

Time Series Prediction of Stock Market Movements by Utilizing the BRO-SVR Hybrid Model: A Case Study of the Shanghai Stock Exchange

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Abstract

Predicting future stock prices is challenging due to numerous uncontrollable factors. However, data-driven methods have enabled more accurate forecasts despite inherent uncertainties. Traditionally, such forecasts relied on technical and fundamental indicators. With advancements in machine learning (ML), prediction accuracy and accessibility have significantly improved. This study presents a novel approach that integrates the Battle Royale Optimization (BRO) algorithm with an enhanced support vector regression model to predict stock prices. Applied to data from the Shanghai Stock Exchange, the proposed model demonstrated high prediction accuracy. It consistently outperformed existing methods, significantly improving time series forecasting of stock values. High R^2 values during both training and testing phases confirm the model's robustness. These results indicate that the BRO-optimized model effectively manages stock market volatility and serves as a reliable tool for analysts and investors seeking accurate and consistent financial forecasting.

Keywords: Stock Price Prediction, Support Vector Regression (SVR), Battle Royale Optimization (BRO), Shanghai Stock Exchange (SSE), Machine Learning (ML), Metaheuristic Algorithms, Time Series Forecasting, Prediction Accuracy Metrics.

Forecasting the stock exchange is challenging because many variables affect the market prices, ranging from political events and economic circumstances to investor outlook Oyewola et al., (2021). This was a result of volatile fluctuations in the stock exchange prices. Predicting the stock exchange requires a high level of expertise in stock analysis. Rather than investing in stocks that experience a progressive decline in value over time, investors acquire equities that are anticipated to experience future price increases. Developing a robust stock exchange algorithm that accurately predicts stock performance is essential to boost profits and diminish investor losses. Conventional statistical tactics may be insufficient for conducting a thorough investigation of the stock exchange. Moreover, the share market is susceptible to several variables that directly influence its volatility in the currency market. The absence of comprehensive stock exchange data substantially hinders predicting future stock values. Investors in equities utilize an assortment of technical indicators to forecast price fluctuations. Even though these indicators are used to evaluate equities, forecasting market trends is challenging. Multiple economic and non-economic variables have an impact on the behavior of stock trends Emin, (2011). In other words, the stock exchange forecast is viewed as the largest barrier to achieving production progress. According to this problem, a method for ML may be necessary to provide good predictions of patterns appearing within the stock exchange.

It helps with ML programming through large sets of data to avoid the different potential risks and blind alleys that enable computers to learn continuously Hua, (2022). These frameworks can recognize patterns, generate predictions based on past occurrences, and adjust their behavior as time advances Jutel et al., (2023). ML methods are often used in academic research to assess and quantify hazards Hegde et al., (2020). ML is a field of computer science that concentrates on extracting patterns from data to boost productivity in diverse activities Sarker, (2021). In 1997, Vapnik et al. introduced the concept of SVR Shoko et al., (2023). SVM is a subset of SVR. It provides effective generalization capability due to the minimization of the upper limit of risk, according to Vapnik (1999), which, in turn, decreases overfitting and helps reduce small generalization errors. A high advantage of SVR is its tendency not to overfit due to the structural risk minimization principle that balances the regression functions' complexity and estimation accuracy. These probably result in some parameters of the traditional regression methods becoming more prominent in size once the undesired data has been removed. Thus, conventional regression methods may overfit, while the SVR shows a good generalization capability due to its optimization object function that keeps the regression function flat. SVR is well-suited for addressing complex modeling and pattern recognition issues, including

nonlinearity, short sample sizes, and high-dimensional data. However, the quality of SVR predictions depends on the penalty coefficient and the value of the radial basis function (RBF) kernel.

Selecting the suitable parameters is a crucial aspect that significantly impacts the performance of SVR. This process may be framed as an optimization problem. Meta-heuristic frameworks, including GA Chugh et al., (2019), ant colony algorithm Colorni et al., (1992), and PSO Shami et al., (2022), are advanced optimization frameworks that can successfully tackle complicated functional and combinatorial optimization problems Kaveh et al., (2023). Utilizing metaheuristic frameworks to search and optimize critical parameters of SVR schemes is a successful approach for enhancing prediction accuracy and generalization ability. Maryam Ouahilall and colleagues combined SVR and the Hodrick-Prescott filter to optimize stock price forecasting Ouahilall et al., (2017). Bruno Miranda Henrique et al. used a machine learning (ML) tactic called SVR to anticipate equity prices for large and small investments in three markets Henrique et al., (2018). Metaheuristic frameworks have emerged as the most suitable options for both feature selection and classification Houssein et al., (2023). The majority of metaheuristic frameworks are designed to address continuous optimization issues. Scientists have been persistently endeavoring to enhance the efficacy of some frameworks by using hybrid frameworks, including others. For example, the use of moth-flame optimization (MFO) Mirjalili, (2015a) Biogeography-based optimization (BBO) Harshavardhan et al., (2022), slime mold frameworks (SMA) Li et al., (2020), ant lion optimization (ALO) Mirjalili, (2015b), and genetic frameworks (GA) Briley et al., (2018).

The optimization approach, referred to as "Battle Royal Optimization" (BRO) Rahkar Farshi, (2021), was recently established and draws inspiration from the popular "battle royal" gaming genre in digital games. BRO is a population-based optimization strategy that emulates the death match play structure of Player Unknown's Battlegrounds (PUBG). In 2020, the advancement of game-based enhancement frameworks led to the introduction of a new category. In game-based frameworks, players compete with adjacent players as potential solutions while exploring their area. Players strive to outperform each adversary and emerge victorious in the game, unlike SI-based frameworks that rely on collaborative efforts to achieve a common goal. The BRO algorithm has unique significance amid the current plethora of optimization frameworks. This tactic has augmented the count of options accessible to metaheuristic frameworks Yavuz et al., (2023). The paper presents the hybrid BRO-SVR model, which has demonstrated remarkable accuracy in predicting stock values. This exploration examined various schemes, including SVR, ALO-SVR, and SMA-SVR. Following this introductory section, the document is outlined as follows: In Section 2 of the research paper, an analytical methodology is used to examine the data resource and its associated components thoroughly. Section 3 comprehensively elucidates the attained outcomes and the pertinent discourse about them. Following this, the primary findings are summarized.

2.1. Data Collection and Preparing

A detailed exploration will require the volume traded and the Open, High, Low, and Close (OHLC) of a specific time. The data was compiled from the Shanghai Stock Exchange (SSE) from January 5, 2015, to June 29, 2023. The SSE is a meaningful stock exchange in China. It is the other autonomous stock exchange operating in Mainland China. Its counterpart is the Shenzhen Stock Exchange. SSE is based in Shanghai, China's financial hub. The SSE provides a marketplace for trading in various financial instruments, such as stocks, bonds, funds, and other securities. The action of obtaining cash, amongst other similar actions, is a vital role played by the actions of Chinese enterprises. The SSE includes many listed corporations, from state-owned enterprises to private and international corporations. The exchange has specified specific listing standards that businesses must meet if they want to be listed in the exchange. Composite Index is the general name for the composite index, which displays the performance of SSE and targets many investors. The Composite Index has been an index of many enterprises with listings in the SSE. The regulatory body behind the SSE is the China Securities Regulatory Commission (CSRS), which oversees and regulates China's securities and futures markets. There have been several steps to increase regulatory mechanisms, permit foreign investment, and introduce transparency into the workings since the beginning of the SSE.

The SSE is followed closely by investors worldwide in studies of Chinese financial markets. China plays a significant role in the global economy and is an integral part of the financial world. To provide the scheme with the necessary training data, the volumes and prices of OHLC were revealed. The scheme was validated throughout the

testing phase using OHLC. Fig. 1 displays that the database was divided into several parts in the following manner: 20% of the resources were designated for testing, while the remaining 80% were employed for training.



Fig. 1. Dividing the database into training and test sets.

3.1. SVR

Conventional regression tactics are designed to minimize the ratio of observed to anticipated values; SVR calculates the ideal value by considering a set threshold, which displays the distance between the hyperplane and the borderline, as shown in Fig. 2. This improvement improves the SVR as a reliable regularization method that allows users to increase the tolerance for errors by adjusting both the acceptable error margin and the tolerance level for the acceptable error rate. Indeed, it reduces both the observed risk and the range of uncertainty. The computational complexity of SVR is independent of the dimensionality of the input space. Evidence demonstrates that SVR performs exceptionally well, especially when working with a restricted tally of samples and various characteristics. Furthermore, it has exceptional generalizability, demonstrating high prediction accuracy. The SVR allows for the specification of an acceptable level of error in the scheme and the identification of an appropriate line (or hyperplane in higher dimensions) that precisely displays the data. This methodology employs the kernel tactic to shift the data from an n -dimensional to an $n + 1$ -dimensional space while maintaining the relation between the points of this data. Computation is made inside this space to find the maximum number of points in the hyperplane. Then, based on this, decision boundaries with allowable error margins are constructed.

The scheme mathematically aims to diminish the function expressed in Eq. (1).

$$\underset{\beta}{\text{minimize}} \quad \|\beta\|^2 + C \sum_{i=1}^n |\xi_i|, \text{ subject to } \|R_{\text{train}} - \hat{r}\|_2^2 \leq \varepsilon + |\xi_i|, \quad (1)$$

The reconstructed reflectance, depicted as $\hat{r}$, is determined using the following formula:

$$\hat{r} = X\beta \quad (2)$$

X displays the matrix containing the independent variables, conversely, the regression model's parameters are included in the vector depicted by β . The symbol ε displays the margin error, whereas ξ depicts the slack variables. The deviation of any value that is beyond ε from the margin may be represented as ξ . C is an extra hyperparameter that specifies the acceptable range for points that fall outside of ε . In addition to the parameters above, mentioning the presence of a gamma variable in the frameworks is essential, which serves as the kernel coefficient. Gamma determines the level of curvature present at the decision border, with a more considerable gamma value indicating a greater degree of curvature Rezaei et al., (2023) Montesinos López et al., (2022) Huang et al., (2022).

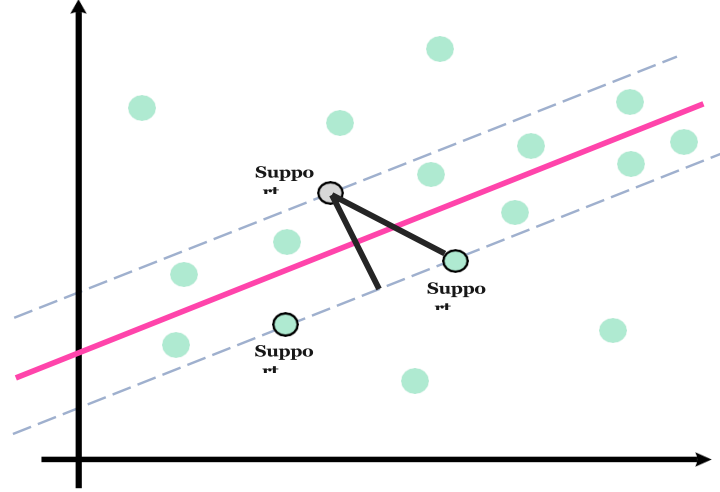


Fig. 2. The stricture of SVR.

3.2. ALO

It was created by Mirjalili and is a novel optimization tactic that draws natural inspiration. This program seeks to emulate the innate hunting tactic used by antlions, an insect. The ALO algorithm is used to seek prey. It consists of five phases: setting up traps, constructing them, capturing ants, pursuing prey, and fixing traps. ALO methodologies have been successfully implemented and evaluated in several engineering and optimization applications. The equations given may be used to provide a precise quantitative description of the stages involved in the ALO process Mirjalili, (2015b).

1. Random procedure

$$X(t) = [0, \text{cumsum}(2r(t_1) - 1), \text{cumsum}(2r(t_2) - 1), \dots, \text{cumsum}(2r(T) - 1)] \quad (3)$$

$$\text{With } r(t) = \begin{cases} 1 & \text{if rand} > 0.5 \\ 0 & \text{if rand} \leq 0.5 \end{cases} \quad (4)$$

$X(t)$ defines a family of stochastic processes, where t displays the count of steps performed in each process. T is the maximum number of repetitions, while $r(t)$ is a stochastic function depending on a random integer, r , within $[0,1]$.

2. Hunting process:

$$X_i(t) = \frac{(X_i(t) - \alpha_i) * (d_i(t) - c_i(t))}{(b_i - \alpha_i)} + c_i(t) \quad (5)$$

The variables α_i and b_i depict the lower and higher limits of the random walk for the i -th variable, accordingly. Meanwhile, $c(t)$ and $d_i(t)$ illustrate the lowest and highest values of the i -th variable during the t -th cycle.

3. After ensnaring its victim in its traps, the antlion seeks and modifies its pit to capture further prey. The behavior may be expressed using the following formula:

$$\text{Antlion}_j(t) = \begin{cases} \text{Ant}_i(t) & \text{iff}(\text{Ant}_i(t)) > f(\text{Antlion}_j(t)) \\ \text{Antlion}_j(t) & \text{iff}(\text{Ant}_i(t)) \leq f(\text{Antlion}_j(t)) \end{cases} \quad (6)$$

At the t -th cycle, the locations of the j -th antlion and the i -th are represented by the variables $\text{Antlion}_j(t)$ and $\text{Ant}(t)$, accordingly. Antlions make strategic adjustments to their postures in reaction to the positions of other ants to increase their likelihood of obtaining fresh meals or other insects. An antlion that has shown the greatest level of performance is chosen and kept as the top performer throughout each cycle. As a result of their increased strength, the elite antlions can direct the behavior of the other antlions during a sequence of cycles. The following is one possible definition of the elitist mechanism:

$$\frac{R_A + R_E}{X(t+1)} = \quad (7)$$

R_E is a stochastic process that moves haphazardly about the antlion that is considered the best at the t -th cycle. ($t + 1$) displays the best solution found so far, and R_A is a stochastic process that moves haphazardly around the antlion, which is picked using the roulette wheel method.

3.3. Slime Mold Algorithm

Recently, Chen recommended a modern optimization algorithm for finding the best route to link food that was influenced by the slime mold's actions Abdel-Basset et al., (2020). The presence of odors in the atmosphere might attract the slime mold toward a food source. The subsequent equation is introduced to depict the pattern of decline and provide a mathematical elucidation of its attributes.

$$\begin{aligned} X^{t+1} &\leftarrow v \cdot X^t + v \cdot b \cdot (W \cdot X^t - X^t), r \\ &\leq p \\ X^{t+1} &\leftarrow X^t + 1, r \geq p \end{aligned} \quad (8)$$

where v progressively decreases from 1 to 0, the parameter $v \cdot b = [-a, a]$, $a = \text{arctanh}(-(t/\text{max_})) + 1$, f indicates the current cycle. The location that currently has the highest concentration of smells identified is depicted by X^t . The vectors X^t_A and X^t_B represent two haphazardly selected vectors from the swarm. X displays the slime mold's location, r stands for a random value in $[0,1]$, and $S, i \in 1,2, \dots, n$ among them displays X 's fitness. The slime mold's weight is shown by W , and the maximum fitness gained throughout all cycles is indicated by DF . The vector W may be computed using the following equation:

$$W^{t+1} = \begin{cases} 1 + r \cdot \log\left(\frac{bF - S(i)}{bF - wF} + 1\right), \text{condition} \\ 1 - r \cdot \log\left(\frac{bF - S(i)}{bF - wF} + 1\right), \text{others} \end{cases} \quad (9)$$

where $\text{Smellindex} = \text{sort}(S)$ indicates that the fitness values in the minimal value issue are organized in ascending order, and the variables bF and wF , accordingly, show the Fittest and Worst values received from the current cycle.

(i) is considered to be in the upper half of the population according to Condition. The mathematical procedure for determining the current location of slime mold is:

$$\begin{aligned} X^{t+1}_A &= \{X_i(t) + v \cdot b \cdot (W \cdot X^t_B - X^t_A), r < p \\ &\quad v \cdot c \cdot X^t_C, r \geq p \end{aligned} \quad (10)$$

LB and UB represent the lower and upper boundaries of the search space, accordingly. These numbers are often selected haphazardly, depending on the problem being addressed. To investigate the limitations of the search space, this article considers LB and UB in conjunction with the prior probability space of the input parameters, depicted as $LB = \mu - RF \times \sigma$ and $UB = \mu + RF \times \sigma$. The parameters μ and σ display the mean and standard deviation of the probability distribution for the input parameters. The abbreviation displays the range factor of the search border RF . Consequently, modifying the value of RF might lead to the expansion or contraction of the search space. The magnitudes of $v \cdot b$ and $v \cdot c$ gradually approach zero as the slime mold's position is continuously updated. Meanwhile, those who are hunting will converge around the optimal location.

3.4. BRO

BRO is used to refer to a meta-heuristic approach that was recommended by Rahkar Farshi, (2021). According to Fig. 3, the software was driven by a popular multiplayer online game in which players are tasked with eliminating their opponents to find a safe zone where they may continue their lives. When players leave the safe zone established inside the game, they risk being hurt or eliminated. The whole procedure of this optimizer is shown in Fig. 4. The subsequent formula is utilized to compute the injury rate for the player who was damaged:

$$x_i. damage = x_i. damage + 1 \quad (11)$$

Hurt players attempt to move to different locations to confront the opponent. The players' most current rankings are shown in the equation below:

$$x_{dam,d} = x_{dam,d} + r(x_{best,d} - x_{dam,d}) \quad (12)$$

In this context, $x_{best,d}$ displays the most favorable option in dimension d , $x_{dam,d}$ indicates the location of the wounded player in dimension d , and r is a haphazardly generated value from a uniform distribution from 0 to 1. The search agents are evenly deployed and scattered over the problem space. The equation provided displays the highest possible value (upper limit) and the lowest possible value (lower bound) in a problem space with d dimensions, represented as ub_d and lb_d correspondingly.

$$x_{dam,d} = r(ub_d - lb_d) + lb_d \quad (13)$$

The least acceptable options are removed, and the equation shows the ideal approach. Given this, it is possible to define the initial value Δ as the $\log_{10}(\text{MaxCicle})$, where MaxCicle is the count of cycles.

$$\Delta = \Delta + \text{round} \left(\frac{\Delta}{2} \right) \quad (14)$$

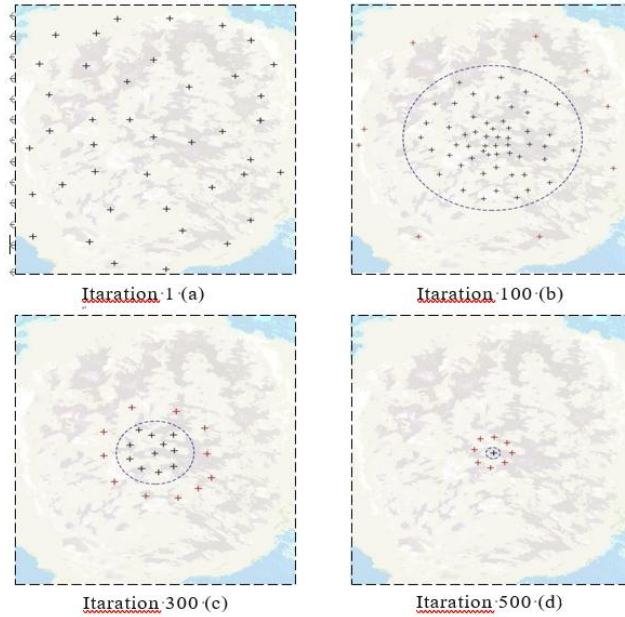


Fig. 3. Players are moved to the best spot throughout the cycle.

4.1. Evaluation Metrics

Many different execution criteria were used to evaluate the accuracy of the future projections. After an exhaustive examination, these criteria were developed to evaluate the predictions' accuracy and dependability. The R^2 score is a quantitative standard that examines the precision of a scheme in representing the data. First, the differences between the observed and the values predicted by the scheme are squared and summed, divided by the sum of the squared differences between each value and the average of all values, and then subtract the quotient from 1. A higher value based on this provides the quality of the scheme, and it should be close to 1.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (15)$$

MAE is a statistical tool for assessing the difference between expected and actual values. First, the exact size of the difference between the expected and actual values needs to be determined. Then, the average of the deviations must be calculated. This metric defines the scheme's accuracy; the lower the MAE, the higher scheme accuracy.

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (16)$$

MSE is used to calculate the deviation between actual and forecasted data. To get this numerical value, one needs to calculate the square of the difference between the actual and forecasted values. Then, the mean of all the squared differences has to be calculated. A lower MSE value signifies a higher level of accuracy.

$$MSE = \frac{1}{n} \sum_{k=0}^n (F_i - Y_i)^2 \quad (17)$$

The RSE is the standard deviation of the residuals for a regression analysis, which displays an estimate of the scheme's prediction precision. This metric identifies the degree of deviation of fluctuation between expected and actual values. The following formula gives the RSE: Lower RSE means greater precision.

$$RSE = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}} \quad (18)$$

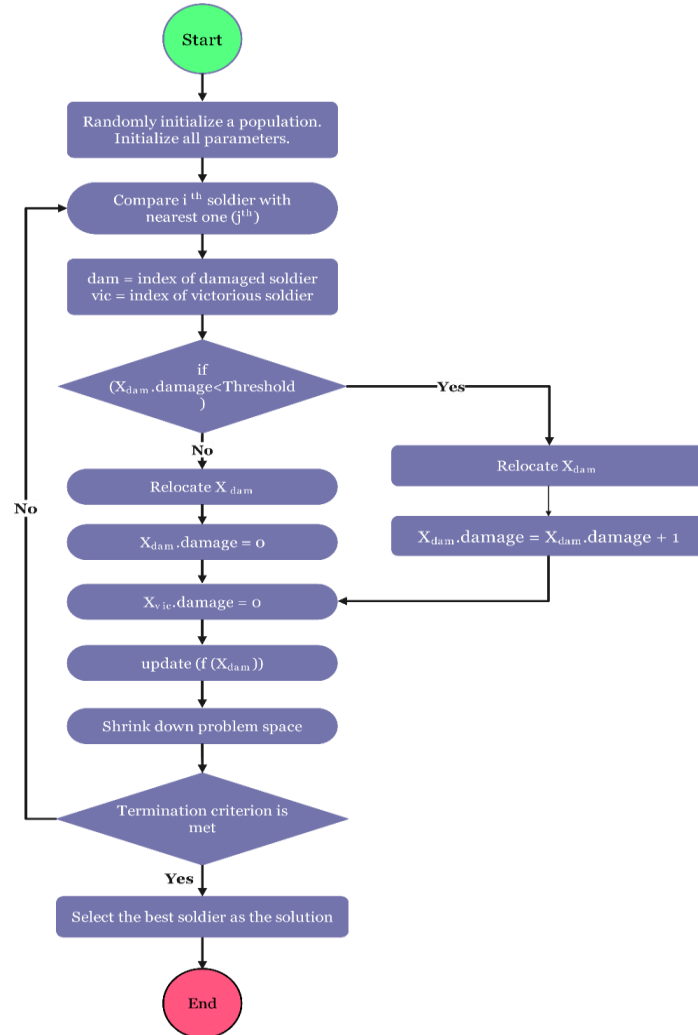


Fig. 4. The flowchart of the BRO optimizer.

4.2. Statistical Values

In the initial phase of the investigation, an exhaustive assemblage of statistical data about the database will be

undertaken. The OHLC prices and volume are presented in Table 1. The provided numbers serve as additional textual information about the subject under evaluation. Statistical measures, including the mean, count, minimum, maximum, kurtosis, and variance, can be utilized to facilitate a more thorough examination of the data.

Table 1. Summary statistics for the database.

	Count	Mean	Std.	Min	25%	50%	75%	Max	Variance
Open	2062.00	3215.85	358.75	2446.02	2987.06	3206.16	3386.34	5174.42	128699.71
High	2062.00	3239.99	364.71	2488.48	3009.20	3230.08	3409.64	5178.19	133016.59
Low	2062.00	3191.98	349.13	2440.91	2968.36	3188.54	3364.42	5103.40	121892.72
Volume	2062.00	26.68	12.25	0.01	16.87	24.37	33.44	85.71	149.94
Close	2062.00	3219.09	358.57	2464.36	2987.97	3210.37	3386.00	5166.35	128573.90

4.3. Analysis and Comparisons

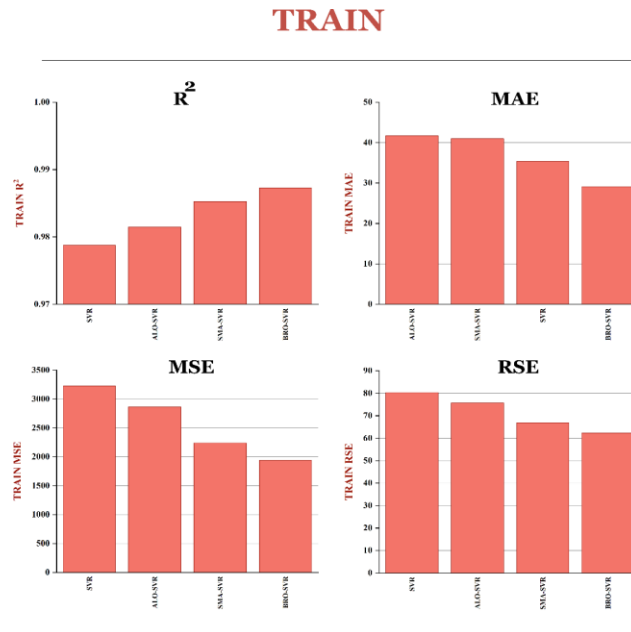


Fig. 5. Values are used to assess the training in every framework.

To generate precise predictions about equity prices, the principal aim of this exploration is to develop and evaluate the most efficient blended framework presently accessible in the market. In pursuit of this objective, an extensive body of research has been dedicated to examining the complex factors that impact stock exchange patterns. This research has yielded the creation of predictive schemes. The objective of this undertaking was to provide reliable information to analysts and investors to facilitate their ability to make informed financial judgments. A comprehensive analysis of the efficacy of each method is presented in Figs. 5 and 6, accordingly.

This article investigates the SVR algorithm and evaluates the optimization tactics utilized, including ALO, SMA, and BRO. Following this, the outcomes produced by these frameworks are thoroughly examined through the documentation process. This endeavor aims to ascertain the method that provides the highest level of accuracy and efficiency when predicting equity prices. The assessment tactics employed comprise the R^2 score, MSE, MAE, and RSE. Thoroughly understanding the test outcomes is crucial to determining the most effective methodology for predicting the equity prices of companies listed on the Shanghai Stock Exchange market.

TEST

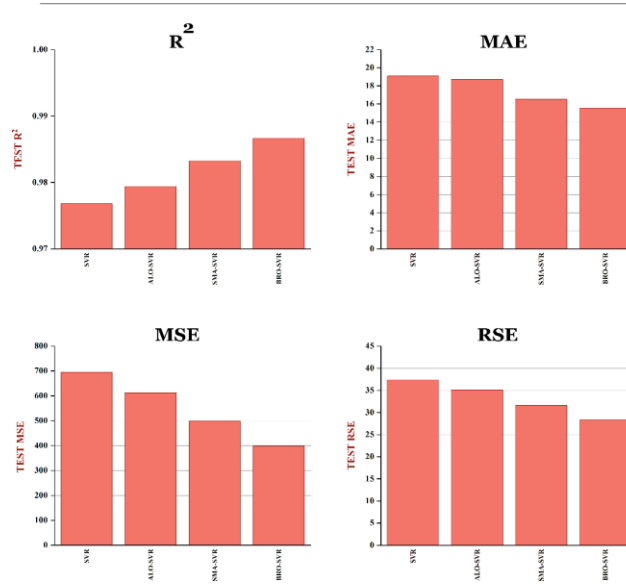


Fig. 6. Values are used to assess the testing in each model.

Table 2. The predicted outcomes of the method evaluation.

Schemes/Metrics	Train Set R2	MAE	MSE	RSE	Test Set R2	MAE	MSE	RSE
SVR	0.979	35.32	3224.47	80.35	0.977	19.08	694.03	37.35
ALO-SVR	0.981	41.73	2865.96	75.76	0.979	18.71	613.23	35.11
SMA-SVR	0.985	40.99	2240.31	66.98	0.983	16.52	498.50	31.65
BRO-SVR	0.987	29.12	1937.17	62.28	0.987	15.54	398.54	28.30

The table shows that the MAE and MSE values for SVR in the test set are 19.08 and 694.03, accordingly. In addition, RSE and R^2 for test sets are 37.35 and 0.977, accordingly. Based on the SVR findings, the scheme's accuracy is insufficient for stock forecasting. In addition, the experimental findings of ALO-SVR outperform those of SVR. This is evident from the decreasing RSE, MAE, and MSE values. The RSE, MAE, and MSE test values are 35.11, 18.71, and 613.23, accordingly. The R^2 shows an upward trend and reaches 0.981 in the training set and 0.979 in the test set. However, unlike the other schemes, SVR and ALO-SVR show lower performance. Based on the data in Table 2, SMA-SVR shows a higher performance level than ALO-SVR. The R^2 is 0.985 for the training data and 0.983 for the test data. In addition, the test findings show a reduction in MAE and MSE with a measured MAE of 16.52 and MSE at 498.50. In addition, the RSE decreases and reaches a value of 31.65 for the test set. Nevertheless, the BRO-SVR evaluation gave better outcomes than the SMA-SVR evaluation. According to the Table, R^2 has increased both in training and in the test. These findings show that BRO-SVR outperforms other methods and predicts a wider range of stock movement. Also, the MAE and MSE show a reduction compared to the training stage. Moreover, the RSE decreases in both the test and training databases and finally reaches the values of 28.30 and 62.28. The outcomes show the accuracy and completeness of this model's ability to anticipate stock price changes.

Utilizing the findings, it is advised that the SSE database be used to estimate future stock exchange values by applying several diverse schemes, including SVR, ALO-SVR, SMA-SVR, and BRO-SVR. According to the outcomes of the RSE, MAE, MSE, and R^2 scores, the BRO-SVR model demonstrates superior performance compared to the other schemes. The method's efficiency can be demonstrated by analyzing the SSE curves shown in Figs. 7 and 8.

This paper demonstrates that combining the BRO algorithm's optimization skills with the SVR is very useful in stock exchange value forecasting using this database.

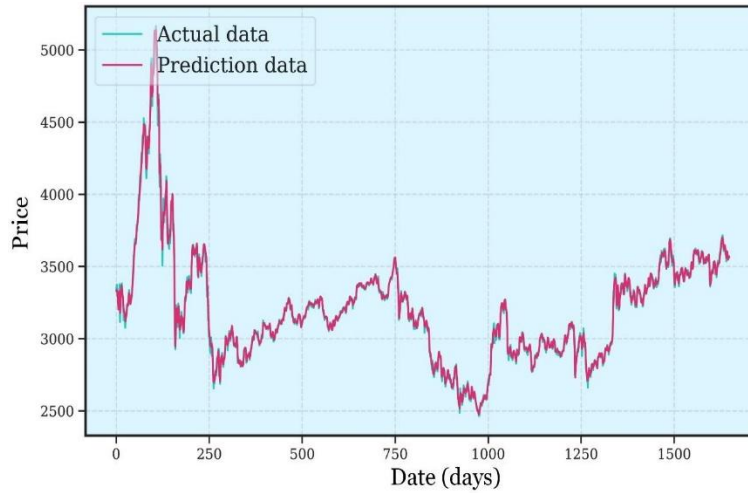


Fig. 7. The train data prediction curve for BRO-SVR.

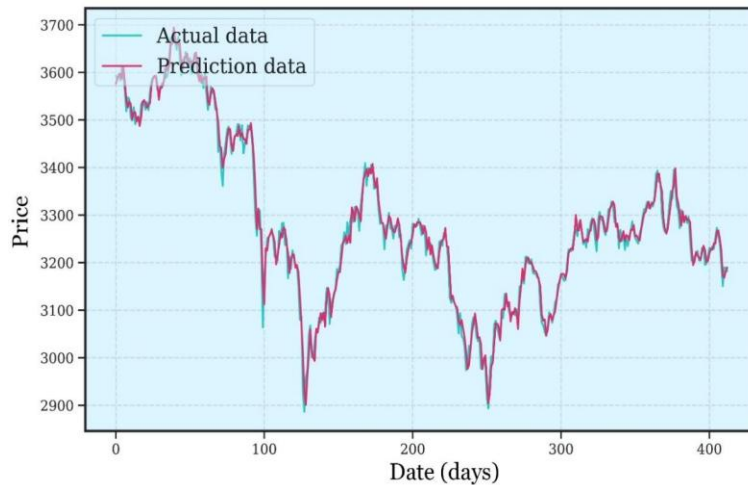


Fig. 8. The test data prediction curve for BRO-SVR.

For traders, investors, and financial managers, predicting stock prices is crucial, but it can be challenging due to noise and nonlinear market behavior. In order to improve prediction accuracy, this study assesses the performance of a hybrid model called BRO-SVR, which combines Battle Royale Optimization (BRO) and Support Vector Regression (SVR). OHLC and $volume$ data from the Shanghai Stock Exchange (SSE) from 2015 to 2023 were used to test the model. BRO-SVR continuously produced better results than SVR, ALO-SVR, and SMA-SVR, according to comparative analysis. Strong precision and dependability were demonstrated by the model, which obtained the highest R^2 value of 0.987, the lowest MAE of 15.54, and an MSE of 398.54. These indicators demonstrate its strong capacity to predict stock prices despite market turbulence. By facilitating well-informed decision-making, BRO-SVR not only increased forecasting accuracy but also demonstrated the potential to boost return on investment. The model's ability to handle intricate financial datasets is further demonstrated by its performance in competitive scenarios. For investors looking to manage and profit from stock market swings, the BRO-SVR framework provides a useful tool for strategic planning and risk mitigation.

All authors declare that they have no conflicts of interest.

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