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Enhancement Support Vector Regression Using Black Widow Optimization for Predicting Foreign Exchange Rate

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ABSTRACT

Prediction of foreign exchange rates is one of the time series problems that have fluctuating value movements. There are several algorithms that can make predictive models for this problem, one of which is Support Vector Regression (SVR). In this study, foreign exchange rate predictions were made using Hybrid SVR and Black Widow Optimization (BWO). This is done with the aim of improving the performance of the SVR in order to produce a better predictive model for the EUR/USD foreign exchange rate data in 2020. The results of the proposed algorithm get better performance in terms of R^2, MSE, RMSE, MAE, and MAPE compared to SVR.

1. Introduction

The movement of foreign exchange rates is difficult to predict because of its fluctuating movements [1]. Some of the causes of the fluctuating movement of currency exchange rates are the country's economy, politics, society, the international situation, and others [2]. This problem is become topic studied by many researchers to form a predictive model.

Predictive model for time series problems can be made using several methods such as Long Short Term Memory (LSTM), Support Vector Machine (SVM), Least Square Method, Support Vector Regression (SVR), and others [3]–[6]. One method that has a good performance in predicting foreign exchange rates is SVR. This method has succeeded in predicting the movement of a value in a time series including the issue of foreign exchange rates[6], [7]. Although SVR can make good predictions, it has disadvantage of high complexity and long computation time due to wide hyperparameter search space [8]. The selection of hyperparameters also greatly affects the performance of the SVR [9]. Several studies have tried to overcome the disadvantage of SVR in model training and one way to overcome this disadvantage is to combine it with optimization algorithm [10]. One of the optimization algorithms that can be used is the evolutionary algorithm.

Evolutionary algorithm is heuristic method that was developed based on the concept of evolution in biology [11]. One of the algorithms that uses the concept of evolutionary algorithm which has better performance compared to several other evolutionary algorithms such as genetic algorithm, particle swarm optimization, or ant bee colony is Black Widow Optimization (BWO) [12]. Several problems have been solved by BWO such as linear and non-linear function problems, image segmentation, and data grouping [12], [13].

Based on the description in the previous paragraph, this study tries to improve performance of SVR by using the BWO algorithm in the hyperparameter selection process

2. Material and Method

2.1 Dataset

This study uses an open dataset of EUR/USD foreign exchange rates with a timeframe of 1 Hour in 2020. This dataset is obtained from the Kaggle Platform. Before the dataset being used as input, the dataset is processed first to generate lag features. In foreign exchange rates, the best lag features are Moving Average (MA) and Moving Average Convergence Divergence (MACD)[14], [15]. Based on this, the input parameters are MA bid price (periods 5,10, and 20), MA ask price (periods 5,10, and 20), MACD bid price (short period 12 and long periods 26), and MACD ask price (short period 12 and long periods 26).

2.2 Support Vector Regression (SVR)

SVR is an algorithm that in principle forms a model structure or hyperplane with the smallest error rate [16]. The equation of a hyperplane can be formulated as follows [6], [17]:

$$f(x) = \sum_{i=1}^{l}(\alpha_i - \alpha_i^*)\langle x_i, x\rangle + b \tag{1}$$

Where the variable $(\alpha_i - \alpha_i^*)$) is a dual coefficient formed from the langrange method, b is the bias constant and $\langle x_i, x\rangle$ is the result of dot product between x (input set) and x_i (support vector). The best hyperplane that can be formed by the SVR algorithm must optimize the following equation:

$$min\ \frac{1}{2}\ \|\omega\|^2 + C \sum_{i=1}^{l}(\xi_i + \xi_i^*) \tag{2}$$

subject to

$$y_i - \langle\omega, x\rangle - b \leq \varepsilon + \xi_i \tag{3}$$

$$\langle\omega, x\rangle + b - y_i \leq \varepsilon + \xi_i^* \tag{4}$$

$$\xi_i, \xi_i^* \geq 0 \tag{5}$$

Where the variable ε is the size of the feasibility range of a point from f(x) dan ξ is the amount of the penalty imposed on a point that is outside the feasibility range.

2.3 Kernel Function

The kernel that has the most stable performance is the gaussian-radial basis function (RBF) [18]. The gaussian-radial basis function kernel equation is formulated as follows:

$$K(x_i, x) = exp(-\gamma\|x - x_i\|^2) \tag{6}$$

Where x and xi are input sets and γ is an independent constant that measures the influence between two points on each other. The advantage of RBF compared to other kernels is that it can increase the dimensions of the input set to an infinite dimension due to exponential expansion [19].

2.4 Hyperparameter

SVR algorithm with RBF kernel has three hyperparameters namely ε, C, dan γ. This hyperparameter is greatly affects on the performance of SVR [20]. One method that is proven to be successful in finding optimal hyperparameters is to use a grid search algorithm and cross-validation [21]–[23]. he best hyperparameter values for SVR to predict foreign exchange rates are ε with value of 0.01, C with value of 100, and γ with value of 0,125 [24].

2.5 Scoring

Performance evaluation of a predictive model used several error rate calculation equations [19][25]. The equations used to calculate the error rate are Mean Square Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Coefficient of determination (R^2).

2.6 Black Widow Optimization (BWO)

The flowchart of this algorithm shown in Fig. 1. At the initial stage, BWO creates an initial population and calculates the fitness value of each initial individual. After that, there are random select parents, procreate, cannibalism, and mutation stage that are repeated several times. This algorithm has three constants namely procreate rate (PP=0.6), cannibalism rate (CR=0.44), and mutation rate (PM=0.4)[12].

2.7 Enhancement SVR Using BWO

The flowchart of this algorithm shown in Fig. 2. At the initial stage, a population of 100 individuals is initialized with a structure containing hyperparameter values (ε, C, and γ). Each individual will be used to form an SVR model with 5-Fold Cross Validation and calculate the fitness value based on the R2 value. After that, there are randomly select parents, procreate, cannibalism, and mutation stage that are repeated 500 times.

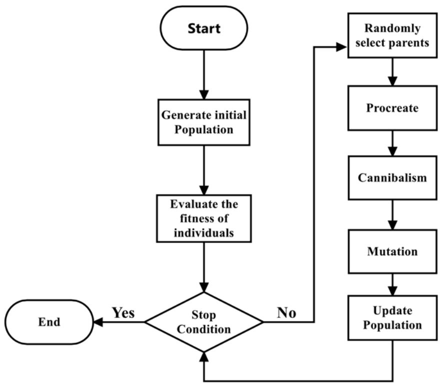

Figure 1. Flowchart BWO algorithm

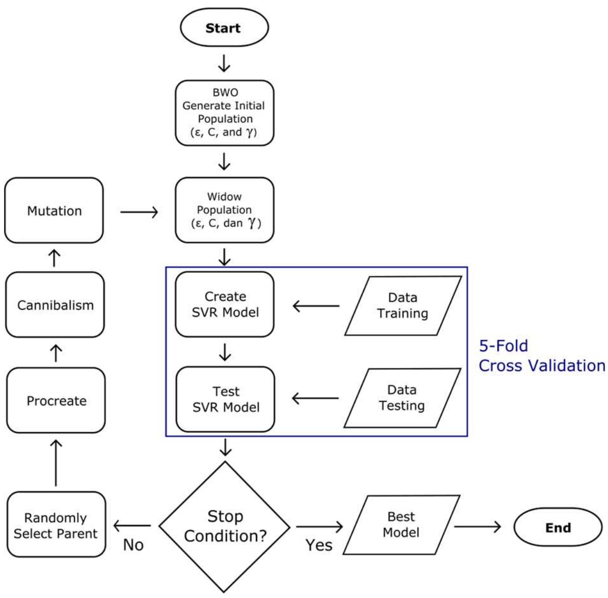

Figure 2. Flowchart enhancement SVR using BWO

3. Result and Discussion

3.1 SVR Result

The results of the SVR algorithm (ε=0.01, C=100, and γ=0,125) with 5-fold cross-validation shown in Table 1. Based on these results, SVR can form a predictive model with an R^2 Figure 3.

Table 1. Results of SVR algorithm

Scoring	Value
Coefficient of determination (R^2)	0.971317
Mean Squared Error (MSE)	0.000007015
Root Mean Square Error (RMSE)	0.00208029
Mean Absolute Error (MAE)	0.00189076
Mean Absolute Percentage Error (MAPE)	0.00260564

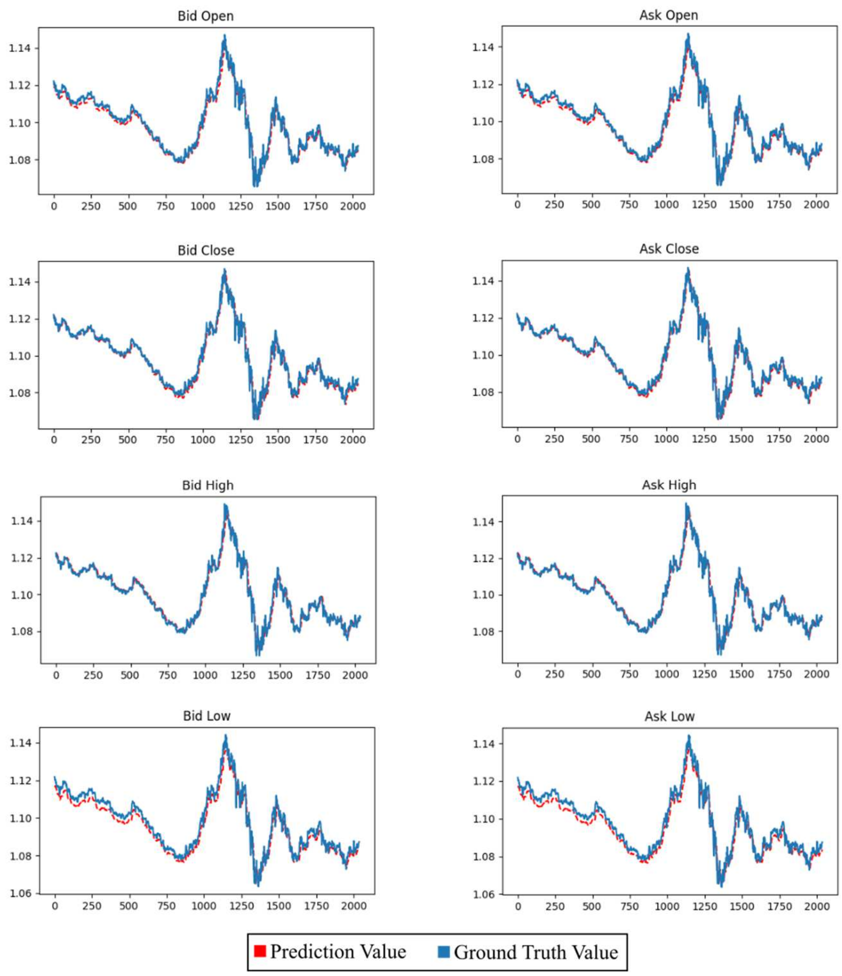

Figure 3. Prediction results of SVR algorithm

3.2 Enhancement SVR Using BWO

The results of the hybrid SVR and BWO algorithms with 5-fold cross-validation shown in Table 1 and the development graph of the R^2, MSE, MAPE, MAE, and RMSE values for each iteration shown in Fig. 4. Based on these results, this algorithm can form a best predictive model on 107th iteration with an R^2 value of 0.989910873. Fig. 5 shows the prediction results).

Table 2. Results of Enhancement SVR Using BWO

Iter.	R^2	MSE	MAE	MAPE	RMSE
1	0.9892	0.00000287	0.00122	0.00111	0.00169
2	0.9892	0.00000287	0.00122	0.00111	0.00169
.	.	.	.	.	.
106	0.9899	0.00000268	0.00116	0.00106	0.00163
107	**0.9899**	**0.00000267**	**0.00116**	**0.00105**	**0.00163**
.	.	.	.	.	.
499	0.9899	0.00000268	0.00117	0.00106	0.00163
500	0.9899	0.00000268	0.00117	0.00106	0.00163

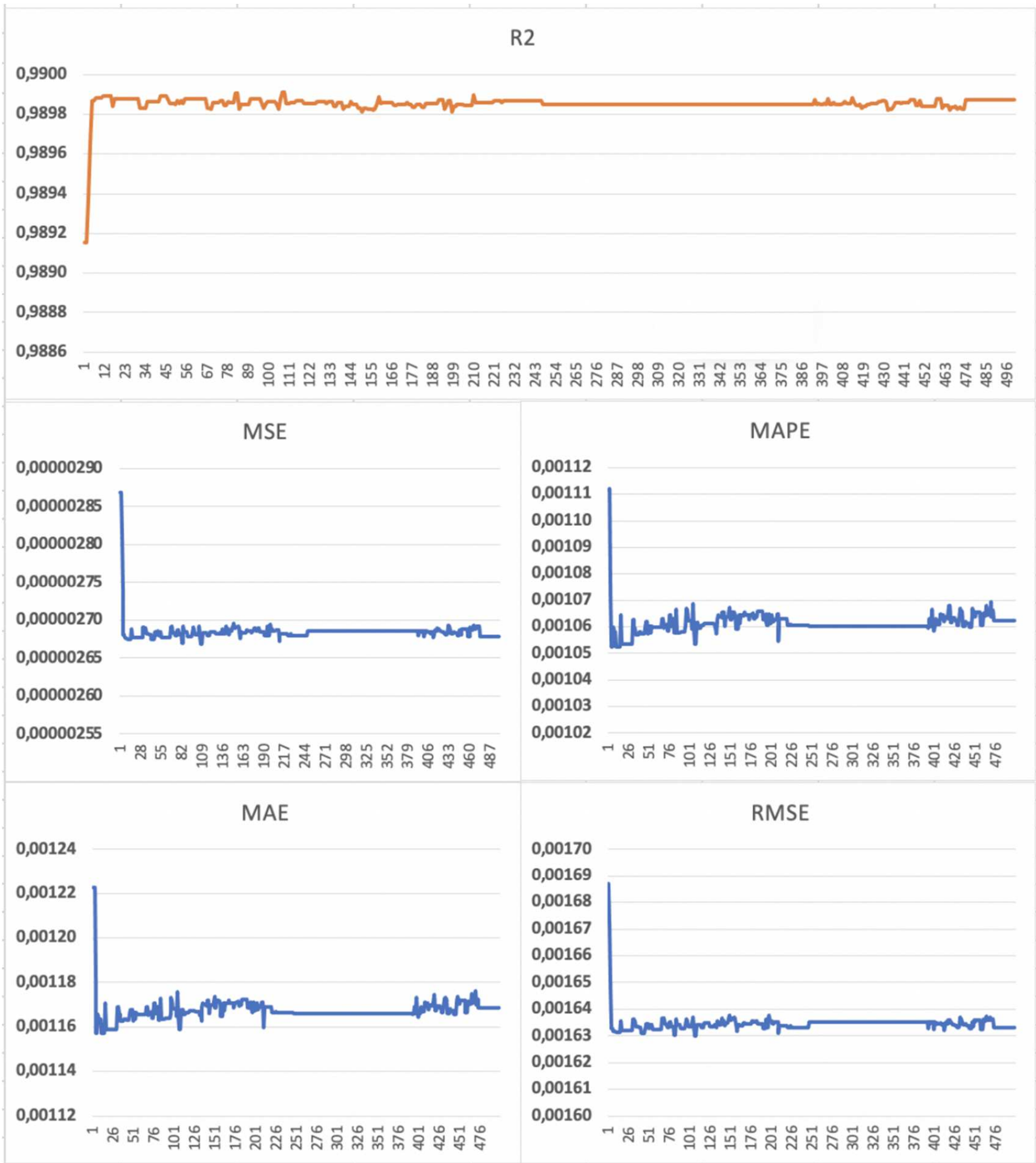

Figure 4. Error value each iteration

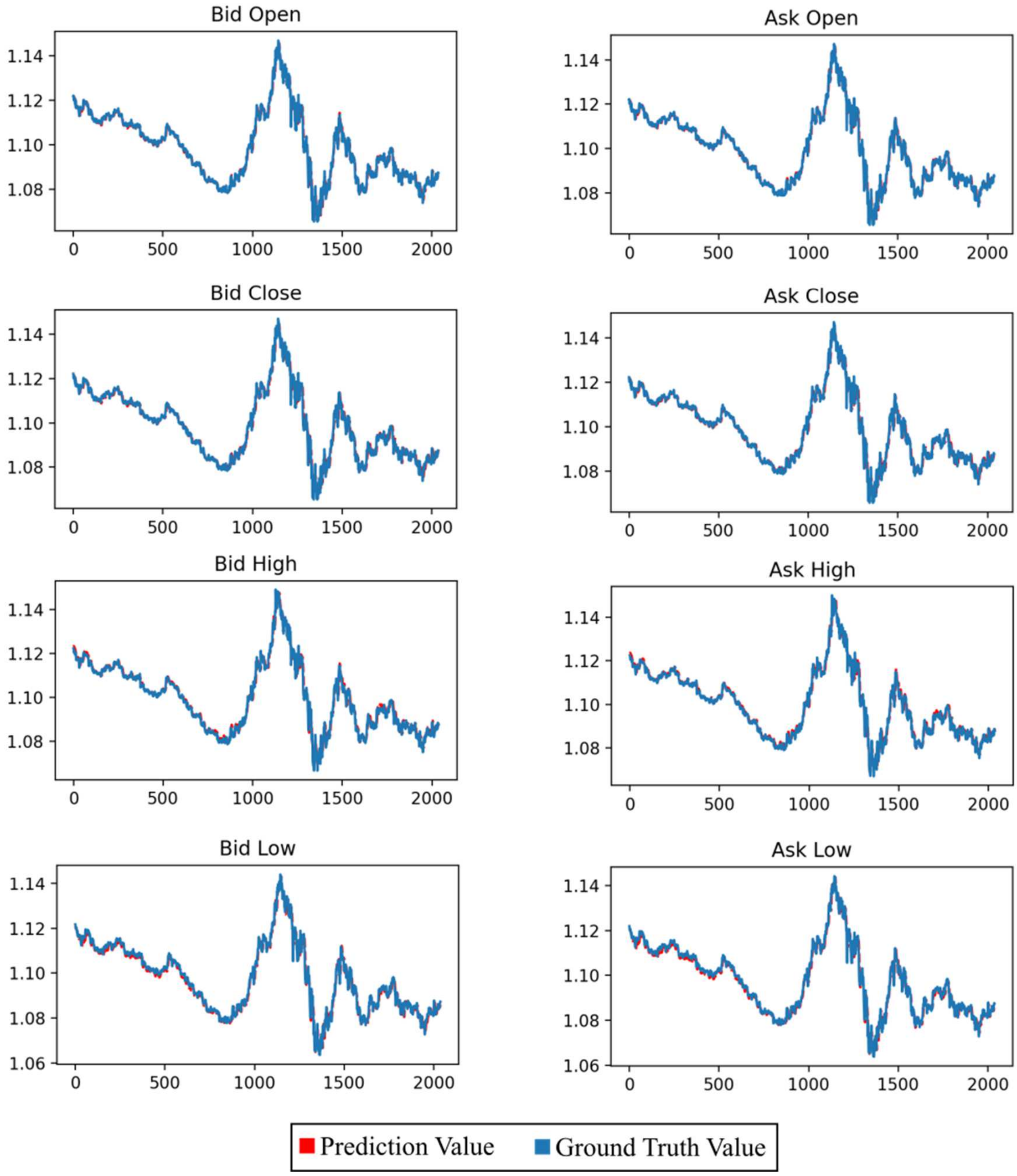

Figure 5. Prediction results of enhancement SVR using BWO

4. Conclusion

Hybrid SVR and BWO performance increased in R2 score from 0.971317 to 0.9899, MSE score from 0.000007015 to 0.00000267, MAPE score from 0.00260564 to 0.00105, MAE score from 0.00189076 to 0.00116, and RMSE scores from 0.00208029 to 0.00163 compared to the SVR algorithm. Based on this performance improvement, it can be concluded that BWO improves the performance of SVR in forming predictive models.

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