A Hybrid Framework for Evaluating Financial Market Price: An Analysis of the Hang Seng Index Case Study

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***Abstract*—The accurate prediction of financial outcomes presents a considerable challenge as a result of the intricate interaction of economic fundamentals, market dynamics, and investor psychology. The task of accurately forecasting stock prices in the securities market is a challenging undertaking owing to the presence of non-stationary, non-linearity, and significant volatility in the time series data of stock prices. The utilization of conventional approaches possesses the potential to enhance the precision of predictive modeling. It is crucial to acknowledge that these methodologies also encompass computational intricacies, hence potentially augmenting the likelihood of prediction inaccuracies. This work introduces a methodology that addresses many issues by integrating support vector regression technology with the Aquila optimizer procedure. The results of this investigation suggest that, when compared to the other models, the hybrid model performed better and had more efficacy. The proposed model performed at an ideal level and demonstrated a significant level of effectiveness, with a low number of errors. The Hang Seng Index data was analyzed in order to assess the predictive model's accuracy in stock price forecasting. The data was accessible for the years 2015 through 2023. The results show that the proposed framework performs well and is reliable when analyzing and predicting the price time series of equities. Empirical data suggests that, in comparison to other methods presently in use, the suggested model forecasts outcomes with a higher degree of accuracy.**

Keywords—Efficient market; Hang Seng Index; stock forecasting; support vector regression; Aquila optimizer

I. INTRODUCTION

The field of financial prediction, particularly about the stock market, has garnered significant attention from both researchers and investors in recent years. The objective of stock market prediction research is twofold: to provide forecasts of market prices or directions, to assist investors in making informed investment decisions, and to mitigate the occurrence of stock market upheaval, which can have significant detrimental effects on the overall growth and stability of a capital market [1]. To achieve this objective, a model was developed to examine the correlation between the past performance of stock prices and their subsequent movements. Contemporary methodologies employed in financial prediction can be categorized into two distinct divisions, namely technical analysis and fundamental analysis. The practice of technical analysis involves the examination of historical pricing data and the use of technical indicators to forecast the future movements of financial time series [2]. While the Efficient Market Hypothesis posits that stock prices instantaneously incorporate all available information, proponents of technical analysis maintain that future prices can be forecasted through the examination of past price patterns. Fundamental analysis is predicated upon an evaluation of both internal and external aspects of a given firm. Interest rates and exchange rates [3] are significant external aspects that must be taken into account. The results of the current study suggest that the hybrid model exhibited superior performance and showed greater effectiveness when compared to the alternative models. Machine learning technologies are extensively employed across various areas, including the stock market, electricity consumption, and healthcare, to enhance the efficiency of forecast generation. The selection of an appropriate method is of paramount significance, [4] as it is contingent upon the nature of the dataset and its intended application. There is a possibility of encountering both time-dependent and time-independent datasets and associated challenges. Time series analysis is a widely used technique in the field of stock market analysis, mostly due to its intrinsic temporal aspect, which is defined by frequent price swings that occur at regular intervals. To develop a robust predictive model for future returns, investors must gather a wide array of data and analyze non-parametric, non-linear, and deterministic chaotic systems. Despite the difficulties involved, businesses, investors, and individuals involved in the stock market continue to strive for practical and efficient approaches to forecast future stock prices. The concept postulates that stock prices effectively incorporate the entirety of available information, [5] including exclusive insights. The utilization of neural network approaches has witnessed a surge in popularity compared to traditional techniques when it comes to analyzing time series data that is characterized by instability and nonlinearity [6]. The algorithms have been purposefully designed to address the difficulties presented by intricate and uncertain datasets, hence enabling the attainment of more precise and dependable outcomes. The usage of state-of-the-art technologies and complicated mathematical models in neural networks enables them to efficiently and expeditiously assess large volumes of data. Numerous strategies have been utilized to accomplish this purpose, including the implementation of feed-forward neural network systems. In the realm of conventional neural network models, it is customary to utilize gradient descent learning as a prevailing approach. However, this technique can be somewhat time-consuming as it necessitates iterative modifications to the model's parameters. Moreover, these models may encounter the occasional obstacle of becoming confined within a local minimum. To tackle this matter, a potential solution has been put out in the form of the support vector regression (SVR) model [7]. By incorporating the SVR algorithm, a complex machine-learning model was created to predict currency exchange rates. Applying the principles of the Support Vector Machine (SVM) to regression problems, [8] SVR is an extension of SVM. Utilizing an analogous algorithmic approach and mathematical framework, this model is customized to forecast continuous numerical values as opposed to class labels. In contrast to SVM, which segments the data into distinct classes, SVR is applied to regression tasks with the objective of locating a hyperplane that fits the data with a satisfactory level of error. SVR is a highly advantageous instrument in the field of financial forecasting, specifically in the domain of stock price prediction [9]. SVR is capable of producing predictions that aid investors in making informed decisions by analyzing the correlation between input variables and the target variable [10] [11].

These methods are founded on probabilistic ideas that are more applicable to sets of solutions than to single ones. Because issue-solving is heavily dependent on the application of predefined rules for decision-making, these people's efforts have had a substantial impact on the field of optimization. These algorithms simulate natural selection to mimic the most effective behavior found in the natural world. This study made use of Particle swarm optimization (PSO) [12], Slime mould algorithm (SMA) [13], and Aquila optimizer (AO) [14]. Among these optimizers, AO made the best results when it was used for the adjusting of the SVR model. The aquila optimizer was initially proposed by Abualigah et al. [14] The AO imitates Aquila's hunting techniques with regard to various species of prey. Four predation strategies afford AO the necessary capability to capture its prey [14]. The impact of supply and demand on the stock market as a barometer of a country's economic health was investigated by Yiming Lu. [15] Biogeography-based Optimization (BBO), the Artificial Bee Colony (ABC) algorithm, and Aquila Optimization with Extreme Gradient Boosting (XGBoost) were all incorporated into the study [15]. The research findings revealed that the integration of AO, a specific optimizer, with XGBoost yielded a substantial enhancement in model performance, establishing the most precise optimization method for forecasting the stock market [15]. Xiaopeng Yang conducted an investigation into the complex realm of stock trading, emphasizing the unpredictable characteristics of stock prices and the continuous pursuit of precise prediction techniques [16]. The study introduced a methodology for forecasting stock prices by integrating the Aquila optimizer with a Gated Recurrent Unit (GRU) [16]. The aforementioned results validated the GRU-Aquila algorithm's exceptional efficacy and precision, showcasing its exceptional capability to predict stock prices and time series data [16].

The current research presents an innovative approach that combines the Aquila optimizer procedure with support vector regression technology, thereby resolving the issues commonly encountered with traditional methods and potentially improving the precision of stock market forecasts. This work assesses the hybrid model's performance by conducting a comparative analysis with employed prediction models, including SVR, SMA-SVR, and PSO-SVR. The results indicate that the hybrid approach consistently demonstrates superior performance compared to alternative methods, underscoring its prominence in terms of accuracy and efficacy. This study can provide practitioners and investors with valuable insights by showcasing the efficacy of the hybrid model as a predictive tool for stock prices. The proposed model has the potential to assist stakeholders in optimizing their portfolios and making informed investment decisions through the provision of precise and dependable forecasts.

The literature review is given in Section II. Methods and materials which contained algorithms, datasets, and assessment metrics, are presented in Section III. The experimental results are provided in Section IV. The discussions and analysis of these results are given in Section V. Lastly, the conclusions, limitations, and future scopes are presented in Section VI.

II. Literature Review

Over the past few years, machine learning algorithms have become increasingly popular for use in stock market forecasting. Shen and Shafiq initiated an investigation with a specific emphasis on the Chinese stock market, wherein they utilized big data and deep learning methodologies to forecast stock market prices and trends [17]. A comprehensive approach was proposed, which incorporated deep learning models and customized feature engineering, based on the collection of two years' worth of data. The solution they developed for forecasting stock market trends comprised dataset preprocessing, numerous feature engineering techniques, and a customized deep learning system [17]. The significance of stock markets in the global financial system and their influence on economic growth and stability were investigated by Kumar et al. [18]. In order to improve the accuracy of stock value forecasting, their research utilized deep learning algorithms, specifically long short-term memory (LSTM) and recurrent neural networks (RNN). Through a comparative analysis of the effectiveness of LSTM and RNN algorithms in stock price estimation, they explored the potential of deep learning to establish a more dependable stock market environment [18]. Utilizing historical market data obtained from the Alpha Vault API, the performance of these models was assessed. The results demonstrated that LSTM exhibited a higher degree of accuracy in forecasting stock prices in comparison to RNN, which faced specific obstacles [18]. Guruprasad and Chandramouli examined the intricacies of stock market modeling within the Indian context, with a specific focus on the era following globalization when market dynamics are influenced by numerous parameters [19]. The authors underscored the fluctuating effects of specific parameters and their cumulative effect over a period of time, suggesting Convolutional Neural Network (CNN) Classifiers as an appropriate modeling instrument. Their objective was to capture the intricacies of the Indian stock market through the utilization of CNNs and the consideration of various parameters that influence stock trends [19]. Hani'ah et al. [20] examined the difficulty that investors encounter when attempting to precisely time stock trades, a factor that may result in financial losses. A novel methodology for forecasting stock prices was put forth, which utilized machine learning to integrate characteristics extracted from Google Trends data, technical indicators, and stock price data [20]. In order to forecast forthcoming stock prices, three widely used machine learning algorithms were implemented: Support Vector Regression (SVR), Multilayer Perceptron (MLP), and Multiple Linear Regression. With an average Mean Absolute Percentage Error (MAPE) of 0.50%, SVR outperformed MLP and Multiple Linear Regression in predicting the prices of Indonesian stocks, according to the test results. SVR exhibited the capacity to forecast stock prices that were in close proximity to the true values [20]. As an area of increasing interest to investors and researchers, time series forecasting for financial markets was examined by Xia et al. [21]. They put forth a framework for predicting stock market behavior by integrating wavelet coherence, multiscale decomposition, and SVR. Subsequent to extracting valuable information from unprocessed data via preprocessing, they implemented SVR to improve the performance of predictions for multidimensional nonlinear data [21]. Comparative experiments were undertaken to assess the efficacy of the framework by utilizing the Shanghai Composite Index and Dow Jones Index [21]. Pangestu et al. [22] examined the complex issue of forecasting stock prices, placing significant emphasis on the necessity for efficient approaches to acquire precise predictions. The authors suggested utilizing machine learning methods, more precisely the SVR model and linear regression, to forecast Apple Inc. stock prices from 2018 to 2023 using daily historical data [22]. The Grid Search method was employed to optimize hyperparameters, including cost, epsilon, kernel, and intercept fit, with a k-value of 5. The linear regression model with all hyperparameters set to k = 5 performed the best, as indicated by the True intercept fit value [22]. Jayaswara et al. [23] conducted a study on forecasting stock prices in Indonesia's emerging capital market, highlighting the significance of precise predictions for making well-informed investment choices [23]. The researchers employed SVR algorithms with both linear and radial basis function kernels to predict the prices of BCA stocks. The selection of SVR was based on its capacity to deliver accurate forecasts and address overfitting problems [23]. The significance of stock market prediction in furnishing investors with insights into forthcoming stock prospects and optimizing profits was underscored by Ahuja et al. [24]. They predicted stock prices using historical data and three prominent regression techniques: SVR, Random Forest, and Linear Regression. The selection of these machine-learning algorithms was based on their widespread usage and high accuracy of results [24].

The literature review reveals that some studies concentrate on a single machine-learning algorithm or technique for stock price prediction, often overlooking the possible advantages of combining multiple methodologies. Some studies mention optimization techniques, but it's possible that they haven't been thoroughly explored or compared in order to improve the performance of predictive models by using metaheuristic optimization algorithms. In many studies, the accuracy of models is assessed over a brief period of time, which may cause the long-term robustness and reliability of predictions to be disregarded. This study presents the introduction of a hybrid model that integrates the Aquila optimizer procedure and support vector regression method. By capitalizing on the respective strengths of these approaches, this work aims to improve the accuracy of the predictions. Three Aquila optimization, particle swarm optimization, and slime mould algorithm are utilized to optimize the support vector regression model's parameters, thereby mitigating computational complexities and potentially enhancing the accuracy of predictions. This study assesses the performance of the proposed model by utilizing data that covers the period from 2015 to 2023. This evaluation offers valuable insights into the model's reliability and efficacy in predicting stock prices over the long term.

III. Method and Materials

A. Particle Swarm Optimization

The particle swarm optimization algorithm is a computational methodology that simulates the collective behavior of a swarm of avian or aquatic organisms to optimize outcomes. Despite the initial dearth of information regarding the whereabouts of the food source, the swarm has a propensity for adhering to meticulous criteria to proficiently navigate towards it by discerningly selecting the most advantageous route. By employing a strategy of collaborative exploration, the collective of organisms ultimately discovers the precise geographical coordinates at which sustenance can be obtained. Over a temporal duration, it can be observed that both fish and bird aggregations will display coordinated motion toward a solution that is in the near vicinity of the optimal solution. The facilitation of a group of birds' progress toward a solution inside the search area is achieved through their adherence to three fundamental principles [12]: separation, alignment, and cohesiveness. Particles undergo a process of spatial dispersion wherein they disperse from one another as a means of mitigating overpopulation. The particles undergo a phenomenon known as alignment, in which they exhibit movement towards their adjacent particles. This alignment process leads to a modification of their positions, which is controlled by the cohesive forces exerted by the adjoining particles. The PSO methodology was introduced by Kennedy and Eberhart as a method to tackle optimization difficulties. The approach employed in this study is influenced by the emergent behaviour observed in a group of particles forming a swarm [12]. The PSO approach exhibits rapid convergence and requires a minimum number of parameters, hence mitigating computer costs. Additionally, the probability of discovering a suboptimal local solution is diminished because of the extensive investigation carried out by multiple particles in search of an ideal solution. The method exhibits a highly efficient global search mechanism and does not depend on the use of derivatives. Inside the PSO algorithm, each constituent particle inside the swarm partakes in a search process spanning many dimensions. The primary aim of this procedure is to locate a solution that closely approximates the optimal solution. The search process commences by creating initial solutions, often referred to as particles, in a stochastic fashion within the search space. The determination of velocity and fitness values for each particle often entails the utilization of the weighted average of classification accuracy and the number of features in the selected subset. After the initial iteration, this computational procedure allows for the modification of both the velocity and trajectory of their respective paths, and this method is thereafter continued until the predetermined termination condition is met. The velocity of the particles in the PSO method is updated according to the subsequent equation:

$$\begin{aligned} \boldsymbol{v_{id}^{t+1}} = \boldsymbol{v_{id}^{t}} + \boldsymbol{C_1 r_1^t}\,(\boldsymbol{Pbest_{id}^t} - \boldsymbol{x_{id}^t}) \\ + \boldsymbol{C_2 r_2^t}\,(\boldsymbol{Gbest_{id}^t} - \boldsymbol{x_{id}^t}) \end{aligned} \tag{1}$$

The velocity of the i −th particle at a specific time iteration is represented as v_{id}^{k} in a search space characterized by d dimensions. The variables $Pbest_{id}^{t}$ and $Gbest_{id}^{t}$ denote the optimal particle and location for each individual and iteration of the i −th function, respectively. The parameters C_1 and C_2 are utilized to adjust the velocity of particles, whereas r_1^t and r_2^t denote random values ranging from 0 to 1. Moreover, the particles within the PSO algorithm can modify their positions, as demonstrated by the equation presented below:

$$\boldsymbol{x_{id}^{t+1}} = \boldsymbol{x_{id}^{t}} + \boldsymbol{v_{id}^{t+1}} \tag{2}$$

The variable x_{id}^{t} denotes the spatial coordinates of the i −th particle at iteration t within a search space described by d dimensions. The epoch for PSO is selected to be 200 and the pop size is 20.

B. Slime mould algorithm

The subject matter was introduced by Li et al. [13] at the SMA conference in 2020. The proposed approach is a groundbreaking methodology inspired by the behavior of slime mold in its natural habitat. The slime mould uses olfaction as a means of perceiving and discerning volatile food aromas present in the surrounding atmosphere, hence facilitating its ability to travel toward its prey. This paper provides a complete portrayal of the overall characterization of SMA. The mathematical description of the slime mould's behavior can be represented by the following equation.

$$\overrightarrow{\boldsymbol{X(t+1)}} = \begin{cases} \overrightarrow{\boldsymbol{X_b(t)}} + \overrightarrow{\boldsymbol{v_b}}\,.\left(.\overrightarrow{\boldsymbol{X_A(t)}} - \overrightarrow{\boldsymbol{X_B(t)}}\right) & \boldsymbol{r < p} \\ \overrightarrow{\boldsymbol{v_c}}.\overrightarrow{\boldsymbol{X(t)}} & \boldsymbol{r \geq p} \end{cases} \tag{3}$$

The variable $X_b(t)$ denotes the precise region of the slime mold that presently displays the greatest concentration of odor. The variables $X(t)$ and $X(t+1)$ represent the spatial coordinates of the slime mold at the $t-$ th and $t+1$ -th iterations, respectively. $X_A(t)$ and X_B represent two randomly chosen locations of the slime mold. The variable v_b undergoes temporal changes within the range of $[-a, a]$, where r is a random number between 0 and 1. The parameter p is defined as $a = arctanh(-(\frac{t}{max\_t}) + 1)$, and v_c is a linearly decreasing parameter that ranges from 0 to 1.

$$\mathbf{p = tanh\,|S(i) - DF|} \quad \mathbf{i = 1, 2, \dots, n} \tag{4}$$

The symbol DF denotes the iteration that possesses the utmost fitness value, while $S(i)$ represents the fitness of vector $\overrightarrow{X}$. The equation depicted below provides a formal representation of weight, symbolized as W:

$$\overrightarrow{W(smell\ index(l))} = \begin{cases} 1 + r.\log\left(\dfrac{bF - S(i)}{bF - wF} + 1\right), condition \\ 1 - r.\log\left(\dfrac{bF - S(i)}{bF - wF} + 1\right), others \end{cases} \tag{5}$$

$$smell\ index = sort(S) \tag{6}$$

The variable $S(i)$ denotes the initial half of the population in the provided equation. The symbol bF is used to symbolize the maximum fitness value, whereas wF is used to denote the lowest fitness value. Furthermore, the term "smell index" pertains to the ordered values of fitness. The spatial coordinates of the slime mold are updated by the utilization of the provided formula.

$$\overrightarrow{X^*} = \begin{cases} rand(UB - LB) + LB & rand < z \\ \overrightarrow{X_b(t)} + \overrightarrow{v_b}.\left(\overrightarrow{W}.\overrightarrow{X_A(t)} - \overrightarrow{X_B(t)}\right) & r < p \\ \overrightarrow{v_c}.\overrightarrow{X(t)} & r \geq p \end{cases} \tag{7}$$

Within the given context, the variable z is subject to limitations that confine its values to a specified interval ranging from 0 to 0.1. The terms LB and UB are used to denote the lower and upper boundaries of the search period, respectively. SMA has chosen an epoch of 200 and a pop size of 20.

C. Aquila Optimizer

The proposed approach emulates Aquila's hunting behavior as displayed in Fig. 1 by illustrating the sequential movement during each phase of the hunt [14]. The overall structure of the AO is indicated in Fig. 2. Consequently, the proposed strategy for optimizing the AO algorithm is presented in four distinct approaches: The selection of the search region is determined by the vertical stoop, [14] which involves soaring at high altitudes. The exploration within a divergent search space is conducted through contour flight combined with short hover attacks. Exploitation within a convergent search space is achieved by flying at low altitudes and executing slow descent attacks. Finally, the prey is captured by swooping down, walking, and grabbing [14]. Aquila's behavior was characterized as a mathematical optimization paradigm that seeks to identify the optimal solution within specified constraints. The subsequent representation presents a mathematical model of the AO. The Aquila species has a two-step process for identifying prey and selecting an optimal hunting site. The initial step involves engaging in a high soar, followed by a vertical stoop, in order to accurately pinpoint the prey's location. The AO algorithm conducts a thorough exploration of the search zone at a significant altitude in order to determine the whereabouts of the prey. The aforementioned pattern is quantitatively expressed.

$$\begin{aligned} \boldsymbol{X_1(t+1)} = \boldsymbol{X_{best}} \times \left(\boldsymbol{1 - \frac{t}{T}}\right) + \boldsymbol{X_M(t)} + \boldsymbol{X_{best}} \\ \times \boldsymbol{rand} \end{aligned} \tag{8}$$

where, the outcome of the subsequent iteration of t, which is produced by the first search process x_1, is represented by $x_1(t+1)$. The optimal solution obtained is $x_{best}(t)$ up to the tenth iteration. It depicts the prey's approximate location.

The enlarged search (exploration) is controlled by the number of iterations using this equation $\left(1-\left(\frac{t}{T}\right)\right)$. The $X_M(t)$mean value of the existing solutions linked at the $t-$ th iteration. Furthermore, the variable $rand$ denotes a stochastic value uniformly distributed between 0 and 1. On the other hand, t and T symbolize the present iteration and the upper limit of iterations, correspondingly.

$$\boldsymbol{x_M(t)=\frac{1}{N}\sum_{i=1}^{N}x_i\,(t),\forall j=1,2,\ldots,Dim} \tag{9}$$

The variable Dim represents the dimension size of the problem, whereas N denotes the population size, which refers to the number of alternative solutions. When the prey area is identified from an elevated position during flight, the Aquila species exhibits a hovering behavior directly over the intended prey, initiates the landing procedure, and thereafter executes an attack. This phenomenon is commonly referred to as curved flight with a short gliding attack. During this phase, AO conducts a thorough investigation of the selected habitat of the target prey in preparation for the impending assault. This behavior can be quantified using numerical expressions, as demonstrated in the Equation below.

$$\boldsymbol{X_2(t+1)=X_{bset}(t)\times Levy(D)+X_R(t)+(y-x)\times rand} \tag{10}$$

The variable $x_2(t+1)$ denotes the outcome of the subsequent iteration of t generated by the second search strategy x_2, within the dimension space represented by D. The term $Levy(D)$refers to the dimension level of D. At the $i-$th iteration, $X_R(t)$ is a random solution picked from the range $[1\ldots N]$.

$$\boldsymbol{Levy(D)=s\times\frac{u\times\sigma}{|v|^{\frac{1}{\beta}}}} \tag{11}$$

Let s be a constant value defined as 0.01, while u and v represent values within the range of 0 and 1. Then, the value of sigma (σ) is determined using the Equation below.

$$\sigma=\left\{\frac{R(1+\beta)\times\sin e(\frac{\pi\beta}{2})}{R(1+\frac{\beta}{2})\times\beta\times2(\frac{\beta-1}{2})}\right\} \tag{12}$$

Let β be denoted as a constant value, specifically 1.5. The equation presented below represents the relationship between y and x, which correspond to the spiral shape observed in the search space. These variables are calculated using the following method:

$$y=r\times\cos\theta \tag{13}$$

$$x=r\times\sin\theta \tag{14}$$

$$r=r_1+U\times D_1 \tag{15}$$

$$\theta=-\omega\times D_1+\theta_1 \tag{16}$$

$$\theta_1=\frac{3\times\pi}{2} \tag{17}$$

r_1 employs a fixed range of numbers, specifically from 1 to 20, for a specified number of search rounds. In contrast, the set U is characterized by a diminutive value of 0.00565. $D_1$is an integer value that is between the range of 1 to the length of the search space, denoted as Dim. In addition, the value of ω is a conservative estimate of 0.005. The third approach is implemented when the specific target area has been accurately determined and the Aquila is prepared to initiate an offensive action. Thus, the Aquila descends vertically, employing an initial strike to assess the response of the prey. This particular method is sometimes referred to as low-altitude flight combined with a steady descent approach to conduct an assault. The AO uses the selected region of the target to approximate its proximity to the prey and initiate an attack. The attack is mathematically represented as follows in Equation:

$$\boldsymbol{X_3(t+1)=\left(X_{best}(t)-X_M(t)\right)\times\alpha-rand+((UB-LB)\times rand+LB)\times\delta} \tag{18}$$

The expression $X_3(t+1)$ denotes the output of the $t-$th iteration generated by the third search strategy X_3. The function $X_{best}(t)$ represents the most optimal solution achieved up to the $t-$ th iteration. Furthermore, $X_M(t)$ represents the average value of the current solution at the $t-$th iteration. The variable r represents a numerical value that spans the interval from 0 to 1. In addition, this study has assigned a low value of 0.1 to the exploitation correction parameters, α and δ. In the given problem, the lower limit is represented by the symbol LB, while the upper bound is represented by the symbol UB. During the fourth approach, when the Aquila nears its target, it employs stochastic movements to strike the prey over the ground. This particular methodology is sometimes referred to as the "stroll and seize" approach. The mathematical formulation of this strategy is expressed as follows in Equation:

$$\boldsymbol{X_4(t+1)=QF\times X_{best}(t)-(G_1\times X(t)\times rand)-G_2\times Levy(D)+rand\times G_1} \tag{19}$$

Consequently, for each iteration of the search, $X_4(t+1)$ represents the outcome of the fourth search method, and QF is a quality function used to balance the search methods. G_1 shows the several AO motions used to track the prey as it elopes. Between 2 and 0, G_2 contains decreasing values that represent the flight slope of the AO that tracked the prey from the initial position (location 1) to the last location (location 0), as determined by Equation:

$$\mathrm{QF(t)=t^{\frac{2\times rand-1}{(1-T)^2}}} \tag{20}$$

$$\mathrm{G_1=2\times rand-1} \tag{21}$$

In a similar vein, the pop size is 20 and the epoch for ALO is set at 200.

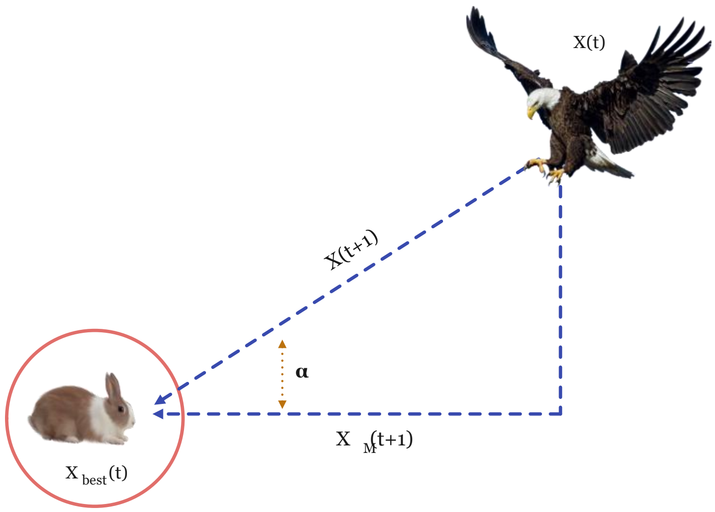

Fig. 1. The illustration of (AO).

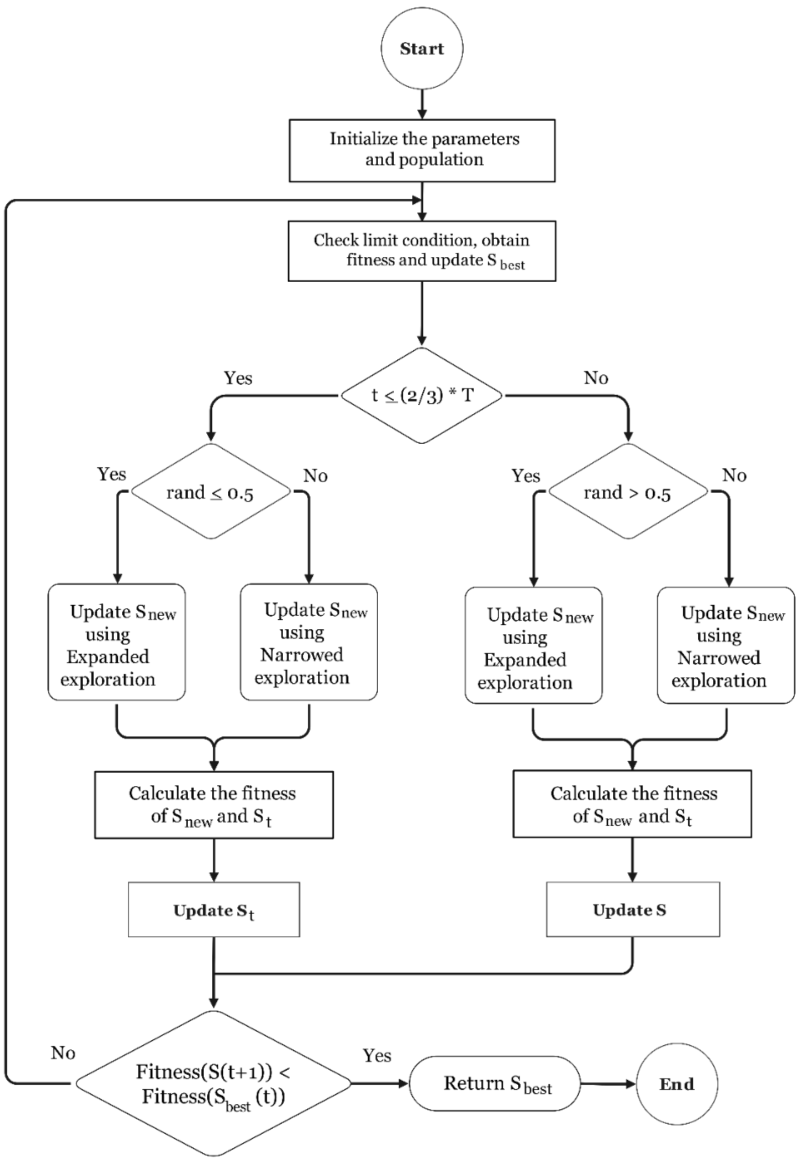

Fig. 2. The framework of (AO).

D. Support Vector Regression

Support Vector Regression (SVR) as demonstrated in Fig. 3 is well recognized as a very dependable approach within the field of machine learning and statistical learning [25]. SVR is an extension of Support Vector Classification (SVC) that is designed to handle continuous response variables. Both SVR and SVC employ the use of kernel functions to accomplish their respective objectives [25][7]. SVR minimizes the ϵ-insensitive loss function, meaning that any loss below the error margin is set to zero and that any loss over that constraint uses the linear loss function as in Equation. In contrast to GPR, which minimizes the squared error (ϵ) loss function and loss for answers, i −th, (quadratic loss).

$$\boldsymbol{I_\epsilon} = \begin{cases} \mathbf{0} \\ |\boldsymbol{y_i} - \boldsymbol{f}(\boldsymbol{x_i})| \end{cases} \tag{22}$$

If the value of $|y_i - f(x_i)|$ is less than ϵ, the loss function of a linear function is displayed as:

$$\mathrm{f(x)} = \beta_o - X_i^t\beta \tag{23}$$

$$\sum_{i=1}^{n}(y_i - X_i^t\beta - \beta_o - \epsilon, 0) \tag{24}$$

where, ϵ is the turning parameter and can be written as a formulation for constraint optimization as seen in Equation:

$$\text{minimize}\,\frac{1}{2}\|\beta\|^2 \tag{25}$$

$$subject\ to \begin{cases} y_i - X_i^t\beta - \beta_o \le \epsilon, \\ -(y_i - X_i^t\beta - \beta_o) \le \epsilon \end{cases} \tag{26}$$

Table I explains the tunning of the hyperparameters of the SVR model by using three different optimizers where each optimizer found the optimal values. The kind of hyperplane that is utilized to divide the data is decided by the kernel function. A single training example's influence is defined by gamma. Other examples must be closer to being impacted by a greater gamma. The regularization parameter C regulates the trade-off between minimizing the weights' norm and obtaining a low error on the training set. Epsilon describes the epsilon tube when the training loss function has no penalty and the predicted points are within epsilon of the actual value. All of the optimal values found by optimizers for these hyperparameters can be found in Table I.

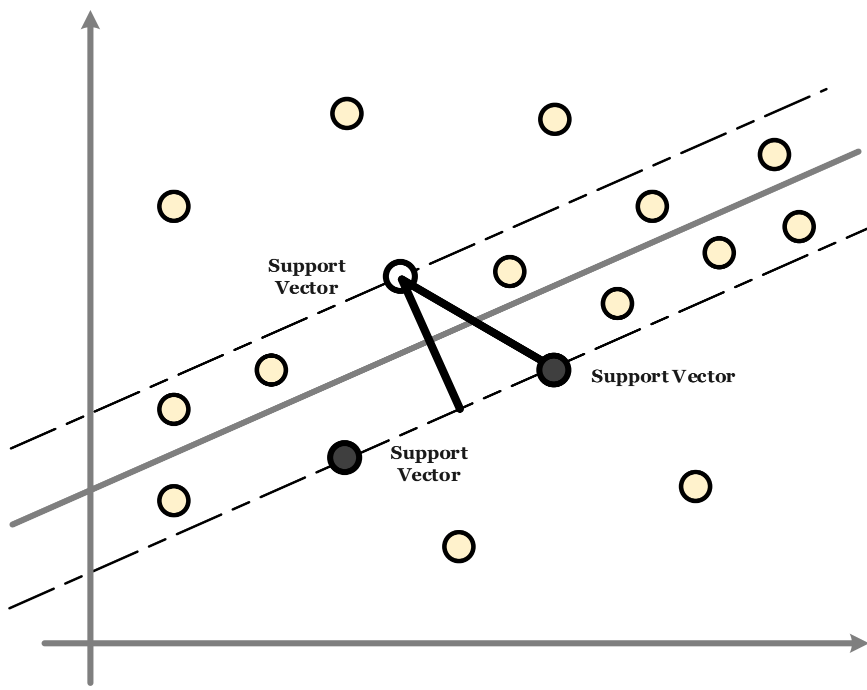

Fig. 3. The illustration of (SVR).

TABLE I. THE SETTING OF THE HYPERPARAMETERS OF THE SVR MODEL BY THREE OPTIMIZERS

SVR		ALO	SMA	PSO
kernal	['linear', 'rbf', 'poly', 'sigmoid']	linear	linear	linear
gamma	[1, 0.5, 0.1, 0.01, 0.001]	0.5	0.1	0.5
C	[0.1, 1, 10, 20, 50, 100]	20	10	50
epsilon	[0.01, 0.05, 0.1, 0.5]	0.05	0.5	0.1

E. Data Collection and Preprocessing

When conducting a thorough analysis of a company, it is imperative to take into account many elements, such as the trading volume and the Open, High, Low, and Close (OHLC) prices during a specific timeframe. The data pertaining to the performance of the HSI index from 2015 to 2023 was obtained solely for the purpose of this specific research. The dataset consisted of information regarding the opening, high, low, and closing prices, as well as the trading volume, for each day within the designated period. An essential component of the preliminary phase involved doing a thorough examination of the data in order to identify any irregularities, exceptional observations, or inconsistencies that could potentially undermine the validity of the results. In order to optimize the performance of the models, two distinct sets of preprocessed data were constructed. The methodology employed in this study utilized a partitioning mechanism, as illustrated in Fig. 4. The study employed a partitioning mechanism in which 80% of the dataset was assigned for training purposes. In contrast, the remaining 20% was allocated for the purposes of validation and testing. The primary goal of this division was to achieve an optimal equilibrium between the requirement for a substantial quantity of data for training the model and the necessity for a substantial and unfamiliar dataset for conducting thorough testing and validation.

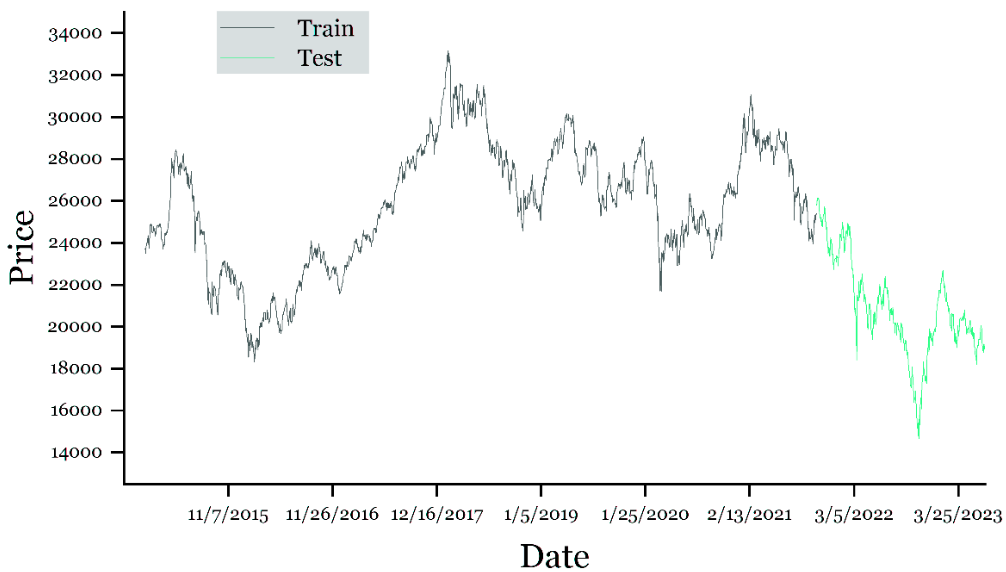

Fig. 4. The process of partitioning the dataset into distinct test and train sets.

F. Evaluation Metrics

The assessment of the precision of the forthcoming forecast was carried out by utilizing multiple performance metrics. The meticulously selected indicators provide a comprehensive assessment of the dependability and accuracy of the forecasts. Numerous parameters were considered during the screening procedure. In the realm of statistical analysis, there are three key metrics that are commonly employed to evaluate the performance and accuracy of a model. These metrics include the mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE). While RMSE penalizes large errors as well, it does so in the same units as the original data because it is the square root of MSE [26]. By combining the advantages of MAE's interpretability and MSE's sensitivity to large errors, it offers a balanced perspective on model performance [27].

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{26}$$

Without taking into account the direction of the errors, MAE calculates the average magnitude of the errors in a set of predictions [27]. It makes it simple to comprehend and convey by offering a clear interpretation of the average prediction error in the same units as the stock prices [28].

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \tag{27}$$

Larger errors are given more weight by the MSE metric, which squares the errors before averaging them [27]. It is especially helpful for stock market forecasting since it penalizes large prediction errors, which can have an important impact on financial choices [28].

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n} \tag{28}$$

Prediction accuracy is expressed as a percentage using the MAPE metric, which is useful in financial contexts where relative error is more significant than absolute error [27]. When comparing forecast accuracy across various stock price scales, MAPE is especially helpful [28].

$$\mathrm{MAPE} = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|\right) \times 100 \tag{29}$$

where, $\hat{y}_i$ serves as the predicted value and y_i denotes the actual value [29].

IV. Results

A. Statistic Values

Table II presents a comprehensive overview of the statistical information encompassed within the dataset, playing a vital role in the investigative process. The incorporation of Open, High, Low, and Close (OHLC) price and volume data in the table improves the comprehensibility and transparency of the information. In order to do a comprehensive and accurate examination of the data, it is advisable to utilize statistical measures such as the arithmetic mean, minimum value, maximum value, standard deviation (referred to as Std.), count, 50th percentile, skew, and kurtosis.

B. Comparison and Analyses

The main objective of this study is to determine and evaluate the most effective hybrid algorithm for forecasting stock prices. This study is grounded in the development of predictive models and a thorough understanding of the multiple aspects that influence stock market trends. The main aim is to provide analysts and investors with pertinent information that empowers them to make informed and judicious investment decisions. Table III, Fig. 5, and Fig. 6 provide a comprehensive analysis of the performance demonstrated by each model in the study. This report presents a thorough assessment of the effectiveness of each strategy. Various metrics are utilized to quantify distinct facets of prediction errors. MAPE provides insight into the relative accuracy of predictions, whereas MSE and RMSE emphasize larger errors and MAE provides a direct measure of average error. By employing a blend of these metrics, a more comprehensive assessment is achieved, encompassing multiple facets of model performance.

TABLE II. THE PROVIDED DATASET IS ACCOMPANIED BY A STATISTICAL SUMMARY

	Open	High	Low	Volume	Close
count	2090	2090	2090	2090	2090
mean	24877.8	25026.72	24689.52	4013.656	24862.03
std.	3492.279	3486.289	3484.234	1462.996	3486.437
min	14830.69	15113.15	14597.31	0	14687.02
50%	25002.49	25118.69	24755.93	3679.685	24973
max	33335.48	33484.08	32897.04	12025.52	33154.12
skew	-0.19992	-0.18469	-0.21056	1.660448	-0.20035
kurtosis	-0.65433	-0.6701	-0.64255	4.339923	-0.64908

TABLE III. THE PROJECTED ASSESSMENT OUTCOMES DERIVED FROM THE MODELS.

MODEL/Metrics	Train set				Test set			
	RMSE	*MAPE*	*MAE*	*MSE*	*RMSE*	*MAPE*	*MAE*	*MSE*
SVR	209.81	0.66	171.34	44018.81	202.41	0.81	161.84	40970.18
PSO-SVR	164.12	0.47	119.52	26936.28	186.22	0.67	137.28	34676.12
SMA-SVR	124.12	0.37	95.46	15406.07	177.89	0.68	137.45	31645.96
AO-SVR	56.88	0.16	41.71	3235.51	156.59	0.60	120.40	24521.82

V. Discussion

The data analysis was assessed using the four widely used metrics of RMSE, MAPE, MSE, and MAE. The aforementioned metrics are widely recognized for their ability to provide an extensive assessment of the overall effectiveness, precision, and dependability of the analysis. The performance of the SVR model has been assessed both with and without the assistance of an optimizer using a number of evaluation metrics. Through the application of this approach, one can generate educated opinions and enhance their understanding of the model's operation. Upon analyzing the training and test sets, it was found that the SVR model produced RMSE values of 209.81 and 202.41 for the training and testing sets, respectively, in the absence of the optimizer. When the results were compared, the MAPE values for the training and testing datasets were discovered to be 0.66 and 0.81, respectively. In addition, the training and testing data sets' MSE values were found to be 44018.81 and 40970.18, respectively. Training and testing sets' matching MAE values were 171.34 and 161.84, respectively. The SVR model's efficiency increased significantly when optimizers were used. The results have significantly improved with the use of the PSO optimizer, as seen by the reduction in the RMSE value to 186.22 for the training dataset and 164.12 for the testing dataset. It was found through a comparative analysis that the SMA-SVR model performed better than the PSO-SVR model. Throughout the training and testing stages, the SMA-SVR model consistently displayed RMSE values of 124.12 and 177.89. It is important to note that the training and testing data sets' MSE values decreased, coming in at 15406.07 and 31645.96, respectively. Parallel to this, MAE and MAPE values decreased to 95.46 and 0.37 for the training dataset, and to 137.45 and 0.68 for the testing dataset. The study's findings indicate that the AO-SVR model outperforms the SMA-SVR model in terms of effectiveness. The notable results from training and testing, 56.88 and 156.59, respectively, demonstrate how effective the AO model is. The training MAPE value of 0.16 and testing MAPE value of 0.60 of the AO-SVR model indicate that it performed better than the other models. The previously described results provide empirical evidence supporting the high degree of accuracy and reliability of the AO-SVR model. These results also validate the model's effectiveness as a useful tool for the specific application under investigation.

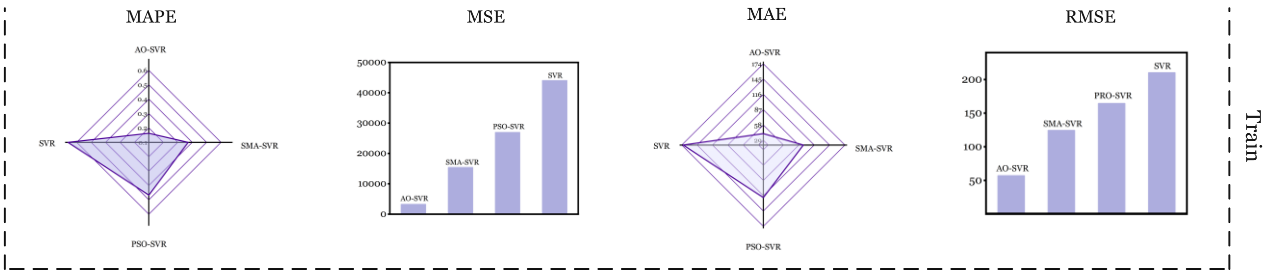

Fig. 5. During the training phase, the model being evaluated produced results for RMSE, MSE, MAE, and MAPE.

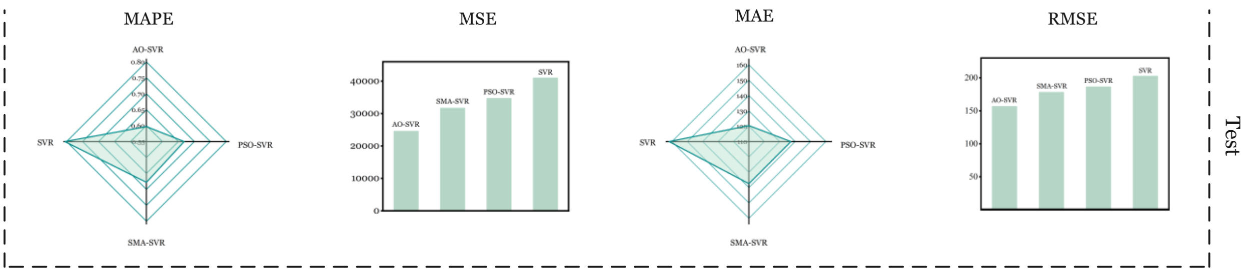

Fig. 6. In the testing phase, the model under consideration generated outcomes for RMSE, MSE, MAE, and MAPE.

Numerous experiments have confirmed the AO-SVR model's effectiveness and shown that it is capable of making accurate stock price predictions. One way to assess the effectiveness of the model is to compare the HSI market curves with the corresponding curves shown in Fig. 7 and Fig. 8. When comparing the AO-SVR model with other models such as SVR, PSO-SVR, and SMA-SVR, it is evident that the AO-SVR model exhibits more accuracy in forecasting stock values. The application of the SVR technique results in a significant enhancement in the quality of the model by reducing the impact of stock price volatility and improving the precision of future trend projections. The AO-SVR model possesses the distinct ability to assimilate knowledge from prior datasets. To attain a satisfactory degree of precision in forecasting stock prices, it is imperative for a model to possess the capacity to adjust to fluctuating market conditions and derive significant insights from historical data. The AO-SVR model has been shown to possess notable levels of accuracy, reliability, and inferential capabilities when applied in conjunction with historical data, hence establishing its efficacy as a strong instrument for forecasting stock prices. The utilization of the SVR method and AO optimizer is favored due to their capacity to dynamically adjust to fluctuations in market conditions, making them highly sought-after by individuals seeking to execute lucrative transactions inside the stock market.

The distinct qualities and characteristics of each dataset account for the variability in the performance of the proposed algorithms across them. Using an analysis of multiple datasets, including Hang Seng Index data spanning the years 2015 to 2023, this research identified variations in error metrics and prediction accuracy. Strong seasonal patterns or long-term trends may be present in particular datasets, which may have an impact on the precision of predictions [30]. The proposed model's capability to detect these patterns may differ based on the frequency and prominence of these trends within the dataset. For example, datasets containing distinct seasonal patterns may enable the model to operate more efficiently as a result of the predictability of these trends [27]. In determining performance, the quality and applicability of the features utilized in the prediction models are also critical factors. Predictions may be enhanced when datasets contain precisely defined and pertinent characteristics that capture the fundamental dynamics of the market, as opposed to datasets that contain noisy or irrelevant features [31].

The results of the analysis suggest that the algorithms that were suggested exhibit robust performance on a diverse range of datasets, with a particular emphasis on datasets that contain intricate patterns and non-linear associations. In conjunction with the optimization functionalities of the Aquila optimizer, the adaptability and resilience of the SVR empower the model to efficiently accommodate diverse categories of data. Traditional linear models may struggle to handle non-linear and complex datasets, but the proposed model excels at handling such data [32]. This characteristic renders it highly suitable for stock market data, which frequently demonstrates such attributes. The integration of SVR and the Aquila optimizer in a hybrid framework demonstrates high efficacy in accommodating dynamic and non-stationary data, thereby delivering resilient forecasts amidst abrupt market fluctuations or trends.

Table IV and Fig. 9 provide a comparative analysis of different methodologies employed in the prediction of stock market prices. Every method enumerated in this table utilized the HSI market dataset to forecast the stock market. Although traditional RNN-based methods produced greater error rates, advanced models that incorporated attention mechanisms, hybrid architectures, and optimizations outperformed their predecessors. The AO-SVR method utilized in this study exhibited superior performance compared to all other methods, as evidenced by its lowest MAE. This indicates that the method effectively predicted stock market prices using the HSI dataset.

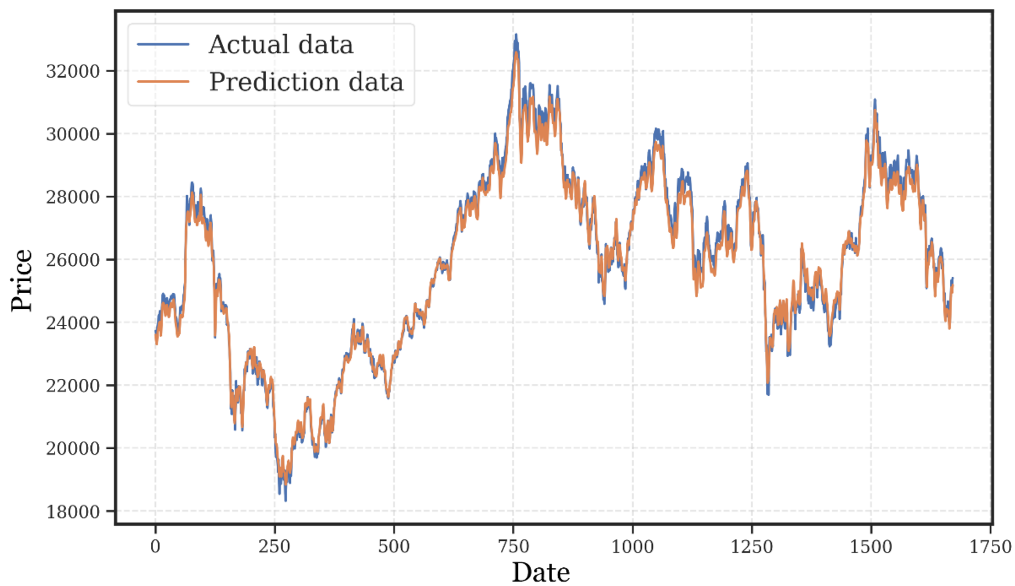

Fig. 7. The application of the AO-SVR approach was employed in the training procedure to build the forecasting curve.

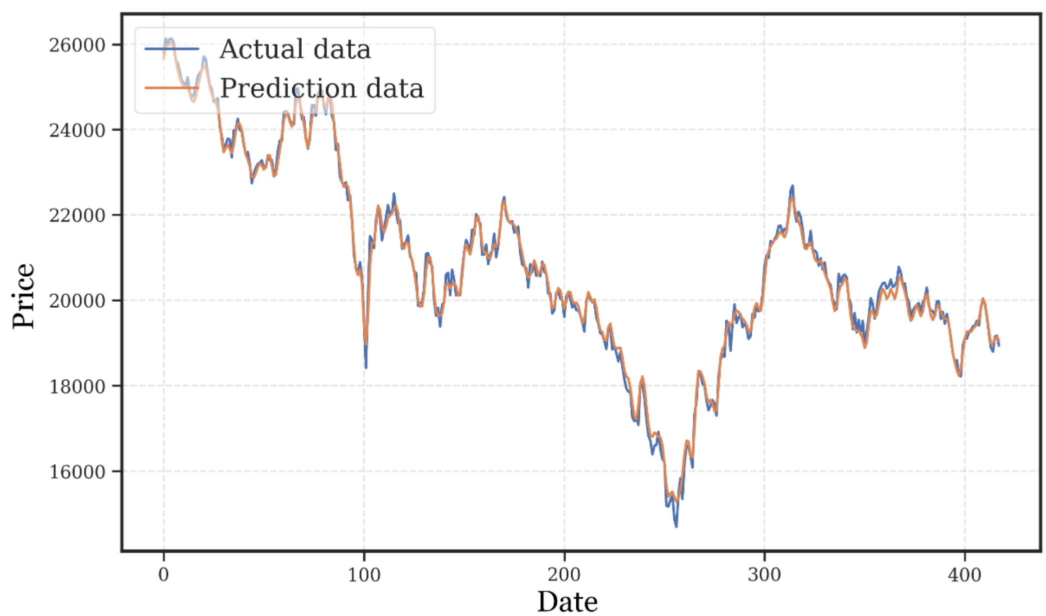

Fig. 8. The application of the AO-SVR approach was employed in the testing procedure to build the forecasting curve.

TABLE IV. THE COMPARISONS OF THE METHOD IN LITERATURE WITH THE CURRENT STUDY

Authors	Methods	MAE
Siami-Namini et al. [33]	RNN	259.94
	LSTM	258.70
	BiLSTM	259.21
Lu et al. [34]	CNN-LSTM	258.68
Lu et al. [35]	CNN-BiLSTM	258.02
	CNN-BiLSTM-AM	257.80
ssTao et al. [36]	Series Decomposition Transformer with Period-correlation (SDTP)	256.02
Present invistigation	AO-SVR	120.40

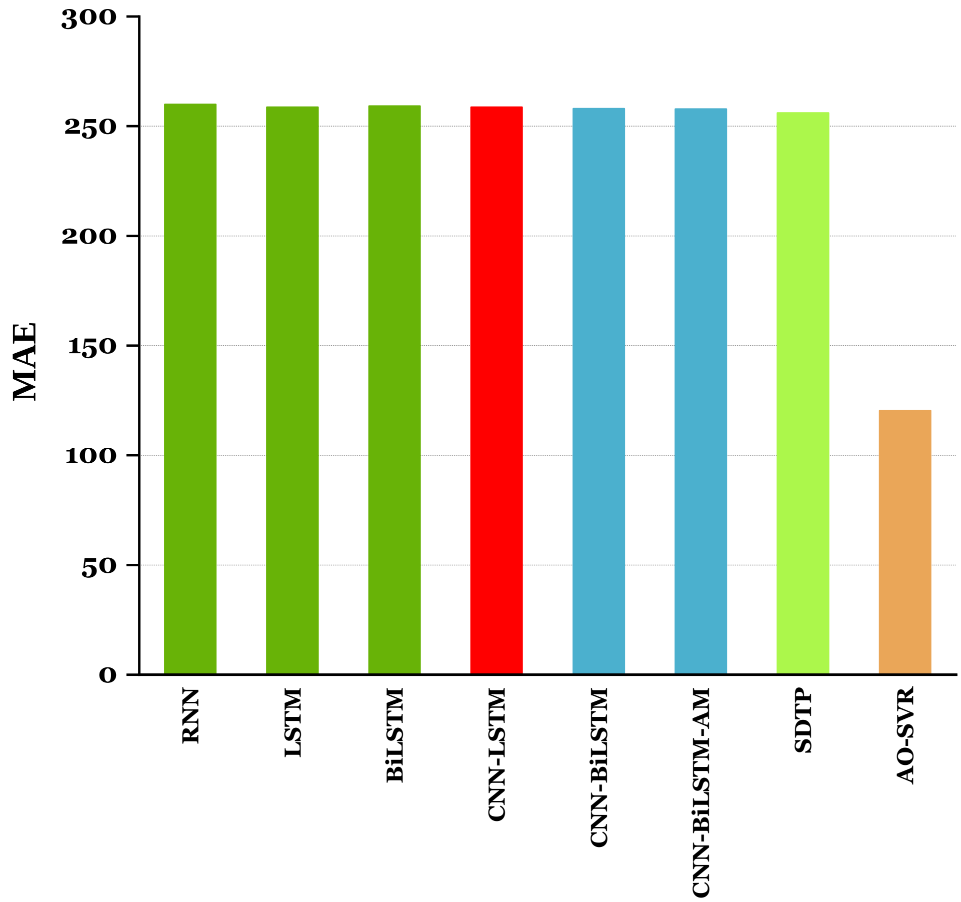

Fig. 9. A Comparison between the present study and the method as depicted in the literature.

A precise forecast of stock prices holds significant importance for investors aiming to maximize the efficiency of their investment portfolios. By utilizing a hybrid predictive model, investors can gain significant insights regarding forthcoming stock valuations. This empowers them to make informed investment decisions, potentially optimizing returns while mitigating risks. The predictive model can be employed by financial institutions and investment firms to evaluate and control the level of risk associated with their portfolios. The identification of potential market fluctuations and the implementation of risk mitigation strategies to safeguard assets can be achieved through the more precise prediction of stock prices. By integrating the hybrid model into algorithmic trading systems, the buying and selling of stocks in response to predictive signals can be automated. By utilizing the model's real-time predictions, algorithmic traders can optimize trade execution and take advantage of favorable market conditions. Both individuals and wealth management firms have the ability to employ the predictive model in order to formulate individualized investment strategies and financial plans. The predictive model can be employed by policymakers, economists, and researchers to estimate the potential impact of economic policies and external factors on financial markets and to forecast stock market trends.

VI. Conclusion

The endeavor of predicting stock prices is a multifaceted endeavor that necessitates a comprehensive comprehension of numerous interrelated aspects. The stock market is susceptible to several influences, encompassing political, sociological, and economic factors. The aforementioned system has a dynamic characteristic and possesses inherent complexity. In order to provide precise forecasts regarding future stock valuations, it is imperative to take into account an extensive array of financial literature, earnings statements, market patterns, and pertinent information. Furthermore, it is imperative to acknowledge that macroeconomic indices, like inflation, interest rates, and global economic conditions, exert a substantial impact on the dynamics of the stock market. The development of precise and reliable prediction models might provide challenges due to the many elements involved in forecasting stock values. In order to attain precise predictions, it is important to develop a comprehensive comprehension of the complex and uncertain characteristics inherent in the field. In addition to providing a workable solution to these problems, the AO-SVR model has proven to be extremely accurate and reliable. The goal of the current study was to evaluate the performance of several stock price prediction models, such as SVR, SMA-SVR, and PSO-SVR. SMA, PSO, and AO were the hyperparameter optimization techniques used to optimize the SVR's parameters. Nevertheless, the AO optimizer approach showed better outcomes when used in conjunction with the SVR strategy. The study utilized OHLC price and volume data for the HSI index, spanning the years 2015 through 2023, as the dataset. The experimental findings illustrate the notable accuracy and reliability exhibited by the AO-SVR model in forecasting stock prices. As an integral part of the research process, a comparative analysis was performed to evaluate the accuracy and predictive capacities of the AO-SVR model in relation to various other models. Based on the obtained data, it can be inferred that the AO-SVR model consistently exhibited superior performance when compared to the other models. The attained MAE score of 120.40 suggests that the prediction models exhibit a notable degree of precision. The model's predictive accuracy was validated by the testing phase, which yielded an RMSE score of 156.59 and an MSE value of 120.40. The model's MAPE score of 0.60 indicates that it has a consistent ability to produce correct predictions. It was shown that the AO-SVR model performed better in terms of accuracy and efficacy than the other models that were being studied. The AO-SVR model is an effective instrument for stock price prediction and provides investors with insightful information to help them make well-informed investment decisions.

The research is predicated upon historical Hang Seng index data spanning the years 2015 to 2023. Although the dataset offers significant insights regarding the predictive model's performance, it might not comprehensively encompass the wide array of market conditions and events that have the potential to impact stock prices. Subsequent investigations may profit from augmenting the strength and variety of the datasets utilized in order to bolster the analysis. The study presents a hybrid predictive model that integrates the Aquila optimizer procedure with support vector regression technology. This integration potentially results in heightened computational demands and longer training and evaluation periods for the model. One possible approach to address these challenges while maintaining accurate predictions is to investigate alternative optimization techniques or simplify the model architecture. The research centers on the Hang Seng index, an indicator of a particular stock market. Although the results illustrate the efficacy of the suggested model within this particular framework, its applicability to alternative stock markets or financial instruments is still ambiguous. Subsequent investigations might delve into the versatility of the hybrid model by examining its suitability across diverse asset classes and markets.

Additional optimization techniques may be investigated in subsequent research endeavors with the aim of further augmenting the predictive model's performance. It is possible to conduct experiments utilizing various optimization algorithms or parameter tuning strategies in order to determine the most effective configurations that simultaneously enhance prediction accuracy and reduce computational burden. Further data sources, including social media activity, economic indicators, and sentiment analysis of news articles, might be integrated to enhance the predictive model and offer a more holistic comprehension of market dynamics. By integrating disparate datasets, it may be possible to capture a more comprehensive array of factors that impact stock prices, thereby improving the accuracy of predictions. To evaluate the predictive model's long-term performance and dependability, a longitudinal study could be undertaken, providing significant insights into its enduring stability and resilience. An examination of its performance throughout various market cycles and economic conditions could substantiate its efficacy and pinpoint possible avenues for enhancement. Incorporating live validation tests and real-time deployment of the predictive model in trading environments could yield valuable practical insights regarding its usability and performance in real-world scenarios. Ongoing assessment of its performance in ever-changing market conditions and modification of model parameters have the potential to enhance its precision and practicality in real-life situations.

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