IFA
Iranian Journal of Finance
Print ISSN 2676-6337
Online ISSN 2676-6345

Evaluation and comparison net assets value of joint investment funds using support machine models versus statistical models - A case study from FEAS member countries

Leila Nateghian

Ph.D. Candidate, Department of Accounting, Urmia Branch, Islamic Azad University, Urmia, Iran. (Email: lnateg99@yahoo.com)

Saeid Jabbarzadeh Kangarlouei*

*Corresponding Author, Associate Prof., Department of Accounting, Urmia Branch, Islamic Azad University, Urmia, Iran. (Email: s.jabbarzadeh@iaurmia.ac.ir)

Jamal Bahri Sales

Associate Prof., Department of Accounting, Urmia Branch, Islamic Azad University, Urmia, Iran. (Email: j.bahri@iaurmia.ac.ir)

Parviz Piri

Associate Prof., Department of Accounting, Urmia University, Urmia, Iran. (Email: p.piri@urmia.ac.ir)

Iranian Journal of Finance, 2023, Vol. 7, No.4, pp. 142-160.
Publisher: Iran Finance Association
doi: https:// 10.30699/ijf.2023.376186.1389
Article Type: Original Article

Received: May 07, 2022
Received in revised form: September 07, 2022
Accepted: June 26, 2023
Published online: December 12, 2023

Abstract

Today, choosing the suitable model for determining the portfolio of investment in financial assets is one of the critical issues of the attention of analysts and capital market activists, and investing in a portfolio consisting of mutual investment funds is the same. With this statement, the purpose of the article is to evaluate and compare the net assets value (return) of the Federation of Asian and European Stock Exchanges (FEAS) member countries by using support machine models in comparison with statistical models. The statistical and sample population included the data of 39 selected traded funds and FEAS members from 12 selected countries (including Iran) between 2014 and 2021.

The data related to the mentioned funds were classified and analyzed using spss-modeler, rapid miner, and Weka software. They were tested with 24 support machine methods and 11 statistical methods, and the results showed that the prediction accuracy of statistical models is lower than that of support machine models. The Mann-Whitney test was used to determine the significance of this difference. Also, the results show that at the 95% confidence level, it can be claimed that the prediction accuracy of machine learning models is higher than statistical models. The average rating of machine learning models was (20.86) much higher than statistical models (10.85).

Keywords: mutual funds of Tehran Stock Exchange, support vector machine, return of investment fund

Introduction

Today, globalization has become an essential issue in different societies. Globalization is a dynamic movement that covers all economic aspects or is affecting them. One of the most important effects of globalization is the structural transformation in the world economy, which provides economic interdependence and the conditions for creating a global economic village. For developing countries not ready to enter the global arena and free trade in the short term, economic convergence and the formation of regional trade blocs can be the most effective way to open up the economy and integrate it into the global economy. Following this trend and regionalism, unions have been formed all over the world for the integration of financial markets. One of the issues considered by these unions and federations is the issue of economic convergence among countries that invest in cross-border markets. Creating the right portfolio requires choosing the suitable model between support vector machine models and statistical models.

Based on this and according to the theory of Harry Markowitz, by investing in various funds and financial assets of different countries instead of using the financial assets of one country, investors will enjoy the benefits of diversification, reducing risk, and increasing returns. On the other hand, due to the growing trend of economic globalization and the need for a more comprehensive presence of countries in international arenas, regional cooperation has been on the agenda of policymakers and governments in the past two decades. The importance of using investment baskets in the portfolio is evident in this regard.

Therefore, the importance of diversifying investment funds with professional management and forming efficient portfolios is more visible. Investors seek to maximize their returns. The Markowitz model is obtained by using the weighted average of the return of each share. However, the critical issue in optimization in recent years is the return estimation, which has become a significant challenge for investors. Meanwhile, the basic econometric models of the moving average process are widely used in estimating and predicting returns according to past returns. With the introduction of the initial model of time series and subsequent statistical models and support machines, today, investors and cross-border and international market activists can use the two categories of recent models in choosing their investment portfolio, which in this article will compare the efficiency of the mentioned models. It has been paid in selected member countries of FEAS. Uncertainty regarding yield fluctuations is one of the other issues of investment portfolio selection that investors seek to predict using information related to past fluctuations in order to reduce the uncertainty related to risk using past information for themselves. For the first time, Markowitz placed the risk category next to yield as an important variable in choosing an investment portfolio and considered standard deviation as a dispersion index, a numerical measure of risk. In this theory, investors should choose an optimal securities portfolio from among the portfolio of securities available on the efficient frontier, according to the contact level of their utility function with the efficient frontier. However, in the ultra-modern portfolio theory, based on the relationship between return and unfavorable risk, the investor's behavior is explained, and the optimal portfolio selection is discussed. The need of investors to solve the uncertainty about the future has led them to seek to use various methods to resolve uncertainty. In the meantime, value at risk is one of the most famous indicators for measuring adverse risk. By removing the assumptions related to other risk metrics, the criterion could be superior to the rest. Investing in optimization models, investors seek to choose the best model for estimating the combination of investment returns from the support machine models and statistical models in determining the optimal portfolio of investment funds (Lin Chang et al., 2008). With this explanation, in this article, 24 support vector machine models have been compared with 11 statistical models. The analysis and implementation of different portfolio modes in mutual investment funds is slightly different from that of stocks, and according to the nature of the investments mentioned above, which are considered low-risk bonds, and on the one hand, the development of international and cross-border markets, the selection of the optimal combination One of the investment funds in different countries and their estimation and implementation can be of great help to many international financial market participants in making investment decisions and choosing the right combination in different countries.

Regarding what was mentioned, the most critical issue of this article is whether the different advanced and statistical investment estimation models have the same portfolio optimization power. Furthermore, studying the literature review, I found that much research was done in the scope of this research, but most of them are organized in capital stock, not in ETFs. So, the theoretical framework and practical dimensions of machine value estimating models in the capital market consider joint venture fund investments.

Literature Review

Mutual investment funds are among the financial instruments in the capital markets, which are considered as a means of managing risk and diversifying financial assets. It invests investors' funds in a diverse portfolio of securities and hands over its investment units to them. Each investment unit of the fund represents a percentage of the securities portfolio that the fund buys and manages on behalf of investors. Investing through mutual funds leads to better decisions to avoid extreme price fluctuations in the capital market, so these funds play an essential role in the country's economy. According to the existence philosophy of these funds, which is to collect small savings but on a large scale, the development of these funds plays an essential role in collecting stagnant savings by the stock market and increasing liquidity in productive activities and by Economic prosperity and inflation reduction play a role (Roshangarzadeh & Rezaei, 2011). Joint venture investments and ETFs have a particular structure in any stock market. The main view of them and practical framework is:

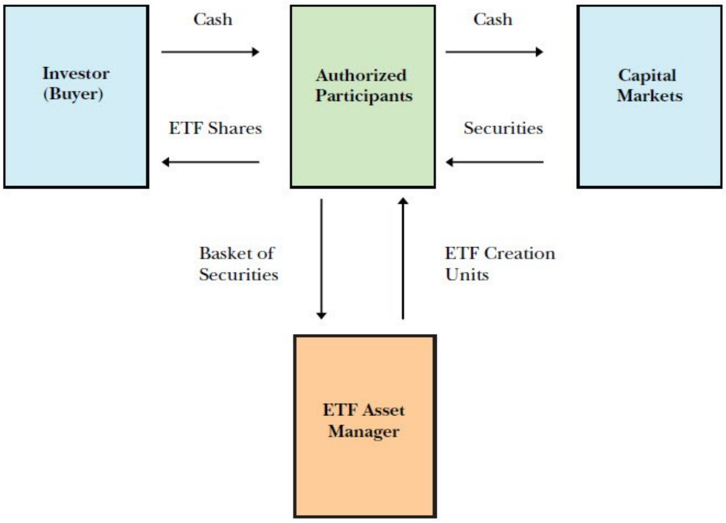

Fig. 1. The ETF Architecture (Martin & Ananth, 2018)

Chen (2022), in research entitled "Value at risk in mutual fund portfolio disclosure," concluded that the funds that have positive price dispersion in the selected portfolio assets have poor performance and are among the funds that tend to report aggressively and keep most of the stocks exposed to old prices. Stocks of more companies before the initial public offering experience net outflows and tend to experience price dispersion again in the next three months, which is significant in a volatile market. Hsiu-Lang. Ch (2022), in research about valuation risk in mutual fund portfolio disclosure, showed that an equity fund that has positive price dispersion in its portfolio holdings, that performs poorly, that belongs to a fund family with an inclination for aggressive reporting, that holds more stocks subject to stale prices, that holds more pre-IPO firms, or that experiences net outflows will tend to show positive price dispersion again in the next quarter.

Sedaghati et al. (2022), in research, entitled "Comparison of optimal portfolio efficiency based on value at risk and optimal potential with conventional models", concluded that updating the model, the efficient frontier, and also using the criterion of value at risk and paying attention to the investor's tendencies in terms of the desire for favorable potentials and risk aversion leads to the improvement of the efficiency of the optimal portfolio.

Chunying et al. (2021), in research about performance between ETFs and traditional index funds, concluded that ETFs have relatively better performance than index funds, both pre-expense and post–expense. Further examination shows that the decentralization effect of ETF during the turbulent period is greater than that of index funds. However, the benefits of diversification through this investment vehicle are limited. Sheidaei et al. (2021), in a research on the capability of network matrix strategy and neural genetic fuzzy model in optimizing the stock investment portfolio of Tehran stock exchange companies, designed and presented a stock investment portfolio optimization model with the use of adaptive neural fuzzy inference system and its combination with genetic algorithm and in the mentioned model, two different categories of technical and fundamental variables were used as model inputs. The research results show that these systems can optimize the stock portfolio. Therefore, a hybrid model of neural networks and fuzzy reasoning theory, along with a genetic algorithm, was used in order to weigh the influential factors in stock portfolio optimization. Raei et al.(2020), in an article titled "Optimization of the Stock Portfolio using the Mean-CVaR Method and the Symmetric and Asymmetric Conditional Variance Heterogeneity Approach," showed that considering the variance heterogeneity in the financial market of Iran and Doing this in the optimization models leads to better performance in the optimization of investment portfolios and also the results showed that the use of CVAR model instead of traditional risk models is significantly effective in improving the performance of these funds. Ramoz et al. (2020), in research titled "Choosing the Optimal Portfolio using the consensual planning model in the Tehran Stock Exchange," showed that using the consensual planning model leads to optimal choices with less risk. Therefore, it can be concluded that the portfolios resulting from applying the consensual planning model are more suitable for investment selection.

Tsolas (2019) used a combination of two gray relationship analysis (GRA) and data coverage analysis methods to select the best exchange-traded investment fund (ETF) in research. For this purpose, they used the information of tradable investment funds in the Greek stock exchange from 2008 to 2010. The results showed that the best ETFs identified by the GRA-DEA approach also have efficient DEA. The proposed GRA-DEA method is superior to conventional DEA in terms of fund ranking and, therefore, is effective as an effective fund selection tool. Ahmadi et al. (2019) optimized the stock portfolio using the EVAR method. The result of their research indicates that the portfolio obtained based on the EVAR method has a better performance compared to the CVAR method.

Paitakhti et al. (2019) showed that the highest weight in the optimal portfolio belongs to stocks with a high expected return and the lowest value at risk in the statistical population. Eghbal Nia and Daliran (2019) investigated a new meta-heuristic algorithm called the unconscious search algorithm to optimize the stock portfolio. To check the strength and accuracy of solving the algorithm, they examined the information of the top 50 companies of the Tehran Stock Exchange. Its results were compared with the algorithms of cumulative movement of particles and genetics, which shows this algorithm's superiority in the stock portfolio optimization problem. It has higher stability than similar research, and the standard deviation of its objective function is lower than others.

Khalifa et al. (2018) argued about supporting Vector Machine for a new Hybrid Information Retrieval System, and the results showed that a series of experiments through Yahoo's databased hybrid information retrieval system returned significantly satisfying results.

Fattahi et al. (2018), in an article about choosing the optimal stock portfolio by using value-based information and balanced evaluation card information, concluded that the criteria used in preparing the optimal stock portfolio have informational content and the addition of each category of criteria leads to an increase in the desirability of the stock portfolio. In an article, Sanzo (2018) measured crude oil yield fluctuations using long-term memory and switching models. The research results indicate that the out-of-sample forecasts of crude oil yield fluctuations using the MS-ARFIMA model are better compared to the MA-GARCH model. Also, time series long-term memory models using the switching approach have better results than the MS-GARCH model. Pour Zamani (2017), with a research entitled "Efficiency of risk criteria in ultra-modern portfolio theory in mutual investment funds during the commercial boom," showed that in the Iranian capital market, there is a significant correlation between the performance of mutual investment funds based on the perspective ratio, omega ratio and return. There is no significant difference between mutual investment fund ratings based on outlook ratio, omega ratio, and actual return during the boom period.

Fallah Shams and Alavi (2016) sought to select the optimal portfolio by using a rule-based fuzzy expert system. For this purpose, a rule-based fuzzy expert system was made to support investment managers in their mid-term investment decisions. The performance of the proposed expert system has been analyzed in terms of risk tolerance and the length of the investment period compared to the market average. The results show that the proposed expert system performs better than the market in most cases and performs better for risk-averse investors in the medium term. Fallah Pour et al. (2013) investigated ‘Prediction of stock price movements using support vector machine based on genetic algorithm in Tehran Stock Exchange.' They concluded that the combination model of support vector machine based on genetic algorithm performed much better in predicting the movement trend of stock prices, and compared to the simple support vector machine method, it has higher accuracy. Chang and Lee (2012) investigated the issue of choosing a suitable portfolio of projects. Their focus was on solving the problem that organizations are facing limitations in using capital resources, and therefore, modeling based on data envelopment analysis, formulation, and fuzzy set theory was used to solve this problem. Using this model and the bee colony algorithm in artificial intelligence, a comparative process regarding the optimization issue regarding ambiguous issues in the industry was investigated, and the efficiency of using the colony model was emphasized.

Table 1. The summary of the articles

Author	year	Title	result
Chang and Lee	2012	A Fuzzy DEA and Knapsack formulation model for project selection	Using the model based on data envelopment analysis and the bee colony algorithm in artificial intelligence, a comparative process regarding the optimization issue regarding ambiguous issues in the industry was investigated, and the efficiency of using the colony model was emphasized.
Fallah Pour et al.	2013	Prediction of stock price movements using support vector machine based on genetic algorithm in Tehran Stock Exchange	The combination model of support vector machine based on a genetic algorithm performed much better in predicting the movement trend of stock prices, and compared to the simple support vector machine method, it has higher accuracy.
Fallah Shams and Alavi	2016	Portfolio Optimization, Using Fuzzy Rule-Based Expert System	In most cases, the proposed expert system performs better than the market, and its performance is better for risk-averse investors in the medium term.
Pour Zamani	2017	Efficiency of risk criteria in ultra-modern portfolio theory in mutual investment funds during the commercial boom	In the Iranian capital market, a significant correlation exists between the performance of mutual investment funds based on the perspective ratio, omega ratio, and return. There is no significant difference between mutual investment fund ratings based on outlook ratio, omega ratio, and actual return during the boom period.
Fattahi et al.	2018	Selection of optimal stock portfolios using accounting information, value-based information, and balanced scorecard information	The criteria used in preparing the optimal stock portfolio have informational content, and the addition of each category of criteria leads to an increase in the desirability of the stock portfolio.

Khalifi et al.	2018	Support Vector Machine for a new Hybrid Information Retrieval System	A series of experiments through the Yahoo databased hybrid information retrieval system returned significantly satisfying results
Sanzo	2018	A Markov switching extended memory model of crude oil price return volatility	The out-of-sample forecasts of crude oil yield fluctuations using the MS-ARFIMA model are better than the MA-GARCH model. Also, time series long-term memory models using the switching approach have better results than the MS-GARCH model.
Ahmadi et al.	2019	Portfolio optimization with entropic value-at-risk	The portfolio obtained based on the EVAR method performs better than the CVAR method.
Eghbal Nia and Daliran	2019	Stock portfolio optimization using a subconscious search algorithm	The algorithm's superiority in the stock portfolio optimization problem is that it has higher stability than similar research, and the standard deviation of its objective function is lower than others.
Paitakhti et al.	2019	Optimal stock portfolio using at-risk value criterion: Evidence from Tehran Stock Exchange	The optimal portfolio's highest weight belongs to stocks with a high expected return and the lowest value at risk in the statistical population.
Tsolas	2019	Utility Exchange Traded Fund Performance Evaluation. A Comparative Approach Using Grey Relational Analysis and Data Envelopment Analysis Modelling	The best ETFs identified by the GRA-DEA approach have efficient DEA. The proposed GRA-DEA method is superior to conventional DEA in terms of fund ranking and, therefore, seems to be effective as an effective fund selection tool.
Raei et al.	2020	Optimization of the stock portfolio using the Mean-CVaR method and the symmetric and asymmetric conditional variance heterogeneity approach.	With the variance heterogeneity in the financial market of Iran, doing this in the optimization models leads to better performance in the optimization of investment portfolios. Using the CVAR model instead of traditional risk models is significantly effective in improving the performance of the funds.
Ramoz et al.	2020	Choosing the optimal portfolio using the consensual planning model in the Tehran Stock Exchange	Using the consensual planning model leads to optimal choices with less risk, and the portfolios resulting from the application of the consensual planning model are more suitable for investment selection.
Chunying et al.	2021	Performance comparisons between ETFs and traditional index funds: Evidence from China	The ETFs have relatively better performance than the index funds, both pre-expense and expense, and the decentralization effect of ETF during the turbulent period is greater than that of index

			funds. However, the benefits of diversification through this investment vehicle are limited.
Sheidaei et al.	2021	Optimization of Network-Based Matrix Investment Portfolio and Comparison with Fuzzy Neural Combination Pattern and Genetic Algorithm	The use of an adaptive neural fuzzy inference system and its combination with a genetic algorithm have the ability to optimize the stock portfolio.
Chen	2022	Value at risk in mutual fund portfolio disclosure	The funds that have positive price dispersion in the selected portfolio assets have poor performance and are among the funds that tend to report aggressively and keep most of the stocks exposed to old prices. Stocks of more companies before the initial public offering experience net outflows and tend to experience price dispersion again in the next three months.
Hsiu-Lang.Ch	2022	Valuation Risk in Mutual Fund Portfolio Disclosure	An equity fund that has positive price dispersion in its portfolio holdings that performs poorly that belongs to a fund family with an inclination for aggressive reporting, that holds more stocks subject to stale prices, that holds more pre-IPO firms, or that experiences net outflows will tend to show positive price dispersion again in the next quarter.
Sedaghati et al.	2022	Comparison of optimal portfolio efficiency based on value at risk and optimal potential with conventional models	Updating the efficient frontier, using the criterion of value at risk, and paying attention to the investor's tendencies in terms of the desire for favorable potentials and risk aversion leads to improving the efficiency of the optimal portfolio.

Research Methodology

Conducting the research is in the framework of deductive-inductive arguments, which means that theoretical foundations and background are through library studies, articles, and websites in deductive format and gathering information to confirm or reject hypotheses in inductive format. The research, in line with other researchers conducted in other countries, has tried to use different statistical models and support machines to optimize the stock portfolio and even mutual investment funds in cross-border markets.

Support vector machines (SVMs) are one of the supervised learning methods used for classification and regression modeling. The SVM algorithm is classified as a pattern recognition algorithm. The SVM algorithm can be used wherever there is a need to recognize patterns or classify objects into specific classes.

The applications of this algorithm can be used on a case-by-case basis: risk analysis system, path simulation, forecasting product needs, forecasting the market situation, forecasting economic indicators, and forecasting investments in the capital market.

The advantages of support vector machines are (D. Shifei, 2011):

- Effective in high-dimensional spaces.
- It is still effective in cases where number of dimensions is greater than the number of samples.
- It uses a subset of training points in the decision function (called support vectors), making it memory efficient.
- Versatile: Different Kernel functions can be specified for the decision function. Common kernels are provided, but it is also possible to specify custom kernels.

In short, machine learning is an essential branch of artificial intelligence that aims to design algorithms that allow computers to develop their behaviors based on experimental data. The most apparent feature of machine learning is knowledge discovery and automatic intelligent decision-making. When big data is desired, it is necessary to use the scale of machine learning algorithms in the execution of the desired tests (Tsolas, 2019).

In this article, 24 models of machine learning are used. In order to collect the required data on investment fund returns, first the data was collected with the help of the client two software and from the FEAS website and sorted using Excel software. According to what was mentioned in this article, 24 valid machine learning models and 11 statistical models were used to determine the best models for determining the net asset value of joint investment funds of selected FEAS member countries, and the results it was examined in line with the Yeoman-Whitney test. In this way, the Yeoman-Whitney and ratio comparison tests were used in SPSS software version 28.

Research data and Sample and statistical population

Regarding the subject of research, necessary data was extracted from the FEAS website. This website gets annual stock market data, including Iran Mutual

Investment Fund data and the selected member countries of the European-Asian Stock Exchange Federation whose data are available. So, a total of 12 countries (Iran et al., Taiwan, Finland, France, China, Portugal, and Netherlands) from 2014 to 2021 were examined. The criteria for selecting 12 countries is the availability of daily information on investment funds in this manner, with 39 funds selected from the mentioned countries. In some cases, we referred to the stock market website of the capital market of each country, like IRAN. Also, considering that daily information on joint investments is needed and software restrictions about big data, we selected 39 joint investment funds.

Research hypothesis and variables

Considering the subject literature, the background of the research, and what was presented in the previous pages, the hypothesis of the current research was explained as follows:

The performance of international investment portfolios based on the net return of mutual funds (NAV) in machine-based models is superior to statistical models.

The research variables were also measured in the following order: Return of investment funds (Rt): the amount of return and profit the investor gets from buying his fund's bonds during the holding period (Tsolas, 2020).

$$R_{it} = ln \frac{p_{it}}{p_{it-1}} \tag{1}$$

Fund portfolio yield: is the weighted average yield of each fund unit in it (Tsolas, 2020):

$$R_P = \sum_{i=1}^{n} W_i \, R_i \tag{2}$$

Results

Table No. 2 presents some concepts of descriptive statistics of variables, including mean, standard deviation, skewness, kurtosis, and the probability of Jarque-Bera statistic. The average, which is the main central index, shows the distribution's balance point and center of gravity and is an excellent index to show their centrality. For example, the average NAV of all funds is equal to 0.7, and the standard deviation value is equal to 2.04. Skewness is actually a measure of the presence or asymmetry of the distribution function. The skewness value is 1.64, which indicates a positive skewness in the funds' data. Elongation is a measure of the sharpness of the curve at the maximum point.

The kurtosis for a normal distribution is 3. Also, the Jarque-Bera test examines whether the data follow the skewness and skewness of the normal distribution. The null hypothesis of this test is the normality of the variable distribution. The probability value of the Jarek-Bara statistic is almost zero, which shows that the distribution of this variable and all variables does not follow the normal distribution at the significance level of 99%. The results confirm the desirability of using the prediction models.

Table 2. Descriptive statistics of returns of investment funds (NAV).

	NAV_TRM	RETURN_TRM
Mean	0.702182	-0.004814
Median	0.000000	0.000000
Maximum	5.761177	0.015970
Minimum	-0.948921	-0.048178
Std. Dev.	2.040297	0.017682
Skewness	1.647797	-1.431947
Kurtosis	4.380760	4.261289
Jarque-Bera	23847.43	18291.20
Probability	0.000000	0.000000
Sum	31477.41	-215.7900
Sum Sq. Dev.	186606.4	14.01468
Observations	44828	44828

Examining the significance of research variables

In order to be able to compare statistical models and machine learning models in the first step, their normality has been investigated. The results of Table number 3 using the Kolmogorov-Smirnov test showed that none of the relevant variables have a normal distribution at the 95% confidence level because the value of the Kolmogorov-Smirnov and Shapiro-Wilk statistics for machine learning models and statistical models is the order was 0.301 and 0.299 (first test). Their significance level is less than 0.001 and 0.011 (first test). Thus, non-parametric tests should be used to compare the prediction accuracy of statistical models and machine learning models.

Table 3. Tests of Normality

Kolmogorov-Smirnov[a]			Shapiro-Wilk		
Statistic	Df	Sig.	Statistic	Df	Sig.
.301	25	<.001	.796	25	<.001
.299	10	.011	.740	10	.003
a. Lilliefors Significance Correction					

Prediction accuracy test in support machine models and statistical models

The results of Tables 4 and 5 show the accuracy of machine learning models and statistical models in predicting the returns of investment funds of 12 countries from 2014 to 2021 and for 45,000 available data using spss-modeler, rapid Miner, and Weka software. As can be seen, out of 35 different models used, 24 items are related to machine learning models, and 11 items are related to statistical models.

Table 4. Results of support machine models

Model	Prediction accuracy	Model	Prediction accuracy
Bayesian networks or TAN structure	0.6035	Linear support vector machine	0.6030
Bayesian networks with Markov structure	0.8715	C5 model tree	0.9999
CART	0.6070	Neural Networks	0.6003
Random Tree	0.6041	Neural perceptron	0.9140
Chaid model tree	0.6045	Deep Learning model	0.6037
Quest model tree	0.6003	k nearest neighbor model KNN	1
Decision stump-model tree	0.9010	Decision List	0.5714
ID3 model tree	0.9999	Decision Tree	0.6039
Fast marginal learning model	0.7030	Random Forest	0.6040
Multi-layer perceptron	0.7547	Gradient Boosted Tree	0.6870
INK	0.5453	Naïve Bayes	0.6120
M5 model tree	0.7439		

Table 5. Results of statistical models

Model	Prediction accuracy	Model	Prediction accuracy
Gumpit	0.6021	Probit	0.6030
Logistic regression model with support vector machine function	0.6214	Login	0.6026
Evolutionary logistic regression l	0.5987	Logistics	0.9997
Meta Additive regression	0.6892	Audit analysis	0.7275
Generalized linear	0.6028	Second-order audit analysis	0.6041
		Regularized Discriminant analysis	0.5047

Predictive accuracy test - U-Man Whitney

The results of Table 6 using the Yeoman-Whitney test showed that the value of the relevant statistic is 53.500 and its significance level is 0.007; considering that the value of the z statistic is -2.613, the prediction accuracy of statistical models is lower than machine learning models. In other words, from the point of view of comparison and reliability of statistical models and support machine, the support machine models are superior, and the research hypothesis is confirmed.

Table 6.Test Statistics

U Mann-Whitney	53.500
Wilcoxon W	108.500
Z	-2.613
Asymp. Sig. (2-tailed)	.009
Exact Sig. [2*(1-tailed Sig.)]	.007[b]
a. Grouping Variable: code	
b. Not corrected for ties.	

Ranking test of statistical models and support machine

Table 7 shows that the average rating of machine learning models (20.86) is much higher than statistical models (10.85). In other words, from the point of view of comparison and reliability of statistical models and support machine, the support machine models are superior, and the research hypothesis is confirmed.

Table 7. Ranks

Code	N	Mean Rank	Sum of Ranks
machine learning	24	20.86	521.50
Statistical	11	10.85	108.50
Total	35		

Results of comparison - test of the parent

The results from Tables 8 to 10 below show that according to the cut-off value of 0.5% and using different approaches of the Wald test, the significance level of different methods for comparing models is less than 0.05 (0.005-0.017-0.001 0.003) and thus at the 95% confidence level, it can be claimed that the prediction accuracy of machine learning models is higher than statistical models. The test is used to compare the net returns of the disputed funds and the comments obtained from the results of machine learning models and statistical models, and the results are in line with the previous test (Yoman-Whitney test). The Yeoman-Whitney and ratio comparison tests were analyzed in spss software version 28.

Table 8. Independent-Samples Proportions Group Statistics

	code	Successes	Trials	Proportion	Asymptotic Standard Error
x >= .50000	= machine learning	24	24	1.000	.000
	= statistical	6	11	.600	.155

Table 9. Independent-Samples Proportions Confidence Intervals

	Interval Type	Difference in Proportions	Asymptotic Standard Error	95% Confidence Interval of the Difference	
				Lower	Upper
x >= .50000	Agresti-Caffo	.400	.155	.092	.668
	Newcombe	.400	.155	.133	.687

Table 10. Independent-Samples Proportions Tests

	Test Type	Difference in Proportions	Asymptotic Standard Error	Z	Significance	
					One-Sided p	Two-Sided p
x >= .50000	Wald	.400	.155	2.582	.005	.010
	Wald (Continuity Corrected)	.400	.155	2.130	.017	.033
	Wald H0	.400	.155	3.360	<.001	<.001
	Wald H0 (Continuity Corrected)	.400	.155	2.772	.003	.006

Conclusion

The analysis of the collected data showed that the supporting machine models had more predictive accuracy than the statistical models in estimating the net return rate of mutual funds in 12 selected FEAS member countries. The Mann-Whitney test was used to determine the significance of this difference. Therefore, using support machines (24 investigated models) compared to statistical models (11 models) has better performance and predictive power. Also, the results showed that the average rank of machine learning models (20.86) was much higher than statistical models (10.85), and considering the cut-off value, which was 0.5%, and using different approaches of the Wald test, the level of significance of different methods to compare models, is less than 0.05. Therefore, at the 95% confidence level, it can be claimed that the prediction accuracy of machine learning models is higher than that of statistical models.

In order to achieve more comprehensive results, according to the obvious differences of mutual investment funds in America in terms of nature, volume, and risk, the data related to mutual investment funds of the New York Stock Exchange by financial market researchers. Review and compare the results with the current research. Also, researchers can conduct current research about transaction costs in different countries and model them with their returns in addition to the fund's rate of return.

Research restrictions

The main restriction of the research was that we could only access the data of some FEAS members' countries. So we chose just 12 countries and 39 available joint investment funds from them. Furthermore, we study the return of funds because of the unavailability of risk and beta Funds.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest concerning the research, authorship and, or publication of this article.

Funding

The authors received no financial support for the research, authorship and, or publication of this article.

References

Ahmadi, J. and Fallah-Tafti, M. (2019). Portfolio optimization with entropic value-at-risk. *European Journal of Operational Research*, 279 (1), 225-241.

Chang, P.T. & Lee, J.H. (2012). A Fuzzy DEA and Knapsack formulation model for project selection. *Computers & Operation Research*, 39. 112–125.

Chunying, W., Xiong, X. and Ya, G. (2021). Performance comparisons between ETFs and traditional index funds: Evidence from China. *Finance Research Letters*, 40.

Eghbal nia, M., and Daliran, M. (2019). Stock portfolio optimization using subconscious search algorithm. *Journal of Investment Knowledge*, 7(32). (in Persian)

Fallahpour, S. Gol Arzi, Gh. and Fatorechian, N. (2013). Prediction of stock price movements using support vector machine based on genetic algorithm in Tehran Stock Exchange. *Journal of Financial Research*, 15(2), 269-288.

Fallahshams, M., and Alavi, S. (2016). Portfolio Optimization, Using Fuzzy Rule-Based Expert System. *Financial Engineering and Portfolio Management*. 6 (25), 125-140. (In Persian)

Fattahi Nafchi, H., Arab Salehi, M. & Ismaili, M. (2019). Selection of optimal stock portfolios using accounting information, value-based information, and balanced scorecard information. *Journal of Accounting Advances*.11 (2), 285–320. (In Persian)

Hsiu-Lang, Ch. (2022). Valuation Risk in Mutual Fund Portfolio Disclosure. The review of Asset Pricing Studies. 12 (1), 243–288.

Khalifi,H., Elqadi, A. and Ghanon, Y. (2018). Support Vector Machine for a new Hybrid Information Retrieval System. Procedia Computer Science, 139-145.

Lettau, M. and Madhavan, A. (2018). Exchange –Traded Funds 101 for Economists. *Journal of Economic perspective*. 32 135-151.

Paitakhti, A., Hadi pour, H. and Aghabagheri, H. (2019). Optimal stock portfolio using at risk value criterion: Evidence from Tehran Stock Exchange. *Journal of Experimental studies in financial accounting*. 15(61). (in Persian)

Pourzamani, Z (2017). The effectiveness of risk criteria in postmodern portfolio theory in mutual funds during a boom. *The financial Accounting and Auditing Researches*. 9(33), 65-79. (in Persian)

Raei, R., Basakha, H. and Mahdikhah, H. (2020). Equity Portfolio Optimization using Mean-CVaR Method Considering Symmetric and Asymmetric Autoregressive Conditional Heteroscedasticity. *Financial Research Journal*, 22(2), 149-157. (in Persian)

Ramoz, N., Aghmashhadi, Z. & Atefatdoust, A. (2020). Selection of the optimal portfolio using the agreed planning model in the Tehran Stock Exchange. *Journal of Financial Management Strategy*. 8(28). (In Persian)

Roshangarzadeh, A. and Rezaei, A. (2010). Comparative study of mutual Fund performance based on Modigliani, Trainer, and Information Ratio Models. Proceedings of the third Conference on the Development of the Finance System in Iran Sharif Finance and Investment Group. 373-351.

Sanzo, S, D. (2018). A Markov switching long memory model of crude oil price return volatility. *Energy Economics*, 74(C), 351–359.

Sedaghati, M., Mehrara, M., Tehrani, R. and Mirlohi, M. (2022). Comparison of Optimal Portfolio Performance Based on Value at Risk and Upside Risk with Conventional Models. *Journal of Financial Management Strategy*. 10 (1). (In Persian)

Sheidaei Narmigi, A., Rahnamay Roodposhti, F. and Radfar, R. (2021). Optimization of Network-Based Matrix Investment Portfolio and Comparison with Fuzzy Neural Combination Pattern and Genetic Algorithm. *Iranian Journal of Investment Knowledge.* 9 (36). (In Persian)

Shifei, D. and Binguan, Qi. (2012). Research of granular support vector machine. *Artificial Intelligence Review*. 38:1-7

Tsolas, I. E. (2019). Utility Exchange Traded Fund Performance Evaluation. A Comparative Approach Using Grey Relational Analysis and Data Envelopment Analysis Modelling. *International Journal of Financial Studies*, 7(4), 67.

Bibliographic information of this paper for citing:

Nateghian, Leila; Jabbarzadeh Kangarlouei, Saeid; Bahri Sales, Jamal & Piri, Parviz (2023). Evaluation and comparison net assets value of joint investment funds using support machine models versus statistical models - A case study from FEAS member countries. *Iranian Journal of Finance*, 7(4), 142-160.