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Asset Shortlisting via Fuzzy Support Vector Machines for Portfolio Optimization Model with Second-Order Stochastic Dominance Criterion

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Abstract

The emergence and underdevelopment of machine learning (ML) methods to effectively process large-scale finance data and make accurate predictions encourage their application to traditional Portfolio Optimization (PO) models. This paper formulates a two-stage hybrid model for portfolio optimization. The first stage involves (i) Fuzzy Support Vector Machines (Fuzzy SVM) shortlisting of assets, which is an effective approach to deal with uncertainty and nonlinearity in finance data. Stage (ii) optimizes the chosen assets under Second-Order Stochastic Dominance (SSD) constraints in the second stage to address the pitfalls of the classical Markowitz model for maximizing investor satisfaction and utility. The new framework is tested on eight international equity markets, such as Bovespa 90 (Brazil), DAX 40 (Germany), Dow Jones Industrial Average (U.S.A.), EURO 50 (Europe), FTSE 100 (U.K.), Hang Seng (Hong Kong), Nifty 100 (India), and Nikkei 400 (Japan), and compared with models having no asset shortlisting and using traditional SVM-based selection. Empirical results indicate that Fuzzy SVM–SSD performs better consistently compared to the benchmarks on various measures of performance, such as average returns, Value at Risk (VaR), Conditional Value at Risk (CVaR), and minimum return. Also, better reward-to-risk performance is witnessed by virtue of higher STARR, Sharpe, and Sortino ratios. On the whole, the findings emphasize the significance of smart asset shortlisting and show the usefulness of combining fuzzy learning processes with risk-sensitive portfolio optimization for better financial decision-making.

Keywords: Portfolio optimization model, Stochastic dominance, Fuzzy support vector machine, Membership function, Shortlisting Assets, Classification, Prediction.

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1 | Introduction

The problem of investment decision-making has always been an important yet challenging task. [1] provides an effective technique for addressing this problem through the famous mean-variance model. The development of the mean-variance model led to the advancement of portfolio optimization (PO) for financial investment decision-making. The PO model with variance as a risk measure is a convex quadratic program; hence, it yields a global minimum. Although it is computationally tractable, the model itself has drawbacks due to the heavy computational demand while estimating the covariance matrix, thereby leading to suboptimal solutions. Despite its shortcomings, it provides an excellent starting point for researchers and investment managers to explore more about PO. Several endeavors are undertaken to propose different PO models by employing alternative risk [2, 3, 4]. Researchers introduce new measures that not only capture risk effectively but also overcome the drawbacks of the mean-variance model. Within the realm of portfolio optimization (PO), the Mean Absolute Deviation (MAD), a staple risk measure [5, 3], holds significant sway. By quantifying the divergence of portfolio returns from their mean, MAD offers a nuanced assessment of risk without necessitating the intricate covariance matrix calculations inherent in traditional models. Thus, the mean-MAD model emerges as a pragmatic alternative to the conventional mean-variance paradigm, particularly given its foundation in Linear Programming (LP) principles. Moreover, in the pursuit of mitigating downside risk, practitioners frequently turn to metrics like Min-Max [6], Value at Risk (VaR) [7], and Conditional Value at Risk (CVaR) [4]. These metrics, tailored to capture and address the specter of extreme losses, become invaluable tools for investors seeking to fortify their portfolios against adverse market conditions. By focusing on the potential for significant downturns, such risk measures contribute to a more holistic understanding of portfolio performance and resilience.

Other modifications to the traditional mean-risk models involve portfolio selection through performance measures [8, 9, 10], using a multi-period PO [11] setting with real-life constraints to incorporate the dynamic nature of the market, etc.

Although the mean-risk models or their variants are widely applied for investment decision-making, [12] note that these models do not cover the entire range of risk preferences of investors and may lead to inferior solutions. Alternatively, stochastic dominance aids in ranking the random variables and is consistent with the utility theory. The famous mean-variance model is generally questioned due to the inconsistency with stochastic dominance criteria, and thus, the resultant optimal portfolio may be an inferior choice. It is worth mentioning some of the articles that involve stochastic dominance criteria for portfolio selection. In particular, second-order stochastic dominance (SSD) is predominantly applied in PO models. The work by [13] is the first attempt to include SSD constraints for optimal portfolio selection successfully. Being an LP model with a large number of constraints, the authors propose to use a cutting plane algorithm to solve the PO model. Further, [14] applies SSD to the application of enhanced indexing, which has the aim of generating an optimal portfolio that dominates the benchmark index in terms of SSD condition. [15] expands on the work by introducing looser SSD criteria for improved indexing. Uncertainty in asset inputs and return probability distributions leads to the development of tractable, robust PO models with SSD restrictions [16, 17]. As pointed out by [18], the third-order stochastic dominance condition is suitable for investors who require lower downside risk and higher upside potential as opposed to the SSD conditions. They propose a PO model where the required portfolio dominates the benchmark based on third-order stochastic dominance conditions.

A common shortcoming of all these models is their inability to incorporate any additional information other than historical returns/prices in the PO model. The dynamic nature of the financial markets makes it imperative to include factors like the company's performance, investor sentiments, and other technical factors that may influence the performance of an asset. Since classical PO models only include asset returns as a factor to yield an optimal portfolio, it may lead to the selection of suboptimal assets by assigning positive weights to those assets that may be inferior to other assets.

Some unique techniques have been applied by researchers to address this issue. In this article, we will specifically concentrate on how machine learning techniques are integrated with PO models to obtain better estimates as opposed to only applying the conventional PO models.

1.1 | Integration of Machine Learning Techniques and Portfolio Optimization

Some authors propose to shortlist the assets before the PO process, i.e., only the shortlisted assets are allowed to take part in the financial decision-making process through optimization. This preliminary selection of assets may depend on various crucial factors that govern the asset performance, which the PO models may fail to capture. An attempt to integrate ML with PO is made by [19] by employing support vector machines (SVM) for asset pre-selection in the PO model by selecting only those assets that have the capacity to reach a certain returns target. [20] proposes to integrate the long short-term memory networks (LSTM) with the mean-variance model for portfolio selection. The primary purpose of LSTM in this work is to capture the long-term dependencies of asset returns and pre-select the assets based on these criteria before PO. A step approach is followed by [21] for portfolio selection, namely (i) asset price prediction through an artificial neural network and fundamental analysis, (ii) asset shortlisting by differential evolution and fundamental analysis, and (iii) PO through a genetic algorithm.

There are other ways in literature by which ML techniques are adopted to facilitate the process of PO. [22] develops the prediction-based PO models by using deep neural networks to forecast asset returns, maximize the portfolio predicted returns, and minimize the downside absolute predicted deviation errors. Monthly excess returns and volatility are forecasted via a random forest model, and optimal weights are computed through a standard linear model. Some clustering techniques are also incorporated in the PO models as a means to reduce the number of assets taken into consideration for the optimization process. [23] apply some commonly used clustering techniques like K-means, fuzzy C-means, and self-organizing maps, and stocks are selected from each cluster for the mean-variance model. Agglomerative hierarchical clustering is used by [24] to arrange resources into a hierarchical structure; the clustering procedure is based on the correlation between the assets. Through extensive analysis, they show that alpha values for different factor models are significantly improved. [25] uses three clustering techniques, namely agglomerative hierarchy, K-means, and partitioning around medoids for dimensionality reduction, and observes the portfolio returns after selecting assets from the clustering process. An investment decision-making strategy is put forward by [26] by applying SVM to classify assets into different classes, and an appropriate set of assets from these classes is selected according to the preference of the investor. [19] develops a portfolio selection strategy with a mean-variance model where assets are shortlisted through SVM. A comparison of the proposed model with other related techniques illustrates the superiority of the developed approach. Stock return prediction through machine learning techniques, including support vector regression integrated with the mean-variance model for optimal portfolio selection by [27].

Moreover, recent work by Kaur et al. [28, 29, 30, 31] gives new directions to the ongoing research on the new field of integration of machine learning techniques, especially SVM with the Markowitz mean-variance portfolio optimization model [28] later on extended to sentiment analysis in a book chapter [29] showcasing investor's sentiment to strategy: machine learning in emotion-based asset allocation. Further revised the mean-variance model to a conditional value-at-risk model based on machine learning techniques, specifically by modifying the more computationally efficient method, Least Squares Support Vector Machines (LSSVM) [30]. Afterwards, extend binary class classification to novel multi-class classification scenarios [31]. Based on getting motivation from recent advancements in the new ongoing motivational field of integrating machine learning with PO, this research gives new avenues to existing literature, starting from Markowitz and moving forward till SSD. Hence, we attempted to integrate SVM with SSD to enhance superior asset classification and obtain optimal portfolios from the shortlisted preselected assets by the SVM model.

1.2 | Motivation and Contribution

Riding on recent developments by Kaur et al. [28, 29, 30, 31], the coupling of machine learning methods—especially Support Vector Machines (SVM)—with traditional portfolio optimization (PO) models is a promising avenue of research in financial modeling. Previous efforts showed how the legacy Markowitz mean–variance model [28] could be improved via machine learning-based asset selection and subsequently progressed towards sentiment-based portfolio building [29]. Later, the Conditional Value-at-Risk (CVaR) model was further improved by the addition of Least Squares SVM (LSSVM) and its fuzzy extension (FLSSVM) [30] for improved representation of tail-risk and effectiveness under uncertainty in markets. Recent developments towards multi-class classification [31] have only extended the application of SVM-based portfolio models further. Taken together, these advances underscore the increasing significance of machine learning-based risk management in portfolio design and inspire research toward still more responsive and dominance-homologous methods.

Nonetheless, there are some unresolved challenges. Most prior research is based solely on optimization-oriented models for investment choice, ignoring the preselection of assets, which is a key component of enhancing portfolio efficiency. Additionally, classical SVM models—albeit robust in classification—place equal weight on all data points and therefore cannot emphasize temporal significance, uncertainty, and noise associated with finance data. It is with this deficiency that Fuzzy Support Vector Machines (Fuzzy SVM) are used as an efficient asset shortlisting process before optimization.

Fuzzy SVM brings with it an important improvement over standard SVM by the inclusion of a fuzzy membership function that attributes different weights to observations according to how reliable or up-to-date they are. This allows the model to give greater weight to more informative and up-to-date data points, thus lowering the impact of outliers and market noise. As illustrated in recent research studies by Kaur et al. [30, 31], fuzzy and hybrid SVM methodologies have exhibited better generalization, stability, and predictive performance in sophisticated financial settings, and hence are especially relevant to turbulent market situations.

After asset shortlisting via fuzzy SVM, the next step is the optimization of the identified assets via Second-Order Stochastic Dominance (SSD) constraints because the Markowitz model cannot provide maximum investor satisfaction or utility. SSD ensures that the resulting portfolio dominates a benchmark in regard to expected utility for any risk-averse investor in accordance with non-decreasing and concave utility functions. In contrast to conventional mean–risk models (e.g., mean–variance), SSD optimization is consistent with investor rationality and describes a more realistic risk–return trade-off. Mathematically, it can be presented as an LP problem, which ensures computational tractability.

Motivation Summary

- **Preselection of Assets:** All PO models optimally make a balance between larger asset weights, which usually result in inefficiency and overfitting. It is beneficial to include a fuzzy SVM-based preselection step to enhance portfolio quality and computational efficiency.
- **Relevance and Effectiveness of Data:** Fuzzy SVM is computationally more efficient and reduces the impact of noise and uncertainty due to the presence of a membership function, thereby enhancing adaptability to dynamic financial environments.
- **Dominance-Consistent Optimization:** SSD constraints are helpful in logical decision-making according to the needs of risk-averse investor behavior by getting rid of the deficiencies of classical mean–risk models.
- **Computational Efficiency:** Fuzzy SVM (convex quadratic formulation) and SSD (linear program) both achieve global optimality, whereas the cutting-plane algorithm ensures scalability to large datasets.

In conclusion, this study proposes a two-stage smart framework—Fuzzy SVM for asset categorization and SSD-constrained optimization for portfolio allocation—promoting a more adaptive, dominance-consistent, and risk-sensitive approach to contemporary portfolio management.

1.3 | Organization of the Paper

The structure of the paper is as follows: Section 2 covers the mathematical notations and preliminaries of the PO model with SSD constraints, and also explains the SVM and FSVM models in more detail. Section 3 describes the methodology carried out in this study, along with the data set. It further includes the performance measures and out-of-sample comparison analysis of the optimal portfolios obtained from the proposed model. Additionally, the integration of both SVM and FSVM scenarios provides a comparative analysis of out-of-sample optimal portfolios generated from the SSD model. Section 4 includes the observations, and Section 5 concludes the article.

2 | Preliminaries

This section presents a brief overview of the second-order stochastic dominance portfolio selection model, SVM, and FSVM models for asset selection as part of the literature review. We may refer [32], and [16] for various notations and definitions.

2.1 | Mathematical Notations

Assume n number of assets considered for investment, and we take u as $n\times 1$ vector where each component u_i, $i=1,...,n$ of vector u is the weight assigned to the respective asset. Thus $\sum_{i=1}^{n} u_i=1$ and $u_i\geq 0$, since we assume that short-selling is not allowed. Take U to be a polyhedral set of admissible portfolios. As we note the price of a stock at a discrete finite-time point called scenarios, let us take the total number of T scenarios with probability vector $p=(p_1,p_2,...,p_T), \sum_{j=1}^{T} p_j=1, p_j\geq 0, \forall j=1,2,...,T$. Let $R_j=(r_{1j},r_{2j},...,r_{nj})$ represents the return of assets at j^{th} time point $j=1,2,...,T$. So the return of the portfolio u at any time point j denoted by $R_j(u)=\sum_{i=1}^{n} r_{ij}u_i$. Thus the portfolio return is a random variable R_u finitely distributed over $(R_1(u),R_2(u),...,R_T(u))$ with the probability $p_j, j=1,2,...,T$. Hence, the expected value of portfolio return is $E[R_u]=\sum_{j=1}^{T}(\sum_{i=1}^{n} r_{ij}u_i)p_j=\sum_{i=1}^{n}(\sum_{j=1}^{T} r_{ij}p_j)u_i$. Let $(\sum_{j=1}^{T} r_{ij}p_j)=\hat{r}_i$. Therefore, $E[R_u]=\sum_{i=1}^{n}\hat{r}_i u_i$.

Now consider the case when all the T scenarios are equally probable i.e., $p_j=\frac{1}{T}$, $j=1,2,...,T$. Let $(R_1(u),R_2(u),...,R_T(u))$ and $(R_1(\hat{u}),R_2(\hat{u}),...,R_T(\hat{u}))$ be the portfolio returns of portfolio u and $\hat{u}$ respectively.

2.2 | First Order Stochastic Dominance for Portfolio Selection

A portfolio u is preferred to portfolio $\hat{u}$ concerning FSD iff the corresponding portfolio returns $R_u=(R_1(u),R_2(u),...,R_T(u))$ and $R_{\hat{u}}=(R_1(\hat{u}),R_2(\hat{u}),...,R_T(\hat{u}))$ are such that

$$R_1(u) \leq R_2(u), \leq \ldots, \leq R_T(u) \qquad \text{and} \qquad R_1(\hat{u}) \leq R_2(\hat{u}), \leq \ldots, \leq R_T(\hat{u})$$

we have

$$R_j(u) \geq R_j(\hat{u}), \quad j=1,2,\ldots,T, \quad \text{with at least one strict inequality.}$$

2.3 | Second Order Stochastic Dominance for Portfolio Selection

Let F_{R_u} be the cumulative distribution function for portfolio u. Mathematically, $F_{R_u}(\eta)=P(R_u\leq\eta)$. Then the portfolio u dominates another portfolio $\bar{u}$ w.r.t. first order stochastic dominance if $F_{R_u}(\eta)\leq F_{R_{\bar{u}}}(\eta)$ $\forall\eta\in\mathbb{R}$. Equivalently, under the discrete distribution of returns, if $q_1,...,q_T$ are portfolio returns for u and $\bar{q}_1,...,\bar{q}_T$ are portfolio returns for $\bar{u}$, arranged in ascending order, then $q_t\leq\bar{q}_t$, For each j in the range 1 through T, inclusively, there is a presence of at least a single strict disparity.

The portfolio u dominates portfolio $\bar{u}$ w.r.t. SSD if $E((\eta-R_u)^+)\leq E((\eta-R_{\bar{u}})^+)$ $\forall$ $\eta\in\mathbb{R}$ where $E(.)$ is the expectation. Equivalently, under the discrete distribution of returns, if $R_1(u),R_2(u)...r,R_T(u)$ and $R_1(\bar{u}),R_2(\bar{u}),...,R_T(\bar{u})$ are the portfolio returns for u and returns for u and $\bar{u}$, arranged in ascending order, then $\sum_{t=1} R_t(u)\geq\sum_{t=1} R_t(\bar{u})$, $r=1,...,T$ with atleast one strict inequality.

2.4 | Portfolio Optimization Model in SSD Criteria

The PO model that determines the optimal portfolio dominating benchmark/market index, say M w.r.t. SSD, is given by [13]:

$$\begin{aligned} &\max\ E(R_u) \\ &\text{subject to: } E((\eta - R_u)^+) \leq E((\eta - M)^+)\ \forall \eta \in \mathbb{R}, \\ &u \in U, \end{aligned}$$

Here, M represents the stochastic variable characterizing benchmark returns. Let $m_1, m_2, \ldots, m_T$ be the benchmark returns in respective T scenarios.

$$\begin{aligned} &\max\ E(R_u) \\ &\text{subject to: } E((\eta - R_u)^+) \leq E((\eta - M)^+), \quad \forall \eta = m_1, m_2, \ldots, m_T, \\ &u \in U, \end{aligned}$$

In the scenario of discrete return distributions, we derive the subsequent model:

$$\begin{aligned} &\max \sum_{i=1}^{n} \hat{r}_i u_i \\ &\text{subject to: } \sum_{j=1}^{T} \left(m_k - \sum_{i=1}^{n} r_{ij} u_i \right)^+ p_j \leq \beta_k, \quad k = 1, 2, \ldots, T \\ &u \in U, \end{aligned}$$

where $\beta_k = E[(\eta_k - M)^+]$. Introducing the auxiliary variable

$$d_{jk} = \left(m_k - \sum_{i=1}^{n} r_{ij} u_i \right)^+$$

The foregoing quandary lends itself to the formulation of the subsequent Linear Programming (LP) model:

$$\begin{aligned} (SSD)\ &\max \sum_{i=1}^{n} \hat{r}_i u_i \\ &\text{subject to: } \sum_{j=1}^{T} d_{jk} p_j \leq \beta_k, k = 1, ..., T, \\ &d_{jk} \geq \left(m_k - \sum_{i=1}^{n} r_{ij} u_i \right), k = 1, ..., T, j = 1, ..., T, \qquad (1) \\ &d_{jk} \geq 0, k = 1, ..., T, j = 1, ..., T, \\ &u \in U \end{aligned}$$

Although the above SSD model is an LP, it has a large number of constraints due to (1). Therefore, in instances where the number of scenarios is sufficiently large, [13] recommends the utilization of the cutting plane algorithm to effectively expedite the computational process for resolving the (SSD) model.

2.5 | Support Vector Machines

The concepts of SVM for two-class classification problems are summarized in this subsection. A mathematical description of hyperplanes serves as the foundation for SVM. The SVM algorithm aims to find a hyperplane in an m-dimensional space, where m is the number of features that distinctly classify the data points.

Let L be the number of training points partitioned into two classes. Let $(x_l, y_l) \in \mathbb{R}^m \times \{-1, 1\}$ denote a point, where m represents the number of observed features for each $x_l; l = 1, 2, \ldots, L$ and y_l indicates to which of the two classes the point belongs. If the training points are linearly separable, there exists $w = (w_1, w_2, \ldots, w_m) \in \mathbb{R}^m$ and $b \in \mathbb{R}$ such that for each $x_l = (x_l^1, x_l^2, \ldots, x_l^m) \in \mathbb{R}^m$, we have:

$$b + w_1 x_l^1 + w_2 x_l^2 + \ldots + w_m x_l^m \geq +1, \text{ for which } y_l = +1$$

and

$$b + w_1 x_l^1 + w_2 x_l^2 + \ldots + w_m x_l^m \leq -1, \text{ for which } y_l = -1.$$

The SVM Problem determines the hyperplane $f(x_l)=w^T x+b$, which optimally separates the training points into two classes. Here, optimality is two-fold. The goal is to minimize the cumulative classification errors and increase the margin between two parallel hyperplanes supporting vectors from different classes. In the traditional hard margin SVM model put forward by [33], reducing the empirical risk—a trade-off between the previously listed goals—and taking care of the structural risk are the main priorities.

The SVM approach solves the following optimization problem to determine the ideal hyperplane of separation between two classes of data points:

$$\begin{aligned} (SVM) \qquad & \min \frac{1}{2}\|w\|^2 + C\sum_{l=1}^{L}\xi_l \\ \text{subject to: } & y_l(< w, \phi(x_l) > +b) + \xi_l \geq 1, \ l = 1, 2, \ldots, L, \\ & \xi_l \geq 0, \ l = 1, 2, \ldots, L. \end{aligned} \tag{2}$$

The vector w, spanning m dimensions, encompasses variables w_j alongside b, both inhabiting $\mathbb{R}$, denoting the coefficients of twin parallel hyperplanes $w^T x+b=1$ and $w^T x+b=-1$. In the objective function of (2), the initial term $\frac{1}{2}\|w\|^2$ signifies structural risk; $\|w\|$ has a magnitude equal to twice the reciprocal of the separation between these hyperplanes. The empirical risk is expressed as $C\sum_{l=1}^{L}\xi_l$, which is the product of the cumulative deviations of incorrectly categorized objects and C, a parameter controlling the trade-off between objectives. The parameter C determines the significance of avoiding misclassification within the training dataset. In the subsequent analysis, we address the two primary objectives: $\frac{1}{2}\|w\|^2$ and $C\sum_{l=1}^{L}\xi_l$ separately.

The nonlinear function $\phi: R^n \to R^p$, $(p>n)$ maps the input data in the high-dimensional space so that the transformed data set in the feature space R^p is linearly separable.

In writing the Lagrangian dual of the above primary problem, the equivalent quadratic optimization problem, designated as $(DSVM)$ so obtained is as follows:

$$\begin{aligned} (DSVM) \quad & \max \sum_{l=1}^{L}\alpha_l - \frac{1}{2}\sum_{l=1}^{L}\sum_{l_1=1}^{L}\alpha_l\alpha_{l_1}y_l y_{l_1}K(x_l, x_{l_1}) \\ \text{subject to: } & \sum_{l=1}^{L} y_l\alpha_l = 0, \\ & 0 \leq \alpha_l \leq C, \ l = 1, \ldots, L. \end{aligned} \tag{3}$$

where α_l is a Lagrange multiplier and

$$K(x_l, x_{l_1}) = \langle\phi(x_l), \phi(x_{l_1})\rangle = \exp\left(-\frac{(x_l - x_{l_1})^2}{2\sigma^2}\right)$$

is The well-known RBF kernel function, which is positive definite, makes the above optimization problem a convex quadratic.
Then, we arrive at the nonlinear decision function for the linearly nonseparable case defined as:

$$y(x) = sgn\left(\sum_{l=1}^{L}\alpha_l y_l K(x_l, x) + b\right).$$

The ability to determine whether a given input data point is noisy or fully belongs to any specified class is a feature that SVMs lack. Hence, by adding a fuzzy membership function to each input feature data point, [32] applies fuzzy SVM. The membership function can lessen the impact of outliers in the SVM since it adds weight to the input data points.

[32] reformulate the SVM model by defining a fuzzy membership $0<s_l\leq 1$ for each input data point x_l, $l=1,2,\ldots,L$ in the following manner:

$$(FSVM) \quad \min \frac{1}{2}\|w\|^2 + C\sum_{l=1}^{L} s_l\xi_l$$
$$\text{subject to: } y_l(< w, \phi(x_l) > +b) + \xi_l \geq 1,\ l = 1, 2, \ldots, L,$$
$$\xi_l \geq 0,\ l = 1,\ 2, \ldots, L.$$

The Lagrangian of the above optimization problem with Lagrange variables $\alpha_1,\alpha_2,\ldots,\alpha_L$, and $\beta_1,\beta_2,\ldots,\beta_L$ is given by:

$$\mathscr{L}(w,b,\xi,\alpha,\beta)=\frac{1}{2}\|w\|^2+C\sum_{l=1}^{L} s_l\xi_l+\sum_{l=1}^{L}\alpha_l(1-\xi_l-y_l<w,\phi(x_l)>+b)-\sum_{l=1}^{L}\beta_l\xi_l.$$

To obtain the dual, we differentiate the Lagrangian w.r.t. $w,\ b,\xi$ and respectively obtain the following conditions:

$$w = \sum_{l=1}^{L}\alpha_l y_l z_l,$$
$$\sum_{l=1}^{L}\alpha_l y_l = 0,$$
$$s_l C - \alpha_l - \beta_l = 0, \quad l = 1,\ 2, \ldots, L.$$

Using these conditions, we obtain the following dual of the above model:

$$(DFSVM) \quad \max \sum_{l=1}^{L}\alpha_l - \frac{1}{2}\sum_{l=1}^{L}\sum_{l_1=1}^{L}\alpha_l\alpha_{l_1}y_l y_{l_1}K(x_l, x_{l_1})$$
$$\text{subject to: } \sum_{l=1}^{L} y_l\alpha_l = 0,$$
$$0 \leq \alpha_l \leq s_l C,\ l = 1, 2, \ldots, L.$$

Once the dual optimal variables $\overline{\alpha}_l,\ (l=1,2,\ldots,L)$ are obtained, then the decision function of a (DFSVM) model is represented by

$$f(x) = \text{sign}\left(\sum_{l=1}^{L}\overline{\alpha}_l y_l K(x_l, x) + b\right),$$

3 | Experiment

On the assets that have been shortlisted, we use the (SSD) model for portfolio optimization. Fuzzy SVM is used to shortlist these assets based on their past performance. It is natural to compare the performance of the optimal portfolios when shortlisted assets are obtained with SVM and fuzzy SVM, and all assets are considered without any shortlisting. As a result, we compare and contrast the following three models:

- SSD Model: Portfolio optimization framework incorporating SSD constraints without asset shortlisting.
- SVM_SSD: Portfolio optimization framework incorporating SSD constraints where assets are shortlisted using the SVM model.
- FSVM_SSD: Portfolio optimization framework incorporating SSD constraints where assets are shortlisted using the fuzzy SVM model.

The following subsections explain the datasets used for empirical analysis, methodology, and the concluded results.

3.1 | Datasets

The datasets sourced from the Thomson Reuters Eikon data stream are utilized for comparative analysis among the aforementioned models. We use the daily closing price, opening price, high, low, and volume traded of each asset from 1 January 2015 to 8 August 2022 for designing the feature vectors used in SVM/FSVM.

- Dataset 1: Bovespa 90 (Brazil)

- Dataset 2: DAX 40 (Germany)
- Dataset 3: Dow Jones Industrial Average (U.S.A.)
- Dataset 4: EURO 50 (Europe)
- Dataset 5: FTSE 100 (U.K.)
- Dataset 6: Hang Seng (Hong Kong)
- Dataset 7: Nifty 100 (India)
- Dataset 8: Nikkei 400 (Japan)

Further, daily closing prices of the market index and its constituents are employed for PO through SSD. The number of assets for Datasets 1 to 8 is 71, 35, 29, 47, 94, 55, 80, and 379, respectively. Note that to prove the viability of the suggested strategy, we have made an effort to include significant marketplaces worldwide.

3.2 | Methodology

Table 1. Technical indicators for SVM and FSVM model.

Technical Indicators	Description
r_1	Rate of change of closing price taken over 1 time period, calculated as: $\frac{P_t^{(i)}-P_{t-1}}{P_{t-1}}$
r_3	Rate of change of closing price taken over 3 time periods, calculated as: $\frac{P_t-P_{t-3}}{P_{t-3}}$
SMA_5	Simple moving average of 5 time periods, calculated as $\frac{P_t+P_{t-1}+P_{t-2}+P_{t-3}+P_{t-4}}{5}$
EMA_5	Exponential moving average of 5 days, calculated as $P_t \times k$ $+EMA_{t-1} \times (1-k)$, where $k=\frac{2}{5+1}$
MACD	Moving average convergence/divergence, calculated as EMA_{12}-EMA_{26} ([34])
RSI_{14}	Relative strength index that indicates the weakness or strength of the price of a stock, calculated as $100-\frac{100}{1+\frac{\text{Average gain over a period of 14 days}}{\text{Average loss over a period of 14 days}}}$ ([35])
SO_{14}	Stochastic oscillator that indicates the signal of a stock being overbought or oversold, calculated as the SMA_3 of $\frac{P_t-L_{14}^{(ii)}}{H_{14}-L_{14}}$ ([34])
AD	Accumulation/distribution that indicates if the stock is being accumulated or distributed, calculated as $\frac{P_t-L_t^{(iii)}-(H_t-P_t)}{H_t-L_t} * V_j^{(iv)}$ ([36])
William % R	Similar to SO, it also indicates if the stock is overbought or oversold, calculated as $\frac{\text{Highest high of last 14 days} - P_t}{\text{Highest high of last 14 days-Lowest low of last 14 days}}$
MFI_{14}	Money flow index over indicates if the stock is overbought or oversold, calculated as $100-\frac{100}{1+\frac{\text{Positive money flow over 14 days}}{\text{Negative money flow over 14 days}}}$ where money flow is given by $\frac{H_t+C_t+L_t}{3} \times V_t$

$^{(i)}$ Here P_j is the closing price at time j $^{(ii)}$ L_{14} (H_{14}) is the lowest (highest) price over the last 14 days, $^{(iii)}$ L_t (H_t) is the lowest (highest) price at time period t, $^{(iv)}$ V_j is the volume traded at time period t

(i) **Feature selection**
Table 1 describes the technical indicators to be used as independent variables in SVM and FSVM models. We select the same technical indicators as used in [37] for feature selection in SVM and FSVM models.

(ii) **Feature scaling and principal component analysis**
For each feature, say x, feature scaling is done through the following process:

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}}.$$

The scaled features then go through the process of principal component analysis for feature reduction.

(iii) **Parameter selection**
We solve the SVM/FSVM model with several values of the regularisation parameter C and RBF kernel parameter σ. The value of the fuzzy membership function variable σ' is also varied. Table 2 summarizes the values of parameters taken for training the model.

Table 2. Values of different parameters in SVM / FSVM model.

Parameter	Values
C	1,5,10,20,100,500,1000
σ	0.2,0.4,0.6,0.8,0.9
σ'	0.1,0.2,0.4,0.6,0.8

(iv) **Decision about the dependent variable**
For each asset $i{=}1,2,...,n$, the dependent variable y_i in SVM and FSVM takes the value $+1$ if $r_{it}{\geq}0.002$ and $y_i{=}{-1}$ when $r_{it}{<}0.002$. Let us denote P_{it} as the i^{th} asset's closing price at time t. Then r_{it} is defined as $r_{it}{=}\frac{P_{it}-P_{i(t-1)}}{P_{i(t-1)}}$.

(v) **Fuzzy membership function**
While all data points are handled equally in SVM, many real-world classification problems may favor some data points over others. The fuzzy membership function in the FSVM framework assigns fuzzy membership values to individual data elements based on their relative importance. We can create a learning system in which current data points are given more weight than data points from distant periods. In this scenario, time is the main property; hence, the fuzzy membership value s_l can be expressed as a function of time t_l. Let $t_1{\leq}t_2{\leq}...,t_L$ is the time of the arrival of the point x_l, $l{=}1,2,...,L$. Since we wish to make the most recent observation x_L (arriving at time t_L) the most important and the first observation to be least important, we should choose $s_L{=}f(t_L){=}1$ and $s_1{=}f(t_1){=}\sigma'({>}0)$. Suppose we choose a linear fuzzy membership function, We use $s_l{=}f(t_l){=}at_l{+}b$ where a and b are constants and can be calculated using the conditions $s_L{=}f(t_L){=}1$ and $s_1{=}f(t_1){=}\sigma'$. The sequential arrival times of the points within the system are represented by $t_1{\leq}t_2{\leq}...,{\leq}t_L$ in this case, and the value of σ' we use is tuned between 0.1,0.2,0.4,0.6, and 0.8. The boundary requirements that we impose allow us to get

$$s_l = f(t_l) = \left(\frac{1 \quad \sigma'}{t_L \quad t_1}\right) t_l + \frac{t_l \sigma' - t_1}{t_L \quad t_1}$$

(vi) **Rolling window strategy and portfolio optimization**
The rolling window approach is what we use for empirical analysis. The SVM/FSVM model is first trained by taking a 180 day training period (let's say $[1,180]$) for each asset and a 1 day testing period (i.e., for the 181-th time point) to forecast the dependent variable's value. We shortlist the asset for the PO process using SSD if $y_i{=}{+1}$; if not, we reject the asset. The same 180 days ($[1,180]$) used to train the SVM/FSVM model are also used to train the shortlisted assets for PO with SSD. For the next sixty days ($[181,240]$), the optimal portfolios developed offer out-of-sample portfolio returns. We repeat this process, using 180 days of training time for the SVM/FSVM model from $[61,240]$ and a 1 day testing period. Once more, the aforementioned criteria are used for asset shortlisting. The assets that make the shortlist are trained on the SSD model for 180 days ($[61,240]$) with out-of-sample returns on $[241,300]$ time points. The out-of-sample returns from each window are concatenated after this technique is done 27 times, yielding 1620 ($27{\times}60$) out-of-sample optimal portfolio returns.

3.3 | Performance Measures

The out-of-sample returns from all rolling windows are concatenated to perform the comparative analysis on the basis of the following measures. With $t{=}1,...T_1$, which represents the total number of out-of-sample data points, let r_t be the out-of-sample returns.

- Average: Out-of-sample mean returns calculated as $\hat{r}{=}\sum_{t=1}^{T} r_t/T_1$.
- Median: Out-of-sample median returns.
- Min: Minimum out-of-sample return, i.e., min= $\min_{t=1,\ldots,T_1} r_t$
- Max: Maximum out-of-sample returns, i.e., max= $\max_{t=1,\ldots,T_1} r_t$

- SD: Out-of-sample standard deviation given by SD = $\sqrt{\frac{\sum_{t=1}^{T_1}(r_t-\hat{r})^2}{(T_1-1)}}$
- $\text{VaR}_{0.95}$: Out-of-sample value at risk (VaR) at confidence level 0.95.
- $\text{CVaR}_{0.95}$: Out-of-sample conditional value at risk ([4]) at confidence level 0.95.
- SR: Sharpe ratio (SR) ([38]) is defined as the ratio of excess average returns over the risk-free returns and the standard deviation, SR=$\frac{\hat{r}-r_f}{SD}$. This ratio is defined only when $\hat{r}>rf$. For convenience, we take $r_f=0$.
- STARR: Stable Tail-Adjusted Return Ratio (STARR) is defined in a similar manner as SR, except the risk measure used to compute STARR is taken as CVaR_α, i.e., STARR=$\frac{\hat{r}-r_f}{CVaR_\alpha}$. Again the ratio is defined only when $\hat{r}>r_f$ and $CVaR_\alpha>0$. We take $\alpha=0.95$
- Sortino: Sortino is defined as follows: $Sortino=\frac{E(R_p)-r_f}{\sigma_d}$ where $E(R_p)$ is the expected portfolio return and σ_d is the downside risk standard deviation.

For convenience and comparison purposes, we take $r_f=0$.

3.4 | Out-of-Sample Analysis

Tables 3,4, 5 and *6* report the performance results of the out-of-sample returns on all eight data sets. We compare the performance of FSVM_SSD with SVM_SSD and SSD in the following subsections.

3.4.1 | Comparison analysis FSVM_SSD with SVM_SSD

Constructive results are seen for the proposed FSVM_SSD model in comparison to the SVM_SSD model, especially in terms of average returns and performance ratios, namely STARR, SR, and Sortino. Seven out of eight data sets generate higher average returns, and all risk-adjusted performance ratios are considered in the paper. This pattern is not seen in only one market, EURO 30, where SVM_SSD yields positive average returns and thus well-defined performance ratios, whereas FSVM_SSD generates negative average returns. A notable difference in average returns between SVM_SSD and FSVM_SSD is especially seen in Bovespa 90, Dow Jones, and Hang Seng, wherein average returns of FSVM_SSD are substantially higher than SVM_SSD.

A comparison of risk (SD, Min, VaR, CVaR) generated by optimal portfolios from both models indicates mixed results, as we note lower risk values in DAX 40, Dow Jones, Euro 30, and Nifty 100 for FSVM_SSD, whereas SVM_SSD achieves less risk in only two datasets, namely Bovespa 90 and Hang Seng. In the other two datasets, FTSE 100 and Nikkei 400, we note mixed or very close risk values from both models.

Overall, the proposed model FSVM_SSD has the capacity to perform well by achieving high returns and performance ratios in comparison to the SVM_SSD model. This clearly indicates the significance of introducing fuzziness in the SVM model for the purpose of portfolio selection.

3.4.2 | Comparison analysis of FSVM_SSD with SSD

Comparison of the PO model with SSD measure without shortlisting and FSVM_SSD again indicates outperformance of the FSVM_SSD model. The model generates high out-of-sample average returns in seven out of eight datasets, thereby making the proposed model a preferred choice for return-seeking investors. Shortlisting through fuzzy SVM generates portfolios that yield higher performance ratios (STARR, SR, Sortino) in contrast to the simple SSD model in seven datasets. At the same time, we also note an overall low risk in almost all datasets in the portfolio from the FSVM_SVM model.

The above results clearly indicate the advantages of the FSVM_SSD model over the SSD model, as the proposed model outperforms the latter in terms of all metrics over almost all datasets.

Summarizing the above results, we note that the optimal portfolios from the FSVM_SSD model achieve the best results among all the considered models and have clear financial benefits. These observations indicate two important results: (1) There is a special requirement to shortlist assets while obtaining portfolios through the optimization process. This is required to discard assets that may otherwise give small weights in the optimal portfolio and thus generate inferior out-of-sample results. (2) The importance of fuzziness in FSVM over the SVM model for financial decision-making is clearly justified by the above results. The effect of the outlier is significantly reduced through fuzzy SVM and thus recommended over the SVM model.

Table 3. Out-of-sample performance metrics (×103) for Bovespa 90 and DAX 40.

	Bovespa 90			DAX 40		
Metric	SSD	SVM_SSD	FSVM_SSD	SSD	SVM_SSD	FSVM_SSD
Average	0.70724	0.48654	**1.16257**	0.68668	0.54338	**0.70701**
Median	**1.48222**	0.57274	1.43522	**0.88123**	0.61624	0.84138
Min	**-199.06**	-173.69	-177.02	-147.73	**-174.49**	-123.6
Max	**165.795**	96.9396	115.943	100.333	**118.527**	109.207
SD	22.8727	**20.2449**	21.6447	17.0165	15.8031	**15.2618**
STARR	13.5335	10.5838	**24.5534**	17.4077	14.486	**19.8813**
SR	30.9207	24.0328	**53.7118**	40.3536	34.3842	**46.3255**
Sortino	29.4989	22.9702	**52.0328**	38.9058	32.843	**45.2844**
$VaR_{0.95}$	35.4202	**30.6635**	31.4509	25.4243	24.9701	**23.5566**
$CVaR_{0.95}$	52.2584	**45.9704**	47.3488	39.4467	37.5104	**35.5615**

Table 4. Out-of-sample performance metrics (×103) for Dow Jones and Euro 30.

	Dow Jones			Euro 30		
Metric	SSD	SVM_SSD	FSVM_SSD	SSD	SVM_SSD	FSVM_SSD
Average	0.7058	0.41797	**0.7284**	-0.0059	**0.23247**	-0.0872
Median	1.24451	0.77923	**1.25279**	-0.1788	**-0.0834**	-0.3186
Min	-102.46	**-132.37**	-109.04	-60.231	-71.62	**-86.789**
Max	90.3699	**176.122**	164.093	**127.269**	**127.269**	**127.269**
SD	14.9743	16.208	**14.1061**	12.9017	13.5087	**12.8866**
STARR	20.128	10.8922	**22.3129**	-	8.32479	-
SR	47.134	25.7876	**51.637**	-	17.2088	-
Sortino	45.3078	25.3214	**50.4085**	-	18.6657	-
$VaR_{0.95}$	21.8689	22.9638	**19.2402**	19.7234	19.6167	**19.364**
$CVaR_{0.95}$	35.0657	38.3731	**32.6448**	27.9692	27.925	**27.1466**

Table 5. Out-of-sample performance metrics (×103) for FTSE 100 and Hang Seng.

	FTSE 100			Hang Seng		
Metric	SSD	SVM_SSD	FSVM_SSD	SSD	SVM_SSD	FSVM_SSD
Average	0.62021	0.7038	**0.97672**	0.71697	0.49174	**0.8732**
Median	**0.94979**	0.75923	0.84329	**1.05883**	0.07318	0.85566
Min	-130.08	-154.467	**-154.47**	**-150.86**	-128.302	-142.881
Max	127.683	**156.747**	**156.747**	142.858	95.9608	89.1172
SD	**16.9561**	18.2721	18.303	19.0384	**17.2749**	17.3861
STARR	15.0093	17.277	**24.1022**	16.1645	13.2587	**22.7828**
SR	36.5774	38.5179	**53.3639**	37.6593	28.4656	**50.2244**
Sortino	34.8759	39.3999	**54.8117**	36.3344	29.1699	**50.2722**
$VaR_{0.95}$	23.3324	23.8204	**22.9315**	28.9664	**26.5169**	26.5211
$CVaR_{0.95}$	41.3218	40.7366	**40.5241**	44.3548	**37.0879**	38.3274

Table 6. Out-of-sample performance metrics (×103) for Nifty 100 and Nikkei 400.

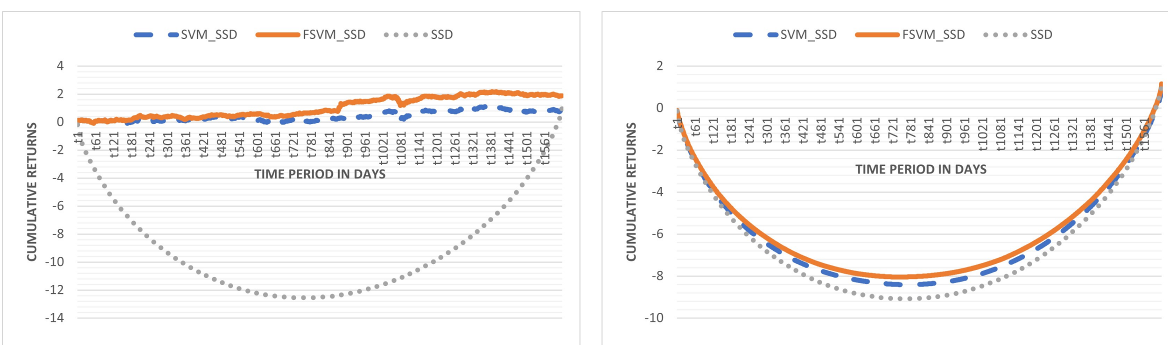
	Nifty 100			Nikkei 400		
Metric	SSD	SVM_SSD	FSVM_SSD	SSD	SVM_SSD	FSVM_SSD
Average	0.98832	0.95467	**1.10977**	0.43595	0.6907	**0.92434**
Median	0.81429	**1.09395**	0.7567	0.24633	**1.06906**	1.21797
Min	**-90.567**	**-90.5673**	**-90.567**	**-107.58**	-72.0266	-87.7442
Max	**99.0492**	**99.0492**	**99.0492**	91.0586	**98.6199**	**98.6199**
SD	15.502	15.0416	**14.9661**	20.0387	18.0772	**17.7729**
STARR	28.808	28.4782	**33.8102**	9.60011	17.4845	**24.0506**
SR	63.7542	63.4687	**74.1524**	21.7556	38.2082	**52.0086**
Sortino	64.8276	63.2067	**76.243**	21.7302	38.3919	**51.8057**
$VaR_{0.95}$	24.1065	22.7496	**22.557**	31.7529	**28.3863**	28.5691
$CVaR_{0.95}$	34.307	33.5229	**32.8236**	45.4113	39.5035	**38.4332**

4 | Observation

The cumulative returns per model for the out-of-sample period are displayed in *Fig. 1a* for Dataset 1 (Bovespa 90), *Fig. 1b* for Dataset 2 (DAX 40), *Fig. 2a* for Dataset 3 (Dow Jones), and *Fig. 2b* for Dataset 4 (Euro Stoxx 50). Their respective box plots per model are shown in *Fig. 5a*, *Fig. 5b*, *Fig. 6a*, and *Fig. 6b*, respectively.
Fig. 1a depicts that the cumulative returns (CR) of Bovespa 90 and the CR of the FSVM_SSD model are positively increasing, while the CR of the SSD model is negatively increasing, and clearly the CR of the FSVM_SSD model is superior to the SVM_SSD and SSD models. *Fig. 1b* depicts the cumulative returns (CR) for the DAX 40 dataset, *Fig. 2a* for the Dow Jones, *Fig. 2b* for the Euro Stoxx 50, *Fig. 3a* for the FTSE 100, *Fig. 3b* for the Hang Seng 57, *Fig. 4a* for the Nifty 100, and *Fig. 4b* for the Nikkei 400. In all these figures, the CR of all three models shows a downward trend, but the FSVM_SSD model consistently outperforms both the SVM_SSD and SSD models.

The cumulative returns per model for the out-of-sample period for Dataset 5 to Dataset 8 are shown in *Fig. 3a* for FTSE 100, *Fig. 3b* for Hang Seng 57, *Fig. 4a* for Nifty 100, and *Fig. 4b* for Nikkei 400. Their respective box plots per model are presented in *Fig. 7a*, *Fig. 7b*, *Fig. 8a*, and *Fig. 8b*.

Fig. 5a illustrates the box plot (BP) of the Bovespa 90 dataset, where the FSVM_SSD model clearly outperforms the SVM_SSD and SSD models. Similarly, *Fig. 5b* for DAX 40, *Fig. 6a* for Dow Jones, *Fig. 6b* for Euro Stoxx 50, *Fig. 7a* for FTSE 100, *Fig. 7b* for Hang Seng 57, *Fig. 8a* for Nifty 100, and *Fig. 8b* for Nikkei 400 show that the FSVM_SSD model consistently produces superior box plot results compared to the SVM_SSD and SSD models.

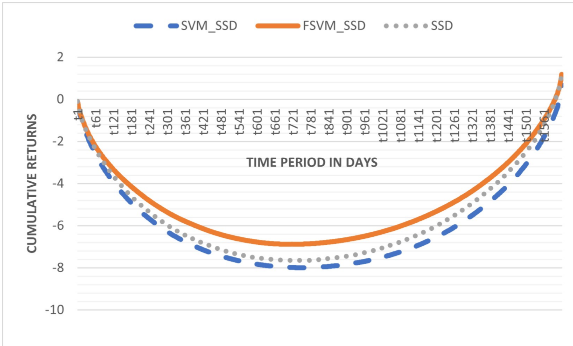


(A) Bovespa 90 Cumulative Returns per model. (B) Dax 40 Cumulative Returns per model.

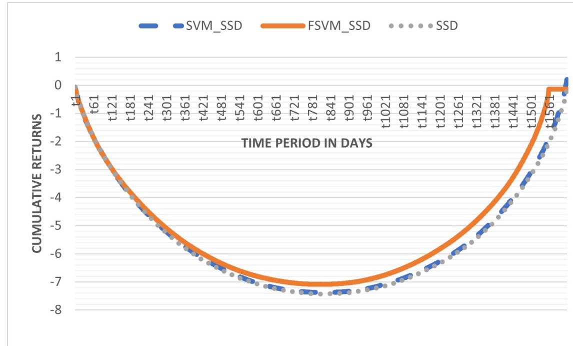
Fig. 1. Cumulative Returns per model for Bovespa 90 and Dax 40.

5 | Conclusions

In summary, the coupling of machine learning (ML) algorithms with traditional portfolio optimization (PO) models gives rise to a robust avenue toward optimizing contemporary investment decision-making. By utilizing Fuzzy Support Vector

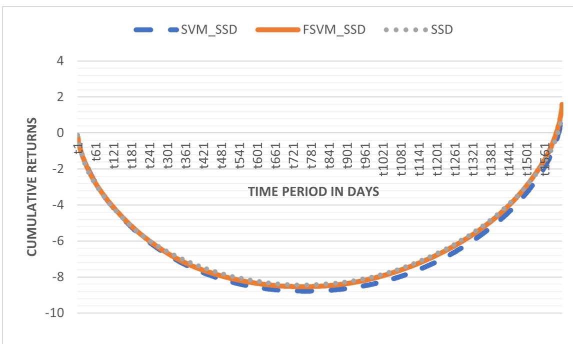


(A) Dow Jones Cumulative Returns.

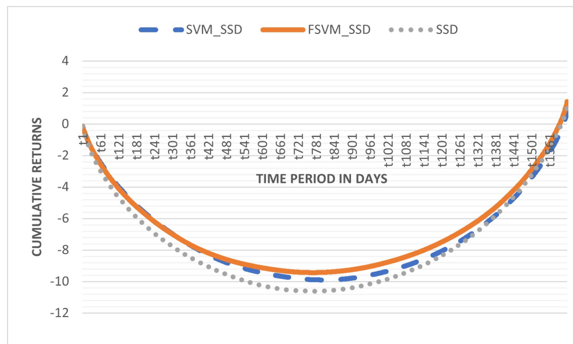


(B) EURO 50 Cumulative Returns per model.

Fig. 2. Cumulative Returns per model for Dow Jones and EURO 50.

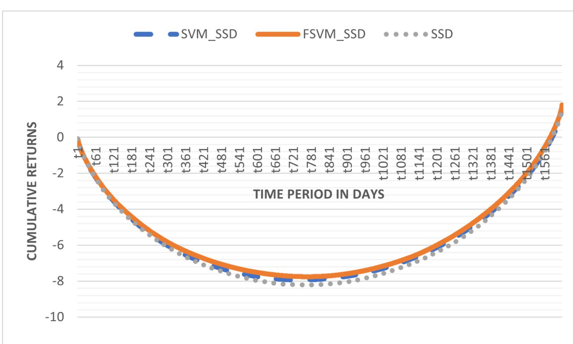


(A) FTSE 100 Cumulative Returns per model.

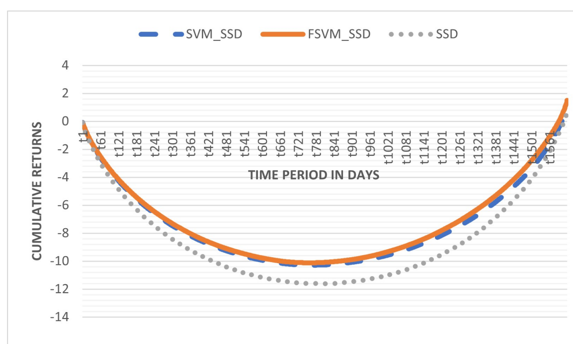


(B) Hang Seng 57 Cumulative Returns per model.

Fig. 3. Cumulative Returns per model for FTSE 100 and Hang Seng 57.



(A) Nifty 100 Cumulative Returns per model.

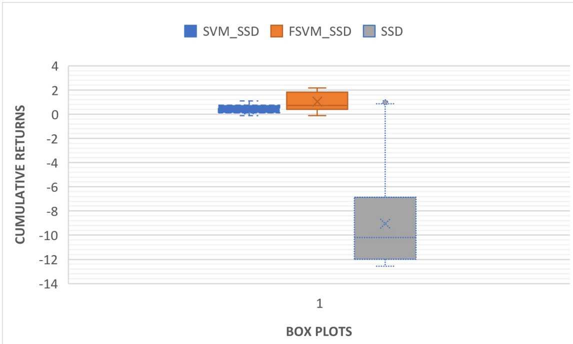


(B) Nikkei 400 Cumulative Returns per model.

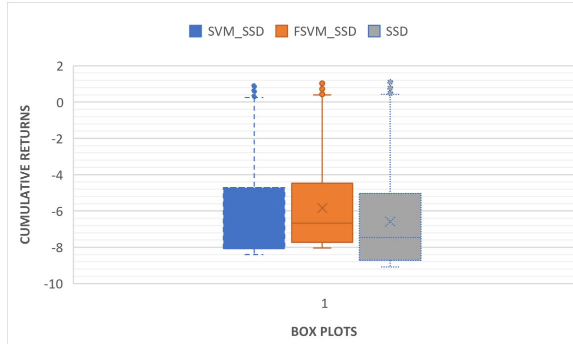
Fig. 4. Cumulative Returns per model for Nifty 100 and Nikkei 400.

Machines (FSVM) for smart shortlisting of assets, complemented by optimization subject to dominance-based constraints for maximum returns, this study takes portfolio construction methods a step forward. The empirical comparison in eight global markets is shown here to establish the universal dominance of the developed FSVM–SSD approach over traditional methods. Portfolios developed by the use of machine learning techniques based on asset preselection are found to have significantly better returns and stability, which points towards the key role that data-driven preprocessing plays in achieving maximum portfolio efficiency.

Performance tests, including mean returns, Value at Risk (VaR), Conditional Value at Risk (CVaR), and the Sharpe, Sortino, and STARR ratios, confirm the superiority of the proposed model. Moreover, a comparison between fuzzy and

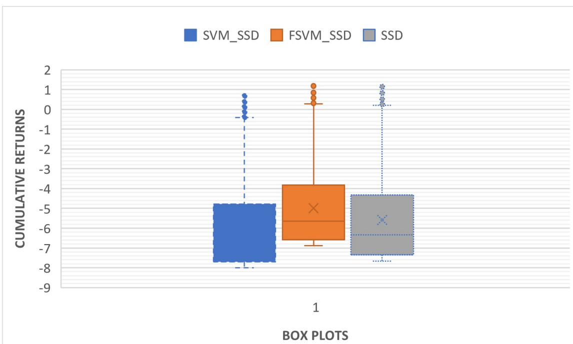


(A) Daily Returns Box Plot of Bovespa 90.

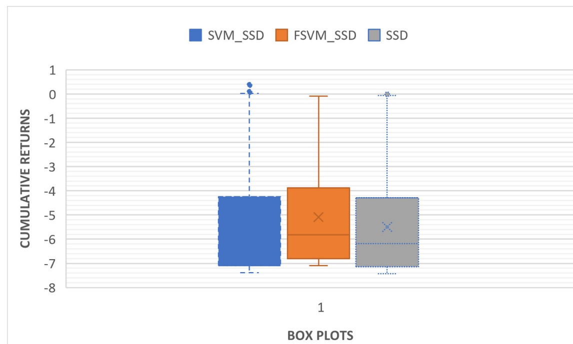


(B) Daily Returns Box Plot of Dax 40.

Fig. 5. Daily Returns Box Plot for Bovespa 90 and Dax 40.

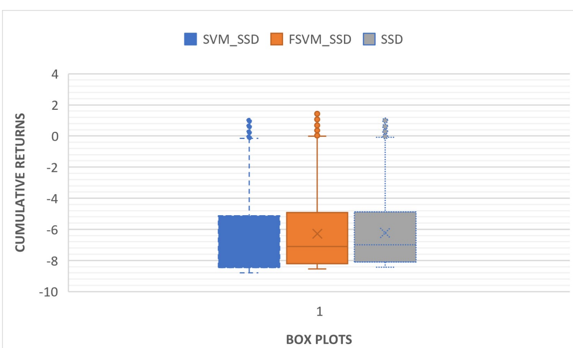


(A) Daily Returns Box Plot of Dow Jones.

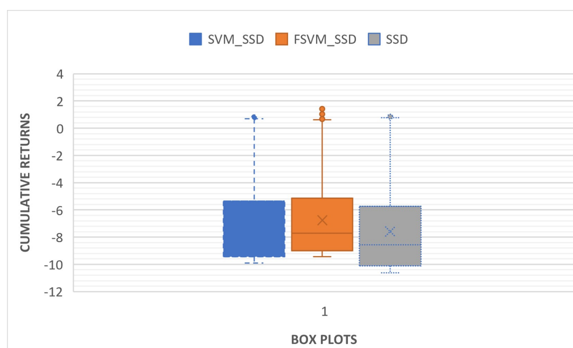


(B) Daily Returns Box Plot of Euro 50.

Fig. 6. Daily Returns Box Plot for Dow Jones and Euro 50.



(A) Daily Returns Box Plot of FTSE 100.



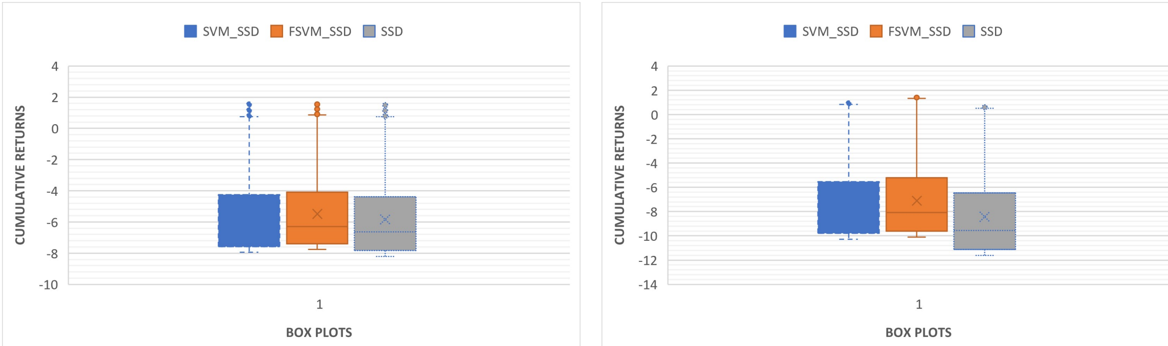
(B) Daily Returns Box Plot of Heng Seng.

Fig. 7. Daily Returns Box Plot for FTSE 100 and Hang Seng.

conventional SVM-based methods demonstrates that the fuzzy SVM yields superior flexibility and stability in changing financial environments to yield superior decision-making outcomes.

Portfolios constructed through ML-based asset preselection are revealed to possess significantly better returns and stability, underscoring the critical contribution made by data-driven preprocessing in achieving optimal portfolio efficiency.

Also, performance assessments confirm the validity and reliability of the proposed model. Furthermore, a comparison between fuzzy and conventional SVM-based decisions shows that the fuzzy counterpart offers greater flexibility and robustness under changing financial environments, leading to improved decision-making outcomes.



(A) Daily Returns Box Plot of Nifty 100. (B) Daily Returns Box Plot of Nikkei 400.

Fig. 8. Daily Returns Box Plot for Nifty 100 and Nikkei 400.

Broadly, the study indicates the need for merging ML algorithms with risk-sensitive optimization approaches like SSD to build adaptive and dominance-consistent portfolios. Emerging studies in the future will focus on integrating additional machine learning classifiers—such as ensemble and deep learning models—into portfolio optimization tools for increased predictive power, risk management, and computational effectiveness in evolving financial markets. In addition, efforts will be made to generalize this study into multi-class classification and fuzzy LSSVM models and subsequently into regression-based approaches, thereby providing a broader and richer research overview.

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Author Contribution

Simrandeep Kaur: writing, software, editing, and analysis. Ruchika Sehgal: methodology and writing. Arti Singh: editing and analysis. Abha Aggarwal: editing and analysis. All authors have read and agreed to the published version of the manuscript.

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Data Availability

All data supporting the reported findings in this research paper are provided upon request to the authors.

Conflicts of Interest

The authors declare that there is no conflict of interest concerning the reported research findings.

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