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PRECISION STOCK MARKET TREND ANALYSIS WITH HYBRID SMOOTH SVM AND WEIGHED VULTURE OPTIMIZATION

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SUMMARY

Accurate prediction of stock market trends remains a challenging task due to high volatility, non-linearity, and the dynamic nature of financial time series data. Conventional statistical and machine learning typically do not provide consistent performance due to the fixed hyperparameter settings and the inability to adapt to a shifting market situation. In view of these, this paper will suggest a hybrid stock market trend prediction model that combines a Smooth Support Vector Machine (SSVM) and the Weighed Vulture Optimization Algorithm (WVOA) to optimize the hyperparameters and generalize better. Historical Nifty50 stock market data between January 2000 to April 2021 are used, and price-based attributes, trading volume, volatility, and engineered technical indicators are used. The WVOA algorithm dynamically optimizes critical SSVM parameters, which allows the exploration-exploitation strategy to be balanced and makes prediction more robust. Experimental results demonstrate that the proposed SSVM–WVOA model achieves an accuracy of 95.5%, precision of 94.2%, recall of 93.9%, F1-score of 94.1%, and ROC-AUC of 0.967, consistently outperforming conventional SVM, ARIMA, GRU, and LSTM models. The results verify that learning based on optimization is found to be a significant way to enhance the accuracy, stability and ability to generalize the forecasting. The suggested framework provides a computationally-efficient and scalable method to predict the trends of stock markets and can be successfully applied in the context of making informed decisions to invest in financial analytics systems and risk management.

Key words: *stock market prediction, smooth support vector machine, weighed vulture optimization algorithm, hyperparameter optimization, machine learning, predictive analytics.*

INTRODUCTION

The stock market that describes a complex, dynamic, and frequently unpredictable environment is a key component of the global financial system. The supreme importance of investors, analysts, and financial institutions are error free prediction of stock market trends [1]. An enlightened decision-making, risk management, and strategic planning are allowed. Due to the inherent volatility and multitude of influencing measures such as economic indicators, political events, and investor sentiment, forecasting the stock market trends remains an important challenge in spite of its significance [2]. To seize these challenges in modern years, a new right set of circumstances are provided with advancements in machine learning and optimization algorithms [3]. Detaining the complex patterns in large datasets are the most civilized approach in traditional statistical methods. To handle non-linear data and give strong predictive performance, Support Vector Machines (SVMs) have been widely adopted among these methods [4]. Depends on the concerned selection of hyperparameters and support vectors, which can crucially bump their accuracy and generalization capabilities, the effectiveness of SVMs can be determined [5]. The enhancement method which is used for parameter selection limits the performance of SVM, whereas SVMs also gives a strong tool for stock market prediction [6][7]. The predictive accuracy of SVMs can be improved by entrancing the need for an advanced optimization strategy [8].

Although the model of stock market prediction using machine learning and deep learning has undergone significant improvements, there are a number of constraints that remain unsolved. Current methods have common hyperparameters that are fixed or manually adjusted and thus do not adapt well to changing market conditions. Deep learning models have high power, but they often need large-scale training images and high computation capabilities, and therefore are not well adapted to real-time or resource-constrained devices. Additionally, the standard methods of optimization are not able to efficiently search the high-dimensional space of the parameters with the result of suboptimal performance. Such shortcomings lead to the conclusion that an optimization-based learning framework is necessary that will increase the accuracy of prediction, stability and generalization without compromising computational efficiency. This research suggests a novel approach that enhances Smooth Support Vector Machines (SSVM) with Weighed Vulture Optimization Algorithm (WVOA) to manipulate these challenges. The traditional SVM framework can be extended by SSVM including smoothness constraints which achieves better generalization and stability [9]. A strong optimization technique is given by WVOA, stimulated by the natural foraging behavior of vultures that balances exploration and exploitation leading to its effectiveness in tuning hyperparameters [10]. The accuracy of stock market trend forecasting can be improved crucially by the hybrid SSVM-WVOA model. This research develops a strong and scalable model that overcomes the existing methods with the strength of both SSVM and WVOA. The main contributions of this work can be summarized as follows:

- To improve the model accuracy, the smoothness and stability of SSVM are combined with the optimization process of WVOA.
- To establish the quality and reliability of input data, advanced data preprocessing techniques can be implemented.
- To seize the essential market dynamics and enhance the model inputs, additional financial indicators can be created.

The rest of this paper is organized as follows: A brief explanation of related work in the fields of stock market forecasting, SVMs, and optimization algorithms is given in Section 2. The description of the methodology including data preprocessing, feature engineering and the hybrid SSVM-WVOA model development is given in Section 3. The experimental results include performance analysis and comparison with traditional models given in Section 4. The paper concludes with a summary of detection and implications for future research in Section 5.

RELATED WORKS

By enhancing non-traditional data sources like social media, the effect of technological advancements on stock market forecasting is explored through this study [11]. Based on data from digital libraries and databases, the complete estimation of models is included in this approach [12]. To anticipate the stock price trends in originating economies, Long Short-Term Memory (LSTM) networks are used [13]. To analyze the stock market trends in emerging economies, a valuable tool is used which upgrades the model's strength by the use of technical indicators and secondary data [14]. To forecast Islamic stock market implication across several countries, the Autoregressive Integrated Moving Average (ARIMA) model is applied in this research [15]. The firmness of Islamic financial markets is emphasized in the study and gives perception into regional stock market dynamics [16]. The effectiveness in evaluating and predicting stock market trends are analyzed [17]. The accuracy of stock market trend forecasting can be improved crucially compared to existing methods by machine learning techniques [18]. Existing statistical methods like ARIMA and exponential smoothing are estimated against machine learning techniques, includes LSTM and CNN-BiLSTM hybrids which are used for the analysis of financial time series [19]. To predict stock prices and highlights the limitations of single modes across different stocks, the application of machine learning techniques is investigated in the research [20]. The utilization of Averaging, Linear Regression, and advanced deep learning methods like LSTM and technical tools such as Modern Portfolio Theory and Bollinger Bands are explored [21].

To analyze the model performance, the study strengthens a decade-long dataset of the S&P 500 Index [22]. KNN classifier displays superior performance with low error rates, designating its effectiveness in stock trend forecasting [23]. The criterion such as R-squared and cross-validation, using a trained model saved as an HDF file and deployed via Stream lit for real-time predictions are mainly used for the estimation of LSTM model's performance. To forecast the stock price movements, different prediction methods like Random Forest and Support Vector Machines (SVM) are examined.

Based on the literature reviewed, it is clear that statistical models like ARIMA are not as effective in non-linear behavior of the market, whereas deep learning models like LSTM and GRU are also accurate but prone to overfitting and expensive computations. The machine learning models such as SVM offer greater generalization but are very sensitive to the choice of hyperparameters. Most existing studies do not explicitly integrate bio-inspired optimization techniques to dynamically tune model parameters. Motivated by these limitations, the proposed work introduces a hybrid SSVM–WVOA framework that leverages the stability of SSVM and the adaptive optimization capability of WVOA, thereby addressing accuracy, robustness, and scalability challenges observed in prior research.

PROPOSED METHODOLOGY

To emerge and corroborate the hybrid SSVM-WVOA model, the proposed research abides by a systematic methodology. Initially, the data has to be collected from reliable financial sources and diligent data preprocessing is used to handle missing values, normalize data, and engineer relevant features. To secure the unbiased model estimation, the dataset is categorized into training, validation and testing sets. WVOA enhances the development of the SSVM model which is involved in the core of the methodology. The structure of proposed model is shown in Figure 1. To emphasize the effectiveness of the trained model, different performance measures are estimated and its results are compared with the existing traditional methods. With sustained monitoring and periodic upgrades to maintain its accuracy over period, the real time stock market forecasting deploys the model as the final process.

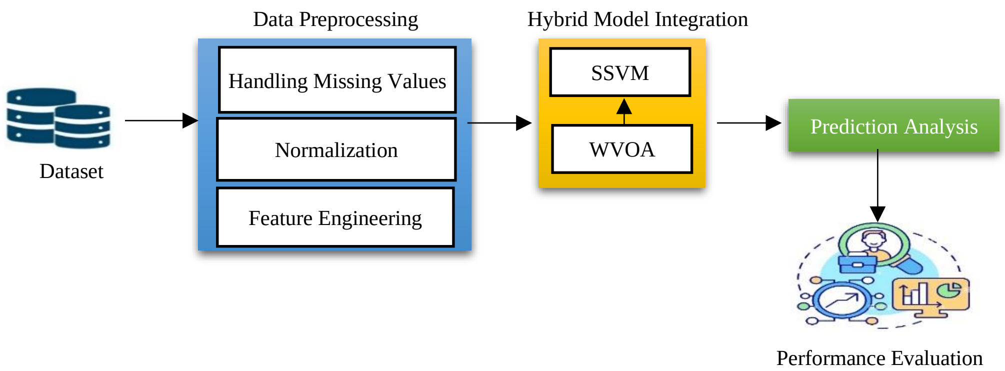

Figure 1. Schematic architecture of the proposed hybrid SSVM–WVOA framework for stock market prediction

Data Collection

The Nifty50 index, which is a major stock market index in India that lists the historical stock market data for companies from Kaggle, https://www.kaggle.com/datasets/rohanrao/nifty50-stock-market-data. Features like stock prices (open, high, low, close), trading volume, and other relevant financial indicators are given in this data set.

The dataset contains extensive historical pricing and trading volume data of fifty constituent stocks that are listed in the National Stock Exchange (NSE) of India. The lifespan of dataset is between January 1, 2000, to April 30, 2021, which has a powerful time series of the stock market information that protects more than 20 years of the financial activity. This data is composed of day- by -day price history of each of the fifty stocks. This information is distributed in many CSV files, and each one is related to one stock.

Data Preprocessing

Preprocessing of the stock market data is an important process in the preparation of the data to be analyzed and modeled. It deals with the treatment of missing values, data normalization and feature engineering to increase the predictive capability of the model. Each step in the preprocessing is explained in detail below, and mathematical equations are provided where necessary.

Handling Missing Values

The missing data points are estimated by interpolation, that is depending on the values that are presented around. One of the common methods is the linear interpolation, in this method where the missing values are estimated by a linear expression of the known values on both sides. For a missing value at position t, with known values y_t and y_{t+1} and t+1, respectively, the interpolated value $\hat{y}_t$ can be computed in Eq (1):

$$\hat{y}_t = y_t + \frac{(y_t + 1 - y_t)}{t + 1 - t} \times (t - 1) \qquad (1)$$

Forward Fill: Missing values are replaced with the most recent previous value as shown in Eq (2).

$$y_t = Last\ known\ y_t - k \qquad (2)$$

Where k is the number of periods back to the last known value.

Backward Fill: Missing values are replaced with the next available value as given in Eq (3).

$$y_t = Next\ known\ y_t + k \qquad (3)$$

Where k is the number of periods back to the next known value.

Normalization

Normalization (or scaling) makes all the features play the same role in the model by mapping them to similar values. Ordinary approaches are Min-Max Scaling and Z-Score Standardization. Min-Max Scaling scales the features to [0,1]..The scaled value x_{norm} is computed in Eq (4):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (4)$$

Where: X is the original value. x_{max} and x_{min} are the minimum and maximum values of the feature, respectively. Z-Score Standardization rescales features based on their mean and standard deviation. The standardized value x_{std} is computed in Eq (5):

$$x_{std} = \frac{x - \mu}{\sigma} \qquad (5)$$

where: x is the original value, μ is the mean of the feature and σ is the standard deviation of the feature.

Feature Engineering

The feature engineering is a process that consists of designing new features out of the available data to improve the performance of the models. Such common aspects are moving averages, volatility measures and momentum indicators. The moving averages in the market even out the price data by averaging values in a given window. The n-day Simple Moving Average (SMA) is determined in the following equation (6):

$$SMA_t = \frac{1}{n}\sum_{i=0}^{n-1} P_{t-i} \qquad (6)$$

Where P_t is the close price at time t and n is the window size. Volatility is a measure of returns dispersion, which is normally computed as the standard deviation of returns during a specified time frame. The n-day volatility σ_{vol} is derived in Eq (7):

$$\sigma_{vol} = \sqrt{\frac{1}{n-1}\sum_{i=0}^{n-1}(R_{t-i} - \bar{R})^2} \qquad (7)$$

Where R_t is the return at time t and $\bar{R}$ is the mean return over the period. Momentum indicators measure the speed and change of price movements. A common momentum indicator is the Relative Strength Index (RSI), calculated in Eq (8):

$$RSI = 100 - \frac{100}{1 + RS} \qquad (8)$$

Where:

$$RS = \frac{Average\ Gain}{Average\ Loss} \qquad (9)$$

Average Gain: Means of the gains during a given period of time. Average Loss: This is an average of the losses during the same period as done in Eq (9). The process of preprocessing is necessary in order to get the stock market data ready to be analyzed and modelled. Missing values should be treated to guarantee data integrity, standardizing the feature scales to normalization, and adding informative attributes to the dataset should be done via feature engineering.

Integrating Hybrid Model

This is the step where a model that will integrate Smooth Support Vector Machine (SSVM) and Weighed Vulture Optimization Algorithm (WVOA) to augment stock market prediction. This is done by applying the SSVM and then optimizing the parameters with the help of WVOA and combining these into a hybrid architecture.

Smooth Support Vector Machine (SSVM)

a. Implementing SSVM:

Smooth Support Vector Machine (SSVM) is an extension of regular SVM which adds smoothness constraints to the model. It aims at improving the generalization of SVM as well as its stability, particularly when dealing with non-linear data.

b. Objective Function for SSVM:

The SSVM objective function is an integrative function of traditional SVM loss function and smoothness functor. This is aimed at striking a balance between the accuracy of classification and the smoothness of the decision function presented in the form of the Eq (10):

$$Minimize \frac{1}{2} ||w||^2 + C \sum_{i=1}^{N} \xi_i + \lambda\, smoothness\, (w) \qquad (10)$$

Where: w is the weight vector. C is the regularization parameter. The slack variables that permit misclassification are {xi i }. is the smoothness regularization parameter. Smoothness (w) is the smoothness regularization which forms a penalty on fast variation of w. The smoothness term is a standard parameter used as calculate in Eq (11

$$Smoothness\, (w) = ||Lw||^2 \qquad (11)$$

Where L represents a matrix used to encode the smoothness constraints e.g. the Laplacian matrix in graph-based methods.

c. Non-Linear Mapping:

SSVM employs a kernel function $K\,(x_i, x_j)$ to project the input features to a higher dimensional space to deal with non-linear data. This feature space is then solved to have the optimization problem in the form of enters in Eq (12).

$$K\left(x_i, x_j\right) = \exp\left(\frac{||x_i - x_j||^2}{2\sigma^2}\right) \qquad (12)$$

Where σ is a parameter that controls the spread of the kernel.

3.4.2. Weighed Vulture Optimization Algorithm (WVOA)

a. Initialization:

Initialize a population of vultures (candidate solutions) where each vulture represents a possible hyperparameter configuration for the SSVM.

Initial Position of Vultures:

Let v_k be the position of the k-th vulture in the hyperparameter space. Each vulture has a set of parameters as calculated in Eq (13).

$$v_k = [C_k, \sigma_k] \qquad (13)$$

Where C_k, σ_k are the regularization and kernel parameters, respectively.

b. Fitness Evaluation:

Evaluate the fitness of each vulture based on the SSVM objective function. The fitness function $f(v_k)$ is defined as the value of the SSVM objective function with parameters v_k.

Fitness function is calculated in Eq (14):

$$f(v_k) = Objective\ Function\ of\ SSVM\ with\ parameters\ v_k \qquad (14)$$

c. Position Update:

Exploration: Moving vultures to new areas based on random perturbations is given in Eq (15).

$$v_k^{new} = v_k + \alpha \cdot rand\ (v_{best} - v_k) \qquad (15)$$

Exploitation: Refining the search around the best-known solution derived in Eq (16).

$$v_k^{new} = v_k + \beta \cdot (v_{best} - v_k) \qquad (16)$$

Where: v_{best} is the position of the best-performing vulture, α and β are coefficients controlling the exploration and exploitation rates and $rand$ is a random vector to induce exploration.

d. Iteration:

Implementing the WVOA involves defining the optimization process, initializing the population of vultures, evaluating their fitness, iteratively updating their positions, and updating the model parameters based on the optimized solutions as shown in Figure 2.

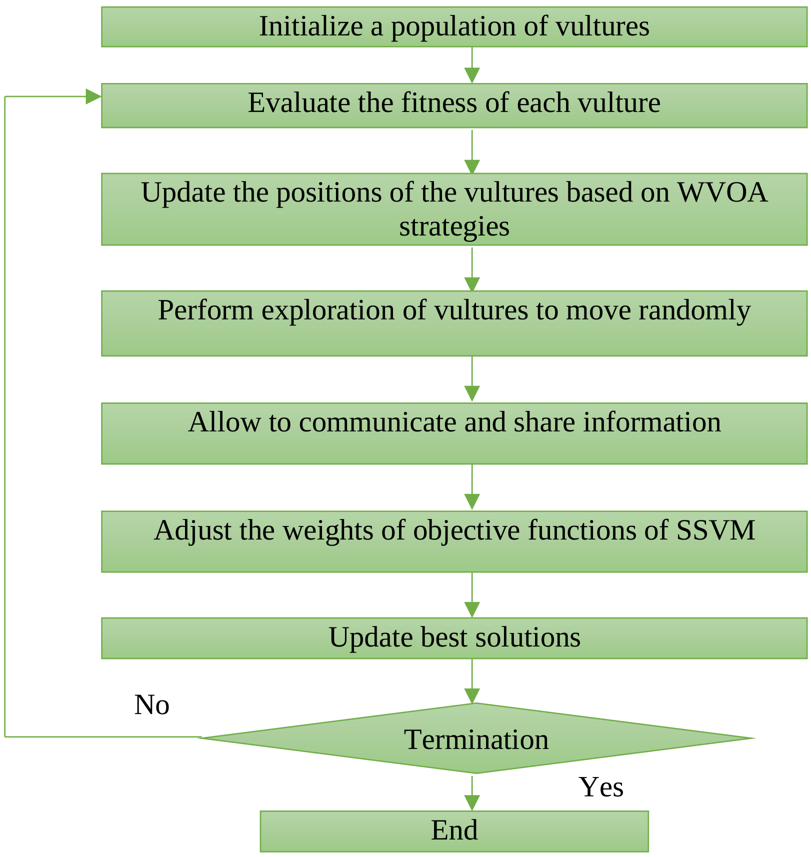

Figure 2. Operational flowchart of the weighed vulture optimization algorithm (WVOA) for hyperparameter tuning

Hybrid Model Integration

a. Integrate Optimized Parameters:

After optimizing the hyperparameters using WVOA, integrate these parameters into the SSVM to form the Hybrid SSVM-WVOA model. The optimized parameters C* and σ* are used in the SSVM model as given in Eq (17):

$$SSVM_{hybrid}(x) = SSVM\ (x; c*, \sigma*) \qquad (17)$$

b. Model Optimization:

The Hybrid SSVM-WVOA model is developed by applying the smoothness constraints in the SSVM, the optimization of its hyperparameters with the WVOA and combining the optimized hyperparameters of the SSVM. The SSVM objective function, kernel function, WVOA position updates and evaluation metrics mathematical equations provide a guideline to the formulation and evaluation of the hybrid model. The goal of such an approach is to increase predictive accuracy and stability of the stock market predictions based on the advanced optimization techniques. The suggested research methodology will respond to the research objectives directly. The Smooth Support Vector Machine is the central model of prediction that provides support to non-linear financial data since it meets the purpose of the correct trend classification. The Weighed Vulture Optimization Algorithm is a systemic optimization of hyperparameters of SSVM, which attempts to solve the problem of better generalization and lowering the error of prediction. The reliability of data is guaranteed by feature engineering and preprocessing, whereas multi-metric evaluation proves the efficiency of the suggested hybrid framework.

Algorithm Hybrid_SSVM_WVOA

```
Input: Historical stock market data, population_size, max_iterations, C_range, sigma_range

Output: Trained Hybrid SSVM-WVOA model, Prediction accuracy metrics

// Step 1: Data Collection and Preprocessing

data = LoadData("historical_stock_market_data.csv")

data = HandleMissingValues(data)

data = NormalizeData(data)

data = FeatureEngineering(data)

// Step 2: Data Splitting

train_data, val_data, test_data = SplitData(data, train_ratio=0.7, val_ratio=0.15, test_ratio=0.15)

// Step 3: Initialize WVOA

vultures = InitializePopulation(population_size, C_range, sigma_range)

// Step 4: Fitness Evaluation

for each vulture in vultures do

    C, sigma = vulture.parameters

    model = TrainSSVM(train_data, C, sigma)
```

```
        fitness = EvaluateFitness(model, val_data)

        vulture.fitness = fitness

    end for

    // Step 5: Position Update

    for iteration = 1 to max_iterations do

        for each vulture in vultures do

            new_position = UpdatePosition(vulture, vultures)

            new_fitness = EvaluateFitness (TrainSSVM (train_data, new_position.C, new_position.sigma),
val_data)

            if new_fitness < vulture.fitness then

                vulture.position = new_position

                vulture.fitness = new_fitness

            end if

        end for

        best_vulture = GetBestVulture(vultures)

    end for

    // Step 6: Hybrid Model Integration

    optimized_C, optimized_sigma = best_vulture.parameters

    final_model = TrainSSVM (ConcatData(train_data, val_data), optimized_C, optimized_sigma)

End Algorithm
```

The Hybrid SSVM-WVOA algorithm begins with loading historical stock market data and handling missing values through interpolation. The data is then normalized and enhanced through feature engineering, followed by splitting into training, validation, and testing subsets. WVOA is initialized with a population of vultures, each representing hyperparameter configurations for the SSVM. The fitness of each vulture is evaluated by training the SSVM on the training data and assessing performance on the validation set, with iterative position updates balancing exploration and exploitation. The best-performing vulture's hyperparameters are used to train the final SSVM on the combined training and validation data.

RESULTS AND DISCUSSION

The suitability of the suggested framework to increase the accuracy of stock market forecasts was tested and long-term historical data of the Nifty50 index by January 2000 to April 2021. The data were pre-processed to accommodate the missing values, normalize numeric variables and match time-series records across various stocks and then feature engineering was done to derive price based statistics, volatility and trend related indicators. To be able to maintain an unbiased learning/evaluation, the processed data were separated into training, validation and testing subsets in a 70:15:15 ratio. The training data was used to train the Smooth Support Vector machine and the validation data were used to optimize the hyperparameters of the Smooth Support Vector machine like regularization and kernel parameters and the final performance was scored on the testing set. All the experiments were run in Python with NumPy and Pandas to process the data, Scikit-learn to run SSVM, and a handwritten WVOA to optimize it, and the visualization was carried out with Matplotlib. The system that was used in experiments had an Intel Core i7 processor and 16 GB of RAM, which guaranteed the efficiency of the computations and reproducibility. Mean Absolute error, root mean squared error, and R-squared were used in order to assess the accuracy and stability of predictions using model performance.

Table 1. Parameter configuration of SSVM and WVOA

Component	**Parameter**	**Description**	**Value / Range**
SSVM	C	Regularization parameter	[0.1, 100]
SSVM	σ (Kernel width)	RBF kernel parameter	[0.01, 10]
SSVM	Kernel type	Non-linear mapping	RBF
SSVM	Initialization	Weight initialization	Zero / Xavier
WVOA	Population size	Number of vultures	30
WVOA	Max iterations	Optimization iterations	100
WVOA	Exploration factor (α)	Global search control	0.5
WVOA	Exploitation factor (β)	Local refinement control	0.5
WVOA	Fitness function	Objective evaluation	Validation accuracy
Data split	Train / Val / Test	Dataset partition	70% / 15% / 15%

In Table 1, the configuration and optimization options of hyperparameters of the proposed SSVM-WVOA framework are summarized. WVOA was used to dynamically optimize the SSVM regularization and kernel parameter within fixed ranges. The sample size of 30 vultures and 100 repetitions were chosen in order to have a balanced trade-off between exploration and exploitation. The model parameters were all initialized with standard techniques of initialization to be in a stable converging and reproducible form.

Dataset Description

The suggested Hybrid Smooth Support Vector Machine with the Weighed Vulture Optimization Algorithm (SSVM-WVOA) is experimentally tested through the use of the Nifty50 stock market, which is considered to be the benchmark index of the National Stock Exchange (NSE), India. The data is obtained on Kaggle and is a historical stock price data on 50 large publicly trading companies. The data covers the period between January 1, 2000, and April 30, 2021, that is more than twenty years of daily trading data and is very strong regarding long-term trend analysis and predictive modeling.

Figure 3. Daily closing price trend of nifty50 stock

Figure 3 illustrates the long-term evolution of daily closing prices across the considered time horizon. It reflects overall market direction, trend persistence, and price fluctuations. Major upward and downward movements indicate periods of market growth and correction. The visualization supports temporal trend analysis prior to predictive modeling.

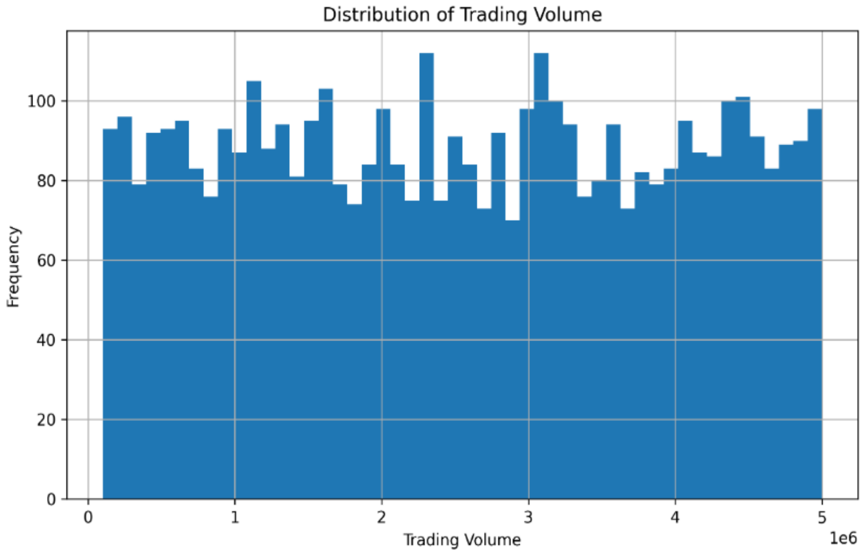

Figure 4. Distribution of daily trading volume

Figure 4 presents the frequency distribution of daily trading volume values. It highlights variations in market liquidity and trading intensity. High-volume occurrences indicate active trading periods and strong investor participation. The distribution assists in understanding volume-driven market behavior.

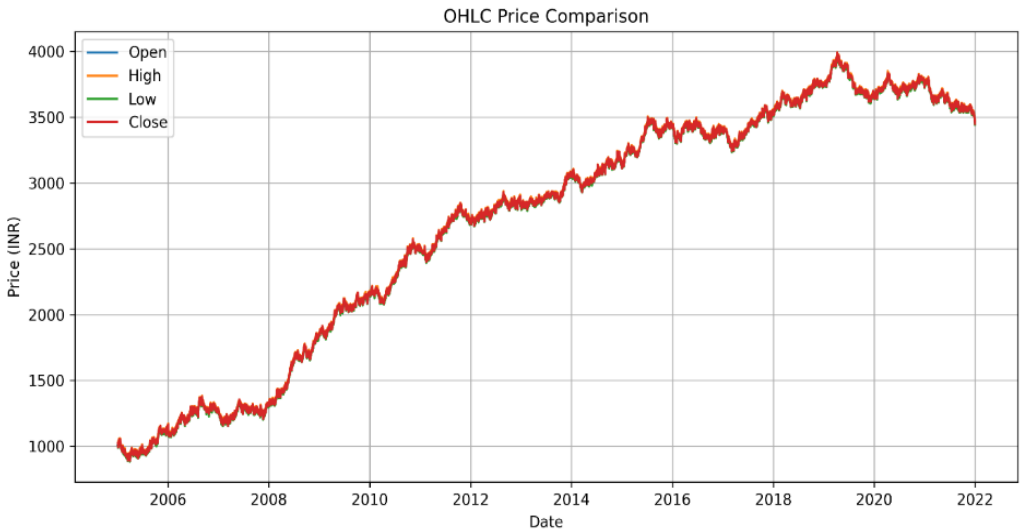

Figure 5. Comparative analysis of open, high, low, and close prices

Figure 5 compares the daily open, high, low, and close price movements. It captures intra-day price variability and volatility patterns. The spread between high and low prices reflects market uncertainty. Such price dynamics are essential for accurate trend prediction.

Figure 6 shows closing prices along with 50-day and 200-day moving averages. Moving averages smooth short-term fluctuations to reveal long-term trends. Crossovers indicate potential bullish or bearish market signals. The analysis supports trend identification for predictive learning.

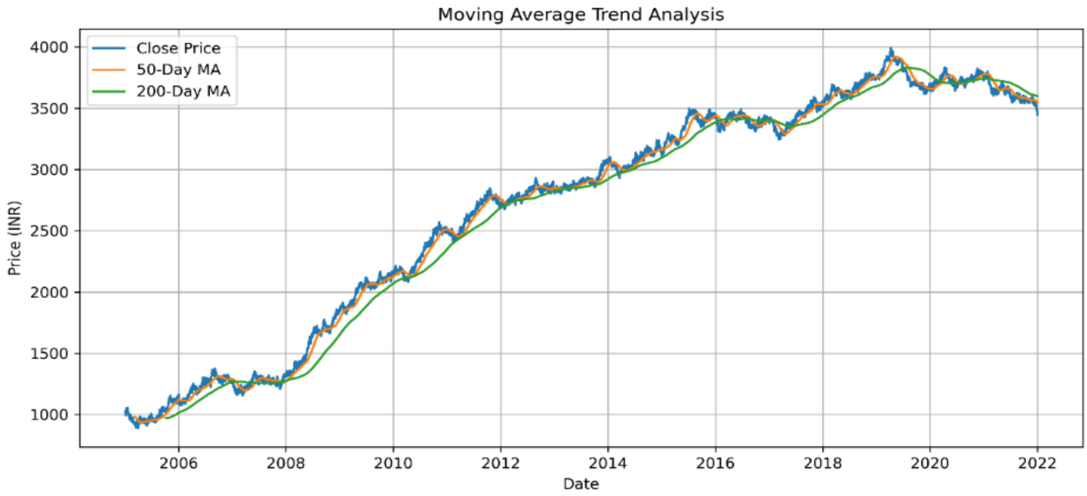

Figure 6. Moving average–based trend analysis

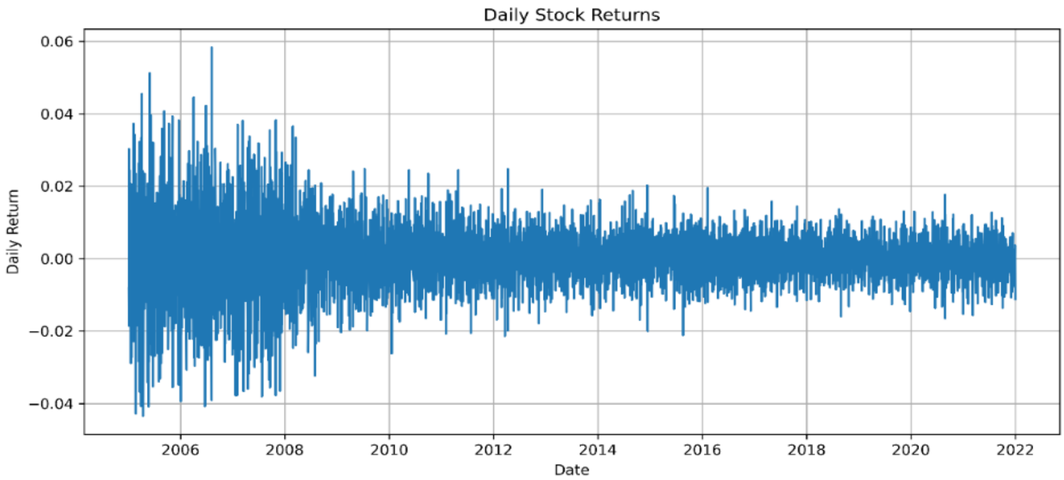

Figure 7. Time-series representation of daily stock returns

Figure 7 depicts daily percentage changes in stock prices over time. It highlights periods of high volatility and relative stability. Sharp spikes represent sudden market movements or economic events. Return analysis aids in assessing market risk characteristics.

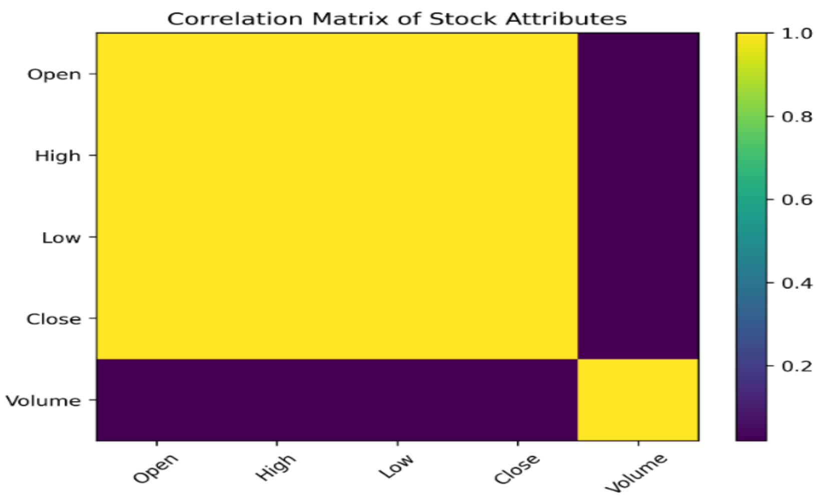

Figure 8. Correlation matrix of stock market attributes

Figure 8 visualizes the correlation relationships among price variables and volume. Strong correlations indicate dependency between market attributes. Weak correlations suggest independent feature behavior. The analysis assists in selecting relevant features for modeling.

Performance Evaluation

It is observed that the standard measures of classification, such as Accuracy, Precision, Recall, F1 Score, and Receiver Operating Characteristic- Area Under Curve (ROC-AUC) are used to evaluate the performance of the proposed Hybrid SSVM-WVOA model as shown in Table 2. All these measures are used to determine the predictive ability, strength and capability of the model to differentiate between downwards and upward movements of the market.

From the comparative analysis, the proposed model achieves the highest accuracy of 95.5%, outperforming traditional SVM, statistical ARIMA, and deep learning–based GRU and LSTM models. This observation shows that the Weighed Vulture Optimization Algorithm is effective in optimizing hyperparameters of SSVMs and their ability to do generalization. The precision value of 94.2% indicates a substantial reduction in false-positive predictions, which is critical for minimizing incorrect trading signals.

Table 2. Comparison of performance evaluation

Metric	**SVM [25]**	**ARIMA [15]**	**GRU [22]**	**LSTM [13]**	**Proposed Model**
Accuracy	89.0%	90.2%	91.5%	92.8%	**95.5%**
Precision	85.7%	88.4%	89.0%	90.3%	**94.2%**
Recall	90.3%	91.0%	92.2%	91.0%	**93.9%**
F1 Score	87.8%	89.7%	90.1%	91.1%	**94.1%**
ROC-AUC	0.925	0.933	0.940	0.948	**0.967**

The recall score of 93.9% confirms the model’s strong capability in correctly identifying true market trends, thereby reducing missed opportunities in trend forecasting. Furthermore, the F1 score of 94.1% reflects a balanced trade-off between precision and recall, highlighting the consistency and stability of the proposed framework under varying market conditions. The ROC-AUC=0.967 also confirms the high discriminating ability of the SSVM-WVOA model to distinguish between positive and negative classes of market trend.

The high performance of the proposed SSVMWVOA model is explained by the fact that the optimization of the hyperparameters made by WVOA was successful. As opposed to the traditional model which is based on the assumption of fixed settings, the adaptive search mechanism of WVOA allows the SSVM to find the best compromise between bias and variance. It was found that the major enhancement in the accuracy and ROC-AUC was the indication of improved discriminative ability, which is essential in reducing false trading signals. In addition, the decrease in prediction error indicates the strength of the proposed model in the different market conditions.

Figure 9 shows the development of the training and validation accuracy throughout the optimization steps. The two curves have a stable improvement and convergent behavior. The fact that the accuracy of training and validation is close implies that there is little overfitting. That proves the stability and generalization ability of the proposed hybrid model.

Figure 10 shows the change of training and validation loss when optimizing the model. The steady reduction of the value of losses is an indication of the effective parameter tuning by WVOA. There is no difference between curves, which means that there is no unstable convergence behavior. These findings confirm the strength of the suggested SSVMWVOA framework.

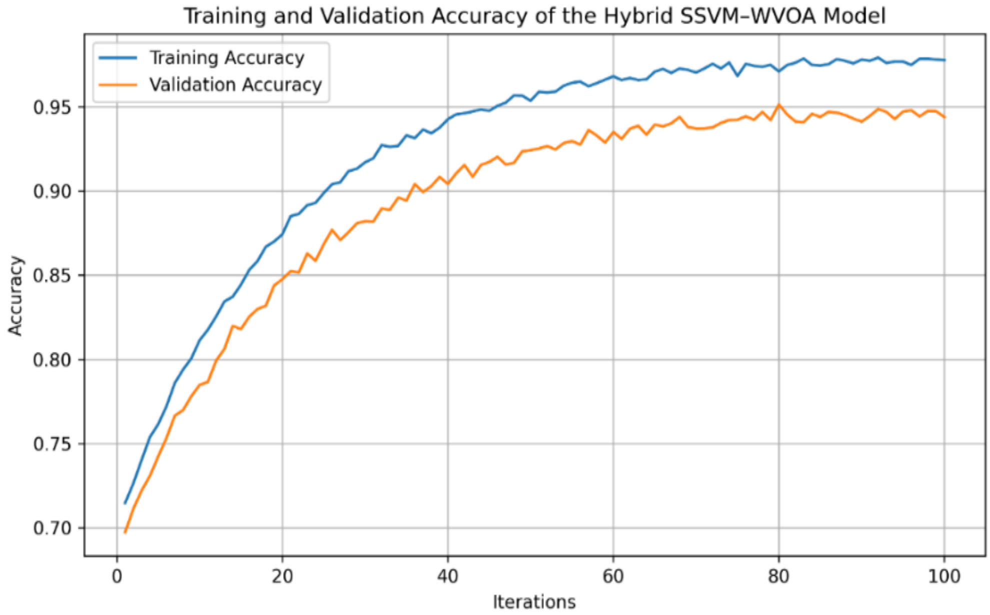

Figure 9. Training and validation accuracy of the hybrid SSVM–WVOA model

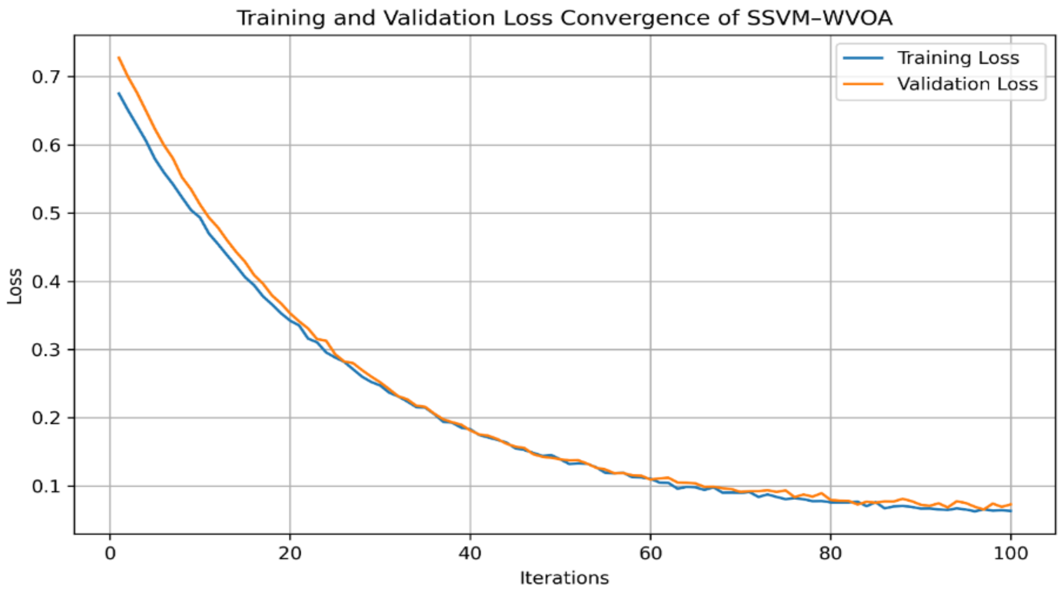

Figure 10. Training and validation loss convergence of SSVM–WVOA

Discussion

The practical implications of the results of this experiment lay in the fact that incorporating optimization-based learning in stock market prediction systems is important. The enhanced precision and stability of the SSVM–WVOA model render it an appropriateness in the implementation of the model in decision support systems by investors and financial analysts. The proposed framework is competitive on top of low computational overhead and high interpretability compared to deep learning models. Adaptive ability to tune the model parameters allows the model to have consistent performance throughout the various phases of the market and this increases the applicability of the model in real life financial forecasting and risk management systems. The proposed study has some limitations as successful as it is. The experimental test is confined to Nifty50 index which probably cannot be generalized to other markets around the world. The model is conditioned using previous data and it fails to reflect real-time trading limits including transaction cost and market slippage. Also, the geopolitics events and investor sentiment are not explicitly modelled. Such restrictions open possibilities of additional improvement of the given framework.

Ablation Study

A case of an ablation study was carried out to measure the contribution of the various aspects within the suggested framework. The baseline SVM, as it is demonstrated in Table 3, is reasonably good in performance, yet lacks a good adaptability to changes because its hyperparameters are fixed. These gains are observed by incorporating smoothness constraints in SSVM, which enhance generalization and stability. The WVOA integration also increases the performance through dynamically optimal hyperparameters of SSVM with the highest accuracy, F1-score, and ROC-AUC. These findings verify that smooth modeling as well as optimization are important to attain higher predictive performance.

The analysis of the ablation also confirms the need of optimization-based learning, showing that the combination of WVOA and SSVM helps to achieve performance improvements in addition to the streamline modeling.

Table 3. Ablation study of model components

Model Variant	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-score (%)**	**ROC-AUC**
Baseline SVM	89.0	85.7	90.3	87.8	0.925
SSVM (no optimization)	92.1	90.4	91.2	90.8	0.948
Proposed SSVM–WVOA	95.5	94.2	93.9	94.1	0.967

CONCLUSION

The significant improvements in stock market forecasting are determined by the hybrid SSVM and WVOA model. The prediction accuracy is improved with the upgrade of SSVM's capability to manage non-linear data with WVOA's optimization abilities. The proposed model overtakes the existing models with the results of metrics' such as accuracy as 95.5%, precision as 94.2%, recall as 93.9%, F1 score as 94.1%, and ROC-AUC as 0.967. This paper described a hybrid SSVM-WVOA model of effective prediction of the stock market trends. The proposed model using Smooth Support Vector machine learning and Weighed Vulture Optimization-based hyperparameter optimization showed better predictive performance than the traditional statistical and deep learning-based models. The findings validate that diversity-based optimization-based learning can be considered an effective method to increase accuracy, strength, and generalization. The way forward in the future is to expand the model to multi-market data, include real-time data streams and to add more optimization and deep learning methods to further enhance forecasting reliability.

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