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Multivariate LSTM-Based Intraday Gold Price Prediction with Rolling Time Series Validation

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Abstract

Projecting XAUUSD (gold vs. US dollar) prices on a one-hour interval is particularly challenging due to the market's dynamic and nuanced character. To address short-term financial forecasting, an advanced deep learning methodology utilizing Long Short-Term Memory (LSTM) models was employed. Historical XAUUSD data for 2024 was resampled to hourly intervals and supplemented with SMA, RSI, MACD, and Bollinger Bands to understand the market structure better. An LSTM model was developed using open, high, low, and close prices as inputs, with the close price designated as the output target. Data normalization was performed via MinMaxScaler. The model was validated using Time Series Cross-Validation (TSCV) with a rolling origin expanding window over five splits—a sophisticated method for evaluating performance. The results demonstrated the LSTM model's capability, showcasing a mean RMSE of 9.9574, a mean MAE of 7.4411, an R^2 score of 0.9535, and a remarkably low MAPE of 0.3009%. These findings indicate the advanced model effectively predicts intraday prices, even while grappling with complex and nonlinear patterns, offering a powerful instrument for trading professionals and researchers to cut through market noise.

Keywords : *LSTM; XAUUSD; Intraday price prediction; 1-Hour Timeframe; Time series cross-validation*

1 Introduction

The capacity of agents to manually predict intraday prices is limited due to the dynamic, multifaceted, and nonlinear nature of price movements [1]. These factors include fluctuations in macroeconomic news events, changes in interest rate policies, and global geopolitical risks [2]. Many conventional technical analysis methods can be helpful; however, they often fall short and fail to reveal time-based relationships and complex patterns that enable timely, insightful trading decisions, particularly when the window of opportunity is narrow. Market requirements are rapidly changing [3]. The result of incorrect predictions can be a tremendous financial loss for traders, thereby underlining the necessity to seek more powerful predictive methods [4].

In order to minimize such drawbacks, one of the state-of-the-art techniques is to use deep learning, given its capability to learn complex representations and hierarchies from sequential information and data [3], [4]. Some branches of deep learning are the use of Long Short-Term Memory (LSTM) models, which have the unique ability to learn and capture long-range nonlinear dependencies, complex relationships, and are very common in most financial time series [5]. The way the model's layers are designed helps the model to learn information while going through the data, and to also prevent the loss of data related to the problem of vanishing and exploding data [6]. From this,

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data that have high levels of volatility, such as assets and gold (XAU/USD), can be predicted from its use [7].

In the past, researchers have used LSTM and other deep learning frameworks to predict the prices of commodities, including gold. However, the majority of these works concentrate on the daily and weekly time frame [5], [8], [9]. A few other works also apply LSTMs and use simple train-test splits, often with little regard for robust evaluation[10]. Moreover, many of them use only univariate features (e.g., the closing price), which might hinder the model from adequately capturing the short-term intraday dynamics that are heavily influenced by volatility, momentum shifts, and rapid price changes[11].

Despite considerable advancements, a substantial research gap persists. The current literature rarely addresses 1-hour intraday gold price prediction, although intraday traders depend on timely signals for entry and exit strategies. Furthermore, studies employing multivariate methods within the intraday context are especially limited. In addition, few studies implement Time Series Cross-Validation (TSCV) to assess model reliability across different temporal segments. This deficiency highlights the necessity for a comprehensive, context-aware framework that reflects actual market dynamics, where predictive models must adapt to sudden regime changes and significant intraday volatility.

This study addresses existing gaps by introducing a multivariate LSTM model to predict intraday gold price movements (XAU/USD) at a 1-hour interval. The model uses several technical indicators to provide richer information during training. To make the results more realistic and reliable, the evaluation uses a rolling-origin expanding-window Time Series Cross-Validation (TSCV), which better matches real trading conditions. With this method, the study offers an early example of using an LSTM for 1-hour XAU/USD forecasting, shows how technical indicators can improve predictions, and underlines the value of TSCV for stable intraday forecasts. The goal is to help develop more effective data-driven trading strategies and give useful insights to both practitioners and researchers in computational finance.

2 Literature Review

Investors who want to create effective trading plans need to be able to accurately predict asset prices, especially in highly volatile markets such as gold (measured against the US dollar, XAU/USD) and foreign exchange (forex) [7]. Deep learning has emerged as one of the most effective methods for predicting time series over the past few years. Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), have gained popularity among deep learning architectures due to their ability to address the issues of vanishing and exploding gradients when handling long sequences [6]. This makes them especially good at capturing temporal dependencies. Previous research consistently demonstrates the efficacy of LSTM-based models in predicting a diverse array of commodities and financial instruments.

Applications to gold price forecasting demonstrate LSTM's strong predictive capability. For daily gold price prediction, an LSTM model trained on 70% of the data and tested on 30% achieved a MAPE of 2.71% [8]. Hybrid architectures, such as CNN-LSTM, have also been explored. For example, a CNN-LSTM model using PT Antam Tbk. 's daily gold prices achieved favorable results, with a training RMSE of 5,811.51 and a testing RMSE of 13,236.10 at epoch 100 [6]. Comparative analyses of recurrent models reveal mixed outcomes: while LSTM frequently outperformed alternatives, one study found that the Gated Recurrent Unit (GRU) surpassed LSTM under an 80:20 train–test split for Indonesian gold prices[5], whereas another study showed LSTM outperforming Bidirectional LSTM (BiLSTM) for the same task [12]. These findings suggest that the choice of architecture and hyperparameter tuning have a substantial impact on predictive performance.

Beyond gold forecasting, deep learning methods have been widely applied to other financial and commodity markets. LSTM, combined with Time Series Cross-Validation (TSCV), has been successfully used to model palm oil production, demonstrating its robustness in handling sequential data [13]. In forex prediction, LSTM models delivered promising results for the EUR/USD currency pair using 70:15:15 and 80:10:10 train–validation–test splits [10]. Moreover, integrating attention mechanisms into LSTM (LSTM+Att) further reduced RMSE compared with standard LSTM when forecasting currency exchange rates [11]. Comparative research across Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), RNN, and LSTM concluded that CNN achieved the lowest MAE, MSE, and RMSE, highlighting the potential of convolutional architectures for price forecasting tasks [9]. These studies collectively confirm the versatility and effectiveness of deep learning architectures for financial time series.

While there are several literature works which have used LSTM and other deep learning models for financial forecasting, the majority operate on daily or weekly frequencies as well as simple train-test splits, thus underexploiting the fast dynamics in intraday markets. Furthermore, related research has generally used univariate models or limited feature sets, and seldom have applied sound evaluation techniques such as Time Series Cross-Validation (TSCV). This research, however, justifies its contribution by offering some new challenges, such as forecasting based on LSTM methods targeting especially the 1-hour intraday XAU/USD domain, introducing a more complex multivariate input with OHLC prices and key technical indicators (SMA, RSI, MACD, and Bollinger Bands), and using a rolling-origin expanding- window TSCV model to provide more resilient generalization across very different market conditions. LSTM is preferred because of its capacity to model nonlinear temporal dependency in ultra-high frequency data, and the decision to use technical indicators further increases the sensitivity of the model towards momentum, volatility, and trend characteristics that are more indicative of intraday trading. Taken together, these methodological contributions enhance the originality of this work and establish it firmly in the research field as offering an integrated bridge between classical LSTM forecasting techniques and their practical application in intraday financial decision-making.

3 Research Methods

The methodology is applied to investigate the performance of the LSTM model for intraday XAUUSD price prediction. The aim is to develop an accurate forecasting model that can predict price movements within 1 hour for intraday trading. The performance of the LSTM model will be evaluated using various criteria, and its predictability will be tested using TSCV.

A clear and systematic process is used for financial time-series forecasting is shown in Figure 1. The workflow starts with getting, cleaning, and preparing historical intraday XAU/USD data, then normalizing it so that features are on the same scale. Feature engineering adds market indicators to show trend, momentum, and volatility. For fair and consistent model checks, the data is split using a rolling Time Series Cross-Validation that preserves the data order. The forecast model is built with a Long Short-Term Memory (LSTM) network, and its setup is improved by tuning its parameters. Finally, performance is checked using standard metrics to judge how well the LSTM–TSCV process works.

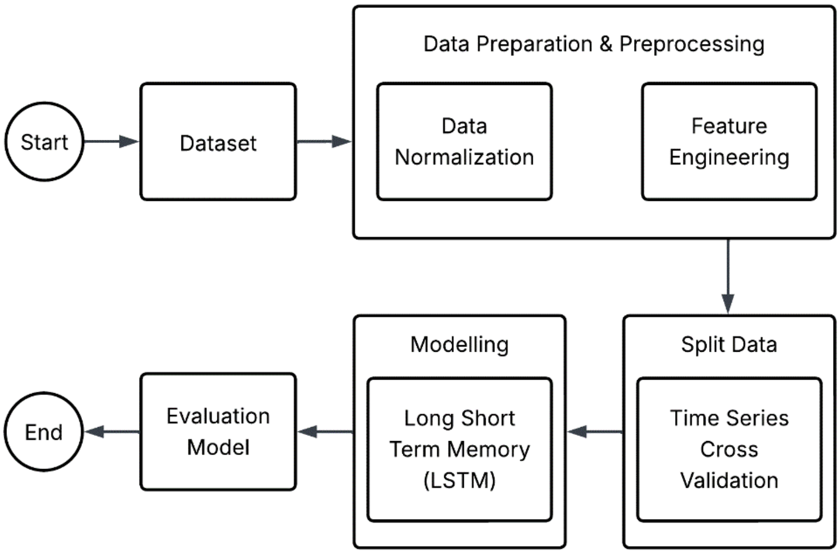

Figure 1 Research Methods

3.1 Dataset

The dataset for this study was sourced from HistData.com and contains minute-level gold versus US dollar (XAU/USD) quotations from 1 January 2024, 18:00 UTC, to 31 December 2024, 16:00 UTC, totaling approximately 355,592 records with date–time, open, high, low, close prices, and trading volume [14]. To enhance feature representation, the date and time columns were merged into a single datetime field, ensuring proper sequencing before input to the model. The minute-level data were then resampled to 1-hour intervals, resulting in 8,759 observations that align with the intraday forecasting objective. Gold was selected because XAU/USD is highly traded and volatile, making it an appropriate benchmark for intraday forecasting [15]. The volume column, which contained only zeros due to decentralized forex reporting, was removed to maintain a clean and reliable dataset for model development [16].

3.2 Data Preparation & Preprocessing

Multiple feature engineering procedures were applied to enrich the resampled hourly XAU/USD dataset and provide the LSTM model with more comprehensive market information, thereby improving prediction accuracy. The objective was to derive meaningful features, such as technical indicators, that capture underlying price dynamics beyond raw values [17]. Among these indicators, the Simple Moving Average (SMA) was implemented to smooth short-term price fluctuations and highlight broader market trends, as formulated in Equation (1) [17].

$$\mathrm{SMA_t} = \frac{1}{\mathrm{N}} \sum_{\mathrm{i=t\text{-}N+1}}^{\mathrm{t}} \mathrm{Close_i} \tag{1}$$

The Relative Strength Index (RSI) was calculated as a momentum indicator to assess overbought or oversold conditions, as shown in Equation (2) [17].

$$\text{RSI} = 100\text{-}\frac{100}{1\text{+RS}}, \quad \text{RS} = \frac{\text{Average Gain}}{\text{Average Loss}} \tag{2}$$

To capture directional momentum changes, the Moving Average Convergence Divergence (MACD) was included, formulated in Equation (3) [17].

$$\text{MACD Line} = \text{EMA}_{12}\text{-EMA}_{26} \tag{3}$$

Additionally, Bollinger Bands were computed to measure market volatility and identify potential price reversals, as defined in Equation (4) [17].

$$\text{Upper Band} = \text{SMA}_\text{n}\text{+k}\sigma, \quad \text{Lower Band} = \text{SMA}_\text{n}\text{-k} \tag{4}$$

These indicators, calculated from the hourly close prices, provide complementary perspectives on trend, momentum, and volatility. Following feature engineering, a multivariate LSTM model was configured using open, high, low, and close prices as input variables, with the close price designated as the target for prediction [18]. To ensure stable learning and avoid scale imbalances, all features were normalized to a [0,1] range using MinMaxScaler [11]. This preprocessing pipeline ensured that the enriched dataset retained temporal consistency and was optimally prepared for model training.

3.3 Split Data

To accurately evaluate the model's generalization performance on unseen data, the dataset was divided using Time Series Cross-Validation (TSCV), a technique designed to preserve the temporal order of observations [13]. TSCV prevents data leakage by ensuring that each training set strictly precedes its corresponding validation set in chronological order[13]. In this approach, the dataset is partitioned into sequential train-validation blocks: the model is first trained on an initial segment of historical data and validated on the immediately following segment[19].

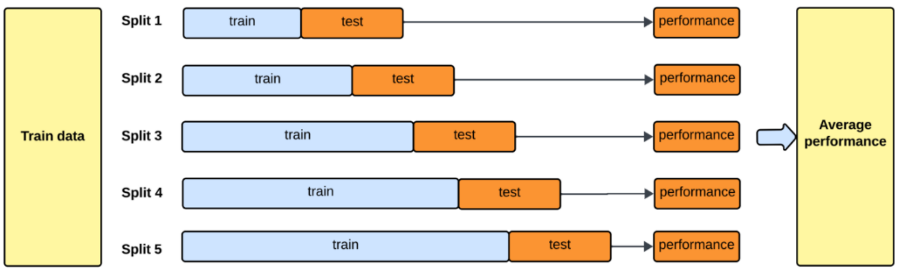

Figure 2 Time Series Cross Validation

Figure 2 shows the five folds cross validation, adopting a rolling-origin expanding-window methodology in which the training window progressively expands to include previously validated data. In contrast, the validation window advances to the following time period. Using five folds provides a balanced compromise between computational efficiency and a robust assessment of model performance. This evaluation strategy yields a comprehensive and temporally consistent measurement of predictive accuracy for intraday gold price forecasting.

3.4 Modelling

The predictive model adopted in this study is a Long Short-Term Memory (LSTM) neural network, a specialized variant of Recurrent Neural Networks (RNNs) designed to process sequential data effectively [6]. LSTM networks incorporate three primary gates namely: forget, input, and output, to regulate the flow of information through internal cell states [20]. This gating mechanism enables the network to retain or discard information selectively, allowing it to preserve long-range temporal dependencies and overcome the vanishing gradient problem commonly encountered in standard RNNs [20]. These properties make LSTM particularly well-suited for analyzing and forecasting complex financial time series.

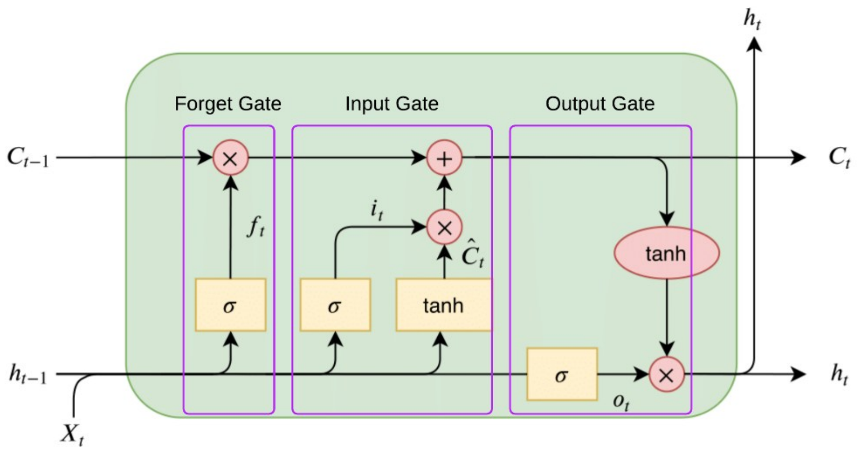

Figure 3 LSTM configuration

A multivariate LSTM configuration in Figure 3 was employed to leverage the whole dynamics of the market. The open, high, low, and close (OHLC) prices of XAU/USD were used as input features, with the close price serving as the target for prediction. Incorporating multiple features allows the model to capture inter-variable relationships and hidden patterns that a univariate approach would fail to represent, thereby improving forecast accuracy and robustness [13].

To optimize the model's performance, candidate configurations were iteratively evaluated, and the final architecture was selected based on predictive stability and accuracy. Table 1 summarizes the hyperparameter settings adopted for the LSTM model.

Table 1 Configuration Model

Parameter	**Value**
Time step (sequence length)	90
LSTM layers and units	2 layers: 256, 128
Dropout rate	0.3
Batch size	128
Epochs	100
L2 regularization (λ)	0.001
Early stopping patience	15 epochs
Input features	Open, High, Low, Close

3.5 Evaluation Model

Model evaluation is crucial for assessing the performance of a predictive model. Four standard metrics were employed to determine the forecasting accuracy, providing complementary insights into model performance, and are widely recognized in time-series forecasting studies.

Since this study forecasts a continuous variable, accuracy is not used because it is suited to classification, not regression. Instead, evaluation uses RMSE, MAE, MAPE, and R^2, which better quantify error magnitudes between predicted and actual values and provide a robust assessment of regression-based model performance [21].

RMSE is a measure of variation between predicted and observed data that ranges from 0 to positive infinity; increased differences are weighted more than smaller ones. This characteristic makes RMSE particularly important when substantial deviations are unacceptable. The smaller the RMSE, the better the model fitting in Equation (5) [6].

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{5}$$

The MAE measures the average absolute deviation of the predicted value from the actual observation, regardless of trade. MAE, however, in contrast to RMSE, is less sensitive to outliers; the smaller the MAE value is, the more accurate the forecasting result obtained, as shown in Equation (6) [5].

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{6}$$

The Mean Absolute Percentage Error (MAPE) measures the absolute percentage error relative to the actual values and provides a significant metric for assessing model performance across different datasets. However, for small values, the explicit estimates approach zero, which may lead to instability as seen in equation (7) [8].

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{7}$$

Finally, the Coefficient of Determination (R^2) indicates the percentage of variance in the observed data that the linear model explains. A higher R^2 reflects a better prediction-observation fit according to Equation (8) [12].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{8}$$

4 Results and Discussion

This study assesses the importance of the LSTM model in predicting XAUUSD, accompanied by a comprehensive analysis of the results achieved. A Time Series Cross-Validation (TSCV) technique with five splits is used to analyze the model's performance, guaranteeing a comprehensive evaluation of the generalization capacity on fresh time series test data. Multiple evaluation indices, such as RMSE, MAE, R^2 (coefficient of determination), and MAPE, are utilized to offer a thorough assessment of performance accuracy and reliability as shown in Table 2.

Table 2 Result Model with TSCV

Fold	RMSE	MAE	R^2	MAPE (%)
1	10.0444	7.1637	0.9843	0.3131
2	9.0568	6.8000	0.9127	0.2893
3	10.0321	7.7336	0.9599	0.3158
4	8.2947	6.2447	0.9891	0.2369
5	12.3590	9.2637	0.9214	0.3496
Average	**9.9574**	**7.4411**	**0.9535**	**0.3009**

The use of Average Time Series Cross-Validation (TSCV) provides a comprehensive and unbiased evaluation of model performance across varying intraday market conditions, resulting in a more reliable assessment of the model's generalization capability. Based on five TSCV folds, the model achieved an RMSE of 9.9574, MAE of 7.4411, R^2 of 0.9535, and a MAPE of 0.3009%, indicating strong predictive accuracy. In intraday trading applications, such low error rates are particularly valuable, as they enable traders to more accurately identify short-term price trends, determine optimal entry and exit points, and enhance risk management in fast-moving market environments. The improved precision can also support the development of automated trading strategies and reinforce data-driven decision-making.

Although the LSTM model demonstrates consistently strong performance across all five folds, each fold presents distinct market characteristics that influence forecasting accuracy. Fold 1 records a relatively higher RMSE of 10.0444 because the model is being exposed to the data patterns for the first time, requiring initial adaptation before stabilizing its temporal representation. In Fold 2, the RMSE decreases to 9.0568 as the model becomes more familiar with the underlying dynamics; this improvement is supported by a predominantly sideways test segment that is inherently easier to predict. However, in Fold 3, the RMSE rises again to 10.0321, coinciding with an upward-trending test window that introduces new structural dynamics, conditions often shaped by macroeconomic announcements that temporarily alter short-term price behavior.

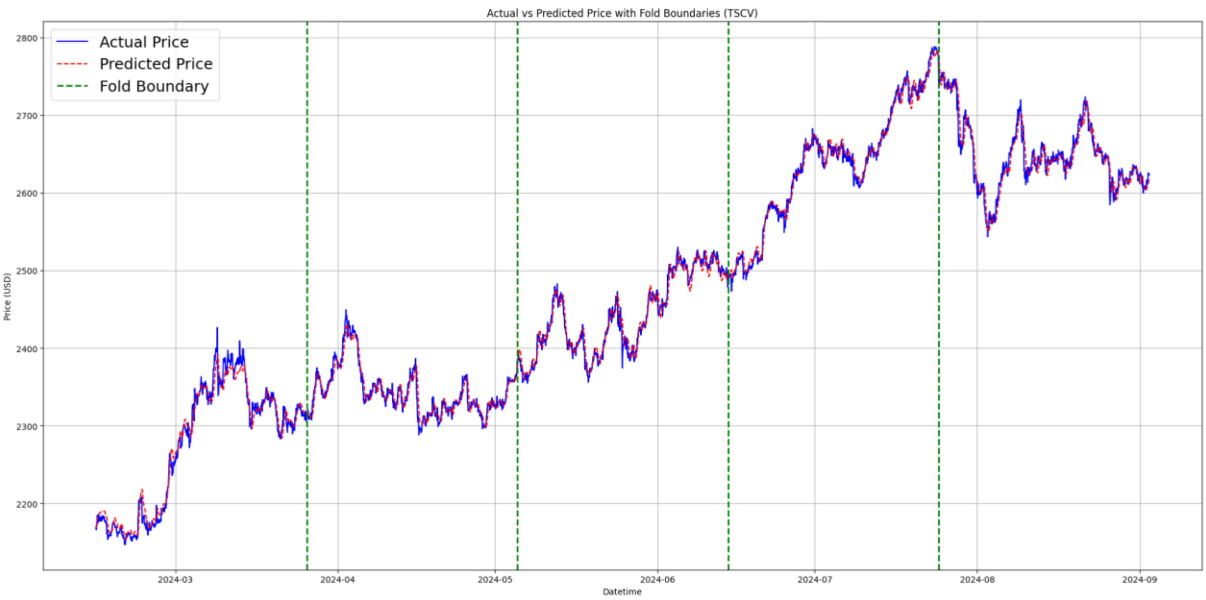

Figure 4 Actual vs Predicted Price with Fold Boundaries (TSCV)

Fold 4 achieves the best performance, with the RMSE dropping to 8.2947, as the test period exhibits a stable and smooth upward trend that aligns closely with the model's learned temporal dependencies. In contrast, Fold 5 shows the highest RMSE, reaching 12.3590, driven by a sharp downward movement and substantially elevated volatility relative to earlier folds. This sudden regime shift, including a candle-range expansion of more than 30%, presents conditions that deviate significantly from the predominantly bullish patterns seen during training, thereby challenging the model's generalization ability. Collectively, these variations demonstrate that LSTM performance is highly sensitive to the prevailing market regime of each fold, particularly shifts in trend direction and volatility intensity.

As shown in Figure 4, the training and validation losses fell rapidly early in the epochs for most folds before gradually converging to a low, stable value. This convergence pattern, for example, that the validation loss follows the trend of the training loss, indicates that the model's performance is learning without overfitting to the training set. The rule of stopping early was essential to prevent overfitting, which can occur during long training, and to ensure the model's optimal use in unseen conditions. The convergence of the learning process across all folds demonstrates the strength and generalization capabilities of the model structure (LSTM) combined with the selected hyperparameters.

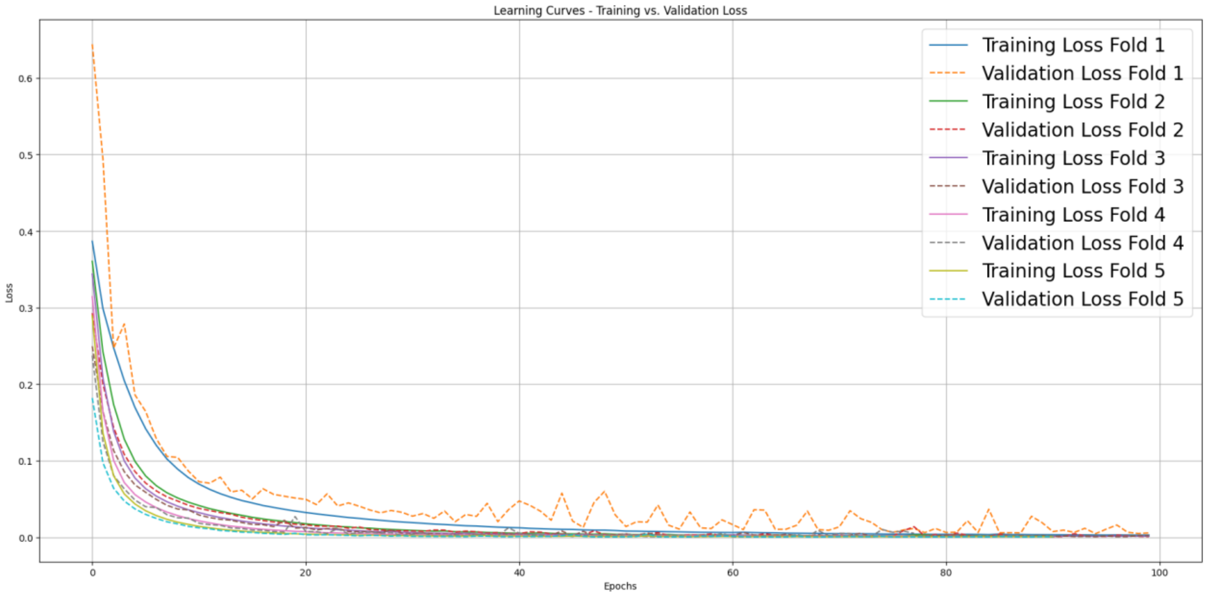

Figure 5 Learning Curves

Figure 5 illustrates a significant correlation between the "Actual Price" and "Predicted Price" curves. The predicted prices align closely with the overall trend and notable fluctuations of the actual prices. Minor deviations are noted, particularly during sharp price movements or heightened volatility; however, the model effectively captures the underlying price dynamics. The visual confirmation corresponds with the elevated R2 score and minimal error metrics, underscoring the LSTM model's capacity to learn and predict the intricate, non-linear patterns present in financial time series data.

Figure 6 Comparison of Actual vs. Predicted Price

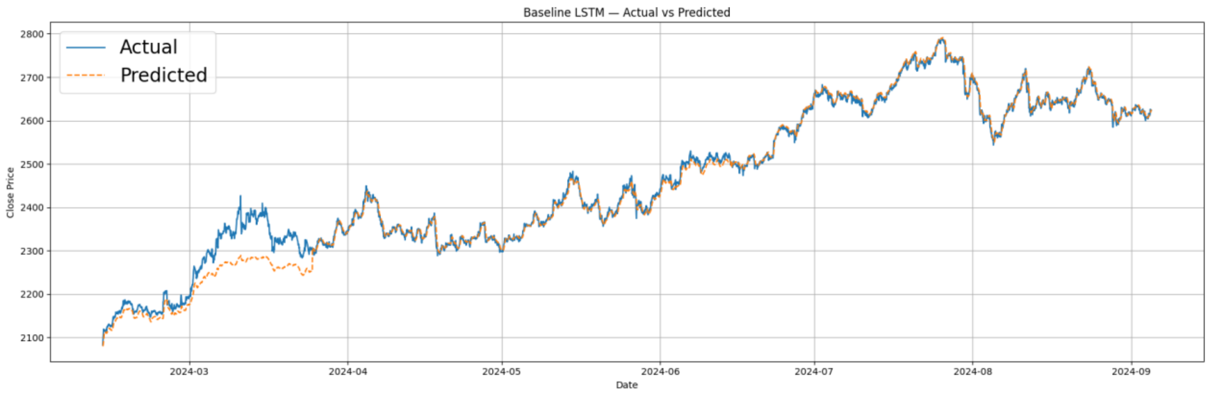

Figure 7 Baseline LSTM

To demonstrate the model's improvement, a comparison with the baseline LSTM was conducted using TSCV. The average metrics obtained were RMSE 17.67, MAE 13.97, R^2 0.8958, and MAPE 0.58%, as shown in Figures 6 and 7. Although these results are reasonably good, the performance across folds still shows considerable variation, and the model is unable to capture highly volatile price spikes. This indicates that the baseline remains unstable under different data conditions. Therefore, incorporating multivariate variables, applying feature engineering, and performing hyperparameter optimization are necessary to improve accuracy and produce a more consistent model.

The improved model achieved an MAPE of 0.30%, compared to 58% for the baseline model, representing a 28% reduction in prediction error. This substantial improvement highlights the effectiveness of incorporating multivariate features, feature engineering, and Time Series Cross-Validation (TSCV). In practical intraday trading, such a low MAPE provides traders with highly accurate guidance for determining precise entry and exit points. Furthermore, the model can be integrated into algorithmic trading systems to generate short-term directional forecasts, supporting scalpers and intraday traders in navigating fast-moving and volatile market conditions.

The actual and predicted prices of XAUUSD are also listed in Table 3, confirming the accuracy of our model. On February 14, 2024, the predictions were quite accurate, although a slight discrepancy was observed. The tables confirm the visual explanation and demonstrate the operational use of the model for hourly price prediction. The proposed multivariate LSTM model demonstrates strong predictive performance for intraday gold prices, achieving an RMSE of 9.9574, MAE of 7.4411, R^2 of 0.9535, and a MAPE of 0.3009%. The integration of multivariate features, feature engineering, and Time Series Cross-Validation (TSCV) allows the model to capture short-term price dynamics more effectively than conventional methods. Compared to previous studies, the model outperforms Lasijan et al. [8], who applied a multivariate LSTM with a 70:30 train-test split (MAPE 2.71%), and hybrid CNN-LSTM architectures [6] evaluated on the same dataset under similar training conditions. These results indicate that TSCV not only enhances generalization across varying market conditions but also surpasses standard data splitting approaches.

Table 3 Actual vs. Predicted Prices for XAUUSD

Datetime	Actual Price	Predicted Price
2024-02-14 20:00:00	2168.368	2163.1503
2024-02-14 21:00:00	2168.158	2164.7508
2024-02-14 22:00:00	2165.905	2166.3508
2024-02-14 23:00:00	2171.065	2167.5439
2024-02-15 00:00:00	2170.715	2168.7459
2024-02-15 01:00:00	2177.115	2169.8580
2024-02-15 02:00:00	2180.575	2171.2498
2024-02-15 03:00:00	2184.895	2173.0324
2024-02-15 04:00:00	2174.265	2175.3684
2024-02-15 05:00:00	2176.245	2176.9565

From a practical perspective, the model's high accuracy provides valuable insights for intraday traders, enabling better identification of price trends, optimization of entry and exit points, and improved risk management. The outputs can also support automated trading strategies based on volatility or momentum. Nevertheless, the study has limitations, including difficulty capturing extreme short-term price movements and the influence of external factors such as monetary policy or global economic shocks. Future research could explore hybrid architectures, larger datasets, or models more adaptive to high volatility, potentially further enhancing predictive performance and practical applicability.

5 Conclusion

The predictive accuracy of the LSTM model was strong, with a mean MAPE of 0.3009% and an R^2 of 0.9535%, indicating its applicability in financial time series Forecasting. The architecture's capacity to retain long-term temporal dependencies, combined with dropout regularization between stacked layers, staved off overfitting and yielded improved generalization. The introduction of technical features, including SMA, RSI, MACD, and Bollinger Bands, has more than doubled the space for feature inputs beyond regular price. The input representation of momentum, volatility, and trend behavior was enriched to improve forecast accuracy. Consistent results through multiple time periods (proved by TSCV) verify that a combination of LSTM and TSCV constitutes an effective method to predict gold (XAU/USD) at the hourly level. However, model predictions could still be sensitive to unexpected exogenous shocks such as political events or macroeconomic releases. Future research may build on these results by adding sentiment analysis or more fundamental variables with a better ability to increase predictability.

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