driven decision-making at the organizational level. From a strategic analytics perspective, this study demonstrates that gold price forecasting systems should not function merely as prediction tools but as integrated decision-support systems. The hybrid approach proposed in this research transforms raw predictive outputs into structured business intelligence, bridging the gap between advanced analytics and practical implementation.

In the specific context of Pegadaian, the proposed forecasting framework provides a structured mechanism to support daily operational decisions and longer-term strategic planning. High-accuracy LSTM-based forecasts can be utilized as reference indicators for gold savings pricing, pawn valuation thresholds, and short-term inventory adjustments, while Machine Learning-derived feature importance offers transparent justification for pricing and risk-related decisions. This combination ensures that forecasting outputs are not only statistically robust but also institutionally actionable, reinforcing the role of predictive analytics as a core component of decision support within bullion-based financial institutions. Overall, the implications of this study extend beyond technical performance improvements. By aligning predictive modeling with strategic business needs, the proposed framework supports more efficient, transparent, and resilient decision-making processes in the bullion industry. This alignment is particularly relevant for state-owned or regulated financial institutions such as Pegadaian, where forecasting accuracy, interpretability, and accountability must coexist within a single analytical framework.

4. Conclusions

This study develops and validates a hybrid forecasting framework that integrates Machine Learning and Long Short-Term Memory models to support operational planning and institutional decision support in the bullion business. By treating gold prices as a nonlinear and temporally dependent phenomenon, the proposed approach moves beyond conventional static forecasting paradigms and demonstrates the necessity of time-aware learning mechanisms in volatile commodity markets. The findings affirm that accurate gold price forecasting requires not only numerical precision but also an analytical structure that reflects the sequential nature of financial behavior.

The primary contribution of this research lies in balancing predictive accuracy and interpretability within a unified forecasting framework. The Long Short-Term Memory model achieved the best forecasting performance with a Mean Absolute Percentage Error (MAPE) of 2.27%, substantially outperforming Random Forest (6.97%) and XGBoost (7.69%). While the Long Short-Term Memory model effectively captures long-term temporal dependencies and delivers high-precision forecasts, ensemble-based Machine Learning models provide transparent insights into the key drivers of gold price movements. This dual-model structure helps address a common limitation in existing forecasting studies, where high-performing models often operate as black boxes and provide limited decision-relevant insights.

From an applied perspective, the proposed framework offers substantial value for strategic and operational decision-making in the bullion industry, particularly for institutions such as Pegadaian. Accurate and temporally responsive forecasts can support more effective procurement planning, inventory control, pricing strategies, and risk mitigation in gold-backed financial products. At the same time, interpretable feature importance indicators enable decision-makers to align business actions with observable market signals, enhancing transparency, accountability, and organizational confidence in data-driven strategies.

In conclusion, this study contributes to the advancement of applied financial analytics by presenting a forecasting framework that is both methodologically robust and institutionally relevant. By aligning advanced Machine Learning and Deep Learning techniques with institutional forecasting requirements, this research demonstrates that forecasting systems can function as integrated decision-support tools rather than isolated predictive models, particularly in regulated and risk-sensitive financial institutions. A limitation of this study is its reliance on a single publicly available gold price dataset. Consequently, the findings may not fully capture institution-specific operational conditions or alternative market environments. Future research may extend this framework by incorporating macroeconomic indicators, real-time market signals, and institution-specific data to further strengthen its applicability in dynamic and regulated financial environments.

Acknowledgement

The authors would like to thank all parties who provided valuable input and support during the preparation of this manuscript, including constructive discussions and technical assistance that contributed to the improvement of the study.

Author Contribution

Conceptualization, R. A. Ikasatya.; Methodology, R. A. Ikasatya, C. Apriliani, and F. J. Firdaus.; Software, R. A. Ikasatya; Validation, R. A. Ikasatya, C. Apriliani, and F. J. Firdaus.; Formal Analysis, R. A. Ikasatya.; Investigation, R. A. Ikasatya and C. Apriliani.; Data Curation, R. A. Ikasatya.; Writing – Original Draft Preparation, R. A. Ikasatya; Writing – Review & Editing, C. Apriliani and F. J. Firdaus. All authors have read and agreed to the published version of the manuscript.

Funding

This research received funding support from PT Pegadaian (Persero) under the Call for Paper Bersama Pegadaian 2025 program.

Ethical Review Board Statement

Not available.

Informed Consent Statement

Not available.

Data Availability Statement

The data used in this study are publicly available and were obtained from Kaggle, an open-access data repository. The dataset used is XAU/USD Gold Price Historical Data (2004–2024), which contains historical gold price information covering the period up to 2025 across multiple timeframes, and is accessible under Kaggle's standard usage license.

Conflicts of Interest

The authors declare no conflict of interest. The funder had no role in the design of the study; in the collection, analysis, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Declaration of Generative AI Use

During the preparation of this work, the authors used ChatGPT (OpenAI, GPT-5.5) to assist in improving language clarity, grammar, and academic writing quality. The tool was used solely for language refinement and manuscript editing. After using this tool, the authors carefully reviewed, revised, and validated all content and took full responsibility for the content of the publication.

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