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ANALYSIS OF GOLD PRICE PREDICTION USING COMMODITY AND FOREIGN EXCHANGE MARKET INDICATORS WITH UNIDIRECTIONAL AND BIDIRECTIONAL DEEP LEARNING MODELS

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ABSTRACT

Gold is an important precious metal widely traded in global financial markets, and its price dynamics interact with various commodity and financial indicators. The current study investigates the performance of unidirectional and bidirectional deep learning architectures in gold price forecasting through comparative analyses. The empirical application consists of a dataset containing daily closing prices for Gold (ALT), Silver (GMS), Platinum (PLT), Copper (BKR), Crude Oil (BTL), Exchange Rate (USDTL) and the Dollar Index (DXY). Daily closing prices for the period between June 8, 2018 and February 3, 2026 were obtained and the relationships between the variables were evaluated using Pearson correlation analysis. The findings showed that precious metals exhibit strong positive correlations among themselves, while crude oil clearly diverges from this group. Specifically, there is a strong positive correlation between ALT and GMS, and between GMS and PLT, while there is a very weak negative correlation between precious metals and BTL. Relationships with the dollar index generally exhibit a limited and heterogeneous structure. During the prediction phase, the data set was split into 80% training and 20% testing using LSTM, GRU, Bi-LSTM and Bi-GRU models. Model performance was evaluated using RMSE, MAE and MAPE metrics. The results revealed that GRU and Bi-GRU architectures have lower error values for some variables, while the Bi-LSTM model does not provide a general performance advantage. Overall, the results demonstrate that deep learning-based approaches offer an effective tool for modeling the price behavior of commodities and foreign exchange markets affected by gold and constitute a strategic decision support mechanism for sustainable finance.

KEYWORDS: Time Series Forecasting, Recurrent Neural Networks (RNN), Bi-LSTM, Bi-GRU, Crude Oil, Silver, Copper, Platinum, Dollar Index, Exchange Rate Volatility.

1. INTRODUCTION

Gold, the yellow shiny metal, has been a favorite of humanity throughout the ages. From jewelry making to its use as an investment tool, gold has brought convenience and prosperity to human life by covering a very wide range of uses. Such metals have been bought and sold worldwide for centuries. Gold carries a safe-haven value, is inherently stable and does not fluctuate significantly, making it a preferred investment option against currency depreciation. Gold T+D, gold ETFs, gold concept stocks and other investment forms have the potential for long-term value appreciation. Although the price of gold fluctuates in the short term, it serves as a safe haven, particularly during periods of political and economic instability, to preserve the value of assets. In addition, it can curb inflation, act as an indirect medium for international payments and guarantee countries' payment power. Gold reserves are also an important resource for stabilizing the national economy and curbing inflation. Investing in spot gold can outperform inflation and risk hedging (Yiying, 2023).

Rapid developments in modern industry, science and technology have further increased gold's economic importance and diversified its uses. Due to its conductivity in the electronics industry, its biocompatibility in medicine and its durability in space technology, gold has become an indispensable input for high-tech products. These developments have led to an increase in demand for gold not only for investment purposes but also for industrial uses. Therefore, gold prices are affected not only by developments in financial markets but also by industrial production, technological innovations and global growth dynamics. In recent years, increasing geopolitical tensions, regional wars and economic crises around the world have deepened the climate of uncertainty and further strengthened demand for gold. During this period, gold has been seen as a hedge against inflation in many countries; uncertainties in monetary policy and global liquidity conditions have made fluctuations in gold prices more pronounced (Ghande & Bhat, 2026).

The complex structure of the gold market causes prices to exhibit high volatility in the short term and to follow certain trends in the long term. Numerous factors, such as interest rates, exchange rates, global liquidity conditions, geopolitical risks and macroeconomic uncertainties, affect gold prices simultaneously and non-linearly. This multifactorial structure makes gold price forecasting quite challenging and underscores the limitations of traditional statistical methods (Zangana & Obeyd, 2024). These limitations have increased the need for more flexible, data-driven methods capable of capturing non-linear relationships in gold price forecasting. Linear time series models, widely used in the literature, can produce satisfactory results under certain assumptions, but they can be inadequate during periods dominated by sudden regime shifts, volatility clustering and non-linear dependencies.

In addition to the gold market addressed in the current study, other commodities and financial indicators such as silver, platinum, copper, crude oil, the dollar index and exchange rates are also priced within the global economic system through different but interrelated dynamics. Silver and platinum stand out as hybrid assets that respond simultaneously to both investor behavior and real sector demand, owing to their higher share of industrial use compared to gold. Silver is sensitive to industrial cycles due to its widespread use in electronics, renewable energy and medical applications; however, it also tends to move in tandem with gold during periods of financial uncertainty, reflecting its safe-haven characteristics (Pushpa et al., 2025). Platinum, on the other hand, has a highly sensitive price structure to changes in global production volume, environmental regulations and industrial policies, particularly due to its intensive use in the automotive sector for catalytic converter production. This dual-character structure causes both short-term fluctuations and medium-term regime shifts to be observed simultaneously in the price series of these commodities, necessitating the use of advanced time series modeling techniques (Xu et al., 2023).

Copper and crude oil are among the most fundamental indicators of global economic activity and react extremely quickly to disruptions in supply-demand balances. Copper is often referred to as the "thermometer of the economy" because it is directly linked to infrastructure investments, industrial production and the green energy transition in developing economies, particularly in China. China's growing demand for copper and platinum in electric vehicles, renewable energy infrastructure and the defense industry links the prices of these metals not only to financial speculation but also to long-term structural transformations (Zhang et al., 2025). Crude oil, on the other hand, is a strategic commodity shaped by OPEC+ decisions, global stock levels and geopolitical supply risks. It has been subject to significant price shocks in recent years, particularly due to the Russia-Ukraine war, ongoing conflicts in the Middle East and energy-based political tensions between the US and Venezuela (Zhou et al., 2026).

Such geopolitical developments lead to sudden regime shifts and volatility clusters in the oil market, significantly complicating the predictability of price series.

In the context of financial indicators, the dollar index (DXY) and exchange rates are at the intersection of global and local economic dynamics. The dollar index exhibits sensitivity to tightening or easing steps in US monetary policy, recession expectations in Europe and America and global capital flows. The US Federal Reserve's interest rate policies, debt crises in Europe and fluctuations in global risk appetite indirectly affect commodity prices through the dollar index (Hossain et al., 2024). The risk perception created by global developments such as the Russia-Ukraine war, the conflicts between Iran and Israel and the instability in the Middle East is reflected in commodity markets through both the dollar index and the exchange rate channel, and this multi-layered network of interactions makes modeling financial time series more complex (Denie et al., 2024). Therefore, evaluating all the variables considered in the current study together allows for a more comprehensive and realistic analysis of market dynamics.

The aim of the current study is to expand research in this field and provide a more in-depth analysis by focusing on the application of deep learning models in gold price forecasting. The objective of the study is to better understand the potential of deep learning architectures in financial forecasting and analysis. In recent years, deep learning-based models have gained increasing importance in the financial forecasting literature, particularly due to their ability to learn long-term dependencies and complex patterns in time series data. Recurrent neural network architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) can effectively model time dependencies in sequential data and selectively retain past information in memory. The gate mechanisms offered by these models provide more balanced learning processes, especially in the face of noisy structures and sudden shocks frequently observed in financial time series. The literature frequently reports that these models offer more successful prediction performance compared to traditional methods in highly volatile and multifactorial series such as gold (Wibawa et al., 2022).

The study aims to comparatively examine the performance of LSTM, GRU, Bi-LSTM and Bi-GRU deep learning models in predicting gold prices and to reveal the extent to which these architectures can capture different time series dynamics. Within the scope of the study, the explanatory power of unidirectional and bidirectional recurrent neural network architectures on the nonlinear structure of gold prices is empirically evaluated. Thus, it is aimed to contribute to the literature methodologically by analyzing which model types can more effectively represent the complex and dynamic structure of the gold market. The findings are expected to be instructive for both academic studies and investment decisions.

2. LITERATURE REVIEW

In recent years, the digitization of global markets has led to a marked increase in the academic literature on commodity and exchange rate markets. These developments are paving the way for new research paradigms at the intersection of environmental sustainability and financial innovation.

Saracık and İncekırık (2023) applied LSTM and GRU methods in the Google Colab software program to predict the stock prices of five companies listed on the XELKT index of the Istanbul Stock Exchange. The data set used covers the period from January 2, 2013 to December 30, 2022. The most successful predictions were determined in analyses conducted over four different days. Since the model performance metrics obtained were below 1 for MSE and below 5% for MAPE, it was concluded that both techniques performed successfully. When these two techniques were compared, it was observed that the LSTM technique was slightly more successful than the GRU technique.

Yousufi and İncekırık (2024) studied the fundamental components of the digital economy and the prediction of Ethereum's price movements in the cryptocurrency market using deep learning techniques. In the study, RNN, LSTM and GRU models were used for Ethereum price predictions and the performance of these models on time series data was measured. The data underwent various preprocessing steps such as scaling, sequence generation and model training, and performance evaluation was analyzed using metrics such as MSE, MAE and MAPE. The analysis results revealed the potential and reliability of deep learning algorithms in financial market predictions.

Kayathıngal et al. (2025) used Wolfram Mathematica to examine the application of seven deep neural network architectures (LSTM, CNN, MLP, MLP-CNN, MLP-LSTM, LSTM-CNN and LSTM-CNN-LSTM) in predicting the prices of precious metals. Ten-year daily price series for gold, silver and platinum were obtained. Model performances were evaluated using RMSE, MAPE and RMSE metrics. The results showed that all neural network models perform strongly, as these techniques capture long-term dependencies for better decision-making in commodity markets. Compared to individual neural networks, the hybrid neural network demonstrated superior performance. The LSTM-CNN-MLP model is a highly reliable and robust technique for predicting precious metals. This clearly demonstrates that neural networks play an important role in predicting time series data.

Varshini et al. (2024) aimed to predict metal futures in commodity markets, including gold, silver, copper, platinum, palladium and aluminum, using various machine learning and deep learning models. Stacked Long-Short Term Memory, Convolutional LSTM, Bidirectional LSTM, Support Vector Regressor, Gradient Boosting and Gated Recurrent Unit models were used. Model performance was evaluated using multiple metrics, such as Root Mean Square Error, Mean Absolute Error and Mean Absolute Percentage Error. The study simultaneously addressed multiple metal commodity futures and combined both Machine Learning and Deep Learning models. Additionally, different inputs from 30-day and 60-day periods were used for robustness checks. The Mean Absolute Percentage Error values showed that different machine learning and deep learning models are effective in predicting future metal prices. However, model performance varies significantly depending on metal selection, sampling period and the impact of inputs on prediction performance.

Cohen and Aiche (2023) explored the potential of advanced Machine Learning (ML) methodologies to predict fluctuations in gold prices. The study used data from leading global stock indices, the S&P500 VIX volatility index, major commodity futures and 10-year bond yields from the US, Germany, France and Japan. Three machine learning models were applied to predict future gold prices: Random Forest, Gradient Boosted Regression Trees (GBRT) and Extreme Gradient Boosting (XGBoost). This study found that the most effective stock indices for prediction were the ASX, S&P500, TA35, IBEX and AEX with one-day lagged data, along with U.S. and Japanese bond yields and lagged data for gas and silver. The models in the study identified that the one-day lagged VIX score and the VIX dummy variable have a significant effect on the gold price, demonstrating that economic uncertainty affects gold prices.

Foroutan and Lahmiri (2024) applied 16 deep learning models to predict the daily prices of West Texas Intermediate (WTI) crude oil, Brent crude oil, gold and silver markets. The deep learning models used in the study are: long short-term memory (LSTM), BiLSTM, gated recurrent unit (GRU), bidirectional gated recurrent units (Bi-GRU), T2V-BiLSTM, T2V-BiGRU, convolutional neural networks (CNN), CNN-BiLSTM, CNN-BiGRU, temporal convolutional network (TCN), TCN-BiLSTM and TCN-BiGRU. To evaluate the prediction performance of deep learning models, the mean absolute error (MAE), mean absolute percentage error and root mean square error criteria were used, and they were compared with basic random forest, LightGBM, support vector regression and k-nearest neighbor models. Considering different sliding window lengths, the prediction performance of the models was examined. It was found that the TCN model performed better than the others for WTI, Brent and silver, achieving the lowest MAE values of 1.444, 1.295 and 0.346, respectively. The BiGRU model showed the best performance for gold with an MAE of 15.188 using a 30-day input sequence. Furthermore, LightGBM showed comparable performance to TCN and was the best performing machine learning model overall.

Derakhshani et al. (2024) conducted a study to address the gap in copper price prediction using a one-dimensional convolutional neural network (1D-CNN). The analysis was performed using data covering the period from November 1991 to May 2023. To evaluate the performance of the CNN model, standard evaluation metrics such as the R-value, mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE) were used. The proposed artificial intelligence algorithm demonstrated high accuracy in predicting global copper prices. Future global copper prices were predicted by CNN through 2027 and compared with forecasts published by the International Monetary Fund and the International Automation Association. Thus, CNN's outstanding performance was demonstrated.

Roy et al. (2024) focused on predicting the future values of gold and silver futures using advanced machine learning algorithms in their study. The study evaluated the performance of four unconventional machine learning algorithms: Gaussian Processes, Quantile Regression Forests, Overfitting Machines and RBF-kernel Support Vector Regression. The dataset used contained monthly transaction data for gold and silver futures. The findings of the study showed that these machine learning models significantly improved prediction accuracy. In this study, RBF-kernel Support Vector

Regression showed the highest accuracy in gold futures predictions, while Overfitting Machines demonstrated competitive performance for silver futures.

In Guo (2024), an LSTM (Long Short-Term Memory Network) gold price prediction model was proposed. Data from 2013 to 2023 was used. The results showed that the model has an excellent prediction effect with an accuracy rate of 96.9%. This study used an LSTM network to predict gold prices and verified the model's performance and accuracy through a series of data processing, model training and evaluation steps.

In their recent published paper, Sari et al. (2025) used a long short-term memory (LSTM) artificial intelligence model to predict copper prices. To increase the efficiency of the long short-term memory (LSTM) model, they employed a simulated annealing (SA) algorithm to find the best hyperparameter combination. The feature engineering problem of the artificial intelligence model was then solved using correlation analysis. Three economic indicators highly correlated with copper prices - West Texas Intermediate Crude Oil Price, Gold Price and Silver Price - were selected as inputs for the training and prediction model. Three different copper price time periods, 485, 363 and 242 days, were taken for model predictions. The prediction errors were 0.00195, 0.0019 and 0.00097, respectively. Compared to the current literature, this study's prediction results were found to be more accurate and contain fewer errors.

This literature review provides a comprehensive conceptual foundation on commodity and foreign exchange markets, price prediction models, investor sentiment and sustainability-focused market dynamics. The large dataset, which encompasses the holistic modeling of multivariate long-term datasets using modern deep learning techniques, aims to contribute to the literature both methodologically and practically with its multidimensional variable structure and prediction models.

3. DEEP LEARNING TECHNIQUES

Machine learning is defined as a set of algorithms that improve their performance through experience (Mitchell, 1997), while deep learning represents an advanced subfield that can automatically learn complex and non-linear patterns in data through multi-layered artificial neural networks (LeCun et al., 2015). The ability to model long-term dependencies, especially in time series data, makes deep learning methods critical for financial price forecasting. In the current study, LSTM, GRU and bidirectional extensions of these architectures, which belong to the Recurrent Neural Networks (RNN) family, were used to forecast gold prices. To evaluate the prediction performance of deep learning models, three fundamental performance metrics widely accepted as standard in the financial time series literature were used: Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). These metrics help evaluate both the absolute error magnitude and the relative prediction success of the models. While MAE provides an intuitive and directly interpretable measure of model performance, RMSE, with its ability to weight large errors more heavily, more clearly reveals the model's error stability, particularly during sudden price jumps and periods of extreme volatility in financial markets. MAPE, on the other hand, expresses prediction errors as a percentage, enabling comparability between financial series with different scales. Particularly in financial time series where high volatility and regime changes are frequently observed, the combined use of MAE, RMSE and MAPE allows for a more comprehensive evaluation of the models' generalization ability and prediction stability.

3.1. Long Short-Term Memory (LSTM)

The Long Short-Term Memory (LSTM) network was developed by Hochreiter & Schmidhuber (1997) to address the gradient vanishing and gradient explosion problems frequently encountered in traditional RNN architectures. The LSTM architecture enables the effective modeling of long-term dependencies through memory cells and gate mechanisms (Chen et al., 2023).

This structure is defined by the following equations:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + V_i c_{t-1}) \quad (1)$$

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + V_f c_{t-1}\right) \quad (2)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + V_o c_{t-1}) \quad (3)$$

$$\tilde{c}_t = tanh(W_c x_t + U_c h_{t-1}) \quad (4)$$

$$c_t = f_t^i \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (5)$$

$$h_t = o_t \odot tanh(c_t) \quad (6)$$

Here, `$x_t$ ` represents the input vector, `$h_t$ ` represents the hidden state and `$c_t$ ` represents the cell state. `$i_t$ `, `$f_t$ ` and `$o_t$ ` represent the input, forget and output gates, respectively; `σ ` represents the logistic sigmoid function, `tanh` represents the hyperbolic tangent function and `⊙ ` represents the element-wise multiplication. The forget gate controls how much of the previous cell information is added. The output gate regulates how the cell state is reflected in the hidden state and, consequently, in the model's output (Althelaya et al., 2018). The LSTM architecture consists of three basic gates: the input gate, the forget gate and the output gate. This mechanism enables the selective preservation of past information and the modeling of long-term dependencies (Adesina & Obokoh, 2025).

3.2. Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU) was developed by Cho et al. (2014) as a simpler and computationally more efficient alternative to the LSTM architecture. The GRU architecture manages information flow through a single hidden state rather than defining separate cell states and combines the input and forget gates under a single update mechanism (Saracık & İncekırık, 2023).

The mathematical representation of the GRU is as follows:

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (7)$$

$$\tilde{h}_t = tanh(W_h x_t + U_t(r_t \odot h_{t-1}) + b_h) \quad (8)$$

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (9)$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \quad (10)$$

In these equations, `$z_t$` represents the update gate, while `$r_t$` represents the reset gate. The update gate determines the ratio at which the past hidden state and the new candidate information are combined, while the reset gate controls the extent to which the previous information is considered. Through this structure, GRU executes a dynamic memory update process without completely erasing past information or carrying it unnecessarily (Zhao et al., 2017). Due to its simpler structure, GRU can offer similar prediction performance with fewer parameters and exhibits faster convergence properties, especially in limited data sets (Naas & Zouaoui, 2024). Figure 1 presents a schematic representation of the LSTM and GRU architectures.

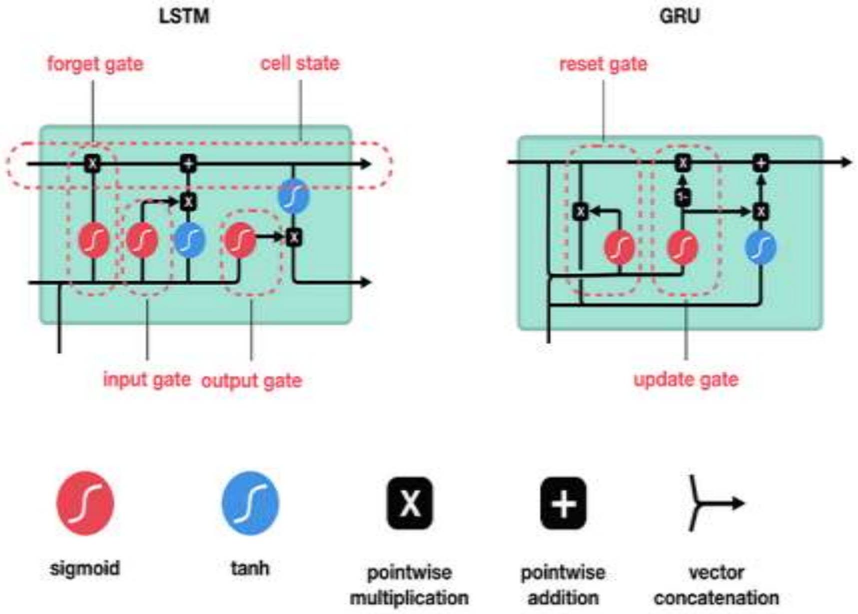

Figure 1. Comparative schematic representation of LSTM and GRU architectures
Source: (Yousufi & İncekırık, 2024).

Figure 1 shows how information flow is controlled through gate mechanisms in LSTM and GRU architectures. In the LSTM structure, there is a separate cell state with input, forget and output gates; in the GRU architecture, there is a simpler structure with hidden state updates through reset and update gates.

3.3. Bidirectional Long Short-Term Memory (Bi-LSTM)

Bidirectional Long Short-Term Memory – Bi-LSTM is an extended version of the classic LSTM architecture within a bidirectional RNN framework. In this structure, there are two separate LSTM layers, one processing the input sequence in the forward direction and the other in the reverse direction. This allows the model to represent both past and future contextual information simultaneously for each time step (Tang & Xie, 2025).

Mathematically, the forward and backward hidden states in Bi-LSTM are defined as follows.

$$\vec{h}_t = LSTM_f(x_t, \vec{h}_{t-1}, \vec{c}_{t-1}) \quad (11)$$

$$\overleftarrow{h}_t = LSTM_b(x_t, \overleftarrow{h}_{t-1}, \overleftarrow{c}_{t-1}) \quad (12)$$

The resulting forward and backward hidden states are typically concatenated to form the final representation:

$$h_t = [\vec{h}_t, \overleftarrow{h}_t] \quad (13)$$

This structure significantly increases the model's representation capacity, especially in time series where long-term dependencies and temporal interactions are strong (Foroutan & Lahmiri, 2024). The general structure of the Bi-LSTM architecture is presented in Figure 2.

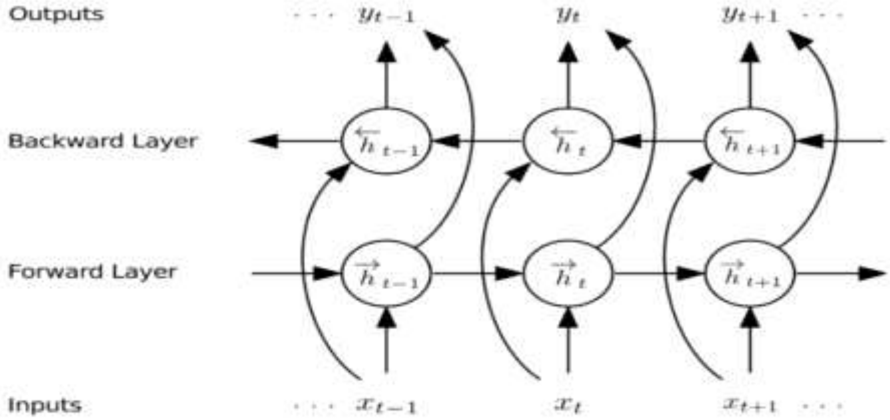

Figure 2: Schematic Representation of the Bi-LSTM Architecture
Source: (Ferdiansyah, 2023).

3.4. Bidirectional Gated Recurrent Unit (Bi-GRU)

Bidirectional Gated Recurrent Unit – Bi-GRU is a model obtained by applying the GRU architecture within a bidirectional RNN structure. This structure processes the input sequence through two separate GRU layers operating in the forward and backward directions, thus gaining the capacity to learn both past and future temporal information simultaneously (Zubair & Huang, 2026). Its mathematical representation is as follows:

$$\vec{h}_t = GRU_f(x_t, \vec{h}_{t-1}) \quad (14)$$

$$h^{\leftarrow}_t = GRU_b(x_t, h^{\leftarrow}_{t-1}) \quad (15)$$

In the Bi-GRU structure, the forward and backward hidden states can be expressed as follows:

$$h_t = [\vec{h}_t, h^{\leftarrow}_t] \quad (16)$$

The Bi-GRU architecture offers a more computationally efficient structure than LSTM-based bidirectional models because it contains fewer parameters; however, it can provide strong prediction performance by preserving bidirectional contextual information (Wang et al., 2026). The general schematic representation of the Bi-GRU architecture is shown in Figure 3.

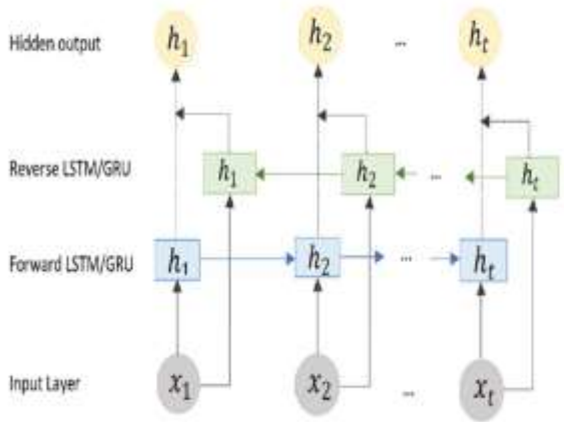

Figure 3: Schematic Representation of the Bi-GRU Architecture.
Source: (Foroutan & Lahmiri, 2024).

4. DATA SET AND APPLİCATİON

In the current study, deep learning-based time series models were used to forecast gold prices on a daily basis. In addition to gold prices, the analysis included silver, copper, platinum and crude oil prices, as well as the dollar index and exchange rate data, which are considered to be related to gold in terms of market dynamics. Within this framework, the prediction performance of single-variable models based solely on past gold prices was compared with that of multi-variable models incorporating multiple commodities and financial indicators.

The data set used in the study consists of daily closing prices covering the period from June 8, 2018 to February 3, 2026. Gold (ALT), Silver (GMS), Copper (BKR), Crude Oil (BTL), Dollar Index (DXY), Platinum (PLT) and Exchange Rate (USDTL) price data were obtained from the Investing.com database.

4.1. Pearson Correlation Matrix

Before proceeding to the modeling stage, Pearson correlation analysis was applied to examine the linear relationships between variables and possible multicollinearity structures. The resulting correlation matrix is presented in Table 1.

Table 1: Pearson Correlation Matrix.

	ALT	BKR	BTL	DXY	GMS	PLT	USDTL
ALT	1	0.7735	-0.0273	0.1919	0.9181	0.7947	0.8615
BKR	0.7735	1	0.4054	0.1574	0.7555	0.6928	0.7438
BTL	-0.0273	0.4054	1	0.4913	-0.0183	-0.0084	0.2541
DXY	0.1919	0.1574	0.4913	1	0.0390	-0.1259	0.5502
GMS	0.9181	0.7555	-0.0183	0.0390	1	0.9287	0.7003
PLT	0.7947	0.6928	-0.0084	-0.1259	0.9287	1	0.5145
USDTL	0.8615	0.7438	0.2541	0.5502	0.7003	0.5145	1

Table 1 shows that the precious metals group exhibits a high level of co-movement within itself. The correlation coefficient between ALT and GMS is approximately 0.92, while the coefficient between GMS and PLT is 0.93. It is noteworthy that BKR has high correlation values with this group (ALT-BKR: 0.77; GMS-BKR: 0.76). These findings indicate that the price movements of these commodities are largely shaped by common market dynamics. In contrast, BTL exhibits very weak correlation values with the analyzed precious metals and clearly stands apart from this group. The fact that crude oil's correlation coefficients with gold, silver and platinum are negative and close to zero (-0.03; -0.02; -0.01) indicates that oil prices are primarily determined by unique dynamics such as supply-demand conditions and geopolitical factors. This divergence reveals that BTL provides a different set of information in the modeling process. The relationships between DXY and the variables are generally limited. While a moderate positive relationship of 0.49 is observed between DXY and BTL, a correlation of 0.55 is detected between DXY and USDTL. The correlation between PTL and DXY is weak and negative, with a value of -0.13. Furthermore, the relatively high positive correlation values between USDTL and precious metals and BKR (0.86, 0.70 and 0.74, respectively) indicate that the price movements of these markets are significantly related to a common currency-based dynamic. This finding indicates that the USDTL variable provides explanatory and complementary information on price levels in the modeling process.

4.2. Tools Used in Preparing the Data Set for Modeling and the Training Process

In the modeling process, the ALT price was used as the dependent variable, while GMS, BKR, BTL, DXY, PLT and USDTL prices were used as independent variables. All time series were synchronized based on date, considering only common trading days. Missing observations due to holidays in different markets were removed from the dataset to ensure data integrity. To enable deep learning models to be trained effectively, the data set underwent various preprocessing steps. To eliminate scale differences between variables, all series were scaled to the [0,1] range using the Min-Max normalization method. To prevent data leakage, normalization parameters were obtained only from the training dataset and the same parameters were applied to the test dataset. In line with the nature of the time series prediction problem, the dataset was converted into input-output pairs using a sliding window approach. In the current study, window lengths were set to 7, 15 and 30 days; each model input contained price information from past days, while the model output was defined as the gold price for the next day. This structure aimed to enable the models to learn short-, medium-, and relatively long-term time dependencies.

The generated dataset was split into two subsets, with 80% for training and 20% for testing, while maintaining temporal integrity. The training data was used to learn the model parameters and the test data was used to evaluate the prediction performance. LSTM, GRU, Bi-LSTM and Bi-GRU architectures were applied in the study. All the models were constructed on a common skeleton structure; following the input layer, two recurrent neural network layers were used, followed by a dropout layer at a rate of 25% to reduce overfitting, a fully connected layer and a single-neuron output layer. The models were trained using the MSE loss function and the Adam optimization algorithm. During training, the number of epochs was set to 20, 50 and 100, while the batch size values were set to 16, 32 and 64. These hyperparameters were selected by considering values commonly used in the literature and taking model stability into account. The prediction performance of the models was evaluated using MAE, RMSE and MAPE metrics; lower error values were interpreted as indicating more successful prediction performance. Through these metrics, the univariate and multivariate structures of the LSTM, GRU, Bi-LSTM and Bi-GRU models were analyzed comparatively.

To interpret the model performance comparisons in Table 2, it is necessary to highlight the methodological framework regarding the hyperparameter configurations used in the study. In the current study, assuming that model performances cannot be reduced to a specific architecture or a single set of hyperparameters, different day windows, epoch counts and batch sizes were systematically evaluated. In this context, combinations of window lengths (7, 15 and 30 days), batch sizes (16, 32 and 64) and epochs (20, 50 and 100) were tested separately for four different deep learning architectures. This approach is based on the assumption that financial time series may contain variable-specific dynamics and that consistent model success across all series may not always be achievable with a fixed set of hyperparameters.

Table 2: Model Performance Comparison.

Variables	Performance Metrics	Models							
		Bi-GRU		Bi-LSTM		GRU		LSTM	
		Day-Epoch-Batch		Day-Epoch-Batch		Day-Epoch-Batch		Day-Epoch-Batch	
ALT	MAE	7-50-32	34.5818	30-100-64	38.9004	15-20-16	35.6023	15-100-64	43.9792
	MAPE		0.9883%		1.1273%		1.0242%		1.2852%
	RMSE		56.5666		67.8750		58.8027		69.1024
BKR	MAE	15-100-64	0.0660	15-100-64	0.0718	7-100-64	0.0640	15-100-64	0.0779
	MAPE		1.3621		1.4944		1.3284		1.6045
	RMSE		0.1101		0.1179		0.1095		0.1221
BTL	MAE	30-50-32	0.9870	7-100-64	1.1256	7-50-32	0.9922	30-50-32	1.1565
	MAPE		1.4210		1.6113		1.4226		1.6661
	RMSE		1.3192		1.4935		1.3055		1.5578
DXY	MAE	30-100-64	0.3472	7-100-64	0.3796	15-100-64	0.3402	30-100-64	0.3808
	MAPE		0.3413		0.3740		0.3351		0.3735
	RMSE		0.4570		0.5123		0.4544		0.4937
GMS	MAE	30-20-16	0.9574	15-50-32	1.0377	15-50-32	0.8857	15-100-64	1.1110
	MAPE		1.9115		2.1009		1.8349		2.0932
	RMSE		2.2265		2.5119		2.0922		2.5616
PLT	MAE	7-50-32	23.9215	15-20-16	26.2778	30-20-16	25.0982	30-100-64	24.0877
	MAPE		1.6402		1.7984		1.7425		1.6486
	RMSE		46.2555		52.3245		46.8061		46.9806
USDTL	MAE	15-50-32	0.1293	15-100-64	0.2107	30-50-32	0.1161	7-50-32	0.1082
	MAPE		0.3537		0.5529		0.2990		0.2952
	RMSE		0.1699		0.2444		0.1470		0.1537

The findings presented in Table 2 show that deep learning-based time series models generally exhibit high and consistent prediction performance in commodity, exchange rate and dollar index series. When evaluated on a variable basis, Bi-GRU and GRU architectures produced lower MAE, MAPE and RMSE values in most series; LSTM and Bi-LSTM models, on the other hand, were relatively weaker, especially in series where short- and medium-term dependencies were dominant. This indicates that GRU-based architectures with a simplified gate structure can adapt more effectively to rapid regime changes and short-term dynamics frequently observed in financial time series. In the gold series, the most successful prediction performance was achieved by the Bi-GRU model with a 7-day window, 50 epochs and a batch size of 32. This structure captured daily gold price movements with high accuracy, achieving values of 34.5818 MAE, 56.5666 RMSE and 0.9883 MAPE. The combination of sudden shocks caused by central bank purchases, geopolitical risks and global uncertainty indicators, along with delayed dynamics spread over several weeks, enhances the performance of medium-length 15-day window structures. In this context, the flexible learning structure provided by the Bi-GRU architecture obtained more comprehensive contextual information compared to unidirectional models in the gold series, capturing daily price movements with near-perfect accuracy and producing balanced results with a MAPE value below 1%. In the crude oil series, the Bi-GRU model achieved the most successful results with a 30-day window, 50 epochs and 32 batch configuration, reaching 0.9870 MAE, 1.3192 RMSE and 1.4210% MAPE values. The fact that oil prices are shaped by supply-demand dynamics that persist for weeks, such as production quotas, OPEC+ decisions, geographic supply disruptions and stock adjustments, necessitates the use of longer time windows. This situation shows that long-lag dependencies play a decisive role in price formation in the crude oil series. Bi-GRU's ability to process these long-term lagged dependencies in both directions provided a distinct advantage over the other architectures in crude oil. In the platinum series, the Bi-GRU model's production of the lowest error values at a 7-day window length (23.9215 MAE, 46.2555 RMSE and 1.6402% MAPE) can be attributed to this metal's relatively low liquidity structure and industrial demand-heavy price formation process. The fact that price movements in the platinum market are shaped more by short-term production and demand shocks limited the additional advantage provided by long window structures.

In the copper series, the GRU architecture demonstrated the most successful performance with values of 0.0640 MAE, 0.1095 RMSE and 1.3284% MAPE in a 7-day window and 100 epoch configuration. This is because copper, referred to as the "pulse of the world", is sensitive to global industrial production, an indicator of industrial demand and especially to high-frequency data flows originating from China, which makes predictions made with short time windows more effective. The high number of epochs indicates that the noisy data structure in this series requires a more intensive learning process. For the dollar index, the GRU architecture produced the lowest error metrics with values of 0.3402 MAE, 0.4544 RMSE and 0.3351 MAPE at a 15-day window length, which can be explained by this index having a more balanced and medium-term dynamics due to its multi-currency basket structure. The relatively low volatility and high liquidity of the DXY resulted in a limited reflection of the additional information advantage provided by two-way architectures. In the silver series, the prominence of the GRU architecture with a 15-day window points to the complex price dynamics of this commodity, stemming from its dual nature as both an industrial commodity and an investment tool. This dual-character structure ensures that neither very short nor very long window lengths are optimal. The configuration of 50-epoch and 32-batch yielded the most successful results, achieving 0.8857 MAE, 2.0922 RMSE and 1.8349% MAPE. While these complex interactions can be best modeled with a 15-day window, the adaptive structure of GRU handled these multiple factors more flexibly.

In the exchange rate series, it is seen that the LSTM model achieved the lowest error values of 0.1082 MAE, 0.1537 RMSE and 0.2952% MAPE with a 7-day window, 50 epoch and 32 batch configuration. The existence of policy-induced shocks in exchange rates, which are rare but create lasting effects, increases the importance of long-term dependencies; the advantage of the LSTM architecture in modeling such dependencies becomes more apparent in the USDTL series. In contrast, the sufficiency of the short window length indicates that rapid price adjustments and high-frequency information flow are dominant in foreign exchange markets.

The findings clearly demonstrate that model success in financial time series is determined by series-specific structural characteristics. In markets such as ALT, BTL and PLT, which are sensitive to geopolitical risks and exhibit distinct volatility clusters, Bi-GRU architectures that can simultaneously process bidirectional temporal context produced the lowest error metrics, as observations were meaningfully dependent not only on past values but also on the forward temporal context. In contrast, GRU models with simpler gate mechanisms showed more stable performance in series with more limited directional dependency structures, such as BKR, GMS and DXY, which are driven by supply-demand dynamics or macroeconomic indicators. In the USDTL series, the relative dominance of long-term dependencies explains the superiority of the LSTM architecture, which can maintain long memory through cell states. These findings demonstrate that a single universal model approach is invalid in the context of financial time series and that model selection requires an asset-based optimization process that considers volatility structure, dependency direction and temporal memory characteristics.

A key methodological finding is that the optimal window length, epoch count and batch size differ significantly across both variables and model architectures. This clearly demonstrates that achieving universal success with a fixed set of hyperparameters in financial time series is impossible and that model performance requires a systematic hyperparameter optimization process sensitive to the data structure. Within the scope of the current study, combinations of 7, 15 and 30-day window lengths, 16, 32 and 64 batch sizes and 20, 50 and 100 epochs were evaluated separately for four different deep learning architectures, testing a total of 252 different model configurations for seven variables. The results obtained show that deep learning models have high accuracy potential in commodity and foreign exchange markets, but this potential can only be effectively utilized with data-specific and model-specific optimization approaches.

Figures 4-10 present a comparative overview of the prediction accuracy of deep learning models trained under different window lengths and hyperparameter combinations, showing their alignment with actual values in the relevant price series.

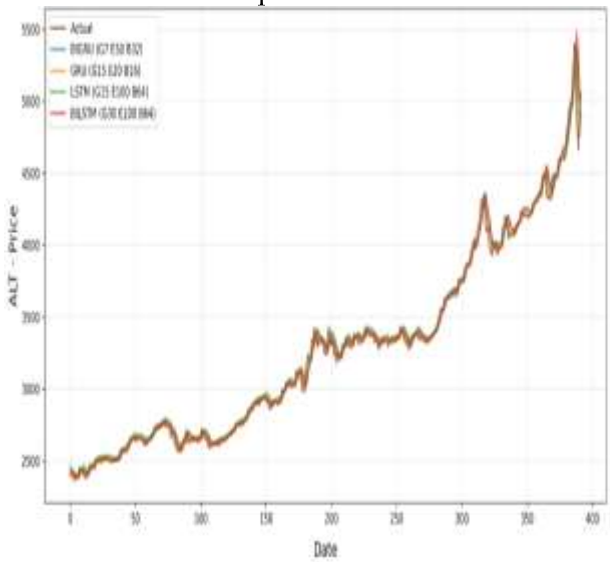

Figure 4: Comparison of Actual and Predicted Values for the Gold (ALT) Price Series.

In Figure 4, while all the models follow the general price trend, differences in predictions are observed during periods of increased volatility.

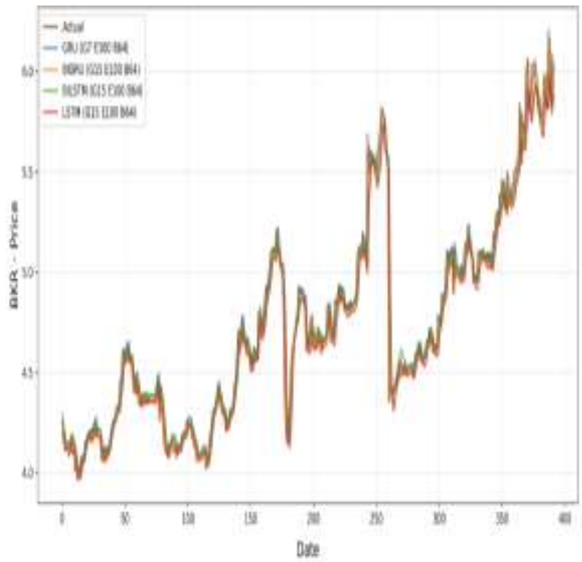

Figure 5: Comparison of Actual and Predicted Values for the Copper (BKR) Price Series.

Figure 5 shows that predictions closely follow actual values in the BKR price series, with limited divergence between models.

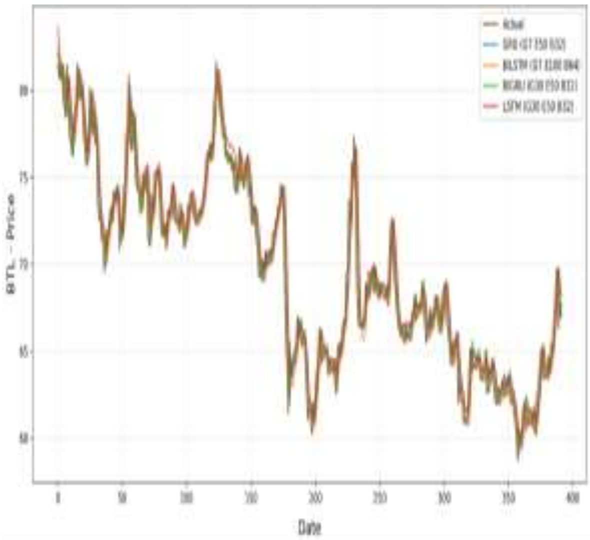

Figure 6: Comparison of Actual and Predicted Values for the Crude oil (BTL) Price Series.

Figure 6 shows that during periods of sudden fluctuations in BTL prices, some models exhibit short-term deviations.

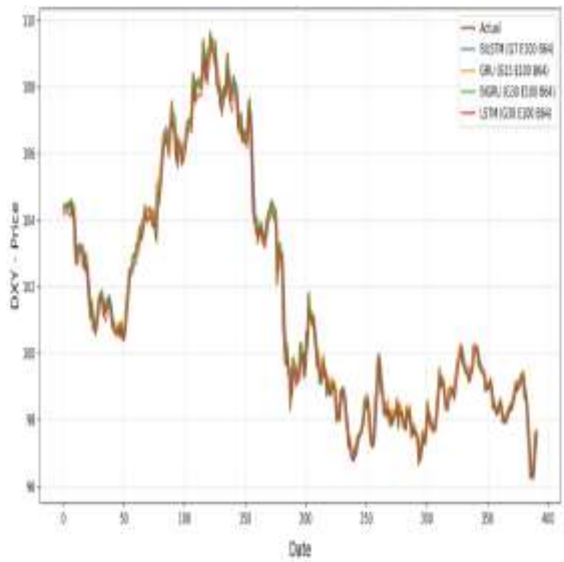

Figure 7: Comparison of Actual and Predicted Values for the Dollar Index (DXY).

Figure 7 shows that the predictions largely coincide with the actual values in the DXY series and that there is no significant difference between the models.

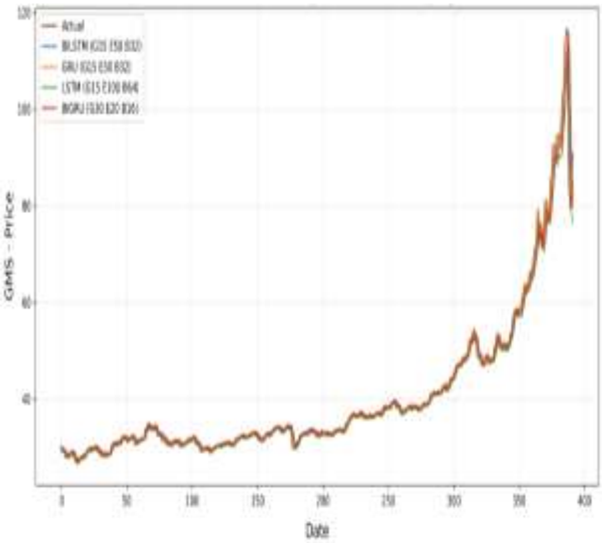

Figure 8: Comparison of Actual and Predicted Values for the Silver (GMS) Price Series.

Figure 8 shows that while the general trend in GMS prices is successfully captured, prediction errors relatively increase during periods of heightened volatility.

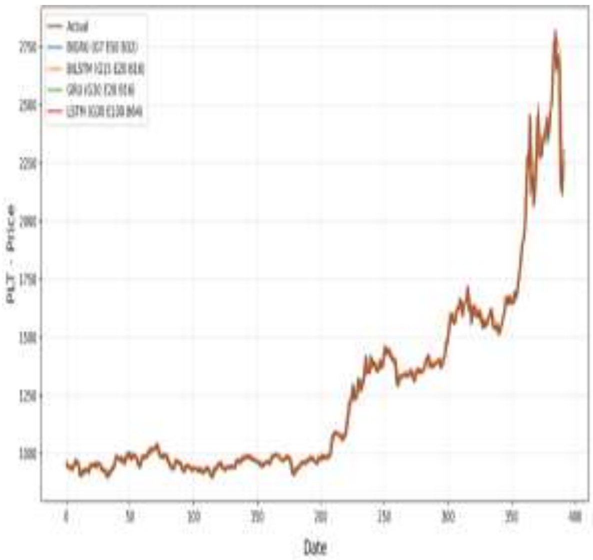

Figure 9: Comparison of actual and predicted values for the platinum (PLT) price series.

In Figure 9, it is observed that the models follow the actual values at different levels in sections where fluctuations are intense in the PLT price series.

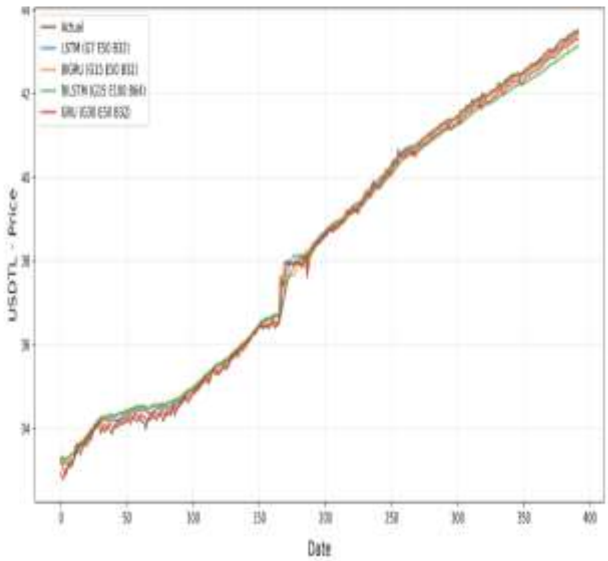

Figure 10: Comparison of Actual and Predicted Values for the Exchange Rate (USDTL) Price Series.

Figure 10 shows that while the long-term trend in the USDTL series is captured by all the models, the forecasts diverge in short-term movements.

When Figures 4-10 are evaluated together, it is seen that all the models successfully track the general trend in the relevant price series, but prediction errors become more pronounced during periods of increased volatility. Differences between models emerge particularly in segments with intense sudden price movements; some architectures respond more quickly to short-term fluctuations, while others produce smoother and delayed forecasts. These visual findings show that structural differences in model architectures directly reflect prediction dynamics and that performance evaluation should be considered not only in terms of error metrics but also in terms of temporal alignment and response characteristics. Figure 11 presents the learning behavior obtained during the training process and the prediction performance during the test period of the Bi-GRU model, selected as the best model, in a time series view.

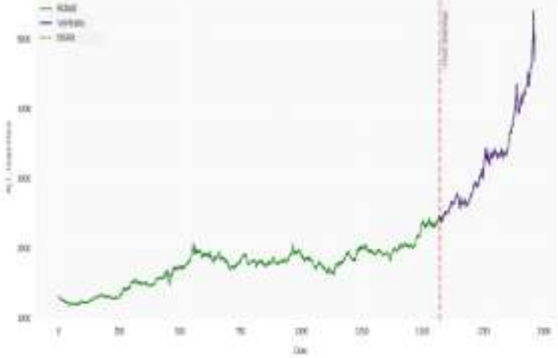

Figure 11. Bi-GRU Model Prediction Result for the ALT Price Series.

Figure 11 shows that the forecasts generated by the Bi-GRU model closely follow the actual ALT closing prices after the test starting point. It is observed that the forecasts generally align with the overall trend, especially during periods of accelerated upward momentum, while limited deviations occur during short-term fluctuations.

The findings of the current study reveal that deep learning-based time series models have a high potential for accurately predicting price movements in commodity and foreign exchange markets. When visual and numerical results are evaluated together, it is seen that the models successfully track general trends, but prediction deviations increase relatively during periods of heightened volatility. Performance differences between model architectures are closely related to the temporal dependency structures and volatility characteristics of price series, indicating that no single model approach produces optimal results for all market conditions. In this context, the findings emphasize the need to consider model selection and hyperparameter tuning in a data structure-sensitive manner.

5. DISCUSSION AND CONCLUSION

In the current study, the effectiveness of deep learning-based time series models in predicting gold prices on a daily basis was comprehensively examined within the framework of univariate and multivariate structures. The analysis process began with a correlation analysis conducted prior to the modeling stage; subsequently, the prediction performance of deep learning models trained under different architectures, window lengths and hyperparameter combinations was comparatively evaluated. This two-stage approach allowed for both a structural understanding of the relationships between variables and an empirical test of how these relationships translate into prediction accuracy. The correlation analysis findings revealed that precious metals exhibit a high degree of co-movement among themselves and that the strong positive correlations between gold and silver and platinum are shaped by the common market dynamics of these assets. In contrast, crude oil produced weak and mostly insignificant correlation values with precious metals, indicating that the price formation process of this commodity is largely determined by supply-demand conditions and geopolitical factors. The dollar index and exchange rate variables were observed to have a strong correlation with price levels, particularly through USDTL; this finding confirms that exchange rate-based effects provide complementary information for modeling gold and other commodity prices. These results clearly support the theoretical rationale for the multivariate modeling approach.

Deep learning-based prediction results clearly demonstrate that model performance in commodity and foreign exchange markets is determined by time-series-specific temporal dependency structures. The prominence of Bi-GRU and GRU architectures, producing lower MAE, RMSE and MAPE values in most series, demonstrates that simplified gate structures can adapt more quickly to regime shifts and short-term dynamics frequently observed in financial time series. The superior performance of bidirectional architectures in series containing both sudden shocks and delayed effects, such as gold and crude oil, reveals that the simultaneous processing of forward and backward time contexts is critical in such markets. In contrast, GRU architectures produce more stable results in series with more balanced or unidirectional dependency structures, such as copper, silver and the dollar index, indicating that model complexity does not always provide an advantage. The emergence of the LSTM architecture in the exchange rate series emphasizes the importance of preserving long-term memory through cell states in markets dominated by long-term dependencies.

One of the key methodological findings of the current study is that the optimal window length, epoch count and batch size differ significantly across both variables and model architectures. The findings obtained by testing a total of 252 model configurations for seven different financial series clearly demonstrate that achieving universal success with a fixed set of hyperparameters in financial time series is not possible. It is evident that model performance is highly sensitive to data structure, and a systematic optimization process that considers volatility level, dependency direction and temporal memory characteristics together is essential. This result reveals that the "one model-one setting" approach in deep learning applications is no longer valid in financial markets.

The visual comparisons presented in Figure 4-10 show that all the models successfully tracked the general price trends; however, prediction errors became more pronounced during periods of increased volatility. Differences between models emerged particularly during sub-periods with intense sudden price movements; some architectures were observed to respond more quickly to short-term fluctuations, while others produced smoother and delayed predictions. These findings indicate that performance evaluation should not be limited to error metrics alone; it must also consider qualitative characteristics such as temporal alignment, response speed and trend tracking. The results graph presented for the Bi-GRU model confirms that actual price movements were tracked with high accuracy during the test period and that a meaningful alignment was achieved, particularly during trend changes.

Future studies may explore different methodological and data-based extensions to further advance deep learning-based time series forecasting performance. Beyond LSTM and GRU-based architectures, attention mechanisms and the capacity of Transformer-based models to capture long-term dependencies can be tested in the context of financial time series. Including macroeconomic and exogenous variables such as interest rates, inflation indicators, central bank policy decisions and geopolitical risk indices in the model inputs could contribute to a more comprehensive representation of the price formation process. Instead of a fixed training-testing split, the stability of models under different market conditions can be analyzed using sliding window structures and regime-sensitive evaluation strategies. Furthermore, evaluating probabilistic forecasting approaches that incorporate uncertainty and risk dimensions, rather than focusing solely on point estimates, can strengthen the use of results in decision support processes. Finally, moving beyond single-asset-centered structures, the contribution of cross-market interactions to forecasting performance can be investigated through multi-task learning frameworks that simultaneously model multiple assets.

In general, the current study demonstrates that deep learning-based time series models have high predictive potential in commodity and foreign exchange markets; however, this potential can only be effectively utilized when a data-specific, model-specific and hyperparameter-sensitive approach is adopted. The findings clearly reveal that there is no universal model architecture for financial time series and that model selection must be optimized by considering the structural characteristics of each asset. In this respect, the study contributes methodologically to the academic literature and provides a guiding framework for practitioners in the design of deep learning-based forecasting systems.

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