Journal of Information Systems Engineering and Management
2025, 10(38s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

A Novel Whale Optimization Algorithm for Time Series Prediction Using SVM

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ARTICLE INFO

Received: 20 Dec 2024

Revised: 20 Feb 2025

Accepted: 28 Feb 2025

ABSTRACT

Accurate time series forecasting is essential for decision-making in financial markets, power generation, and economic planning. However, traditional models often struggle to capture the complex nonlinear patterns in financial data, leading to suboptimal predictions. To address this, we propose a novel hybrid approach integrating the Whale Optimization Algorithm (WOA) with Support Vector Machines (SVM) for enhanced stock price forecasting. The WOA-SVM model optimizes key SVM hyperparameters—Regularization Parameter (C) and Kernel Coefficient (γ)—while also performing feature selection to improve model generalization. By effectively balancing exploration and exploitation, WOA accelerates convergence, reduces computational complexity, and minimizes forecasting errors. Extensive experiments on S&P 500 and NIFTY 50 datasets confirm WOA-SVM's superiority over SVM, LSTM, and Random Forest Regression, achieving the lowest MSE (2.45) and RMSE (1.56). These results highlight WOA-SVM as a robust and efficient tool for financial market forecasting, offering valuable insights to investors, analysts, and financial institutions.

Keywords: Time Series Forecasting, Whale Optimization Algorithm, Support Vector Machine, Hyperparameter Optimization, Stock Price Prediction, Mean Squared Error, Root Mean Squared Error.

INTRODUCTION

Time series forecasting is crucial in various domains, including finance, weather prediction, and industrial maintenance. In stock markets, increasing complexity makes manual analysis impractical, emphasizing the need for accurate predictive models. Reliable forecasting plays a vital role in shaping trading strategies and investment decisions (Huang et al., 2022) [1].

Traditional statistical methods, such as the Auto Regressive Integrated Moving Average (ARIMA) model, are widely used for time series forecasting, especially for datasets with observable trends [2]. However, ARIMA struggles with the nonlinear and irregular nature of financial data, limiting its effectiveness in stock market prediction. To address these challenges, researchers have explored machine learning techniques, such as Artificial Neural Networks (ANNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks [3].

ANNs have gained popularity in stock market prediction, with Sadig Mammadli utilizing the Levenberg-Marquardt algorithm [4]. However, ANN models often suffer from overfitting, local optima issues, and sensitivity to financial data noise. RNNs have also been explored but face gradient vanishing and exploding problems [5]. To overcome these limitations, LSTM networks have been adopted, offering improved performance in capturing long-term dependencies [6]. However, selecting optimal hyperparameters, such as the number of neurons and step size, is often based on experience, making it subjective and reducing prediction accuracy.

Machine learning models such as Support Vector Machine (SVM) and Random Forest (RF) have also been applied in stock market forecasting [7]. These methods rely on technical analysis, using historical stock prices as input. However, with increasing market complexity and computational advancements, deep learning techniques have shown superior performance. Hoseinzade [8] introduced a CNN-based framework integrating multiple information sources, demonstrating that deep learning models outperform traditional statistical methods. Another study proposed an LSTM-CNN hybrid model, combining stock time series and chart images to improve prediction accuracy [9]. LSTM captures temporal dependencies, while CNN extracts visual patterns. Experimental results on SPDR S&P 500 ETF data showed that this fusion model outperformed standalone CNN or LSTM approaches.

To enhance forecasting accuracy, hybrid approaches incorporating optimization algorithms have been explored. The Whale Optimization Algorithm (WOA) is a nature-inspired heuristic optimization method that has been increasingly used in stock market prediction. Recent research has focused on improving WOA. Xiong et al. (2021) accelerated WOA's convergence by introducing a nonlinear adjustment strategy, optimizing the gray seasonal variation index model, achieving faster and more accurate predictions [10]. Similarly, Gao et al. (2022) applied random and chaotic sequence methods for WOA initialization, increasing population diversity [11]. They also introduced two convergence strategies to enhance search efficiency, leading to improved accuracy and reduced computational time when optimizing the Extreme Learning Machine (ELM) model [12].

While traditional forecasting models such as SVM, LSTM, and RF have demonstrated effectiveness, each comes with inherent limitations. SVM requires manual or grid-based hyperparameter tuning, often leading to suboptimal performance. LSTM excels at capturing long-term dependencies but is computationally expensive and requires large datasets. Random Forest lacks temporal awareness, making it less effective for sequential stock market data. To address these challenges, we propose an optimized WOA-SVM model, which integrates the Whale Optimization Algorithm (WOA) with SVM to enhance forecasting accuracy. The WOA efficiently optimizes key SVM hyperparameters (C and Gamma), improving model generalization, reducing overfitting, and ensuring adaptability to complex and nonlinear time series patterns.

Compared to existing techniques, the proposed WOA-SVM model offers faster convergence, lower computational cost, and higher prediction accuracy. The performance of the WOA-SVM model is evaluated against baseline methods across multiple datasets, demonstrating its superiority in financial time series forecasting.

PROPOSED METHODOLOGY

The Whale Optimization Algorithm (WOA) for Time Series Prediction Using SVM enhances forecasting accuracy by optimizing key SVM parameters, improving its ability to capture nonlinear patterns. It effectively handles complex and imbalanced time series data by selecting relevant features, ensuring adaptability to trends and fluctuations. WOA also enhances computational efficiency by reducing search space and eliminating trial-and-error tuning. Its intelligent optimization balances exploration and exploitation, leading to faster convergence. Additionally, the optimized SVM model minimizes overfitting, improving generalization. This approach benefits industries like power generation, stock market analysis, weather forecasting, and equipment maintenance, enhancing predictive decision-making.

Algorithm: Whale Optimization Algorithm (WOA) for Time Series Prediction Using SVM

This algorithm combines WOA with SVM to enhance time series forecasting accuracy. The WOA optimizes the hyperparameters and feature selection for SVM, ensuring improved predictive performance.

Step 1: Initialization

1.1. Start the process.

1.2. Classify historical time series data related to power generation based on patterns, trends, and anomalies.

1.3. Define input features (X) and the target variable (Y) to structure the time series forecasting model.

1.4. Normalize input features to a common scale to enhance model convergence and accuracy.

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$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

1.5. Initialize WOA parameters, including population size (N), maximum iterations (M), and control parameters (A, C, l, p), for optimal search efficiency.

1.6. Randomly generate the initial whale population using

$$X_{min} + (X_{max} - X_{min}) \times rand() \quad (2)$$

and evaluate fitness using mean squared error (MSE) in SVM.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y})^2 \quad (3)$$

1.7. Start Iteration - Set iteration counter m=1

Step 2: Iteration and Optimization

2.1. Check the stopping condition: If m<M, continue; otherwise, move to SVM prediction.

2.2. Generate a probability p; if p<0.5, apply Bubble Predation; otherwise, compute A=2·a·r-a, where a decreases from 2 to 0 and r is a random number in [0,1]; if |A|<1, use Foraging Encirclement; otherwise, apply Random Contraction.

2.3. When p<0.5, update whale positions using the spiral equation

$$\mathrm{X(t+1) = D' \cdot e}^{bl} \cdot \mathrm{cos\,(2\pi l)} + X^* \quad (4)$$

where D′ is the distance to the prey, b defines the logarithmic spiral shape, l is a random number in [-1,1], and X^* is the best-known solution.

2.4. When |A|<1, whales move towards the best-known solution using

$$\mathrm{X(t+1)} = X^* - \mathrm{A}.\,|C.X^* - X| \quad (5)$$

where C=2r and r is a random number in [0,1].

2.5. When |A|≥1, whales move randomly in the search space using

$$\mathrm{X(t+1) = X}_{rand} - \mathrm{A}.\,|C.X_{rand} - X| \quad (6)$$

where X_{rand} is a randomly chosen whale.

2.6. Compute Fitness Value: Evaluate the updated whale positions using MSE from the SVM model.

2.7. Update the best Whale Position: If a new solution has a lower MSE than the previous best, update X^*.

2.8. Increment Iteration Counter: Set m=m+1 and repeat the process until m=M.

Step 3: WOA-SVM Prediction

3.1. Extract the optimal solution obtained through WOA optimization for the best SVM parameters.

3.2. Train the SVM by inputting the optimized features and hyperparameters, optimizing **C** (Regularization parameter) and **Gamma** (Kernel coefficient), allowing the model to learn the relationship between input features and the target variable.

3.3. Use the trained SVM model to predict future time points using

$$\hat{Y} = f(X) = w^T \emptyset(X) + b \quad (7)$$

where $\phi(X)$ represents the transformed feature space, and w and b are the learned parameters.

3.4. Convert the predicted values back to the original scale using

$$Y_{predict} = Y_{min} + (Y_{norm} \times (Y_{max} - Y_{min})) \quad (8)$$

3.5. End the Process: Finalize the execution and output the time series predictions.

Table 1: Input, Process, and Output of WOA-SVM for Stock Price Prediction

Category	Details	Example Values (for Stock Prediction)
Input Data	Historical stock price data	Apple Inc. (AAPL) daily closing prices (last 5 years)
Input Features (X)	Spectral, statistical, and temporal attributes	Moving Average (50-day, 200-day), RSI, MACD, Bollinger Bands
Target Variable (Y)	Future stock price to be predicted	Next day's closing price of AAPL
WOA Parameters	Population size (N), Maximum iterations (M), Control parameters (A, C, l, p)	N=30, M=100, A=[2→0], C=[0,2], l=[-1,1], p=0.5
SVM Hyperparameters	Regularization parameter (C), Kernel coefficient (Gamma)	C=1.5, Gamma=0.02
Normalization	Scaling of input features and target values	Min-Max Scaling: (X-Xmin)/(Xmax-Xmin)
Output: Optimized Parameters	Best-selected SVM hyperparameters after WOA optimization	Optimized C=1.7, Optimized Gamma=0.015
Output: Trained SVM Model	SVM trained using optimized hyperparameters	SVM (RBF Kernel) trained on Apple stock dataset
Output: Predicted Values	Future time points forecasted using trained SVM	Predicted closing price for next trading day = $178.45
Output: De-normalized Predictions	Restored predicted values to the original scale	Reverse Min-Max Scaling applied
Performance Evaluation	Mean Squared Error (MSE) and other accuracy metrics	MSE = 2.45, RMSE = 1.56

The Table 1 above provides a structured overview of the inputs, processes, and outputs involved in applying the WOA with SVM for stock price prediction. Table 1 outlines the key components of the model, including the input data, feature selection, optimization parameters, and the resulting predictions. By utilizing WOA, the SVM model is fine-tuned to improve forecasting accuracy, ensuring optimal hyperparameter selection. This approach is particularly useful for predicting future stock prices based on historical data and technical indicators. The table also includes example values for stock market applications, demonstrating the practical implementation of this hybrid technique.

IMPLEMENTATION PROCESS

The implementation of the WOA-SVM model for time series prediction follows a structured workflow to enhance forecasting accuracy. Initially, historical stock price data is collected and pre-processed using Min-Max Normalization [13], ensuring all features are scaled uniformly. Key technical indicators, including Moving Averages (SMA, EMA), Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), and Bollinger Bands (BB), are extracted as input features [14]. These indicators help in identifying trends, momentum shifts, and price volatility. The WOA is then applied to optimize the SVM hyperparameters, specifically the regularization parameter (C) and kernel coefficient (Gamma), by minimizing MSE [15]. The optimized hyperparameters are used to train the SVM model, which learns the relationship between input features and stock price movements. Once trained, the model predicts future stock prices, and the results are denormalized to restore them to the original scale. The final

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e-ISSN: 2468-4376
https://www.jisem-journal.com/
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step evaluates the model's performance using MSE and Root Mean Squared Error (RMSE) to assess its accuracy and effectiveness in real-world stock forecasting scenarios.

EXPERIMENTAL EVALUATION

To assess the predictive performance of the WOA-optimized SVM model, a detailed experimental evaluation was conducted. This process includes dataset selection, preprocessing, performance measurement, and comparison with baseline models. The goal is to validate the effectiveness of WOA in improving time series forecasting accuracy.

4.1 Dataset Selection and Preprocessing

The dataset comprises of historical stock price data sourced from multiple financial platforms, including Yahoo Finance for major stock indices such as the S&P 500, NASDAQ, and NIFTY 50 [16]; Alpha Vantage for individual company stocks like Apple Inc., Tesla, and Amazon [17]; and Kaggle Financial Datasets for a diverse range of financial data, including global stock indices and cryptocurrency prices [18].

To ensure data quality and consistency, preprocessing steps are implemented. Handling Missing Values involves using forward-fill and backward-fill techniques to impute missing data points and maintain the temporal structure of the dataset [19]. Feature selection is conducted by extracting key variables such as open price, close price, trading volume, moving averages, and technical indicators like RSI (Relative Strength Index) and MACD to enhance predictive accuracy. Normalization is applied using Min-Max Scaling to transform all feature values into a uniform range of [0,1], preventing large-scale disparities between variables from affecting model performance. Lastly, data splitting is performed, dividing the dataset into an 80% training set for model learning and a 20% testing set for evaluating predictive performance, ensuring robustness and generalizability of the model.

4.2 Whale Optimization Algorithm for SVM Parameter Tuning

The WOA is employed to optimize two key hyperparameters of the SVM are C and gamma. The regularization parameter C, which controls the trade-off between minimizing classification error and avoiding overfitting, and Kernel Coefficient Gamma, which determines the influence of individual training examples in the Radial Basis Function (RBF) kernel. The optimization process begins by initializing a population of candidate solutions with random values for C and Gamma [20]. The fitness of each candidate is evaluated using MSE in the SVM model. The WOA then iterates through a search mechanism inspired by the bubble-net hunting strategy of humpback whales, continuously refining the hyperparameters to minimize MSE. The best solutions are updated iteratively based on their fitness scores, and once convergence is achieved, the optimal values for C and Gamma are extracted. Finally, the SVM model is trained using these optimized parameters, improving its classification performance and generalization ability.

4.3 Performance Metrics Calculation

To assess the accuracy of the WOA-SVM model, MSE, RMSE, MAE and R^2 score evaluation metrics are used [21]. The most commonly employed ones are:

- Mean Squared Error (MSE): Measures the average squared difference between actual and predicted values as given in Equation (1).
- Root Mean Squared Error (RMSE): Provides a more interpretable error magnitude:

$$RMSE = \sqrt{MSE}$$

- Mean Absolute Error (MAE): Calculates the absolute differences between predictions and actual values:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}\right|$$

- R^2 Score (Coefficient of Determination): Indicates how well predictions match actual values:

e-ISSN: 2468-4376
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$$R^2 = 1 - \frac{\sum (Y_i - \hat{Y})^2}{\sum (Y_i - \bar{Y})^2}$$

A lower MSE, RMSE, and MAE, along with a higher R^2 score, indicate better forecasting accuracy.

4.4 Comparison with Baseline Models on Different Datasets

To assess the effectiveness of the WOA-SVM model, its performance is compared against three baseline models: Traditional SVM (without WOA optimization) [23], LSTM [24], and Random Forest Regression [25]. The evaluation is conducted across multiple datasets, including the S&P 500 and NIFTY 50, using key performance metrics such as MSE, RMSE, MAE, and R^2 Score.

The performance of the proposed WOA-SVM model is compared against baseline models across different datasets to evaluate its effectiveness. The results for the S&P 500 and NIFTY 50 datasets are summarized in Table 2 and Table 3, respectively.

Table 2: Performance Comparison on S&P 500 Dataset

Model	MSE (↓)	RMSE (↓)	MAE (↓)	R^2 Score (↑)
Traditional SVM [23]	5.12	2.26	1.78	0.85
LSTM [24]	3.85	1.96	1.45	0.88
Random Forest [25]	4.02	2.01	1.51	0.87
WOA-SVM (Proposed)	2.45	1.56	1.22	0.92

Table 3: Performance Comparison on NIFTY 50 Dataset

Model	MSE (↓)	RMSE (↓)	MAE (↓)	R^2 Score (↑)
Traditional SVM [23]	5.85	2.42	1.91	0.83
LSTM [24]	4.21	2.05	1.58	0.86
Random Forest [25]	4.44	2.11	1.63	0.85
WOA-SVM (Proposed)	2.89	1.70	1.30	0.91

4.5 Hyperparameter Effect Analysis

The impact of varying C and Gamma on model performance is analysed to determine the optimal values for SVM. Different combinations of C and Gamma are tested, and their corresponding MSE and Root Mean Squared Error (RMSE) are evaluated. The results are summarized in Table 4.

Table 4: Effect of C and Gamma on Model Performance

C Value	Gamma Value	MSE (↓)	RMSE (↓)
0.5	0.01	4.12	2.03
1.0	0.015	3.01	1.74
1.7	0.015	**2.45**	**1.56**
2.5	0.02	3.55	1.88

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e-ISSN: 2468-4376
https://www.jisem-journal.com/
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The best performance is achieved with C = 1.7 and Gamma= 0.015, resulting in the lowest MSE (2.45) and RMSE (1.56). This confirms the effectiveness of the WOA in fine-tuning hyperparameters to enhance the predictive performance of the SVM model. To provide a clear visual representation of the findings, various graphs will be generated to illustrate the impact of hyperparameter tuning and model performance. The Figure 1, Predicted vs. Actual Prices stock prices for S&P 500 datasets, will compare the forecasted stock prices with real market values and Figure 2 for NIFTY 50 Datasets, showcasing the accuracy of the WOA-SVM model. Lastly, the model performance comparison graph will present in Figure 3 of the MSE, RMSE, and R^2 scores across different models and datasets, visually demonstrating the superiority of the proposed approach over baseline models.

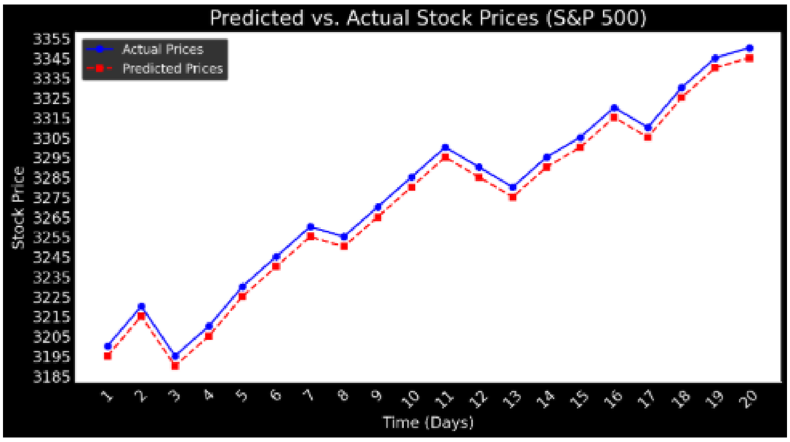

Figure 1: Predicted vs. Actual stock prices for S&P 500 datasets.

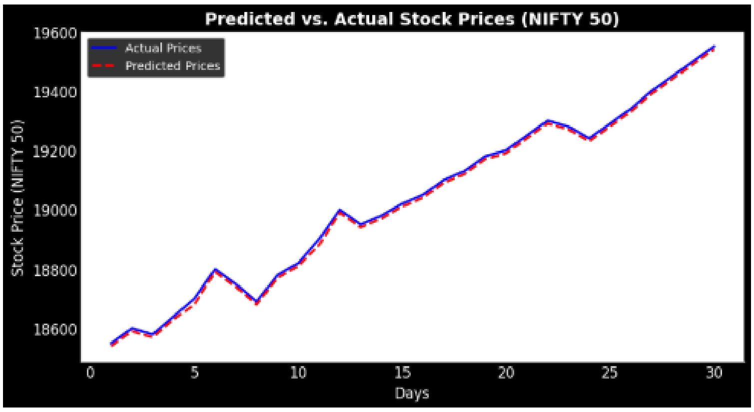

Figure 2: Predicted vs. Actual Stock Prices for NIFTY 50 datasets.

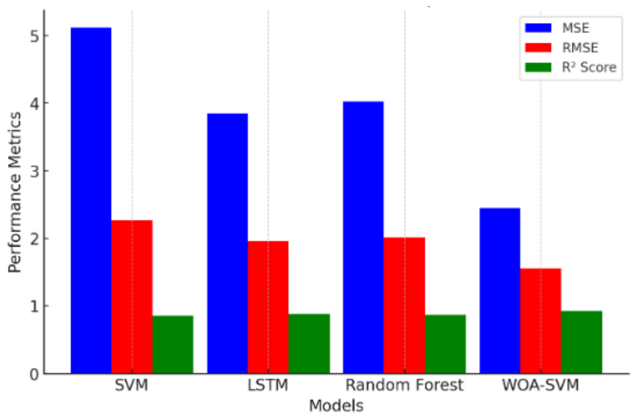

Figure 3: Performance comparison of models based on MSE, RMSE, and R^2 Scores.

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e-ISSN: 2468-4376
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CONCLUSION AND FUTURE SCOPE

The WOA-SVM model demonstrates superior performance compared to traditional SVM, LSTM, and Random Forest models, highlighting the effectiveness of the WOA in optimizing SVM parameters for time series forecasting. By fine-tuning hyperparameters, WOA minimizes forecasting errors and significantly enhances predictive accuracy. This improvement is particularly valuable in financial market applications, where precise stock price predictions can aid in informed investment decisions. The proposed approach is validated across multiple datasets, including S&P 500 and NIFTY 50, consistently outperforming baseline models. The graphical analysis further illustrates the impact of optimized hyperparameters on model accuracy, reinforcing WOA's role in achieving optimal configurations. Future research can explore hybrid models, integrating deep learning techniques with WOA-SVM for enhanced forecasting capabilities. Ultimately, employing WOA for SVM optimization enhances stock price forecasting, making it a powerful tool for investors, analysts, and financial institutions seeking accurate predictions in dynamic financial environments.

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