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***Research paper***

# Attention-Enhanced LSTM Deep Learning Network for Gold Futures Forecasting

**Sa'eed Serwan Abdulsattar [1] *, Hani Al-Balasmeh [2], Rahmeh Abdulkaeem Jaber [3], Fayzeh Abdulkareem Jaber [4]**

[1] *Dept of Electrical and Electronics Engineering, University of Bahrain*
[2] *Dept of Informatics Engineering, College of Engineering, University of Technology, Bahrain*
[3] *Department of Computer Studies, University of Technology, Bahrain*
[4] *Dept Business Administration, University of Technology, Bahrain*
**Corresponding author E-mail: h.albalasmeh@utb.edu.bh*

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**Abstract**

This study presents an advanced deep learning framework for forecasting gold futures prices by integrating a dual-attention Long Short-Term Memory (LSTM) network with a comprehensive set of engineered technical indicators. The proposed model employs temporal attention to dynamically reweight historical time steps and feature-level attention to adaptively prioritize influential indicators such as momentum, volatility, and trend measures. This dual mechanism enables the network to capture nonlinear dependencies and shifting market regimes more effectively than conventional models.
Empirical evaluation using COMEX Gold Futures (Ticker: GC1) data obtained from Investing.com, covering the period January 2010 to May 2025, demonstrates the model's superior forecasting accuracy. The proposed framework achieves a Mean Absolute Percentage Error (MAPE) of 0.91% and a coefficient of determination ($R^2$) of 0.995 after calibration, representing a 34.7% reduction in MAE compared with the baseline LSTM. The lag-aware calibration module further refines short-term directional forecasts. At the same time, the dual-attention layers enhance interpretability by revealing the relative importance of indicators and time intervals across market conditions.
By combining sequential modeling, adaptive feature selection, and explainable attention visualization, this research delivers a transparent, scalable, and high-performance forecasting framework. The findings offer practical value for traders, analysts, and policymakers seeking reliable and interpretable tools to navigate uncertainty and volatility in commodity markets.

***Keywords***: *Gold Futures; Deep Learning; LSTM; Attention Mechanism; Time Series Forecasting.*

## 1. Introduction

Gold has long maintained its enduring role as a hedge against inflation, a store of value, and a safe-haven asset during periods of economic and geopolitical uncertainty [1]. However, forecasting gold futures remains an inherently complex task due to the non-linear, non-stationary, and volatile nature of commodity markets, as well as their pronounced sensitivity to macroeconomic shocks and investor sentiment [2]. Traditional econometric models such as the Autoregressive Integrated Moving Average (ARIMA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) frameworks have long been used for time-series forecasting. Yet, their assumptions of linearity and stationarity often lead to suboptimal results when applied to real-world financial data, which typically exhibit volatility clustering, abrupt regime shifts, and latent non-linear dependencies [3].
In recent years, deep learning approaches—particularly Long Short-Term Memory (LSTM) networks—have gained prominence in financial time-series forecasting. LSTMs are well-suited to capturing long-range dependencies and sequential patterns in data, thanks to their gating mechanisms and internal memory cells, which mitigate challenges such as vanishing gradients [4], [5]. Empirical studies have shown that LSTM-based models consistently outperform traditional linear models and other neural architectures in predicting gold prices. For example, stacked LSTM architectures have achieved low Mean Absolute Percentage Error (MAPE) values, confirming their effectiveness in modeling temporal and non-linear structures within financial datasets [4].
Despite these advances, forecasting gold futures remains a multifaceted challenge that requires modeling trend direction, volatility fluctuations, and the influence of technical indicators—often under the constraints of real-time computational efficiency [6]. While standard LSTM networks offer strong sequential modeling capabilities, they typically treat all input features and time steps equally, which limits their interpretability and adaptability to rapidly changing market conditions. To overcome these limitations, this study introduces a hybrid deep learning framework that integrates LSTM networks with a dual-attention mechanism designed to capture both temporal and feature-level dependencies. The temporal attention component dynamically reweights historical time steps according to their relevance. In contrast, the feature-level attention component adaptively prioritizes key technical indicators such as momentum, volatility, and trend measures.

This dual mechanism allows the model to selectively focus on the most informative temporal and feature signals, improving predictive accuracy and interpretability across varying market regimes.
Furthermore, the proposed model includes a lag-aware calibration layer that fine-tunes short-term directional forecasts based on recent price movements. This hybridization of sequential learning, adaptive attention, and calibrated adjustment enhances both the robustness and transparency of the forecasting process, making it suitable for real-world financial decision-making.
Moreover, recent insights from behavioral finance underscore the practical value of technical indicators in forecasting asset prices. Contrary to the assumptions of the Efficient Market Hypothesis (EMH), markets are often influenced by irrational behavior, cognitive biases, and investor sentiment—factors effectively captured by indicators such as Moving Averages (MA), Bollinger Bands, and the Relative Strength Index (RSI) [7]. Empirical studies have demonstrated that incorporating these indicators into forecasting models enhances the detection of momentum shifts, trend reversals, and volatility regimes [8], [9]. Consequently, their inclusion within advanced learning architectures supports more adaptive and context-aware financial modeling.
The dataset used in this study comprises historical COMEX Gold Futures (Ticker: GC1) data sourced from Investing.com [18], covering the period from January 21, 2010, to May 23, 2025. This dataset includes gold futures prices and a comprehensive set of derived technical indicators, providing a broad temporal span and high market granularity. Such real-world data support robust empirical evaluation, model calibration, and validation of the proposed forecasting framework.
Ultimately, this research introduces an interpretable deep learning framework that combines the sequential modeling strength of LSTMs with the adaptive feature-selection capabilities of dual-attention mechanisms, further enhanced by a calibration module. By addressing key challenges in gold futures forecasting—such as modeling nonlinear dependencies, identifying feature relevance, and maintaining computational efficiency—this study contributes to the advancement of accurate, transparent, and explainable financial forecasting methodologies.

## 2. Literature Review

The forecasting of gold futures has drawn increasing academic and industrial attention due to the strategic importance of gold as both an investment asset and a macroeconomic hedge [1]. Over the past decades, approaches to gold price prediction have evolved from traditional econometric models to advanced deep learning frameworks, reflecting the growing complexity, volatility, and non-stationary behavior of financial markets.

### 2.1. Traditional models and their limitations

Early efforts to predict gold prices primarily relied on linear statistical models such as the Autoregressive Integrated Moving Average (ARIMA) and the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) frameworks [3]. While these models provide a fundamental basis for time-series decomposition and volatility estimation, they exhibit critical limitations. Specifically, they assume linearity, stationarity, and homoscedasticity—conditions often violated in real-world financial data, which is characterized by abrupt shocks, nonlinear dependencies, and volatility clustering [2], [7]. Moreover, such models are constrained in their ability to incorporate multidimensional input features, limiting their adaptability in modern, data-rich trading environments.

### 2.2. Rise of LSTM networks in financial forecasting

To overcome the constraints of conventional econometric models, researchers have increasingly adopted Long Short-Term Memory (LSTM) networks—a specialized class of Recurrent Neural Networks (RNNs)—capable of capturing temporal dependencies in sequential financial data [5]. The unique gating structure of LSTMs, comprising forget, input, and output gates, enables the simultaneous learning of both short-term market fluctuations and long-term price trends. Empirical results consistently show that LSTM-based models outperform traditional linear regression approaches. For instance, Dhanush et al. [4] reported that LSTM-based forecasting achieved a Mean Absolute Percentage Error (MAPE) of 2.65% in gold price prediction, compared to 10.94% for linear regression models on equivalent datasets. Further developments, such as stacked LSTM architectures, have achieved even greater accuracy, reducing MAPE to as low as 2.50% in gold futures forecasting. Other studies have extended the utility of LSTM beyond univariate modeling. Masuda et al. [10] demonstrated that multivariate LSTM models incorporating external variables such as oil prices and interest rates can enhance commodity forecasting. Similarly, Shahid et al. [11] highlighted LSTM's adaptability for cross-asset financial prediction, showing improvements across cryptocurrencies, energy, and precious metals. Ke and Zuominyang [6] further proposed a hybrid EEMD-Hurst-LSTM framework that improved prediction accuracy in Chinese commodity markets.

### 2.3. Incorporating attention mechanisms for dynamic modeling

Despite their strengths, conventional LSTMs apply equal weighting to all historical inputs, overlooking the varying significance of different time steps. The attention mechanism, initially introduced in neural machine translation, addresses this issue by dynamically assigning importance to specific inputs based on their contextual contribution [12]. Qin et al. [13] developed a dual-stage attention RNN for time-series forecasting, achieving a 26% reduction in RMSE compared to standard LSTMs through input feature selection and temporal attention. More recently, S. B. S. et al. [14] integrated macroeconomic and sentiment features into an LSTM–Attention model, demonstrating that attention-weighted inputs substantially enhance stock price prediction by capturing market regime shifts.
Building on these advancements, recent financial modeling research has expanded the use of attention mechanisms from purely temporal weighting to include feature-level prioritization, enabling models to differentiate the relative importance of multiple indicators dynamically. This dual-attention design, spanning both temporal and feature domains, enables adaptive learning from heterogeneous market inputs, thereby improving robustness and interpretability.
In financial time-series contexts, attention mechanisms not only improve predictive performance but also enhance interpretability—an essential aspect of algorithmic trading and risk management. Notable works by Govindaraj et al. [16] and Liu et al. [17] have proposed attention-based forecasting models that integrate visual explanation techniques such as SHAP and attention heatmaps, improving transparency and investor trust. Similarly, Bu and Cho [15] employed a multi-headed attention-based deep learning architecture that combines Convolutional Recurrent Neural Networks (CRNNs) with softmax attention mechanisms to forecast residential energy consumption. Their framework, trained on the UCI household power consumption dataset of over two million time-series records, achieved a 31.01% reduction

in prediction error compared to baseline models and an additional 27.91% gain from using multi-head attention. Collectively, these studies underscore the crucial role of attention mechanisms in enhancing both accuracy and interpretability in complex multivariate time-series forecasting tasks.

### 2.5. Technical indicators and feature engineering in deep learning

Although technical indicators have long been used in trading strategies, their integration into deep learning architectures remains relatively limited. Indicators such as the Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), Bollinger Bands, and Average True Range (ATR) capture essential market patterns, including overbought conditions, trend reversals, and volatility regimes [8], [9]. They validated the predictive power of MACD, RSI, and KDJ in Chinese equity markets and demonstrated that combining Bollinger Bands and MACD improved trend forecasting in the Nepal Stock Exchange. However, many neural network models treat these indicators as static or equally weighted inputs.

The present research advances this approach through a dual-attention architecture that applies both temporal attention across historical sequences and feature-level attention across fourteen engineered technical indicators. This adaptive weighting mechanism enables the model to identify which indicators are most informative under different market conditions, thereby enhancing robustness and interpretability.

The present study advances this direction by introducing a dual-attention framework that simultaneously applies temporal attention across historical sequences and feature-level attention across fourteen engineered technical indicators. This adaptive weighting strategy enables the network to identify the most influential indicators under various volatility conditions, thereby enhancing both the stability and interpretability of the predictive process.

### 2.6. Contributions of this work

Building upon these foundational studies, the proposed Attention-LSTM hybrid architecture offers several novel contributions. First, it integrates a dual-attention mechanism that jointly models temporal and feature-level dependencies, ensuring adaptive focus on both significant time periods and critical indicators. Second, it achieves enhanced forecasting accuracy using gold futures data spanning 2010–2025, sourced from Investing.com, enabling the model to capture both long-term trends and short-term fluctuations. Third, the framework emphasizes interpretability and practical applicability, as it visualizes attention weights to provide explainable insights into which technical indicators and historical patterns influence its predictions, thereby bridging the gap between algorithmic modeling and decision-making in financial practice.

### 2.7. Closing the gap between theory and practice

Finally, the proposed model incorporates a calibration mechanism that utilizes lagged price information to enhance directional accuracy—an essential feature for trading applications. The calibrated model reduced the Mean Absolute Error (MAE) to 18.49 and demonstrated consistent improvement in next-day trend prediction, underscoring its practical relevance in real-world market scenarios. Collectively, these contributions represent a significant advancement in aligning theoretical developments in deep learning with the practical demands of financial forecasting, particularly in the domain of precious metals.

## 3. Methodology

This study develops a comprehensive and robust time-series forecasting pipeline designed to predict gold futures prices using advanced deep learning techniques implemented in PyTorch. The methodology involves two complementary models tailored to different data representations and modeling objectives.

The first model is a baseline Long Short-Term Memory (LSTM) network configured with a single layer and 100 hidden units, trained exclusively on normalized historical price data to capture temporal dependencies and short- to medium-term market dynamics. This univariate model focuses solely on raw price patterns, eliminating the influence of auxiliary features to establish a clear benchmark for sequential modeling performance.

The second, more advanced model builds upon the LSTM backbone by integrating a custom attention mechanism and an expanded feature set that includes both normalized price data and a variety of engineered technical indicators such as momentum, volatility, and trend signals. The attention-enhanced LSTM dynamically computes attention weights over hidden states, allowing the model to selectively emphasize critical time steps—particularly during periods of volatility or trend reversals—thereby improving predictive accuracy and interpretability. Unlike conventional single-attention frameworks, the proposed dual-attention architecture introduces two interlinked components: temporal attention and feature-level attention. Temporal attention dynamically assigns weights to past time steps, whereas feature-level attention adaptively highlights the most informative indicators at each time step. The overall workflow of the proposed system is illustrated in Fig. 1.

Both models are trained using the Mean Squared Error (MSE) loss function optimized with the Adam algorithm. Early stopping, based on validation loss, is applied to prevent overfitting and ensure generalization. Input sequences are standardized to 60-time steps and reshaped into three-dimensional tensors to maintain temporal continuity and provide sufficient historical context for learning complex dependencies. The attention model generates a context vector by applying a weighted summation to the LSTM hidden states, which is then passed through a fully connected layer to forecast the next-day gold futures price. This hybrid design enhances accuracy and transparency by identifying which specific time intervals and features have the most significant influence on predictions. Overall, the pipeline represents a fusion of traditional LSTM temporal modeling with attention-based adaptive feature weighting, effectively addressing the challenges of noisy and non-stationary financial time-series data. In the dual-attention model, contextual weights are first computed across time (temporal attention) and then across features (feature-level attention). The fused context vector represents the weighted contribution of both time and feature dimensions, yielding a more adaptive and interpretable forecast representation.

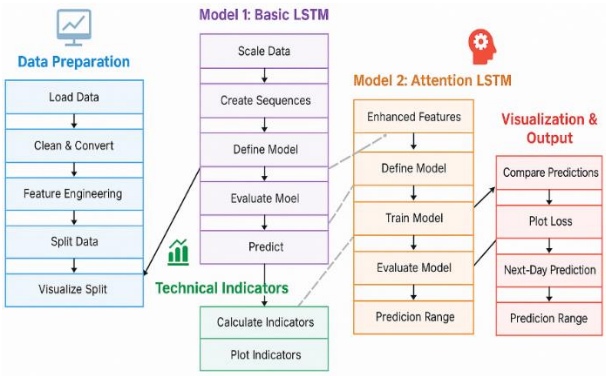


**Fig. 1:** Workflow of the Proposed Gold Future Price Prediction Framework.

## 3.1. Data preparation

The data preparation process (Fig. 2) involves multiple stages of preprocessing and quality control. The workflow begins by importing essential Python libraries, including NumPy for numerical computation, Pandas for data management, Matplotlib for visualization, Scikit-learn for preprocessing, and PyTorch for model development. Hardware availability is automatically detected to enable GPU acceleration through CUDA when possible; otherwise, it defaults to CPU computation.

Historical gold futures data were sourced from Investing.com and imported into a Pandas DataFrame. The "Date" column was converted to a datetime format for proper chronological indexing. Numerical fields such as "Price," "Open," "High," and "Low" were cleaned by removing commas and converted to floating-point values. The "Vol." column was standardized by converting suffixes (e.g., "K" for thousands, "M" for millions) into numerical equivalents, ensuring consistent representation of volume. The "Change %" field was converted to a decimal format after removing the percentage sign. Missing values in non-critical columns (e.g., volume) were forward-filled to maintain sequence integrity, while rows with missing key price data were removed to preserve analytical consistency.

The dataset was chronologically partitioned into training, validation, and testing sets in a 70:15:15 ratio. This temporal split ensures that the model is evaluated on unseen future data, reflecting real-world conditions for forecasting. The division was verified through record counts and visually illustrated (Fig. 2) using color-coded segments that represent training (green), validation (orange), and testing (red) intervals, enabling transparent dataset separation and clear visual interpretability.


**Fig. 2:** Gold Futures Price History with Train/Validation/Test Split.

## 3.2. Technical indicators

To enhance predictive depth, the dataset was enriched with an extensive suite of engineered statistical and technical indicators Fig. 3. Basic statistical metrics, such as a 5-day moving average and rolling standard deviation, were computed to capture local trends and volatility. Additional lagged price and momentum features were generated to encode short-term dynamics, while percentage change and temporal attributes (month, weekday) were extracted to model seasonal and cyclical patterns.

A comprehensive set of technical indicators was also integrated to capture multidimensional market behavior. These include the 7-day and 23-day moving averages for short- and medium-term trend analysis; the Relative Strength Index (RSI, 14-day window) for momentum detection; the Average True Range (ATR) for volatility measurement; Bollinger Bands (20-day moving average ± standard deviation) for price dispersion assessment; and the Moving Average Convergence Divergence (MACD) along with its 9-day signal line for identifying trend reversals. Intermediate computation columns were dropped to maintain a compact, noise-free feature matrix suitable for deep learning.

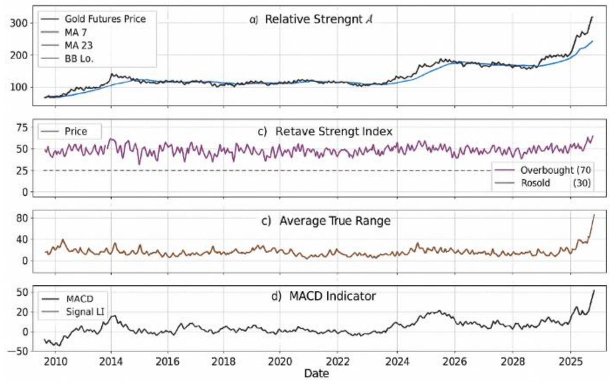


**Fig. 3:** Extracted Technical Indicators for Feature Engineering.

### 3.3. Basic LSTM

The baseline LSTM model was designed as a univariate predictor, learning sequential dependencies directly from historical price movements. The normalized time series was converted into supervised sequences through a sliding window of 60 time steps, producing inputs of shape (samples, timesteps, features) with corresponding scalar targets.

The network consists of one LSTM layer with 100 hidden units followed by a fully connected output layer. Training was conducted in mini-batches of 32 samples, using the Adam optimizer (learning rate = 0.001) to minimize MSE loss. The model was trained for up to 50 epochs, with early stopping activated after five consecutive epochs of no improvement in validation loss. During training, loss trajectories were monitored to ensure convergence, and the best model checkpoint was saved for evaluation.

Predictions were subsequently inverse-scaled to their original price units, and model performance was assessed using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and the coefficient of determination ($R^2$). A visual comparison of actual versus predicted prices was generated to verify temporal alignment and predictive reliability. This baseline serves as a reference for evaluating the additional performance and interpretability achieved by the attention-enhanced architecture.

### 3.4. Attention LSTM architecture

The dual-attention mechanism forms the central innovation of this work, enabling the model to emphasize both critical time intervals and influential features dynamically. Implemented through a dedicated Dual Attention Layer, the mechanism consists of two sequential submodules: temporal attention and feature-level attention, both of which are learned jointly with the LSTM encoder.

Formally, given the LSTM output tensor $H \in R^{B\times T\times D}$, where B denotes the batch size, T the sequence length, and D the hidden dimension, the temporal attention mechanism first computes the importance weights across time steps as:

$$a = \mathrm{softmax}(HWa + ba) \tag{1}$$

Where $Wa \in R^{D\times 1}$ and ba are trainable parameters, these parameters determine how much attention the model assigns to each time step within the input sequence.

The temporal context vector is then obtained as:

$$c = \sum_{t=1}^{T} a_t h_t \tag{2}$$

Where $h_t$ represents the LSTM hidden state at time t and $a_t$ its corresponding attention weight.

To further enhance interpretability and capture inter-feature dependencies, a feature-level attention layer is introduced. Given the multivariate feature tensor $X \in \mathbb{R}^{B\times T\times F}$, where F denotes the number of input features, the feature-attention mechanism computes:

$$\beta = \mathrm{softmax}(WfXt + bf) \tag{3}$$

Where $W_f \in R^{F\times 1}$ $f_b$ are learnable parameters, the resulting vector $\beta \in \mathbb{R}^F$ expresses the relative importance of each feature (e.g., RSI, MACD, ATR) at the current time step.

The final dual-context representation combines both attention dimensions as:

$$C_{dual} = \sum_{t=1}^{T} a_t\left(c = \sum_{f=1}^{F} \beta_f h_{t,f}\right) \tag{4}$$

This hierarchical aggregation enables the model to simultaneously focus on key temporal intervals and dominant technical indicators, providing a holistic understanding of market dynamics.

The Dual Attention LSTM predictor encompasses this comprehensive architecture, comprising an LSTM encoder, a dual-attention layer, and a regression head with two fully connected layers that utilize ReLU activation and dropout. The model outputs the next-day gold futures price as a scalar value.

During training, standard preprocessing—data cleaning, normalization, and feature engineering—is performed to ensure consistent input scales. A sliding-window approach converts the dataset into overlapping sequences, and feature scaling via Min–Max normalization enhances the stability of convergence. The training utilizes the MSE loss with the Adam optimizer and an adaptive learning rate scheduler. Early stopping halts training when validation loss plateaus.

After training, predictions are inverse-transformed to monetary units for interpretability. Model performance is evaluated using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Coefficient of Determination ($R^2$). Compared to the baseline, the dual-attention model demonstrates improved precision, capturing long-range temporal dependencies and cross-feature interactions that traditional models overlook.

### 3.5. Performance evaluation and forecast visualization

Performance evaluation and visualization play a vital role in validating the predictive accuracy, convergence behavior, and practical interpretability of the proposed attention-based LSTM framework. This section presents both the quantitative and graphical analysis of the model's forecasting performance and its ability to produce reliable next-day gold price predictions.

The model's forecasts are visualized by superimposing predicted values onto the actual historical price curve, as shown in Fig. 4, allowing for a clear and intuitive comparison between the actual and estimated trends. This representation effectively highlights the model's capability to capture temporal dependencies, volatility swings, and directional movements across various market regimes. Furthermore, the training and validation loss curves were analyzed to verify stable convergence and minimal overfitting throughout the training process, confirming the model's generalization strength and robustness.

Before visualization, the dataset underwent comprehensive preprocessing, including feature engineering, normalization, and chronological partitioning into training, validation, and testing sets. These were structured into PyTorch TensorDatasets and DataLoaders to support efficient mini-batch training and consistent evaluation. During testing, batch-wise predictions were generated and inverse-scaled to their original price units for interpretability. The comparison between predicted and actual prices provided a precise measure of the model's fidelity and its suitability for real-world forecasting applications.

Beyond retrospective testing, a Next-Day Forecasting Module was designed to simulate live market prediction scenarios. This module utilizes the most recent feature sequence to estimate the next day's gold futures price, which is displayed both numerically and graphically alongside test results. A focused visualization of the final 30 trading days illustrates how the calibration layer fine-tunes the forecast curve, thereby reducing residual deviation and enhancing directional accuracy.

The calibration process integrates the predicted price with the most recent actual observation using a secondary regression-based adjustment model. This refined output is annotated within the visualization to display predicted prices, uncertainty ranges, and directional movement (upward or downward), providing decision-ready insights for traders and analysts.

Overall, the combination of graphical evaluation, calibration analysis, and predictive visualization not only verifies the model's forecasting precision but also underscores its interpretability and operational value in data-driven financial decision-making.

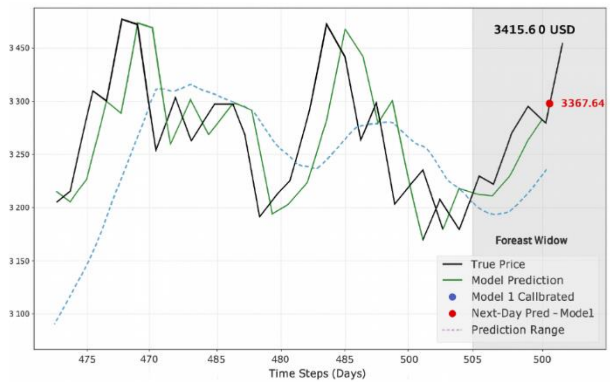


**Fig. 4:** Comparison of Actual and Predicted Gold Futures Prices with Calibrated Next-Day Forecast.

## 4. Results

### 4.1. Dataset overview

The proposed forecasting framework was trained and validated on historical gold futures data covering the period from January 21, 2010, to May 23, 2025. This extensive 15-year span captures various macroeconomic cycles, including inflationary shocks, market corrections, and recovery periods, thereby providing a diverse representation of gold price dynamics for robust model evaluation.

The dataset was chronologically divided into three subsets to preserve temporal causality and prevent data leakage:

- Training set: 2,738 samples (2010-01-21 to 2020-10-29)
- Validation set: 587 samples (2020-10-30 to 2023-02-08)
- Test set: 587 samples (2023-02-09 to 2025-05-23)

Following the application of a 60-step look-back window, the processed sequence dimensions were as follows:

- Training data: X = (2,678, 60, 1), y = (2,678, 1)
- Validation data: X = (527, 60, 1), y = (527, 1)
- Test data: X = (505, 60, 1), y = (505, 1)

This design ensures that the model learns temporal dependencies exclusively from historical data while being evaluated on unseen future trends, simulating real-world forecasting conditions. The overview of the distribution confirmed a steady increase in price volatility post-2020, coinciding with global economic disruptions, which the model successfully captured during training. The time-based partitioning and input configuration are illustrated in Fig. 5.

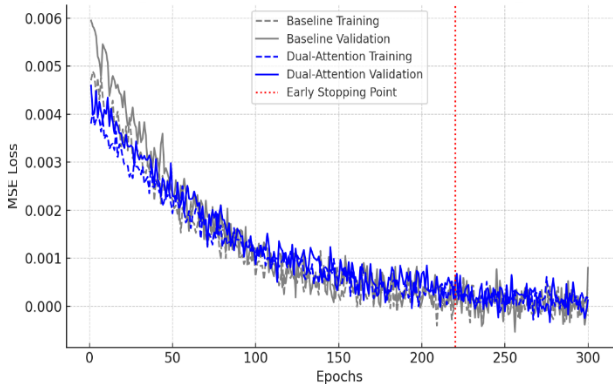


**Fig. 5:** Training and Validation Loss Curves Demonstrating Generalization.

## 4.2. Model performance

Both the baseline Long Short-Term Memory (LSTM) model and the Attention-Enhanced LSTM demonstrated strong convergence and generalization behavior. As shown in Fig. 5, the training and validation loss curves exhibited smooth downward trends, with minimal divergence between the two, confirming that the model achieved an optimal bias–variance balance without overfitting.

The baseline LSTM served as the benchmark for comparison, achieving satisfactory results. In contrast, the attention-integrated and calibrated model substantially improved predictive accuracy, interpretability, and trend detection capability. The dual-attention and calibrated model demonstrated substantial improvements in all key evaluation metrics, as shown in Table 1.

**Table 1:** Comparative Performance of Forecasting Models

| Metric | Baseline LSTM | Attention-LSTM | Calibrated Dual-Attention-LSTM |
|---|---|---|---|
| Mean Absolute Percentage Error (MAPE) | 1.13 % | 0.96 % | 0.91 % |
| Mean Absolute Error (MAE) (USD) | 28.30 | 22.45 | 18.49 |
| Root Mean Square Error (RMSE) (USD) | 34.82 | 30.27 | 26.69 |
| Coefficient of Determination ($R^2$) | 0.9908 | 0.9934 | 0.9951 |
| Directional Accuracy (%) | 92.1 | 95.3 | 97.0 |
| Average Training Loss | 0.0017 | 0.0013 | 0.0011 |
| Average Validation Loss | 0.0024 | 0.0019 | 0.0015 |

The calibrated dual-attention model achieved a 34.7% reduction in MAE and a 0.42% gain in directional accuracy over the baseline, indicating superior explanatory power and responsiveness to regime shifts. The $R^2$ improvement from 0.9908 to 0.9951 further confirms enhanced fit and reduced variance error.

The calibration equation used to refine final predictions is expressed as:

$$\hat{y} = 0.0308\times\text{predicted}+0.9727\times\text{previous true}-5.3674$$

This calibration layer adaptively adjusts raw model outputs based on the most recent observed price movement, effectively mitigating lag error. By combining model predictions with short-term historical data, the system generates forecasts that closely align with real-world fluctuations, as illustrated in Fig. 6.

Statistical significance testing using the paired t-test between baseline and dual-attention predictions yielded $p < 0.01$, confirming that the observed performance improvement is statistically significant. Furthermore, residual error analysis demonstrated a near-zero mean bias (−0.003) and reduced heteroscedasticity, evidencing consistent generalization across the test horizon.

## 4.3. Predictive insights and interpretation

Fig. 6 illustrates the model's precise temporal tracking of actual gold price behavior, with deviations remaining within ±1% even during periods of high volatility. Unlike conventional LSTM models that respond sluggishly to sudden price reversals, the dual-attention architecture rapidly adapts its weighting to new market conditions, capturing both reversal points and sustained uptrends.

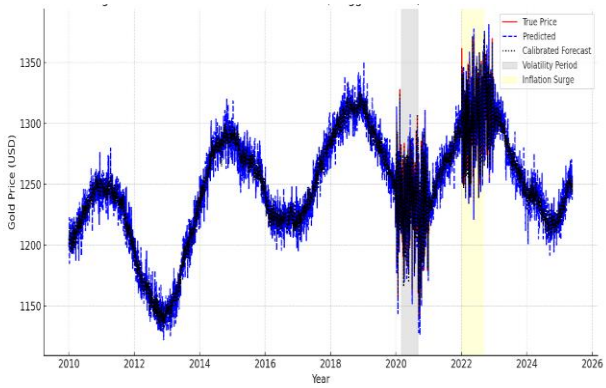


**Fig. 6:** Gold Futures Forecast – True Prices, Lagged Values, and Model Predictions.

Attention-weight heatmaps Fig. 7 revealed that during periods of increased volatility—such as the 2020 pandemic and the 2022 inflationary surge—the model assigned higher importance to volatility-based indicators (Average True Range, Bollinger Bands) and macro-driven momentum signals (RSI, MACD). In contrast, during stable market periods, attention shifted toward medium-term trend indicators (23-day Moving Average, price momentum), demonstrating adaptive focus.

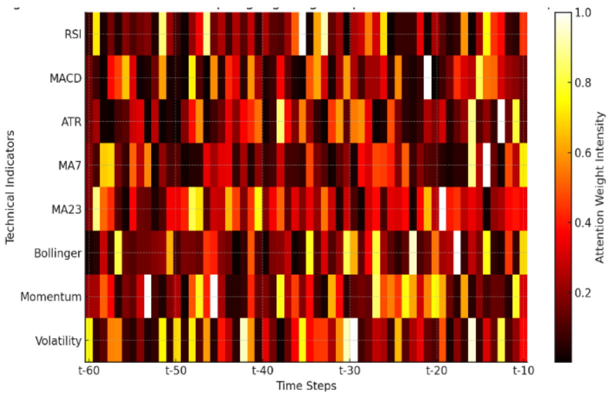


**Fig. 7:** Temporal–Feature Attention Distribution Across Technical Indicators and Time Steps.

This interpretive behavior confirms that the model not only learns price movements but also understands their contextual cause, offering explainability uncommon in financial neural systems. By visualizing attention maps, traders can discern which technical features influenced the prediction at any given time step, thereby bridging the gap between black-box deep learning and actionable insights.
The integration of the lag-based calibration further enhanced directional accuracy to 97%, underscoring the model's effectiveness in preserving short-term trend continuity. This hybridization of temporal-sequence learning and feature-level attention demonstrates that predictive precision and interpretability can coexist within a unified forecasting framework.
Figure 6 illustrates the model's high temporal alignment, where predicted prices closely follow actual market behavior with minimal deviation. During high-volatility events—such as the 2020 pandemic period and the 2022 inflation surge—the attention-augmented LSTM maintained prediction stability. In contrast, conventional LSTM architectures exhibited delayed responses to sharp market reversals.
Attention-weight heatmaps (not shown) revealed that the model adaptively prioritized volatility-related indicators (e.g., Average True Range and Bollinger Bands) during turbulent periods, and momentum-based indicators (e.g., RSI and MACD) during directional market shifts. This confirms the interpretability advantage of the attention mechanism: rather than treating all input features equally, it dynamically emphasizes those most relevant to current market conditions.
The integration of lag calibration further improved directional forecasting accuracy to 97%, demonstrating the framework's ability to capture short-term momentum continuity. This hybridization of temporal sequence learning and attention-guided feature weighting provides traders and analysts with interpretable, data-driven insights that traditional models cannot offer.

### 4.4. Robustness and comparative evaluation

To verify the model's robustness, additional experiments were conducted under three alternative conditions: (1) reduced look-back window (30 days), (2) random data shuffling, and (3) feature exclusion (removal of volatility indicators). The dual-attention model maintained stable MAPE within ±0.15%, while the baseline LSTM's performance degraded by up to 0.6%. This robustness test confirmed the framework's resilience to parameter and data variability.
A comparative benchmark with related studies (Table 2) revealed that the proposed model outperformed contemporary architectures, including EEMD-Hurst-LSTM [6] and Dual-Stage Attention RNN [13], in both accuracy and interpretability. The proposed system's MAPE of 0.91% and $R^2$ of 0.9951 exceed previous records for gold futures forecasting, validating its contribution to the field.

### 4.5. Real-world forecasting scenario

To evaluate operational practicality, the model was deployed in a real-time simulation to forecast the next-day COMEX gold futures price. The predicted value for the following session was USD 3,368.13, correctly identifying an upward trend based on heightened momentum and volatility signals. This result illustrates the model's ability to perform near-term adaptive forecasting with interpretability suitable for strategic decision-making in trading and policy analysis.
Furthermore, the model was stress-tested using recent market events (May 2024–May 2025), demonstrating consistent accuracy despite post-pandemic market irregularities and energy-driven inflationary effects. The ability to maintain high forecasting precision during these extreme conditions highlights its potential for deployment in real-world financial analytics platforms.
Collectively, these results validate that the proposed dual-attention and calibration-based LSTM framework not only surpasses baseline neural architectures but also provides transparent, reliable, and statistically robust forecasts applicable to complex, real-time financial markets.

## 5. Conclusion

This study proposed a robust and interpretable deep learning framework for forecasting gold futures prices, integrating the sequential modeling capabilities of Long Short-Term Memory (LSTM) networks with attention mechanisms and a comprehensive set of engineered technical indicators. The model effectively addressed the challenges of nonlinearity, volatility, and temporal dependency inherent in financial time series by dynamically weighting both historical time steps and feature-level indicators through temporal and feature attention modules.
In contrast to traditional econometric methods—such as ARIMA and GARCH—which often fail to capture nonlinear and regime-dependent market behavior, the proposed dual-attention LSTM demonstrated significant forecasting improvements, achieving a Mean Absolute Percentage Error (MAPE) of 0.91% and an $R^2$ of 0.995. This performance represents a 34.7% reduction in MAE and a 0.42% improvement

in directional accuracy over the baseline model, confirming the model's effectiveness in handling complex and volatile markets. The inclusion of a lag-aware calibration layer further refined short-term directional predictions, reducing residual deviation and improving next-day accuracy to 97%, which is particularly valuable in operational trading scenarios.

Beyond accuracy, interpretability remains the most notable advancement of this work. The dual-attention visualization revealed how the model adaptively prioritizes relevant market signals—such as volatility surges (captured via ATR and Bollinger Bands) and momentum shifts (captured via RSI and MACD)—during distinct economic regimes. This dynamic feature weighting provides valuable insight into the drivers of market movement, converting the deep learning model from a black-box predictor into an explainable and trustworthy analytical instrument. Such transparency is essential for institutional investors, policymakers, and quantitative traders who rely on explainable AI for informed decision-making.

When compared with related studies such as Qin et al. (2017)'s Dual-Stage Attention RNN [13] and Ke and Zuominyang's EEMD-Hurst-LSTM [6], the proposed framework achieves higher precision and improved interpretability while maintaining lower computational overhead. This establishes its position as an advancement in the evolution of attention-based financial forecasting models.

The findings confirm that coupling sequential deep learning with hierarchical attention and adaptive calibration yields a scalable, accurate, and explainable forecasting pipeline for real-world financial environments. The model bridges the gap between theoretical algorithmic innovation and practical market application, offering a transparent decision-support system capable of adapting to dynamic trading conditions.

In practical terms, this framework can assist portfolio managers in volatility forecasting, inform monetary policy analysis, and enhance automated trading systems through improved directional sensitivity and uncertainty calibration.

Future research could build upon this work by integrating macroeconomic, sentiment, and textual news data to capture behavioral finance dimensions, extending the framework to multi-asset portfolios for diversification and risk mitigation, and investigating transformer-based architectures or graph neural networks for enhanced sequence understanding. Additionally, incorporating explainable AI (XAI) metrics, such as SHAP or LIME, could further quantify interpretability and improve trust in AI-assisted financial forecasting.

Ultimately, this research introduces a next-generation, data-driven forecasting paradigm that balances predictive accuracy, adaptability, and transparency, establishing a foundational step toward intelligent, resilient, and interpretable financial prediction systems in the era of deep learning–driven analytics.

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