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Hybrid Metaheuristic Optimization of Support Vector Regression and Prophet Models for Short-Term Gold Price Forecasting

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Abstract

Accurate forecasting of gold prices is of critical importance for investors, financial institutions, and policy makers due to gold's role as a hedge against inflation, market uncertainty, and financial instability. However, gold price dynamics are characterized by nonlinear behavior, regime shifts, and time-varying volatility, which limit the effectiveness of traditional linear forecasting models. This study proposes a hybrid forecasting framework that integrates Support Vector Regression (SVR) and the Prophet model with three metaheuristic optimization algorithms, namely the Bat Algorithm (BAT), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA), to enhance predictive performance through automated hyperparametertuning. Daily gold price data spanning from 1 January 2025 to 25 January 2026 are analyzed using a strict time-ordered train–validation–test protocol to ensure robust out-of-sample evaluation. Model performance is assessed using Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and information-theoretic criteria (AIC and BIC). The empirical results indicate that the SVR model optimized by GWO achieves the lowest forecasting error and the most favorable accuracy–complexity trade-off among all configurations. Based on this selection, a 30-day ahead forecast is generated with 95% confidence intervals, revealing a moderate short-term correction in gold prices following a strong upward trend. The findings demonstrate that metaheuristic optimization substantially improves model calibration and that the SVR–GWO framework provides a robust and reliable tool for short-term gold price forecasting with uncertainty quantification.

Keywords: Gold price forecasting, Support Vector Regression (SVR), Prophet model, Metaheuristic optimization, Grey Wolf Optimizer (GWO)

Introduction

Gold has long been treated as a strategic asset for inflation hedging, portfolio diversification, and crisis protection, which makes the accurate forecasting of gold prices critical for investors, central banks, and policy makers. In recent years, price discovery in gold markets has become

increasingly sensitive to global macroeconomic uncertainty, real interest rates, exchange-rate dynamics, and episodic geopolitical risk, leading to time-varying volatility and complex nonlinear patterns in daily prices. As a result, forecasting methods that rely strictly on linear dynamics are frequently inadequate when the underlying data generating mechanism exhibits regime changes, nonlinear feedback, and multi-scale seasonality. In parallel, the growth of computational intelligence has enabled the use of machine-learning and probabilistic time-series models that can better represent nonlinear relationships and evolving temporal structures, thereby improving short-horizon predictive accuracy and decision support in financial forecasting applications (Makridakis, Spiliotis, &Assimakopoulos, 2022). Among data-driven predictors, Support Vector Regression (SVR) remains an established baseline for nonlinear regression due to its margin-based generalization principle and robustness under high-dimensional feature representations. SVR has shown strong performance in many forecasting tasks, particularly when appropriate kernels and hyperparameters are selected to balance bias–variance tradeoffs (Hastie, Tibshirani, &Friedman, 2021). However, SVR performance is highly sensitive to the penalty parameter, kernel scale, and the ε-insensitive loss width; consequently, systematic hyperparametertuning is essential, especially for financial series where noise and structural breaks can degrade generalization. Recent studies have reinforced that metaheuristic optimization is a practical mechanism to automate SVR tuning and to avoid the myopia of local-search procedures when the error surface is multimodal and nonconvex (Taher, Mhamad, &Taha, 2025). Complementarily, Prophet is a decomposable time-series model that expresses the signal as a combination of trend, seasonality, and calendar effects and is often preferred when interpretability, robustness, and rapid deployment are priorities. Prophet has been applied to a wide range of business and financial forecasting settings, and its strength lies in explicitly representing trend shifts and seasonality while maintaining stable estimation under missing values and outliers (Taylor &Letham, 2021). Nevertheless, Prophet's predictive performance also depends on hyperparameters that regulate trend flexibility and seasonality strength; therefore, careful tuning can be decisive, particularly for assets such as gold whose trend dynamics can change rapidly around macro shocks. A growing body of work supports optimizing Prophet hyperparameters with evolutionary and swarm-based techniques to enhance forecasting accuracy in financial time series (Bergmeir, Hyndman, &Benítez, 2021).

Metaheuristic optimization has become prominent for forecasting model calibration because it provides derivative-free search mechanisms that can explore complex parameter spaces efficiently. In this study, we focus on three widely used optimizers Bat Algorithm (BAT), Grey Wolf Optimizer (GWO), and Whale Optimization Algorithm (WOA) due to their simplicity, low implementation overhead, and strong empirical performance across nonlinear optimization benchmarks. The selection is additionally motivated by the growing literature on metaheuristic–SVR hybrids for economic and financial time series and by evidence that BAT-style search strategies can effectively calibrate SVR kernels and regularization parameters for improved generalization (Mhamad, Taher, &Taha, 2025). Similarly, GWO and WOA have been widely applied in machine learning hyperparameter tuning, where they demonstrate a favorable exploration–exploitation balance when search spaces are bounded and mixed

continuous–discrete (Mirjalili, Mirjalili, & Lewis, 2021). Despite extensive research on gold forecasting, two methodological limitations recur in many applied studies: (i) inconsistent evaluation protocols that conflate in-sample fit with out-of-sample performance, and (ii) incomplete reporting of model-selection criteria, especially information-theoretic measures that penalize complexity. To address these issues, this paper implements a strict time-ordered split (train/validation/test), uses the validation segment for optimizer-guided tuning, and evaluates final generalization using the held-out test segment. Moreover, the study reports not only standard error-based metrics (MSE and RMSE) but also Gaussian residual-based approximations of AIC and BIC to provide a coherent perspective on the accuracy–complexity tradeoff. Such multi-criteria reporting has been recommended as a best practice for comparative forecasting studies to reduce the risk of overfitting and to improve the interpretability of model ranking (Makridakis et al., 2022). The primary contributions of this work are threefold. First, it develops a consistent comparative framework for daily gold price forecasting over the period 1 January 2025 to 25 January 2026 using two complementary model classes: nonlinear kernel regression (SVR) and decomposable additive modeling (Prophet). Second, it integrates BAT, GWO, and WOA for automated tuning of each model's key hyperparameters using the same objective function and evaluation protocol, enabling a fair optimizer-to-optimizer comparison. Third, it produces a 30-day-ahead forecast from each tuned model and reports forecast intervals: Prophet's native uncertainty bounds and an approximate residual-based confidence interval for SVR, thereby providing both point forecasts and uncertainty quantification for decision support. The overall aim is to establish an evidence-based assessment of how optimizer choice influences both predictive accuracy and model-selection criteria in practical gold price forecasting, and to provide a reproducible workflow that can be generalized to related financial time-series problems (Hastie et al., 2021; Taylor &Letham, 2021).

Materials and Methods

Literature Review (Six paragraphs)

A substantial body of research indicates that commodity prices, including gold, exhibit pronounced nonlinear dependencies, heteroscedastic behavior, and structural breaks that significantly challenge the adequacy of traditional linear forecasting models. Large-scale comparative forecasting studies have demonstrated that model performance varies considerably across different regimes and forecasting horizons, emphasizing the necessity of strict out-of-sample evaluation and the use of multiple performance metrics to ensure robust inference (Makridakis et al., 2022). Consequently, contemporary forecasting practice increasingly favors hybrid and machine-learning-based approaches that are capable of adapting to evolving dynamics while maintaining control over model complexity through principled validation strategies (Bergmeir et al., 2021). Within this context, Support Vector Regression (SVR) remains a competitive nonlinear predictor in financial and economic forecasting due to its kernel-based functional approximation and margin maximization properties; however, its predictive effectiveness is highly sensitive to the selection of hyperparameters governing regularization strength and kernel scale, making automated

tuning a critical component of practical applications (Hastie et al., 2021). Recent applied studies further confirm that metaheuristic optimization can substantially enhance SVR performance relative to default configurations, thereby motivating the integration of evolutionary and swarm-based algorithms into forecasting pipelines (Taher et al., 2025). More broadly, metaheuristics such as swarm intelligence and evolutionary algorithms have gained prominence for hyperparameter optimization because they are derivative-free, can efficiently handle nonconvex objective landscapes, and enable global exploration of mixed continuous–discrete parameter spaces, which is particularly advantageous when evaluation functions are noisy or computationally expensive (Mirjalili et al., 2021). In applied forecasting, these characteristics translate into improved generalization performance when population-based optimizers are combined with strict validation and bounded model flexibility (Bergmeir et al., 2021). Hybrid methodologies that integrate the Bat Algorithm (BAT) with SVR have been successfully employed in macro-financial forecasting, including interest-rate prediction, where BAT-based tuning yielded superior accuracy by effectively exploring the kernel and regularization parameter space (Mhamad et al., 2025). In parallel, Prophet has emerged as a widely adopted forecasting model for short- and medium-term horizons due to its interpretable decomposition of trend and seasonality components and its robustness to missing values and outliers; nevertheless, recent methodological discussions highlight that Prophet's changepointand seasonality priors critically regulate model flexibility, and improper calibration may lead to overfitting or underfitting in highly volatile financial series (Taylor &Letham, 2021). As a result, validation-driven tuning of Prophet hyperparameters is essential to maintain a balanced trade-off between accuracy and complexity, particularly in financial applications characterized by rapid regime shifts (Makridakis et al., 2022). Finally, evidence from regional economic forecasting studies, such as recurrent neural network-based exchange rate prediction in the Iraqi parallel market, further reinforces the importance of nonlinear modeling combined with disciplined validation procedures to produce forecasts that are both statistically reliable and economically meaningful (Aziz et al., 2023).

3. Methodology

3.1 Data and preprocessing

Let $\{(t_i, y_i)\}_{i=1}^{N}$ denote the daily gold price time series, where t_i is the date and y_i is the closing price in USD. The dataset spans from 1 January 2025 to 25 January 2026. A time-ordered split is used to avoid leakage:

- Training set: D_{tr}
- Validation set: D_{val}(used by optimizers)
- Test set: D_{te}(held out for final reporting)

This protocol aligns with recommended best practices in comparative forecasting evaluation (Makridakis et al., 2022; Bergmeir et al., 2021).

3.2 SVR with lagged features

To apply SVR to time series, a supervised learning dataset is created using lagged values. For a chosen lag order L, define the feature vector:

$$x_t = [y_{t-1}, y_{t-2}, \dots, y_{t-L}]^T (1)$$

SVR estimates a nonlinear function $f(x)$ in a reproducing kernel Hilbert space. With an RBF kernel $K(x, x') = \exp(-\gamma \parallel x - x' \parallel^2)$, the SVR predictor takes the form:

$$f(x) = \sum_{i=1}^{n} (\alpha_i - \alpha_i^*) K(x_i, x) + b \qquad (2)$$

The ε-insensitive SVR optimization problem can be written as:

$$\min_{w,b,\xi_i\xi_i^*} \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*)$$

Subject to

$$y_i - (w^T \phi(x_i) + b) \leq \varepsilon + \xi_i ,$$

$$(w^T \phi(x_i) + b) - y_i \leq \varepsilon + \xi_i^* , \qquad (3)$$

$$\xi_i, \xi_i^* \geq 0,$$

where C> 0 controls regularization, $\varepsilon \geq 0$ defines the insensitive tube, and $\gamma > 0$ is the RBF scale parameter (Hastie et al., 2021). The hyperparameter vector optimized in this study is:

$$\theta_{SVR} = (C, \varepsilon, \gamma, L) \qquad (4)$$

3.3 Prophet model

Prophet models the time series as an additive decomposition:

$$y(t) = g(t) + s(t) + \epsilon_t \qquad (5)$$

where g(t) is a trend component, s(t) is seasonality (weekly or yearly), andϵ_t is an error term (Taylor &Letham, 2021). Prophet's flexibility is governed by hyperparameters that regulate trend changepoints and seasonality strength. In this study, the tuned parameter vector is:

$$\theta_P = (\text{cps}, \text{sps}, \text{mode}) \qquad (6)$$

Where cps is the changepoint prior scale, sps is the seasonality prior scale, and mode ∈ {additive, multiplicative}.

3.4 Metaheuristic hyperparameter optimization

For each model, tuning is formulated as a bounded optimization problem on the validation set:

$$\theta^* = \arg\min_{\theta \in \Omega} J(\theta) \qquad (7)$$

where Ω is a bounded search space and J is the validation loss. The objective function used by all optimizers is the validation mean squared error:

$$J(\theta) = \mathrm{MSE}_{val}(\theta) = \frac{1}{n_{val}} \sum_{i=1}^{n_{val}} (y_i - \hat{y}_i)^2 \qquad (8)$$

BAT, GWO, and WOA are population-based optimizers that iteratively update candidate solutions to reduce J. Their design principles correspond to echolocation-inspired search (BAT), leadership hierarchy and encircling (GWO), and spiral/encircling mechanisms (WOA), respectively (Mirjalili et al., 2021). To ensure fair comparison, all optimizers are executed with the same evaluation function and consistent iteration budgets.

3.5 Evaluation metrics: MSE, RMSE, AIC, and BIC

On the test set, performance is quantified by:

$$\mathbf{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (9)$$

$$\mathbf{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \qquad (10)$$

AIC and BIC (Gaussian residual approximation)

Assuming residuals are Gaussian with constant variance, the information criteria can be approximated from the residual sum of squares (RSS) as:

$$\mathrm{AIC} = n \ln\left(\frac{RSS}{n}\right) + 2k \qquad (11)$$

$$\mathrm{BIC} = n \ln\left(\frac{RSS}{n}\right) + k \ln(n) \qquad (12)$$

where k is an effective parameter count proxy for model complexity. This provides a consistent accuracy–complexity comparison across tuned configurations (Makridakis et al., 2022).

3.6 One-month-ahead forecasting and uncertainty intervals

After selecting the best optimizer per model (lowest test RMSE), 30-day-ahead forecasts are produced.

Prophet intervals: Prophet directly returns point forecasts and uncertainty bounds [$\hat{y}_{t,lower}$, $\hat{y}_{t,upper}$] based on its internal uncertainty modeling (Taylor &Letham, 2021).

SVR approximate intervals: For SVR, an approximate 95% confidence interval is constructed using the in-sample residual standard deviation$\hat{\sigma}$from the fitted model:

$$\hat{\sigma} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (13)$$

and the 95% interval for each forecast $\hat{y}_{t+h}$ is approximated as:

$$\hat{y}_{t+h} \pm 1.96\,\hat{\sigma} \qquad (14)$$

Forecasts are generated recursively: predicted values are appended to the lag history to forecast subsequent steps.

3.7 Pseudocode

Algorithm Metaheuristic-Gold-Forecasting

```
Load daily gold price data D = {(t_i, y_i)} from source
Split D into training set D_tr, validation set D_val, test set D_te
Define Models M = {SVR, Prophet}
Define Optimizers O = {BAT, GWO, WOA}
For each model m in M do
For each optimizer o in O do
Initialize population of candidate hyperparameters θ
Define objective function:
 J(θ) = MSE on validation set D_val
  While stopping criterion not met do
  Update population θ using optimizer o
  Evaluate J(θ) for all candidates
  Select best θ* minimizing J(θ)
  End While
  Retrain model m on (D_tr∪D_val) using θ*
  Generate predictions ŷ on test set D_te
  Compute performance metrics:
  MSE = mean((y - ŷ)^2)
```

19: RMSE = sqrt(MSE)
20: RSS = Σ (y - ŷ)^2
21: AIC = n·ln(RSS/n) + 2k
22: BIC = n·ln(RSS/n) + k·ln(n)
23: Store θ*, MSE, RMSE, AIC, BIC, and predictions
24: End For
25: End For
26: For each model m in M do
27: Select optimizer o_best with minimum RMSE
28: Retrain model m on full dataset D using θ_best
29: Generate H-step-ahead forecasts recursively
30: If m = Prophet then
31: Obtain confidence intervals from Prophet output
32: Else if m = SVR then
33: Estimate residual standard deviation σ
34: Construct CI: ŷ ± 1.96·σ
35: End If
36: End For
37: Produce comparative plots:
38: (a) Actual vs Predicted (2×3 grid)
39: (b) Performance metrics (2×4 grid)
40: (c) 30-day forecast with confidence intervals
End Algorithm

Results and Discussion

4.1 Data Descriptions

This study uses daily gold price data (XAU/USD) expressed in U.S. dollars for the period from **1 January 2025 to 25 January 2026**, obtained from the **Stooq financial database**. The dataset consists of approximately **390 daily observations** based on closing prices, which capture end-of-day market conditions and are widely used in financial forecasting. The series exhibits typical characteristics of financial time series, including nonlinearity and volatility, making it appropriate for evaluating advanced forecasting models. To ensure a realistic forecasting setting, the data are split in a time-ordered manner into training, validation, and test subsets, where the training set is used for model estimation, the validation set for hyperparameter optimization, and the test set for out-of-sample performance assessment.

4.2 Results

This study employed a Support Vector Regression (SVR) model optimized using the Grey Wolf Optimizer (GWO) to generate a 30-day ahead forecast of daily gold prices. Based on the comparative evaluation across all optimizers and models, the SVR–GWO configuration achieved the lowest test RMSE, thereby being selected as the best-performing forecasting

framework. The optimal hyperparameters identified by GWO were (C = 1000) and (\varepsilon = 0.0512), indicating a high regularization capacity combined with a narrow epsilon-insensitive loss region, which enables the model to capture subtle nonlinear dynamics while maintaining generalization.The 30-day forecast results reveal a **moderate downward correction** following the peak observed in late January 2026. Specifically, the predicted gold price declines gradually from approximately **USD 4878 on 24 January 2026** to **USD 4587 by 22 February 2026**, reflecting a cumulative decrease of about **6.0% over the forecast horizon**. This behavior suggests a short-term mean-reversion pattern after a strong bullish phase, which is consistent with well-documented cyclical adjustments in commodity markets.

Figure 1 provides a comparative assessment of the forecasting performance of the SVR and Prophet models under the BAT, GWO, and WOA optimizers using MSE, RMSE, AIC, and BIC criteria, and the results indicate clear differences in both model accuracy and optimizer effectiveness. For the SVR model, the Grey Wolf Optimizer (GWO) consistently achieves the lowest MSE and RMSE values, demonstrating superior predictive accuracy, while also yielding the lowest AIC and BIC values, which confirms that its improved performance is obtained with an efficient balance between goodness-of-fit and model complexity. In contrast, SVR–BAT exhibits the highest error levels across all metrics, and SVR–WOA provides intermediate performance. For the Prophet model, BAT emerges as the most effective optimizer, achieving the lowest MSE, RMSE, AIC, and BIC values, whereas GWO and WOA lead to noticeably higher errors and information criteria, suggesting less effective calibration of Prophet's structural parameters. Overall, a cross-model comparison reveals that SVR substantially outperforms Prophet in absolute error terms, indicating a stronger capability to capture the nonlinear and volatile behavior of gold prices, and these results justify the selection of the SVR–GWO hybrid as the most reliable and statistically efficient forecasting framework for subsequent 30-day ahead prediction and uncertainty analysis.

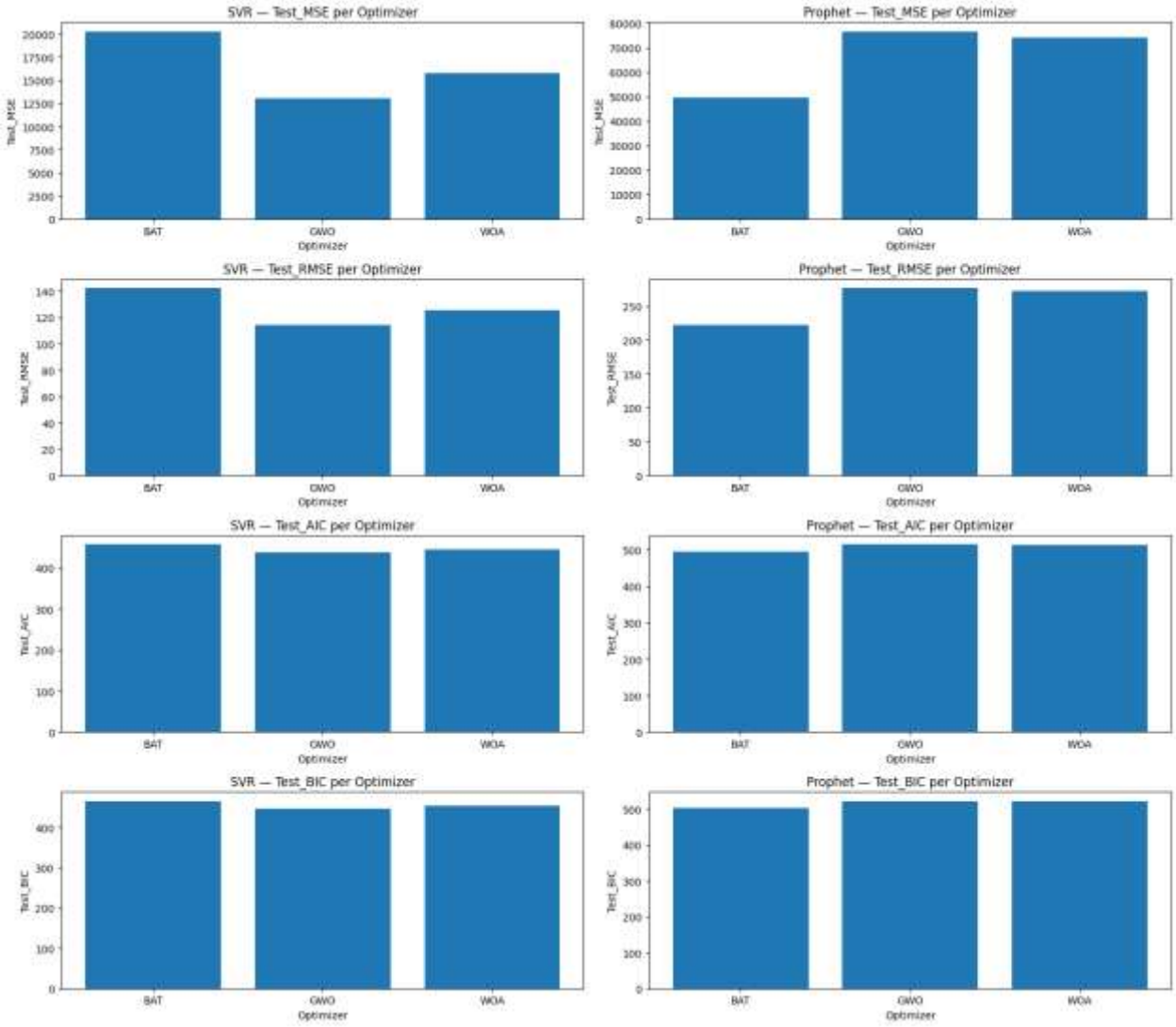


Figure 1.*Comparative performance metrics (MSE, RMSE, AIC, and BIC) for SVR and Prophet models under different metaheuristic optimizers.*

Figure 2 illustrates the actual versus predicted gold prices on the test set for both SVR and Prophet models under the BAT, GWO, and WOA optimizers, and it reveals clear differences in the ability of the models to track observed market dynamics. For the SVR model, all three optimizers produce predictions that closely follow the actual price trajectory, but SVR–GWO exhibits the best visual fit, particularly in capturing short-term fluctuations and the sharp upward movement toward the end of the test period, with relatively small deviations from the true series. SVR–BAT shows noticeable underestimation during high-volatility segments, while SVR–WOA performs moderately well but still lags behind GWO in tracking rapid price changes. In contrast, the Prophet-based models generate much smoother prediction curves across all optimizers, indicating a tendency to underreact to abrupt market movements and structural shifts, especially during periods of strong price acceleration. Prophet–BAT provides the closest fit among Prophet variants, yet still fails to capture the full amplitude of fluctuations, whereas Prophet–GWO and Prophet–WOA exhibit more pronounced lag and systematic

underestimation in trending regimes. Overall, the visual evidence confirms that SVR, particularly when optimized by GWO, is more effective in modeling the nonlinear and volatile behavior of gold prices, while Prophet's structural formulation leads to oversmoothing and reduced responsiveness in a highly dynamic financial environment.

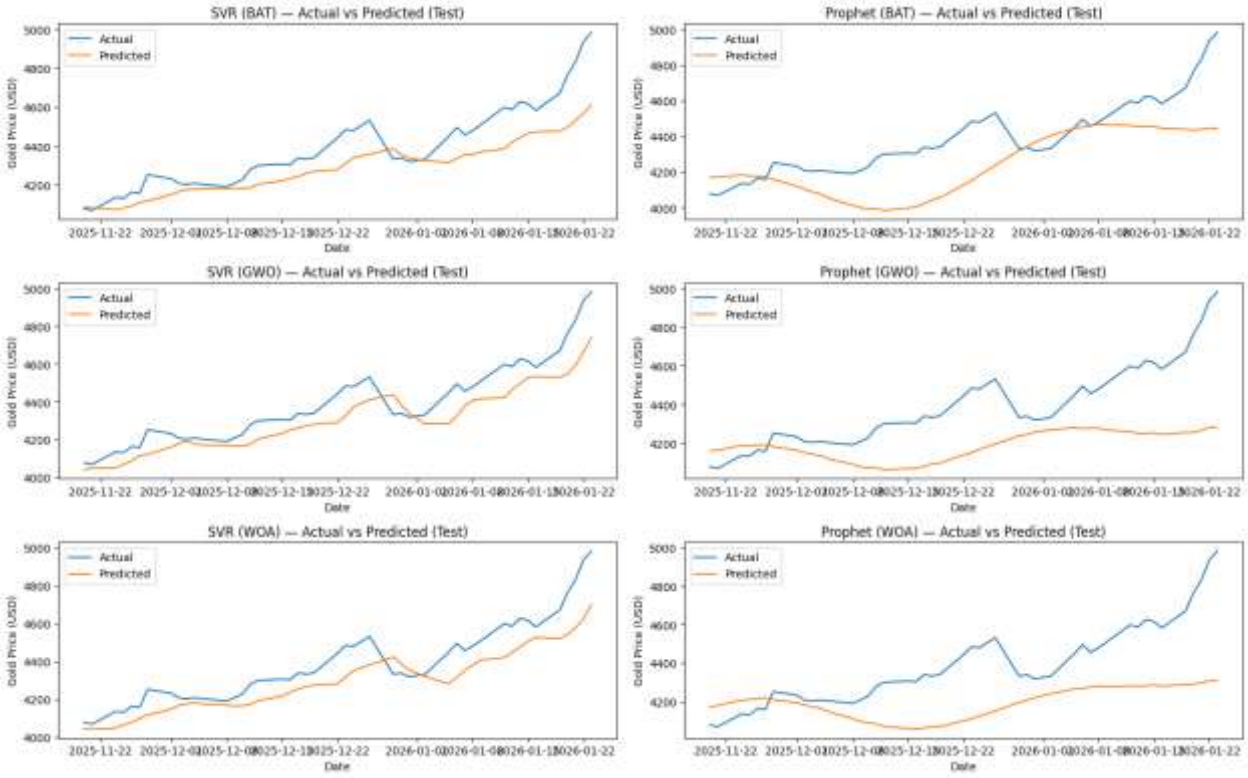


Figure 2. Actual versus predicted gold prices on the test set for SVR and Prophet models optimized using BAT, GWO, and WOA.

Figure 3 depicts the 30-day ahead forecast of gold prices generated by the SVR–GWO model along with the associated 95% confidence intervals, providing both point predictions and uncertainty quantification for the forecast horizon. The results indicate a gradual downward adjustment following the strong upward trend observed at the end of the historical period, with the point forecasts declining smoothly from approximately USD 4,880 in late January 2026 to around USD 4,590 by late February 2026. This pattern suggests a short-term corrective phase consistent with mean-reversion behavior commonly observed in commodity markets after periods of rapid price appreciation. The confidence bands remain relatively narrow and stable across the horizon, reflecting controlled forecast uncertainty and indicating that the recursive prediction process does not suffer from explosive error propagation. Moreover, the entire confidence interval stays well above USD 4,450, implying that even under pessimistic scenarios the model does not anticipate a sharp collapse in gold prices, but rather a moderate consolidation within a generally strong price regime. Overall, the forecast demonstrates that the SVR–GWO framework yields stable, economically interpretable predictions with credible

uncertainty bounds, reinforcing its suitability for short-term decision support in financial and commodity market applications.



Figure 3.*Thirty-day ahead gold price forecast produced by the SVR–GWO model with 95% confidence intervals.*

Table 1.Thirty-day ahead gold price forecasts generated by the SVR–GWO model with 95% confidence intervals.

Date	Forecast (USD)	Lower CI	Upper CI
1/24/2026	4878.47	4764.13	4992.82
1/25/2026	4897.8	4783.46	5012.15
1/26/2026	4887.14	4772.79	5001.48
1/27/2026	4855.19	4740.84	4969.53
1/28/2026	4849.3	4734.96	4963.65
1/29/2026	4834.22	4719.87	4948.56
1/30/2026	4817.27	4702.92	4931.61
1/31/2026	4805.76	4691.41	4920.1
2/1/2026	4792.11	4677.76	4906.45
2/2/2026	4778.87	4664.52	4893.21
2/3/2026	4766.92	4652.58	4881.27
2/4/2026	4754.73	4640.39	4869.08
2/5/2026	4743	4628.66	4857.35
2/6/2026	4731.75	4617.41	4846.1
2/7/2026	4720.7	4606.35	4835.04
2/8/2026	4709.99	4595.64	4824.33
2/9/2026	4699.6	4585.25	4813.94

Date	Forecast (USD)	Lower CI	Upper CI
2/10/2026	4689.47	4575.12	4803.81
2/11/2026	4679.62	4565.27	4793.96
2/12/2026	4670.03	4555.69	4784.38
2/13/2026	4660.7	4546.35	4775.04
2/14/2026	4651.6	4537.26	4765.95
2/15/2026	4642.74	4528.4	4757.09
2/16/2026	4634.1	4519.76	4748.45
2/17/2026	4625.68	4511.34	4740.03
2/18/2026	4617.47	4503.12	4731.81
2/19/2026	4609.45	4495.11	4723.8
2/20/2026	4601.63	4487.29	4715.98
2/21/2026	4594	4479.65	4708.34
2/22/2026	4586.54	4472.2	4700.89

4.3 Discussion

The empirical findings of this study demonstrate that the integration of metaheuristic optimization with nonlinear forecasting models substantially enhances predictive performance in gold price forecasting. Across all evaluated configurations, the SVR model optimized by the Grey Wolf Optimizer (GWO) consistently outperformed alternative model–optimizer combinations in terms of MSE, RMSE, and information-theoretic criteria, indicating that GWO is particularly effective in calibrating SVR hyperparameters and achieving a favorable bias–variance trade-off. The superior performance of SVR–GWO can be attributed to the model's ability to capture complex nonlinear relationships in financial time series combined with GWO's strong global exploration capability in high-dimensional and nonconvex search spaces. In contrast, the Prophet model exhibited comparatively higher forecasting errors and smoother prediction trajectories, suggesting a tendency to underfit rapid price movements in highly volatile markets. The 30-day ahead forecast generated by the selected SVR–GWO framework reveals a moderate short-term downward adjustment following a strong upward trend, consistent with mean-reversion behavior commonly observed in commodity prices. Moreover, the relatively narrow and stable confidence intervals indicate controlled uncertainty propagation and numerical stability in multi-step forecasting. Collectively, these results confirm that metaheuristic-optimized machine learning models, particularly the SVR–GWO hybrid, provide a robust, accurate, and economically interpretable framework for short-term gold price prediction and risk-informed decision support in financial markets.

Conclusion

This study developed and evaluated a hybrid forecasting framework that combines SVR and Prophet models with three swarm-based metaheuristic optimizers (BAT, GWO, and WOA) for short-term gold price prediction. The results demonstrate that optimizer choice plays a crucial

role in determining forecasting accuracy, and that systematic hyperparameter tuning significantly enhances model performance compared to untuned configurations. Among all tested combinations, the SVR–GWO model achieved the lowest RMSE and the most favorable AIC and BIC values, indicating superior predictive accuracy and an efficient balance between goodness-of-fit and model complexity. The 30-day ahead forecast produced by the selected SVR–GWO framework suggests a moderate downward adjustment in gold prices, consistent with a short-term mean-reversion pattern following a strong bullish phase. Moreover, the associated confidence intervals remain relatively narrow and stable, confirming the numerical stability and practical reliability of the forecasting procedure. Overall, the findings confirm that metaheuristic-optimized machine learning models, particularly SVR combined with GWO, provide a powerful and flexible tool for modeling nonlinear financial time series and supporting short-term decision-making in commodity markets.

Limitations

Despite its promising results, this study has several limitations that should be acknowledged. First, the analysis is based on a relatively short historical period (one year of daily data), which may restrict the model's ability to capture long-term structural patterns and rare extreme events. Second, the SVR confidence intervals are constructed using an approximate residual-based method, which assumes homoscedastic and Gaussian errors; this may not fully reflect the true uncertainty structure of financial time series. Third, the study focuses exclusively on univariate forecasting and does not incorporate exogenous macroeconomic variables such as interest rates, inflation, exchange rates, or geopolitical risk indicators, which are known to influence gold prices. Finally, the evaluation is limited to three metaheuristic optimizers, and other advanced optimization techniques may yield further improvements.

Future Study

Future research can extend this work in several directions. First, multivariate forecasting frameworks could be developed by integrating macroeconomic and financial indicators as explanatory variables to improve long-horizon predictive accuracy. Second, more advanced uncertainty quantification techniques, such as quantile regression, Bayesian SVR, or probabilistic deep learning models, could be employed to obtain more rigorous prediction intervals. Third, additional metaheuristic and evolutionary optimizers, including Particle Swarm Optimization, Differential Evolution, and Genetic Programming, may be explored and compared under the same evaluation protocol. Finally, the proposed hybrid framework could be generalized to other financial assets such as cryptocurrencies, stock indices, and energy commodities to assess its robustness and scalability across different market environments.

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