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Improving SVR Horse Herd Optimization Algorithm for Forecasting Daily Gold Prices

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Abstract*—Accurate and correct price prediction of gold is significant to maintain the stability and fair operation of gold markets as well as the efficiency and proper functioning of financial markets related to gold trading. Gold prices have a long history of non-linear and non-stationary behavior that generates highly complex datasets which are very difficult to forecast with high accuracy and reliability. At the same time Support Vector Regression (SVR) has been utilized as a robust information for prediction not only gold prices but also overall metal price movements. First, the predictive capability of SVR is highly sensitive to hyperparameter selection which needs to be thoroughly tuned and optimized for potentially optimal performance. Therefore, the suitable and cautious selection of these hyperparameters can play a significant and direct role in determining the success and precision of SVR. In this study, the focus is on proposing a new technique through horse herd optimization (HHO), which can be used for hyperparameter estimation and tuning of support vector regression (SVR) based on the collective behavior of horse herds to achieve efficient forecasting accuracy and reliability in gold prices. The outcomes and conclusions illustrate that the hybrid algorithm can furnish an increase to the general accuracy of our gold prices, showing superior overall performance as in contrast with two classical benchmark techniques on this area. These enhancements are time to market and useful for enabling faster global economic regeneration and restoration, but also enable the demand side characteristics of integrating international trade commodity price discovery mechanisms into explanations for AI techniques in the context of learning tasks and financial oscular analytics.

***Keywords*—Gold prices; support vector regression; meta-heuristic algorithm; horse herd optimization algorithm; hyperparameter tuning.**

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I. INTRODUCTION

There are not too many challenges more important and complex than analyzing and predicting volatility when we have no complete description of the economy to guide us, so that we make responsible investment decisions, set correct commodity prices, and develop effective economic policies (all based on risk-return assessment). Additionally, volatility forecasting is an essential topic in financial markets, which has garnered sustained, substantial interest from researchers and practitioners alike for many years [1]. Gold, in particular, is a one-of-a-kind asset that serves as money, a metal, and a commodity. These fluctuations and variations in the Gold price have also been well recognized as an important and far-reaching factor influencing broader financial market dynamics [2].

The ever-growing nature of the global economy, the creation and implementation of market conduct standards, both rising and increasing affirmed political occasions and instabilities that characterize stock investors' behavioral inclinations altogether represent noteworthy reasons for the inconstant conditions in the cost of gold [3]. These various factors, some of which are quite unconnected from one another, underlie the juxtapositions and even larger irregularities we see in gold pricing across time.

Nevertheless, the coexistence of these complex and heterogeneous variables makes constructing robust and precise gold buying and selling rate prediction models particularly challenging [4]. In light of this long-overdue research gap, researchers and academics are devoting their time and expertise to understanding the mechanisms of gold price prediction. More generally, however, a number of advanced methods and techniques have emerged from an extensive literature on forecasting metal price movements within two larger classes: artificial intelligence-based approaches and econometric models [5].

In the field of econometrics, price predictions for metals were generally performed by the application of a wide range of established models such as generalized autoregressive conditional heteroskedasticity (GARCH) [6], linear regression (LR) [7] and autoregressive (AR) models respectively, each providing its own set of analytical benefits [8]. However, other artificial intelligence methods, including support vector regression (SVR), artificial neural networks and some other advanced machine learning algorithms have also proven very powerful for a wide variety of nonlinear modeling problems vital in any financial time series forecasting task [9].

Over the past decades, fundamental theories and practical performances of support vector machine (SVM) method have attracted much attention from statisticians, practitioners in industries, or academic researchers that provide a large part of explanations for its excellent performance for both classification and regression tasks. Early on, SVM was mainly used for various classification problems. But, an enhancement for SVM have been observed and used to solve nonlinear regression problems based on the ε-insensitive loss function suggested by [10] that later was made use to develop a specific algorithm so-called support vector regression (SVR) [11]. Despite its robustness, the success of SVR is highly sensitive to the choice and tuning of its hyperparameters which have a major impact on the final performance of the model.

Thus, hyperparameter optimization becomes an important process in effectively taking advantage of the model's predictive power. The main novelty of the current work lies in the introduction of the horse herd optimization algorithm, an advanced meta-heuristic, to improve hyperparameter selection for SVR. This strategic enhancement is intended to markedly improve the precision and reliability of predicting gold price time series, thereby addressing a pivotal issue in financial market prediction [12].

A. Support Vector Regression

Support Vector Regression (SVR) is a machine-learning approach derived from support vector classification for the regression steps using an -sensitive loss function. As SVM are generally linear learning machines, the regression (problem) is also always solved/learned in a linear way. SVM, in the context of nonlinear regression, use a nonlinear mapping to map the data x into some high-dimensional feature space and then do linear regression [13]. Let us consider a training dataset with observations where is vector corresponding to the i th feature, for i =1,...n is a quantitative variable that we called as target variable and ε-insensitive loss function then an SVR can be obtained from solving the following optimization problem.

$$\min_{\boldsymbol{w},b} \left\{ \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C\sum_{i=1}^{n}\left(\zeta_i + \tilde{\zeta}_i\right) \right\}$$
$$\text{S.T.} \quad \begin{cases} y_i - (\boldsymbol{w}\varphi(\boldsymbol{x}_i) + b) \le \varepsilon + \tilde{\zeta}_i \\ (\boldsymbol{w}\varphi(\boldsymbol{x}_i) + b) - y_i \le \varepsilon + \zeta_i \\ \zeta_i, \tilde{\zeta}_i \ge 0, \end{cases} \tag{1}$$

where $C > 0$ is a penalized parameter that determines the trade-off between the models complexity and the training error, ζ_i and $\tilde{\zeta}_i$ are slack variables $\varphi(\boldsymbol{x}_i)$, is a non-linear transformation introduced by kernel function, is vector of weights and is the bias. Then, Eq. After having reformulated problem (1) into its dual it can be solved by the Lagrangian multipliers.

$$\min_{\tilde{\alpha},\alpha} \frac{1}{2} \sum_{i,j=1}^{n}(\tilde{\alpha}_i - \alpha_i)(\tilde{\alpha}_j - \alpha_j)\, K(\boldsymbol{x}_i, \boldsymbol{x}_j) + \varepsilon\sum_{i=1}^{n}(\tilde{\alpha}_i - \alpha_i) - \sum_{i=1}^{n} y_i(\tilde{\alpha}_i - \alpha_i) \tag{2}$$
$$\text{S.T.} \quad \begin{cases} \sum_{i=1}^{n}(\alpha_i - \tilde{\alpha}_i) = 0 \\ 0 \le \alpha_i, \tilde{\alpha}_i \le C, \end{cases}$$

where $K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ stands for kernel mapping, and α_i, $\tilde{\alpha}_i$are Lagrangian multipliers:

$$y_i = f(\boldsymbol{x}_i) = \sum_{x_i = \mathrm{SV}}(\tilde{\alpha}_i + \alpha_i)K(\boldsymbol{x}_i, \boldsymbol{x}_j) + b, \tag{3}$$

where SV is the support vectors set [14].

Until recently, the choice of the kernel function for specific data patterns has been another interesting issue in the use of SVR seemed to be somewhat ad hoc. However, the SVR algorithm is associated with two sets of parameters being as a classification model. The first one is the he parameter C which determines how much the complexity of the function demands frequent mistakes. The second set is the parameter(s) of the kernel functions which actually determines the degree of mapping transformation of the input data to the feature space, as well as the complexity of the model [15].

B. The Proposed Improvement

The performance of SVR yields significantly to changes of its hyperparameters. Nonetheless, there is no technique rooted in mathematics for deciding the exact intended values [16]. Thus, such hyperparameters are the subject of SVR research because of their selection in the process. Many trials have been reported in the literature where different approaches have been employed to enhance the performance of SVR with suitable choice of these hyperparameters [17], [18]. These different procedures that were used to select the hyperparameters of SVR include the nature-inspired algorithms among them [19], [20].

The algorithms they created by taking inspiration from nature have garnered a lot of attention and produced competitive outcomes when used to solve optimization challenges, such as the hyperparameter tuning problem [20]. Numerous works on optimizing SVR hyperparameters with algorithms inspired by nature can be found in the literature, such as [21], [22]. In the recent past, a number of new algorithms are invented by the scientists based on the phenomena, which are found in nature to promote and optimize the further explorations and exploitations of the existing algorithms [23]. Of these newly introduced algorithms, horse herd optimization algorithm which has gained lot of traction recently due to their efficiency.

The horse herd optimization algorithm (HHOA) is one of the newly advanced bio-inspired algorithms developed by [24]. The idea's HHOA draws from behaviors of horses in natural environment such as grazing, hierarchy, sociality, mimicking, shielding, and ranging [25]. These six broad categories of equine behavior across the life span have been used to provide context to proposing the HHOA. As a result, these Horses undergo through several behaviors as they grow in age. Thus, δ horses include horses that are below 5 years of age, γ are horses aged between 5 and 10 years, β are horses between the ages of 10 and 15 and α is the group aged 15 years and above. The movement of the equine during the whole repetition is worked out using Equation (1) [26].

$$X_m^{Iter,AGE} = \vec{V}_m^{Iter,AGE} + X_m^{(Iter-1),AGE}; AGE = \delta, \gamma, \beta, \alpha \tag{4}$$

where $X_m^{Iter,AGE}$ indicates the m^{th} horse position.

Moreover, the response matrix of each iteration in the process should be in detail to determine the age of the horses. Thus, matrix is constructed based on the optimal responses and the first ten percent of the horses lie at the top of the matrix are selected to be α. The horses with the β was the next 20% and those with δ and γ were the next 30% and 40% of the other horses, respectively [27]. The steps that have to be followed in order to mathematically mimic the six behaviors stated above are to attain the velocity vector. Equations 5-8 are.

$$\vec{V}_m^{Iter,\alpha} = \vec{G}_m^{Iter,\alpha} + \vec{D}_m^{Iter,\alpha} \tag{1}$$

$$\vec{V}_m^{Iter,\beta} = \vec{G}_m^{Iter,\beta} + \vec{H}_m^{Iter,\beta} + \vec{S}_m^{Iter,\beta} + \vec{D}_m^{Iter,\beta} \tag{2}$$

$$\vec{V}_m^{Iter,\gamma} = \vec{G}_m^{Iter,\gamma} + \vec{H}_m^{Iter,\gamma} + \vec{S}_m^{Iter,\gamma} + \vec{I}_m^{Iter,\gamma} + \vec{D}_m^{Iter,\gamma} + \vec{R}_m^{Iter,\gamma} \tag{3}$$

$$\vec{V}_m^{Iter,\delta} = \vec{G}_m^{Iter,\delta} + \vec{I}_m^{Iter,\delta} + \vec{R}_m^{Iter,\delta} \tag{4}$$

1) Grazing: Because horses are extended grazers, they are well adapted to pastures, vegetation, water and other forming pastures for example a horse should graze for 16-20 hours in a day. These behaviors in the HHOA can be mathematically characterized in a manner described by Eqs. (9) and (10).

$$\vec{G}_m^{Iter,AGE} = g_{Iter}(\tilde{u} + \rho\tilde{l})[X_m^{(Iter-1)}], \quad AGE = \alpha, \beta, \gamma, \delta \tag{5}$$

$$g_m^{Iter,AGE} = g_m^{(Iter-1),AGE} \times \omega_g \tag{6}$$

where $\vec{G}_m^{Iter,AGE}$ is the movement parameter for i^{th} one of the horses that determine the grazing index of the horse. The grazing variable reduces linearly with respect to the $\omega_g$repetition Similarly the feed forward variable reduces for each repetition by at. represented the extent of the grazing land while 1 represents the extent of free grazing floor. There are some literatures where the number that is suggested for it is 05. The following is the assumptions used in the study The following assumptions have been used in the study: The lower boundary of the grazing area is, and the, 0. This parameter should be at least 95. The variable which is a random integer in the interval (0, 1) is represented by γ. From the given formula it can be presumed that the value of the coefficient should be 1. 5 during all the developmental stages and during every age [28].

2) Hierarchy: Whenever members are in a herd, then there are always those that will act as the herders while the others act as the herded. In consequence, the strongest horses of the herd have to take the responsibilities of herding. This is captured by the law of hierarchy. Here the proclivity of a group of horses to follow the most experienced and the strongest leader is modeled by the coefficient in the HHOA. Several studies illustrate the following observation that indeed horses obey the power in rank in the Middle Ages β and γ groups (5-15 years of age). It is possible to define it using Eq's. (11) and (12).

$$\vec{H}_m^{Iter,AGE} = h_m^{Iter,AGE}[X_*^{(Iter-1)} - X_m^{(Iter-1)}], \quad AGE = \alpha, \beta \text{ and } \delta \tag{7}$$

$$h_m^{Iter,AGE} = h_m^{(Iter-1),AGE} \times \omega_h \tag{8}$$

3) Sociability: Horses are gregarious and have to 'meet' other animals and do this interact in their natural setting or habitat. They have been secure in herds even though most predators are chasing the horses owing to their existence in herds. A diverse population not only increases the likelihood of the person's survival, but also eliminates most of the difficulties connected with the escape from various troubles. Due to the social nature of horses, one will often observe them engaging in some sort of overt aggression with other members of their kind. This is likely to be particularly so given that the horses are unique and thus their irritation could be as a result of their uniqueness. As much as some of the horses prefer company of other animals such as cattle and sheep, what they would not want is to be lonely. All the horses feed a clear interest towards the herd especially those aged 5 to 15 which if put in the Eqs. (13) and (14) [29].

$$\vec{S}_m^{Iter,AGE} = s_m^{Iter,AGE}\left[\left(\frac{1}{N}\sum_{j=1}^{N} X_j^{(Iter-1)}\right) - X_m^{(Iter-1)}\right], \quad AGE = \beta \text{ and } \delta \tag{9}$$

$$s_m^{Iter,AGE} = s_m^{(Iter-1),AGE} \times \omega_s \tag{10}$$

where, is the social movement vector with horse based on general stand of the relevant horse of herd regard to in iteration. Even still, each ride ends up passing along a minuscule amount due to that factor. Also, indicating the total number of horses, indicates the age distribution of each horse in that population. In the sensitivity analysis version of the parameters, the coefficient for both and horses is derived.

4) Imitation: Horses tend to copy each other in terms of their actions and this is regardless of whether such actions may be deemed to have positive effects on them or not. Normally young horses get behaviors from their older fellows, which make it possible for them to stay in secure places. Such behavior includes identifying the right place where pastures should be placed, constructing ways of defense and so on [30].

$$\vec{I}_m^{Iter,AGE} = i_m^{Iter,AGE}\left[\left(\frac{1}{pN}\sum_{j=1}^{pN}\hat{X}_j^{(Iter-1)}\right) - X^{(Iter-1)}\right], \quad AGE = \gamma \tag{11}$$

$$i_m^{Iter,AGE} = i_m^{(Iter-1),AGE} \times \omega_i \tag{12}$$

In the equations above, the vector shows how fast the horse is currently approaching or moving away from mean position of best horses represented by. Herd Total - The herd total shows how many better horses there are; only recommended in a set up that is no more than 10% of the horses complete, out of the full/target number of horses. There is a reduction factor involving in each of the iterations.

5) Defense mechanism: This behavior is understandable since horses, as it is depicted below, are attacked by several types of predators. In order to protect themselves, they are known to act in a manner, which demonstrates the fight back or regarded as the flight response. One would think that their first reaction would be the desire to get as far away from it as possible. Besides this, where they are caught, they buck as well, so as to escape the trap. In their natural environment, through genetic predisposition, horses cannot help but engage in a fight against other horses over issues like access to food and water, competition as well as attack other horses so as to eliminate them next time they are seen as a threat. In the HHOA algorithm, the defensive mechanism of horses comprises of the horses running away from other horses with behaviors much below the ideal ones. The d it is this which determines the strength they possess in the tactical level in the defense department. The defense mechanism can be described by formulations presented by Eqs. (17) and (18) :

$$\vec{D}_m^{Iter,AGE} = -d_m^{Iter,AGE}\left[\left(\frac{1}{qN}\sum_{j=1}^{qN}\check{X}_j^{(Iter-1)}\right) - X^{(Iter-1)}\right], \quad AGE = \alpha, \beta \text{ and } \gamma \tag{13}$$

$$d_m^{Iter,AGE} = d_m^{(Iter-1),AGE} \times \omega_d \tag{14}$$

6) Roaming: Horses are on the constant lookout for food and are most often on the main grazing pastures that are located in open countryside and therefore they are usually on the move from one pasture to the next. Despite the fact that most of the horses are kept in stables, they possessed this characteristic which was pointed out. This means that a horse may suddenly decide to move to another area to take food probably hay. Horses are very inquisitive animals, and due to this, they move around in search of new feed grounds and to have familiarization of new grounds. The appropriate stable also has side walls built in such a manner that allows the horses to monitor each other's presence, which is an interest inherent in those animals. This action is copied in the form of a random motion, and the factor stands for simulation in the presented model. The activity is also observed in young horses who frequently roams but this significantly reduces in old aged horses. This procedure is further shown in the following equations: Thus, this procedure is displayed in the Eqs (19) and (20) .

$$\vec{R}_m^{Iter,AGE} = r_m^{Iter,AGE}\rho X^{(Iter-1)}, \quad AGE = \gamma \text{ and } \delta \tag{15}$$

$$r_m^{Iter,AGE} = r_m^{(Iter-1),AGE} \times \omega_h \tag{16}$$

In SVR, we should consider with three parameters: penalized parameter,, ε-insensitive loss function and kernel parameter. HHOA algorithm considers each of these parameters as a position. So, we have three positions to which each horse in the swarm will look for them. Linking this up with what we are teaching; our proposed algorithm is as follows:

a. Step 1: The number of horses, N_j, is set to 30 and the maximum number of iterations is $t^{max=1000}$.
b. Step 2: Specifying the positions of each horse randomly. The position is globally generated from uniform distribution with 0 and 6 for the. In contrast, for, the position is drawn uniformly at random from between 0.1 and 5. Kernel Parameter Radial Base Kernel is a byproduct of.
c. Step 3: The fitness function is defined as

$$\text{fitness} = min\left[\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_{i(C,\varepsilon,\sigma)})^2\right]. \tag{17}$$

According to Eq. (25), each horse has its fitness value, and, therefore, the personal best values and the global best value are calculated.

d. Step 4: The positions of the horses are updated using their related equations.
e. Step 5: Steps 4 and 5 are repeated until a t^{max} is reached.

II. Materials and Methods

A. Data description

In this research, 6,107 daily gold price data from January 20, 2000 to November 1, 2023 were collected and used as the basic sample data for analysis (as shown in Fig. 1). In your case, the data split was made through-splitting strategy to build both wide and performant model (train subset containing 4,841 daily gold price observations from January 20, 2000 to December 31,2018. The remaining 1,266 daily price entries from January 2, 2019 to November 1, 2023 were kept aside for testing purposes exclusively and thus allowing the model message to be evaluated against unseen data.

B. Forecasting Evaluation Criteria

These well-defined metrics are being used as double-edged sword, such that they are; once being counted and measured for the prognostic correctness & predictability of proposed model, and secondly justify with statistical support to authenticate the expectations & consequences gained from its predictions. Table 1 provides mathematical equations and formal definitions for each key evaluation criterion, offering a more detailed reference to understanding the calculation and interpretation.

TABLE I
FORECASTING EVALUATION CRITERIA

Evaluation criterion	Mathematical formula
MAE	$\frac{1}{n}\sum_{t=1}^{n}\lvert y_t - \hat{y}_t\rvert$
RMSE	$\sqrt{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}$
DA	$\frac{1}{n}\sum_{t=1}^{n} z_t,\quad z_t = \begin{cases} 1, & \text{if}(y_{t+1}-y_t)(\hat{y}_{t+1}-\hat{y}_t) \geq 0 \\ 0, & \text{otherwise} \end{cases}$
R^2	$1 - \left[\frac{\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{\sum_{t=1}^{n}(\hat{y}_t - \bar{y}_t)^2}\right]$

III. RESULTS AND DISCUSSIONS

A. Comprehensive Comparison Tests

To analyze and evaluate the forecasting performance of our newly established approach (HHOA-SVR), we are conducted extensive comparative evaluation tests using the grid search strategy (GS-SVR) and the cross-validation with ten folds (CV-SVR). Tables 2 and 3 systematically exhibit the forecasting performances of the GS-SVR, CV-SVR, and HHOA-SVR models which are assessed through various series of standard evaluation criteria for analysis and comparison purposes. Figure 1 visualizes the complicated price fluctuation pattern of gold daily on a continuous time horizon. It is very clear to see the daily price movements of gold, which are evidently non-linear and non-smooth but strongly erratic in nature as it follows the market dynamics. From the aggregated results provided in Tables 2 and 3 for different evolutionary methods, it is undoubtedly established from the forecasting outcomes of gold prices that HHOA-SVR significantly improves both forecasting accuracy and generalization ability. Evidence of this improvement is apparent in its consistently lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), and a significantly higher Directional Accuracy (DA) as well as coefficient of determination (R^2) scores. Indeed, the data show an indisputable superiority of HHOA-SVR over both GS-SVR and CVSVR approaches for all metrics used to compare.

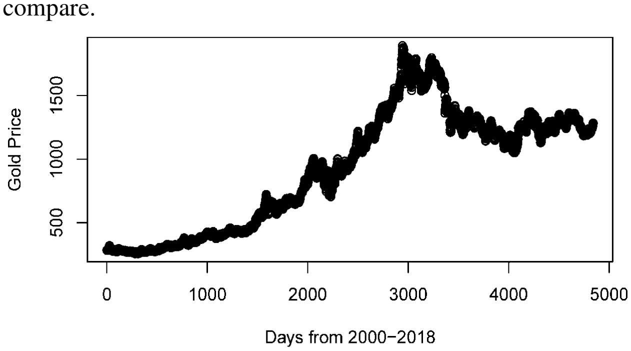

Fig 1. Time series of the daily gold price for the training data set.

B. Comparison between MAE and RMSE

Table 2 shows Comparison of MAE and RMSE achieved via HHOA-GS-SVR, HHOA-CA-SVR against GS-SVR, CV-SVR Correspondingly, when we compare the reduction of MAE and RMSE by HHOA-GS-SVR with those of GS-SVR we notice that HHOA-GS-SVR leads to a drop in MAE of 16.58% and in terms of RMSE achieves an improvement up to 98.39%. Likewise, as illustrated in Table 3 for the testing dataset, it brings about reduction of 77.45% and 99.40%, and 86.51% and 99.70% with respect to GS-SVR and CV-SVR evaluation metrics respectively.

The results presented here demonstrate the enhanced predictive power of meta-heuristic algorithms, which perform strongly even without extensive data preprocessing when compared to more conventional approaches (GS-SVR and CV-SVR). The relatively poor performance of SVR models is probably due to the random and non-optimal hyperparameter selections that are an innate quality in CV and GS methods. In addition, comparison of CV and GS concerning finding the proper hyperparameters can provide that the evaluation indicator results considering each method are much better when using CV for training set indicating its relatively better performance than GS.

TABLE II
THE FORECASTING RESULTS OF THE PROPOSED APPROACH, HHOA-SVR, AND THE BENCHMARK APPROACHES CV-SVR AND GS-SVR FOR THE TRAINING SET

	CV	GS	HHOA-SVR
MAE	0.211	10.957	0.176
RMSE	0.948	26.091	0.388
DA	0.617	0.404	0.813
R^2	0.915	0.384	0.986

The predicted daily gold prices given by the HHOA-SVR model have been closely and even tighter fitted with their corresponding actual observed values, as illustrated obviously in Figures 2 and 3, thus implying the high quality of forecasting for the model. In addition, the HHOA-SVR model is fundamentally improved by including both training and testing price data to better predict currency exchange rate behavior. This robustness is also validated by the noticeably smooth time series generated using HHOA-SVR, which adds to the total accuracy of the model. As a result, the HHOA-SVR model is capable of predicting daily gold prices with high accuracy and confidence. Additionally, as shown in Figures 2 and 3, the price forecasts of gold using the CV-SVR method have a line (actual and predicted gold prices) that fits better than the golden results augmented by HHOA-SVR. In fact, the predictions generated by the GS-SVR approach were surprisingly weak and unstable over time, which was unable to reflect the in-depth characteristics of gold price fluctuations more accurately than other models.

TABLE III
THE FORECASTING RESULTS OF THE PROPOSED APPROACH, HHOA-SVR, AND THE BENCHMARK APPROACHES CV-SVR AND GS-SVR FOR THE TESTING SET

	CV	GS	HHOA-SVR
MAE	2.608	98.665	0.588
RMSE	6.725	306.824	0.907
DA	0.569	0.387	0.784
R^2	0.884	0.206	0.972

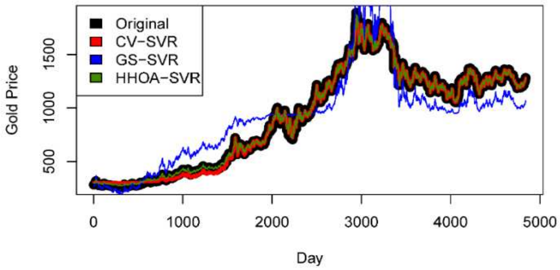

Fig. 2 Forecast results in training dataset based on methods used

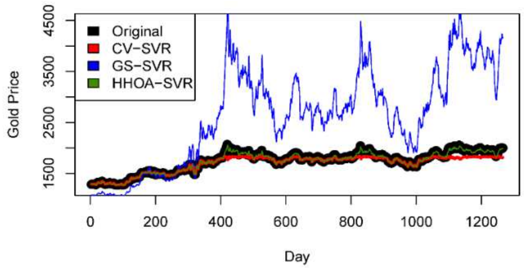

Fig. 3 Forecast results in testing dataset based on methods used

C. Forecast Performance

To reinforce and effectively validate the relative superior forecasting performance of HHOA-SVR model against CV-SVR and GS-SVR model, the Diebold–Mariano (DM) test, which is an established statistical hypothesis testing strategy for comparing predictive accuracies, is performed to test significant differences between the competing models in terms of their accuracy. The specific results for the DM test are demonstrated separately on the forecasted future gold prices predicted from the training dataset and testing dataset (see details in Tables 4 and 5). Evaluation of DM test: Based upon the outcome from DM test, it is conclusive that HHOA-SVR model gives more statistically significant performance advantage over forecasted values obtained with CV-SVR and GS-SVR models at least 95% confidence for gold price prediction. The evidence for this conclusion can be obtained by observing that when the HHOA-SVR is treated as an anchor/target forecasting model, the p-values calculated from such tests are always less than 5%. Furthermore, this statistically significant superiority of HHOA-SVR is not only limited to the training dataset but rather it generalizes strongly a testing dataset as demonstrated in Table 5 which indicates that with >95% confidence the forecasting strategy using HHOA-SVR outperforms considerably other compared methodologies when tested on different datasets.

TABLE VI
DM TEST RESULTS OF THE TRAINING DATASET

	CV-SVR	**GS-SVR**
HHOA-SVR	6.147 (p-value=0.0047)	11.381 (p-value=0.0002)
GS-SVR	6.192 (p-value=0.0004)	

TABLE V
DM TEST RESULTS OF THE TESTING DATASET.

	CV-SVR	**GS-SVR**
HHOA-SVR	7.143 (p-value=0.0021)	14.638 (p-value=0.0001)
GS-SVR	7.608 (p-value=0.0033)	

IV. CONCLUSION

Given the current state of globalization, rising gold prices are necessary for economic growth. To make better financial and investment decisions, it is therefore essential to forecast these prices. Predicting the price of gold is challenging, though, due to its extreme volatility. This study recommended using the GJO method, a meta-heuristic approach, to improve SVR in order to predict daily gold prices. A variety of forecasting evaluation metrics, such as the DM test, R^2, DA, RMSE, and MAE, were utilized to evaluate the forecasting performance of the employed approaches. It is shown that the prediction performance of HHOA-SVR is much better than that of two rival techniques, GS-SVR and CV-SVR. The significance of using the HHOA-SVR technique is highlighted by the results of a second statistical run of the DM test, which was conducted to confirm the outcome. When compared to other options considered, the results indicate that the proposed HHOA-SVR strategy is effective overall.

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