Design of Single Valued Neutrosophic Hypersoft Set VIKOR Method for Hedge Fund Return Prediction

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Abstract

The theory of neutrosophic hypersoft set (NHSS) is an appropriate extension of the neutrosophic soft set to precisely measure the uncertainty, anxiety, and deficiencies in decision-making and is a parameterized family that handles sub-attributes of the parameters. In contrast to recent studies, NHSS could accommodate more uncertainty, which is the essential procedures to describe fuzzy data in the decision-making method. Hedge funds are financial funds, finance institutions that increase funds from stockholders and accomplish them. Usually, they try to make certain predictions and work with the time sequence dataset. A hedge fund is heterogeneous in its investment strategies and invests in a different resource class with various return features. Furthermore, hedge fund strategy is idiosyncratic and proprietary to the hedge fund manager, and the correct skills of fund managers are not visible to the stockholders. These reasons, united, make hedge fund selection a complex task for the stockholders. Different techniques have been analyzed to select the portfolio of hedge funds for investment. Machine-learning (ML) models employed used for performing individual hedge fund selection within hedge fund style classifications and forecasting hedge fund returns. Therefore, this study designs a new Single Valued Neutrosophic Hypersoft Set VIKOR Model for Hedge Fund Return Prediction (SVNHSS-HFRP) technique. The presented SVNHSS-HFRP technique aims to forecast the hedge fund returns proficiently. In the SVNHSS-HFRP technique, two stages of operations are involved. At the initial stage, the SVNHSS-HFRP technique, the SVNHSS is used for forecasting the hedge funds. Next, in the second stage, the moth flame optimization (MFO) system is applied to optimally choose the parameter values of the SVNHSS model. The performance validation of the SVNHSS-HFRP model is verified on a benchmark dataset. The experimental values highlighted that the SVNHSS-HFRP technique reaches better performance than existing techniques

Keywords: Hedge Fund Return Prediction; Moth Flame Optimization; Neutrosophic; Hypersoft Set; Machine Learning;

1. Introduction

The neutrosophic set exhibits truth, indeterminacy, and falsity membership values. This theory is significant in several applications since indeterminacy is extraordinarily checked and falsity, truth, and indeterminacy membership values are independent. The theory of soft set deals with the problems of indeterminate circumstances where it is a parameterized family of subset of the universal set. Soft set is beneficial in multiple ways such as fundamental decision-making, artificial insight, and game hypothesis problems, it assists in determining various functions for benefit values and different parameters against established parameters. In recent time, the basics of soft set theory were pondered over by different researchers. The neutrosophic soft set demonstrated by truth, indeterminacy, and falsity membership values which are independent. The neutrosophic soft set could deal with inconstant, inadequate, and uncertain information whereas the intuitionistic fuzzy soft set could handle partial information. The existing research established an approach for handling uncertainty situation for extending soft set to hypersoft set (HSS) by changing function into multi-decision functions. But once the attribute is multiple and wider deviation, HSS cannot assist in handling these kinds of problems. Therefore, the neutrosophic hypersoft set (NHSS) was presented with tangent similarity measure and aggregate operators and exploited in MCDM.

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Financial economists have discovered an excess of firm features that estimate stock returns in the cross-section. However, recent work has challenged the reliability of such analytical patterns [1]. Furthermore, hedge fund tactics are idiosyncratic and proprietary to the hedge fund managers, and the accurate abilities of fund managers are not directly noticeable to investors. These kinds of reasons, united, create a hedge fund range a challenging task for investors [2]. Numerous techniques are studied for picking a range of hedge funds for investment. The 1st technique contains a due-diligence procedure that comprises monitoring and reviewing mainly operational danger to sort out funds that are probable to fail [3]. Furthermore, the return–risk trade-off at the separate fund level proposes that the performance of a hedge fund is essentially linked to its danger. Counter to this 'anomaly-challenging' element of literature, there has been a developing body of work that reports outstanding asset profitability dependent upon signals emergent from numerous machine learning (ML) models [4]. From a real investment management viewpoint, with the current growth in financial technology (Fintech), there is a rising popularity of utilizing ML tools to recognize novel signals on price movement and progress investment methods which can outdo human fund managers [5].

ML methods can theoretically overcome numerous restrictions with the present methods and procedure economic statement data more effectively in predicting prospect 2 earnings [6]. At first, ML techniques can effectively handle higher dimensional data. The generation of business earnings (or losses) is a difficult procedure connecting many business dealings. The effects of these dealings, as summarized in economic report line items, frequently have dissimilar suggestions for future earnings (e.g., credit sales vs. cash sales) [7]. However, for tractability, the present earnings forecast method concentrates on extremely combined measures like bottom-line earnings and book equity value and avoids possibly rich data in economic statement line items. By accepting a larger set of economic statement line items, ML techniques can potentially improve the model of the variance effects of these items and produce more precise and helpful earnings predictions [8]. Next, in contrast to traditional linear methods, ML techniques can hold more difficult and refined relations among future earnings and financial statement line items. Financial theories and experimental evidence propose the presence of non-linear relations among future earnings and financial statement line items [9]. For instance, the law of reducing returns forecasts non-linear relations between future earnings and capital investment. Previous works also display that the relationship between future and current earnings is non-linear and fluctuates with other economic metrics like capital intensity and firm size [10]. Non-linear ML techniques dependent upon decision trees (DT) and neural networks are somewhat flexible in modeling non-linear relations and interaction effects, delivering another benefit in predicting earnings.

In [11], an effective strategy optimizer utilizing a hybrid ML method is projected for the stock market prediction (HM-SMP). The 1st contributions of HM-SMP method is to present a chaos-enhanced firefly bowerbird optimizer (CEFBO) system for optimum FS method. Next, a hybrid multi-objective capuchin with an RNN (HC-RNN) system is projected for the SMP. Also, the supervised RNN is employed to forecast the final value. Faridi et al. [12] projected a united model of ensemble learning (EL) and genetics to balance the business portfolio. In this, a dual-level united intellectual model and multi-layer perceptron neural networks are used as assorted basic methods of EL in the initial stage. Zhang and Chen [13] proposed a new dual-phase prediction technique that contains a decomposition model, a non-linear ensemble tactic, and 3 individual ML methods. Particularly, in the 1st phase, the stock price time series was decayed into a limited amount of sub-series by variational mode decomposition (VMD). Then, 3 individual ML methods such as SVR, ELM, and DNN were distinctly used. In the 2nd phase, an ELM-based non-linear ensemble tactic is utilized.

Chen et al. [14] projected the modeling tactics dependent upon ML models. The projected model planned a vector autoregression (VAR)-based rolling forecast technique for predicting stock price, and the Gaussian FFNN (GFNN) model-based graphic signal classification model was projected to identify diverse kinds of stock price signs. Wang and Chen [15] presented the Sentiment and Price Combined Model (SPCM) technique, which influences price factors and sentiment features to forecast stock price movement. This new structure unites collective SA with advanced BERT transformer methods and innovative ML approaches. In [16], a first-presented method named HHT-XGB is projected to forecast the altering tendencies in the subsequent close price of stocks.

This study designs a new Single Valued Neutrosophic Hypersoft Set VIKOR Method for Hedge Fund Return Prediction (SVNHSS-HFRP) technique. The presented SVNHSS-HFRP technique aims to forecast the hedge fund returns proficiently. In the SVNHSS-HFRP technique, two stages of operations are involved. At the initial stage, the SVNHSS-HFRP technique, the SVNHSS is used for forecasting the hedge funds. Next, in the second stage, the moth flame optimizer (MFO) algorithm is applied to optimally choose the parameter values of the SVNHSS model. The performance validation of the SVNHSS-HFRP model is verified on a benchmark dataset.

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2. Proposed Methodology

In this study, we have developed a new SVNHSS-HFRP technique. The presented SVNHSS-HFRP technique aims to forecast the hedge fund returns proficiently. In the SVNHSS-HFRP technique, two stages of operations are involved SVNHSS using prediction and MFO using parameter tuning. Fig. 1 illustrates the workflow of the SVNHSS-HFRP technique.

A. Predictive Modeling

At the initial stage, the SVNHSS-HFRP technique, the SVNHSS is used for forecasting the hedge funds. Florentin Smarandache in 1998 developed the neutrosophic concept [17]. The single-valued neutrosophic (SVN) set, neutrosophic-set, and, single-valued trapezoidal neutrosophic set (SVTN) were given below.

Consider X as a point space and $x \in X$. A set of neutrosophic A over X was represented as a truth, indeterminacy $I_A(x)$ and false-membership functions $F_A(x)$, $T_A(x)$, $I_A(x)$ and $F_A(x)$ are standard or non-standard sub-sets of [0 and1]. There is no constraint on the amount of $T_A(x)$, $I_A(x)$ and $F_A(x)$, hence $0- \leq \sup(X) + sup\ x \leq 3 +$.

Consider X as a discourse universe. The object for $A = \{\langle x, T_A(x), I_A(x), F_A(x), \rangle : x \in X\}$, is an SVN set A in X, where $T_A(x): X \to [0,1]$, $I_A(x): X \to [0,1]$ and $F_A(x): X \to [0,1]$ with $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$ for $x \in X$. The $T_A(x)$, $I_A(x)$ and $F_A(x)$ are the degree of truth, the indeterminacy-, and the false membership functions of χ to A, correspondingly. The SVN number is $= (a, b, c)$, whereas a, b, $c \in [0, 1]$ and $a + b + c \leq 3$.

Definition3 Assume that $\alpha_{\tilde{a}}$, $\theta_{\tilde{a}}$, $\beta_{\tilde{a}} \in [0,1]$and a_1, a_2, a_3, $a_4 \varepsilon R$, while $a_1 \leq a_2 \leq a_3 \leq a_4$. Next, the SVTN set $\tilde{a} = \langle (a_1, a_2, a_3, a_4); \alpha_{\tilde{a}},\ \theta_{\tilde{a}}, \beta_{\tilde{a}} \rangle$ refers to a special neutrosophic number on set R, whose functions of indeterminacy, truth, and false membership were given below:

$$T_{\tilde{a}}(x) = \begin{cases} \alpha_{\tilde{a}} \left(\dfrac{x - a_1}{a_2 - a_1} \right) & (a_1 \leq x \leq a_2) \\ \alpha_{\tilde{a}} & (a_2 \leq x \leq a_3) \\ \alpha_{\tilde{a}} \left(\dfrac{a_4 - x}{a_4 - a_3} \right) & (a_3 \leq x \leq a_4) \\ 0 & otherwise. \end{cases}$$

$$I_{\tilde{a}}(x) = \begin{cases} \dfrac{(a_2 - x + \theta_{\tilde{a}}(x - a_1))}{(a_2 - a_1)} & (a_1 \leq x \leq a_2) \\ \alpha_{\tilde{a}} & (a_2 \leq x \leq a_3) \\ \dfrac{(x - a_3 + \theta_{\tilde{a}}(a_4 - x))}{(a_4 - a_3)} & (a_3 \leq x \leq a_4) \\ 1 & otherwise. \end{cases}$$

$$F_{\tilde{a}}(x) = \begin{cases} \dfrac{(a_2 - x + \beta_{\tilde{a}}(x - a_1))}{(a_2 - a_1)} & (a_1 \leq x \leq a_2) \\ \alpha_{\tilde{a}} & (a_2 \leq x \leq a_3) \\ \dfrac{(x - a_3 + \beta_{\tilde{a}}(a_4 - x))}{(a_4 - a_3)} & (a_3 \leq x \leq a_4) \\ 1 & otherwise. \end{cases}$$

While $\alpha_{\tilde{a}}$, $\theta_{\tilde{a}}$ and $\beta_{\tilde{a}}$ are the maximal truth, minimal indeterminacy-, and minimal false-membership grades, correspondingly. This problem is resolved by the SVNHSS based on the VIKOR technique [18]. The SVN handles vague datasets with the hypersoft set, while the VIKOR technique ranks the alternatives. The weight value is calculated by the average model. The SVNHSS steps are presented. Recognizing numerous alternatives and criteria, calculating the weight and ranking the alternatives utilizing the VIKOR technique are the three steps included in the proposed method.

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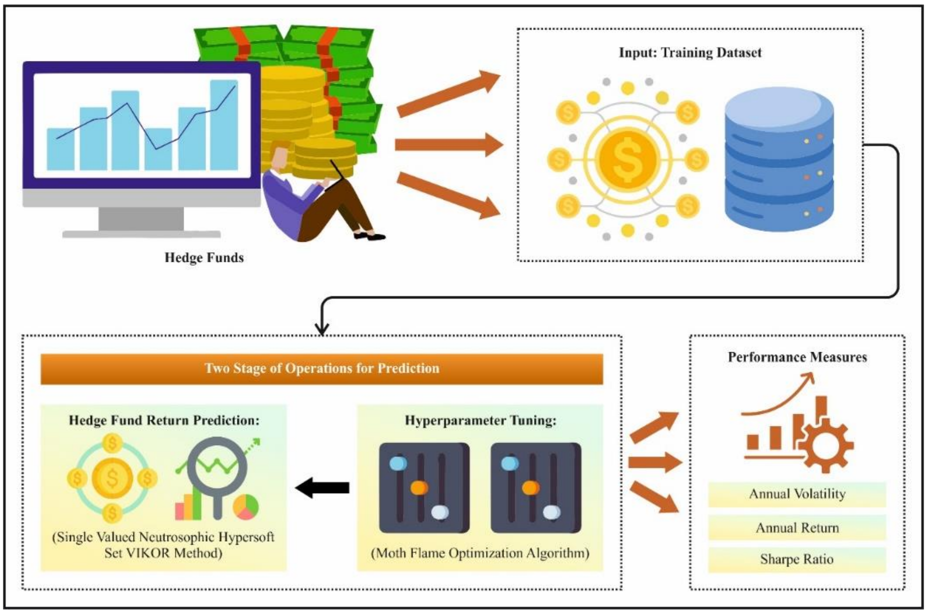

Figure 1: Workflow of SVNHSS-HFRP technique

Identify alternatives and criteria

The decision-makers and experts define the criteria according to the set of alternatives by the literature review and Questioners.

Compute the weight of criteria

We calculate the criteria weight by the average technique. Consider the experts applied the SVN to estimate the alternatives and criteria, and later calculate the criteria weight.

Rank the substitutes by SVNHSS-VIKOR model

Soft-set: Consider $p(\mu)$ the power set of μ, μ as a universe of discourse, and A as an attribute set. Next, the pair $(F,\mu), F: A \rightarrow P(\mu)$ is known as a Soft Set in μ

HyperSoft: Consider $p(\mu)$ the power set of μ. μ as a universe of discourse. Assume $a_1, a_2, \dots, a_n$ for $n \geq 1$, as n distinct attributes, where the attributes are $A_1, A_{2,} \dots A_n$ with $A_i \cap A_j = \emptyset$, for $i \neq j$, and $i, j \in \{1,2, \dots n\}$. The pair $(:A_1 \times A_2 \times \dots A_n \rightarrow p$ is known as a HyperSoft in μ.

Step1. Construct the decision matrix

The decision matrix was created according to the alternatives $5GAL_1, 5GAL_2, \dots 5GAL_m$ and criteria $A5GA_1, A5GA_2, \dots A5GA_n$.

$$A5GA_1 \dots A5GA_n$$

$$A5GF_1 \dots A5GF_n$$

$$X = \begin{matrix} 5GAL_1 \\ \vdots \\ 5GAL_m \end{matrix} \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \quad (1)$$

While $i = 1,2, \dots m; j = 1,2, \dots n$

Step2. The HSS chooses the well-arranged tuple

The HSS chooses the better attributes for the criteria according to the alternatives.

Step3. Employ the score function

The score function shows the crisp value for each SVNN.

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$$S(x_{ij}) = \frac{2+T-I-F}{3} \tag{2}$$

Step4. Calculate the benefit and cost values.

$$b_i = \max[x_{ij}] \tag{3}$$

$$c_i = \min[x_{ij}] \tag{4}$$

Step5. Calculate the utility and regret measure values.

$$u_i = \frac{w_j[b_i - x_{ij}]}{b_i - c_i} \tag{5}$$

$$u_i = \frac{w_j[x_{ij} - b_i]}{b_i - c_i} \tag{6}$$

$$R_i = \max of \left\{\frac{w_j[b_j - x_{ij}]}{b_j - c_j}\right\} \tag{7}$$

Step6. Calculate the VIKOR index.

$$V_i = \phi\left[\frac{u_i - u_i^-}{u_i^+ - u_i^-}\right] + (1-\phi)\left[\frac{R_i - R_i^-}{R_i^+ - R_i^-}\right] \tag{8}$$

Where $u_i^+ = \max u_i$, $u_i^- = \min u_i$, $R_i^+ = \max R_i$ and $R_i^- = \min R_i$. The value ϕ between 0 and 1.

B. Parameter Tuning

In the 2nd phase, the MFO algorithm is used to optimally choose the parameter values of the SVNHSS model. In the MFO algorithm, there is N number of moths in the entire swarm which is represented as a set of candidate solutions to a certain problem based on the matrix formula [19]:

$$X = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \ddots & \cdots & \cdots & x_{2,n} \\ \vdots & \cdots & \ddots & \cdots & \vdots \\ x_{N-1,1} & \cdots & \cdots & \ddots & x_{N-1,\mathrm{n}} \\ x_{N,1} & x_{N,2} & \cdots & x_{N,\mathrm{n}-1} & x_{N,\mathrm{n}} \end{bmatrix} \tag{9}$$

In Eq. (9), the vector $X_i = [x_{i,1}, x_{i,2}, \cdots, x_{i,n}], i \in \{1,2,\cdots,N\}$ is the location of every individual moth.

While 'n' means parameter number. The j^{th} variable of X_i is formulated by scalar $x_{i,j}, j \in \{1,2,\ldots,n\}$ in the$[x_{i-\min}, x_{i-max}]$ boundary range, xan& indicates the minimal and maximal boundaries of the j^{th} parameter of X_i, correspondingly.

For $i \in \{1,2,\ldots,N\}$, let us assume that the fitness value of $X_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,n}]$ is represented as $Fit(X_i)$, where the candidate solution of the fitness function is $Fit(*)$. Next, the related fitness vector of X is shown below:

$$Fit[X] = \begin{bmatrix} Fit(X_1) \\ Fit(X_2) \\ \vdots \\ Fit(X_n) \end{bmatrix} \tag{10}$$

Every individual flies towards the related fame such that the fame matrix has a similar size as X matrix:

$$FM = \begin{bmatrix} FM_1 \\ FM_2 \\ \vdots \\ FM_N \end{bmatrix} = \begin{bmatrix} FM_{1,1} & FM_{1,2} & \cdots & FM_{1,n-1} & FM_{1,n} \\ FM_{2,1} & \ddots & \cdots & \cdots & FM_{2,n} \\ \vdots & \cdots & \ddots & \cdots & \vdots \\ FM_{N-1,1} & \cdots & \cdots & \ddots & FM_{N-1,\mathrm{n}} \\ FM_{N,1} & FM_{N,2} & \cdots & FM_{N,\mathrm{n}-1} & FM_{N,\mathrm{n}} \end{bmatrix} \tag{11}$$

In Eq. (11), FM_i indicates the fame corresponding to the $X_i = [x_{i,1}, x_{i,2}, \cdots, x_{i,n}]$; n represents the parameter value of FM_i, N refers to the number of frames.

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Likewise, the fitness of $M_i = [Fm_{i,1}, Fm_{1,2}, \mathrm{F}m_{i,n}]; i = \{1,2,\cdots,N\}$, we consider that its related fitness value is formulated by $Fit(FM_i)$:

$$Fit = \left[\begin{bmatrix} Fit(FM_1) \\ Fit(FM_2) \\ \vdots \\ Fit(FM_N) \end{bmatrix}\right] \tag{12}$$

Figure 2. Steps involved in MFO

The MFO algorithm consists of two important components namely Moth and Fame. Assume that K and k, $k \in \{1,2,\cdots,N\}$ as the maximal and the existing iteration counter, correspondingly. Moth spirally moves once it approaches the fame thereby, a logarithmic spiral function is used:

$$X_i^{k+1} = \begin{cases} \delta_i \bullet e^{bt} \bullet cos(2\pi t) + FM_i(k), i \le Fl_{no} \\ \delta_i \bullet e^{bt} \bullet cos(2\pi t) + FM_{Fl_{no}}(k), i \ge Fl_{no} \end{cases} \tag{13}$$

In Eq. (13), $\delta_i = \left|X_i^k - FM_i(k)\right|$, denotes the distance between i^{th} moth X_i and its related fame FM_i. Fl_{no} signifies fame number that can adaptively reduce the number of fames using the iteration, the constant b used to identify the spiral fight shape, t indicates any random integer within $[a_1, 1]$ and a_1 represents the convergence constant that dropped linearly from -1 to -2 during the iterative process and it can be mathematically represented as below:

$$a_1 = -1 + k\left(\frac{-1}{K}\right) \tag{14}$$

$$t = (a_1 - 1) \times r + 1 \tag{15}$$

In Eq. (15), r shows the randomly produced number within [0 and 1],

The past and the present positions of fame are organized and gathered by local and global fitness in all the iterations. Other flames are destroyed, and only the optimum Fl_{no} are sustained. Moths in the lower and same orders often take the last fame. For the determination of fame number (Fl_{no}), the subsequent formula is used.

$$Fl_{no} = round\left(Fl_{\max} - k\frac{(Fl_{\max} - 1)}{K}\right) \tag{16}$$

In Eq. (16), Fl_{mox} characterizes the maximum number of flames. $round$ can make the number of $\left(Fl_{max} - k\frac{(Fl_{max}-1)}{K}\right)$ be rounded to its nearby integer and k and K denote the existing and maximal iterations of the population. Fig. 2 defines the steps involved in the MFO algorithm.

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The fitness function (FF) is the significant factor manipulating the performance of the MFO model. The hyperparameter selection procedure contains the solution encode technique to assess the efficiency of the candidate solution. In this work, the MFO system reflects accuracy as the main standard to project the FF, which can be expressed as below.

$$Fitness = \max(P) \quad (17)$$

$$P = \frac{TP}{TP + FP} \quad (18)$$

Here, TP signifies the true positive and FP means the false positive value.

3. Results and Discussion

The predictive results of the SVNHSS-HFRP technique on hedge fund returns are given in this section. Table 1 and Fig. 3 signify the comparison study of the SVNHSS-HFRP model on the equity index in terms of annual return (AR), annual volatility (AV), and Sharpe ratio (SR) [20]. The results indicate that the SVNHSS-HFRP technique offers improved outcomes over other models. Based on AR, the SVNHSS-HFRP technique obtains a reduced AR of 7.08% whereas the HFR, ABK, RF, GBM, and DNN models attain increased AR of 8.72%, 11.89%, 15.86%, 15.63%, and 15.95%, correspondingly. Moreover, based on SR, the SVNHSS-HFRP model acquires a reduced SR of 0.45 while the HFR, ABK, RF, GBM, and DNN techniques get enlarged SR of 0.66, 0.92, 0.94, 0.98, and 0.95, respectively.

Table 1: Equity index analysis of SVNHSS-HFRP technique with existing models

Equity Index						
Methods	SVNHSS-HFRP	HFR	ABK	RF	GBM	DNN
Annual Return (%)	7.08	8.72	11.89	15.86	15.63	15.95
Annual Volatility	6.96	9.13	10.15	13.94	13.03	13.95
Sharpe Ratio	0.45	0.66	0.92	0.94	0.98	0.95

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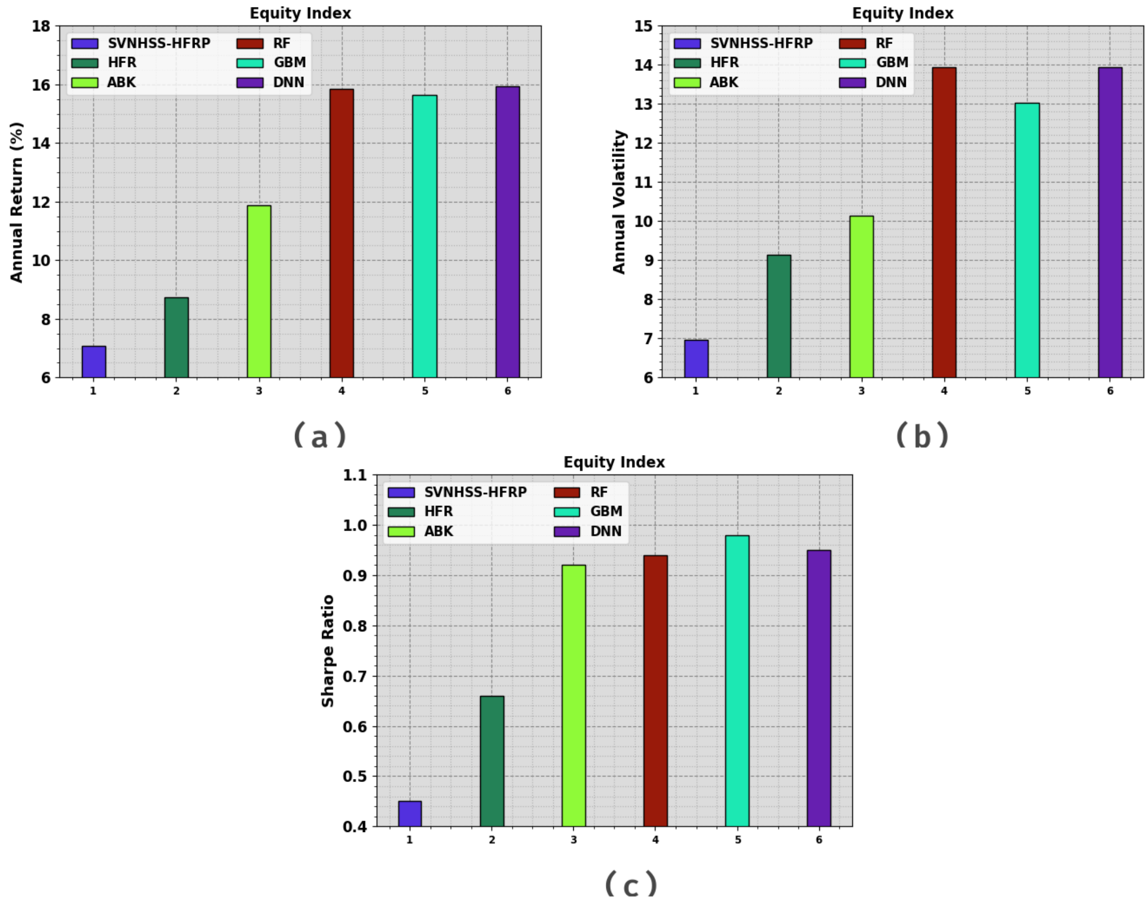

Figure 3: Equity index analysis of SVNHSS-HFRP technique (a) AR, (b) AV, and (c) SR

Table 2 and Fig. 4 signify the comparison study of the SVNHSS-HFRP model on the event-driven index in terms of AR, AV, and SR. The outcomes specify that the SVNHSS-HFRP approach delivers enhanced results over other approaches. Based on AR, the SVNHSS-HFRP system acquires decreased AR of 5.24% while the HFR, ABK, RF, GBM, and DNN approaches achieve enlarged AR of 8.66%, 9.62%, 14.90%, 14.75%, and 14.00%, respectively. Furthermore, based on SR, the SVNHSS-HFRP system gets reduced SR of 0.54 while the HFR, ABK, RF, GBM, and DNN approaches get improved SR of 0.88, 1.07, 1.31, 1.27, and 1.59, respectively.

Table 2: Event-driven index analysis of SVNHSS-HFRP technique with existing models

Event-Driven Index						
Methods	SVNHSS-HFRP	HFR	ABK	RF	GBM	DNN
Annual Return (%)	5.24	8.66	9.62	14.90	14.75	14.00
Annual Volatility	4.32	6.76	6.61	9.08	9.29	6.87
Sharpe Ratio	0.54	0.88	1.07	1.31	1.27	1.59

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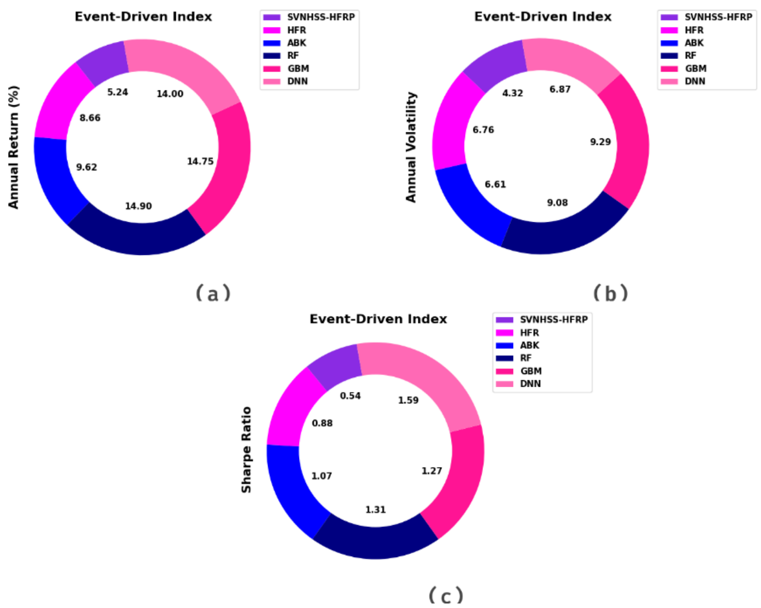

Figure 4: Event-driven index analysis of SVNHSS-HFRP technique (a) AR, (b) AV, and (c) SR

Table 3 and Fig. 5 denote the comparison study of the SVNHSS-HFRP method on the Marco index in terms of AR, AV, and SR. The outcomes specify that the SVNHSS-HFRP approach provides enhanced results over other techniques. Based on AR, the SVNHSS-HFRP system gets a reduced AR of 4.93% while the HFR, ABK, RF, GBM, and DNN techniques achieve increased AR of 6.67%, 8.47%, 11.23%, 11.42%, and 11.32%, respectively. Besides, based on SR, the SVNHSS-HFRP method gets a reduced SR of 0.34 whereas the HFR, ABK, RF, GBM, and DNN methodologies attain improved SR of 0.69, 1.50, 0.77, 0.78, and 0.77, correspondingly.

Table 3: Macro index analysis of SVNHSS-HFRP technique with existing models

Macro Index						
Methods	SVNHSS-HFRP	HFR	ABK	RF	GBM	DNN
Annual Return (%)	4.93	6.67	8.47	11.23	11.42	11.32
Annual Volatility	3.36	5.97	3.91	11.63	11.64	11.68
Sharpe Ratio	0.34	0.69	1.50	0.77	0.78	0.77

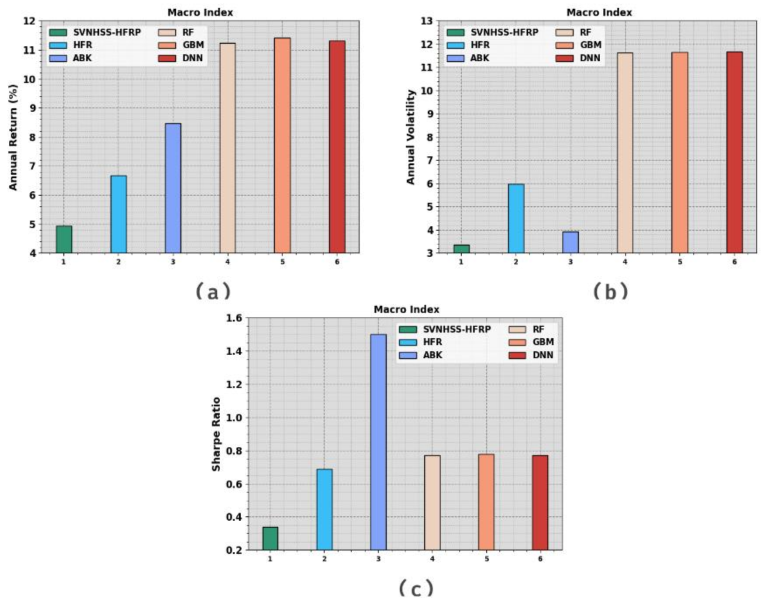

Figure 5: Marco index analysis of SVNHSS-HFRP technique (a) AR, (b) AV, and (c) SR

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Table 4 and Fig. 6 signify the comparison study of the SVNHSS-HFRP system on relative value index in terms of AR, AV, and SR. The outcomes specify that the SVNHSS-HFRP model provides enhanced results over other techniques. Based on AR, the SVNHSS-HFRP system obtains decreased AR of 3.80% while the HFR, ABK, RF, GBM, and DNN approaches achieve improved AR of 7.61%, 9.45%, 17.74%, 16.78%, and 17.59%, correspondingly. Moreover, based on SR, the SVNHSS-HFRP method achieves a reduced SR of 0.72 but the HFR, ABK, RF, GBM, and DNN system get increased SR of 1.16, 2.69, 1.99, 1.90, and 0.00, correspondingly. Therefore, the SVNHSS-HFRP technique can be applied for forecasting the hedge fund returns.

Table 4: Relative value index analysis of SVNHSS-HFRP technique with existing models

Relative Value Index						
Methods	SVNHSS-HFRP	HFR	ABK	RF	GBM	DNN
Annual Return (%)	3.80	7.61	9.45	17.74	16.78	17.59
Annual Volatility	2.04	4.31	2.50	7.21	7.09	7.12
Sharpe Ratio	0.72	1.16	2.69	1.99	1.90	2.00

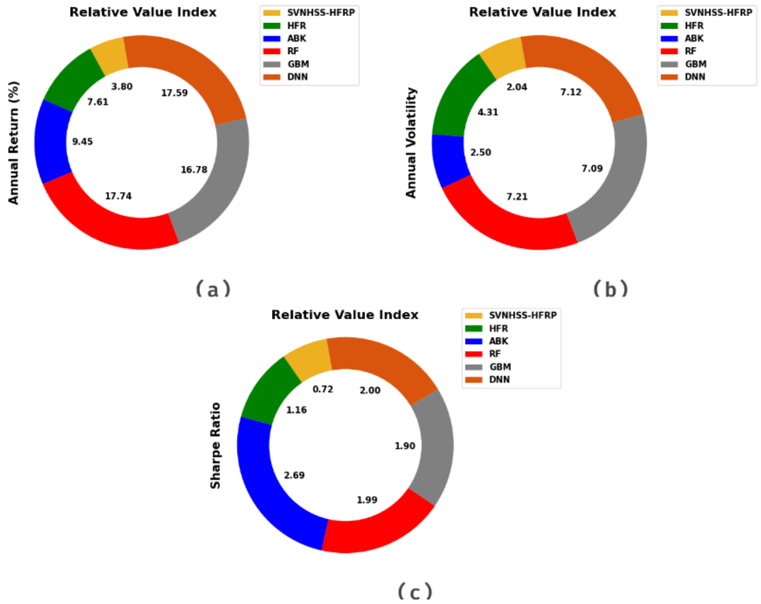

Figure 6: Relative value analysis of SVNHSS-HFRP technique (a) AR, (b) AV, and (c) SR

4. Conclusion

In this study, we have developed a novel SVNHSS-HFRP method. The presented SVNHSS-HFRP technique aims to forecast the hedge fund returns proficiently. In the SVNHSS-HFRP technique, two stages of operations are involved. At the initial stage, the SVNHSS-HFRP technique, the SVNHSS is used for forecasting the hedge funds. Next, in the 2nd phase, the MFO algorithm is employed to optimally choose the parameter values of the SVNHSS model. The performance validation of the SVNHSS-HFRP system is verified on a benchmark dataset. The experimental values highlighted that the SVNHSS-HFRP technique reaches better performance than existing techniques.

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