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The role of market timing in the development of financial products

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Abstract

Research into the development of new financial products in the capital market has received much attention over the decades and one of the financial implications in the capital market is the use of new models in predicting market trends to control risk and increase returns. Which can also be used as a market timer, in this regard, the market timer by adding the market timing system to the process of but since successful market timing strategies depend on superior forecasting ability, Therefore, in this paper, using the market timing approach of new products in the field of capital market trend forecasting to control risk and increase the return on investment presented. for this work with a homogeneous and heterogeneous two-level ensemble learning method (HHEL) to provide the buy, hold and sell signal and market forecast are based on the basic characteristics, technical characteristics and time series of each company's return in the 10 days leading up to the current day. Based on this, 208 companies were selected as active companies between 1390 and 1399. The data of the first 5 years have been used using the begging method to teach the model and the model has been optimized using the genetic algorithm (GA) to increase accuracy and efficiency, and to test the proposed model in stock portfolio to determine options The investment is used and the genetic algorithm (GA) is used as stock portfolio optimization based on maximizing stock portfolio returns and minimizing investment portfolio risk, and finally the return and portfolio risk obtained are compared with the buy and hold strategy. The results showed that the proposed prediction model compared to other comparative models with Accuracy 92.34% and Sensitivity 83.88% and Specificity 92.92 has the highest accuracy and reliability compared to other comparative models. And the average error in trend classification by the homogeneous and heterogeneous two-level combined model is less than other comparative models. Also, the proposed model for daily portfolio formation and daily weighting of selected stocks (HHEL + GA) Compared to buying and maintaining strategies to increase with 63% hit and 70 times higher return on investment and Sharp ratio 14 times higher without commission and having a portfolio with controlled risk help reduce investment risk and maintain portfolio value determining and allocating investment options can determine the time of timely entry and exit.

Keywords: financial product, portfolio optimization, market timing, Ensemble machine learning model.

1. Introduction

Investing in the capital market is one of the most profitable options for investing. And using the products of this market can lead the investor to higher expected returns, including existing financial products, assets and risk management products. At the same time with the formation of the portfolio, portfolio management is one of the most important areas of financial research for researchers and choosing a portfolio with high rate of return and controlled risk is one of the topics that has been considered by many researchers. The optimal portfolio determination model was proposed in 1952 by Markowitz. One of the most important criticisms of Markowitz is the inability of this theory to respond quickly to falling market prices in portfolio management. The inherent nature of modern portfolio theory harms the investor during periods of market downturn by increasing the portfolio risk (Andersen et al., 2014) .

One of the most controversial management techniques, which can be effective in solving the problem of Markowitz theory, is market timing. Market timing is an investment approach in which an investment manager or a professional market timer tries to predict the movement of prices or their trends due to the effect of political, economic and social variables, etc. Because government policies and legal actions have a significant impact on stock market movements. Market scheduling managers use economic data or other data to calculate the appropriate time for change. The market timing approach is the same investment patterns or strategies that use a combination of fundamental and technical analysis as opposed to buying and maintaining strategies and intends to introduce a dynamic investment model (Joe Duarte, 2009). Therefore, portfolio management with active investment strategies became one of the most important areas of financial research for researchers (Mascio et al., 2021). And this challenged many dominant economic theories, including efficient market theory (EMH). According to the efficient market theory stated by Fama (1970), investors cannot defeat the market and use past data to predict the price of financial assets. In other words, market timing is impossible, but the results of recent studies by researchers in this field jeopardize the EMH theory, and more recently, several studies (Bollerslev et al. 2014; Kim et al. 2011; Phan DHB et al. 2015) state that Some markets, such as emerging markets, deserve to be explored. Stock market timing and forecasting for stock price changes is considered a challenging task in financial discussions. The reason for this is the significant financial benefits that result from a successful forecasting model that helps to develop timing strategies. However, predicting stock prices or returns is not an easy task; Because many market participants are involved and their complex structural relationships are not clearly identifiable. On the other hand, the nonlinear and non-fixed features of financial time series, especially stock prices and indices, make predicting them a challenging task. This can be due to the complex dynamics of the stock market, from the impact of financial, political, social, technological news, changes in laws to macroeconomic factors to different time situations and investors' expectations and psychological factors, etc .... and it also includes the relationship between stocks in the market.

And these changes cause prices to rotate during the investment period and affect the risk and return of the investment portfolio. (Ghasemian and Rahnama Rudposhti, 2016) And has caused the capital market as an important part of the economy of any country to feel a constant need to change its position in order to align with and adapt to external changes (Potters et al., 2005). However, it is very difficult to accurately predict the time of entry and exit in the stock market (Yu Qin et al., 2020). Since the early 1980s, the use of portfolio selection and timing criteria for the evaluation and selection of investment units has become common. In the meantime, the use of innovative methods that can fill the gap between modern portfolio theory and market theory and benefit from both is considered as a need for studies in the theoretical foundations of investment. In other words, it seems necessary to adopt an investment approach that has a practical application and its efficiency has been proven experimentally and is also based on theoretical foundations and has scientific order and organization In the financial literature, in general, various techniques for stock market timing are known, which can be classified into approximately four categories: technical analysis, fundamental analysis, time series forecasting, and methods based on Machine learning (Zang et al., 2019) In recent years, the latter two types have become more popular..

Therefore, the need for a tool with accuracy and better performance in forecasting to overcome the market timers over the market is felt that today due to the increasing volume of information and computational power provided by machine learning models can be achieved (Qin Et al., 2020). Examining the above, it can be said that there are two main steps in forming a portfolio. First select the top stocks based on different strategies and then determine the weights of each to be in the portfolio. In this paper, in the first stage, using a homogeneous and heterogeneous two-level model from a series of machine learning models, appropriate samples have been selected to train stock data and to select the best stocks, the proposed model using genetic algorithm (GA) has been optimized. This two-level model includes a 5-tier set of support vector machine (SVM), decision tree (DT), K-nearest neighbor (KNN), neural network (NB), and MLP neural networks as heterogeneous models of collective learning in In the first level and in each class, the basic learning model L is used heterogeneously, which is used by the majority vote method to aggregate opinions. Input variables for model training include 6 technical variables, 8 basic variables and 7 macro variables, and the time series of the price of the last 10 days per month, which has been used at the data level and at the sample level using the bagging method. This proposed model sends a buy or sell or hold signal for future data test samples. In this study, in the first stage, we used the genetic algorithm (GA) for optimization. Stock portfolio optimization is done with the objectives of maximizing stock portfolio returns and minimizing investment portfolio risk. After selecting the top stocks, the genetic algorithm is used to determine the weights of the selected stocks with a single-objective formula based on Markowitz's objective function at the beginning of each day. Therefore, by predicting the market trend, the best investment portfolio can be selected every day and the stock portfolio return can be increased. Therefore, in order to present a new combined method for portfolio formation (HHEL + GA), the data related to Iran Stock Exchange Company during the years 1390 to the end of 1399 have been studied and analyzed. The structure of the article is as follows. In the second part, some of the most important articles on stock portfolio formation with combined models and forecasting models used in market timing are discussed in different ways. In the third part of the mathematical model, the proposed hybrid approach is presented. In the fourth section, the results of the implementation of the approach on the data of listed companies operating in Iran are analyzed and presented. In the fifth section, conclusions and future suggestions of the research are presented.

2. Literature review

Thomas Raffinot et al. In 2018, due to the importance of this issue, conducted a study on investing during business cycles with machine learning and pointed out that due to the non-linear nature of business cycles and the impact of economic shocks on business cycles Determining the right time and identifying milestones in these cycles or points where the trend of business cycles changes is very important. Many parametric models such as Markov switching and probit models are quite effective in identifying milestones when GDP data is available and available, but in the absence of GDP data and knowledge of actual GDP, parametric models are not effective. Non-parametric methods such as machine learning algorithms are effective because they do not rely on GDP data for forecasting.

Improves and combines the opinions of several learners to achieve optimal performance. They used the popular methods of random forest and boosting in the construction of group models. Two features of these algorithms are their ability to entertain a large number of predictions and perform variable estimation and selection simultaneously. Their goal was to use random forests and amplify algorithms to create multiple models with the aim of quickly and accurately identifying the growth points of the growth cycle in real time. Ahmadi et al. 2018 in their research on "Technical Combined Candlestick Technical Analysis Model for Stock Market Scheduling Based on Support Vector Machine and Innovative Imperial Competition Algorithms and Genetic Algorithm" pointed out the importance of forecasting in market timing and the need for tools Powerful and reliable ways to predict stock prices are felt more than ever. They decided to use artificial intelligence that is more accurate than traditional methods. Considering the technical analysis of the Japanese candlestick as an investment method used to schedule the stock market that feeds from a supervised neural network. In this study, SVM is used in conjunction with two meta heuristic algorithms to predict stock price movements. The two meta-innovative algorithms are Genetic Algorithm (GA) and Imperial Competitive Algorithm (ICA), which are used to optimize model parameters and attributes. The purpose of this study is to evaluate SVM using the mentioned algorithms, which affect the combination of input variables on the overall result. In this paper, two combined models for stock market scheduling based on Japanese candlestick technical analysis One is a backup vector machine with a genetic algorithm and the other is a backup vector machine (ICA). In the first model, the SVM and the Imperial Competition Algorithm (ICA) are developed for stock scheduling, in which ICA is used to optimize the SVM parameters. In the second model, SVM is used with genetic algorithm (GA) that GA in addition to optimizing SVM parameters, is also used to select the feature. In this study, they developed two methods. The results show that the performance of SVM-ICA Better than SVM-GA in better forecasting.

XingYu Fu in 2019in a study on "Machine learning structure for stock selection" showed how to use machine learning algorithms to distinguish "good" stocks from "bad" stocks. In their paper, the nature of selecting and distinguishing "good" stocks from "bad" stocks lies in the classification problem scenario. Yadav Juthimani et al. 2019, in their research entitled Stock Trading Decisions Using Group Predictive Models for Timing Objectively, studied the Indian stock market on a case-by-case basis. Share price forecast and market trend suggested a group model in which more than one model is combined. The purpose of this study was to provide trading rules to determine the optimal time for buying and selling decisions, in other words, market timing. To achieve this, they proposed a two-phase group framework consisting of various non-classical decomposition models, and machine learning models (artificial neural networks and backup vector regression), to predict stock prices. The hybrid support vector regression model performed better than the remaining models by analyzing the complete experimental mode of the group with adaptive noise. In addition, trading rules are shown to determine the appropriate time to buy / sell stocks. Group model-based trading rules yielded higher returns on capital than traditional buying and holding strategies. Research in which machine learning methods are used to predict stocks and is the basis of the researchers' work, including research on stock price forecasting by SVM, which have been very popular, such as: 2019. Xiao et al: Tang et al.2019: Henrique et al., 2019: (Luo et al (2019, (2012). Shen, S., Jiang, H., & Zhang, T) as well as research to predict stock prices Artificial neural networks (Jiang and Zhang 2019 (Paiva et al.2019) (ANN; used) can be mentioned and research in predicting and classifying stock price trends by (2019, Kia) (Gicken M, & et al Tsai CF, Hsu YF, Yen DC), (Ren Y, Suganthan P, Srikanth N (2015)) (Opitz D. Maclin R (1999)) (AN. & et all, 2018 ((2014)).

Chen et al. (2021) developed a new stock portfolio optimization approach using a hybrid machine learning-based model for stock forecasting and the Markowitz mean-variance model for stock portfolio selection.In particular, two steps are involved in this model: stock forecasting and portfolio selection. Using the Shanghai Stock Exchange as a case study, the obtained results show that the proposed method is superior to traditional methods (without stock forecasting) and criteria in terms of return and risk.Ma et al. (2021) optimized the stock portfolio by predicting returns based on machine learning and deep learning. They combined two machine learning models, random forest and support vector regression, and three deep simplification models. They used the mean-variance of Markowitz and omega models to evaluate the effectiveness of their proposed methods. Zhu et al. (2021) stated that an investment process consists of two general parts: stock selection and investment weight formulation. They designed a stock selection model using data envelopment analysis including stock trading data, technical indicators, social media data and news data. In addition, they used support vector machines with multi-purpose stock data to predict stock prices and market trends.

In their 2021research on market timing using hybrid forecasting and machine learning, David Massico et al. Point out the importance of being able to predict trends and share prices in market timing. A hybrid model including the LASs0 model used machine learning models and a logistic regression model and an emotion index model presented by Bang et al. (2015) and finally compared the performance of the machine learning model (LASSO) with the index model. Emotion and logistics model and hybrid model for market forecasting and found that machine learning model has better performance in market forecasting than other models. To conduct their research to use the Emotion Index to Predict Share Price Trends, they have conducted research by researchers such as Fisher & Man (2003), Brown and Cliff (2004), Mascio and Fabozzi (2019), and Huang et M. Baker and Wurgler (2015) .al (2006, 2007) cited.

(Qiu, Y et al,2020). Due to the lack of research on market timing with the recursive neural network (RNN) model, a new model called the RNN hybrid model combines multi-layered short-term memory, multi-layered gateway interface unit and single-layer ReLU layer for scheduling. Scholarship offered. The recursive neural network model was used for the shortcomings and problems of the artificial neural network (ANN) model, including the problem of excessive computational complexity. However, recurrent neural networks, or RNNs, have a major problem, and that is long-term dependency, meaning that the current position is affected by its previous position. In this paper, LSTM and GRU have been used to improve the traditional structure of recurrent neural networks. In this study, they used a hybrid model for stock trading on the stock exchange, which is a combination of GRU ISTM and ReLU models, which they named the RNN hybrid model. And to increase performance, the new model pack consists of three LSTM layers, three GRU layers and an advanced ReLU layer. The result of the model performance in classifying, predicting and timing the contribution with other models of machine learning such as decision tree, random forest, K algorithm, nearest neighbor vector machine, Naive Bayes algorithm, etc. and with and technical index. Forecasters compared the technical analysis trend including the moving average, RSI, MACD and several other indicators. The results showed that the mean accuracy of the proposed hybrid model was significantly better than other comparative models and concluded that the proposed hybrid model and recursive neural network classification method can be used as a practical and effective tool. To be considered for stock scheduling. On the other hand, there has been a lot of research that has used LSTM and GRU extensively in stock forecasting (Beck and Kim 2018,; and Kim and Won, 2018; Maine et al. 2018; Liu et al. 2017 Akao et al. Et al. 2019) and their research became the basis of the research work of this group of researchers.

Philip Diaz Paiva et al. (2019) stated in the research that forecasting stock returns is an accurate perspective on financial time series. This study presents a unique decision model for day-to-day stock market investments. In this regard, the model was developed using the machine learning classifier-based classifier method, the support vector machine (SVM) and the mean variance (MV) method for selecting the portfolio. This study also evaluates the performance, classification Main securities, and model returns and risks. The proposed main model showed significant results, although demand for business value could be a limiting factor for its implementation. Nevertheless, this study extends the theoretical application of machine learning and offers a potentially practical approach to stock price forecasting. Asset portfolio theory is an important basis for securities management that is a well-studied but not yet fully captured topic. The MV variance has been proposed to form an optimal portfolio for asset selection in which long-term dependencies on financial time series data can be obtained. 1994 to March 2019. In the first stage, the short-term memory network (homogeneous method) is used to predict the return of assets and select assets with higher potential returns. After comparing the results of short-term memory networks against the vector machine Support, random forest, deep neural networks, and self-regulating moving average model. We find that short-term memory networks are suitable for predicting financial time series. Defeat other benchmark models by a very clear margin. The basis of selected assets with higher returns than the model Medium yance is used to optimize the stock portfolio. The proposed model is clearly better in terms of cumulative returns per year, Sharp ratio every three years, as well as average risk return in each of the other functions.

WeiChen et al. (2021) attributed portfolio success primarily to the future performance of stock markets. Therefore, recent developments in machine imaging have provided good opportunities for combining forecasting theories in stock portfolio selection, but because the research literature has shown that only one forecasting model is not enough to have a suitable portfolio, so they in this research a new approach in building The stock portfolio was developed using a hybrid machine learning-based model for stock forecasting and the mean variance (MV) model for portfolio selection. In particular, two steps are involved in this model: stock forecasting and portfolio formation. In the first step, a hybrid model with a combination of eXtreme Gradient Boosting (XGBoost) with an improved firefly algorithm (IFA) algorithm is proposed to predict stock prices for the next period. IFA was built to optimize XGBoost parameter clouds. Second, stocks with higher potential returns are selected, and the MV model is used to select the portfolio. Using the Shanghai Stock Exchange as a study sample, the results show that the proposed method is superior to traditional methods (without stock forecasting) and benchmarks in terms of returns and risk.

Sadeghi et al. (2021) in their research to predict the trend of foreign exchange market and trading in that market used a combined method of homogeneous classification method svm and fuzzy method NSGA-II. The proposed method has been successfully tested on real forex market data for the EUR / USD currency pair over a period of 6 years from 2014 to 2019. The results show that their proposed method shows its superiority in accuracy, recall and return on investment compared to existing commercial systems. The stock price forecast result shows that the neural network classifier performs well in some cases while the (Multiclass (One V / s One) homogeneous hybrid method in more than two classes) and (One V / s All) performance They have a better overall among other classifiers.

(Tehrani et al,2014) In a study on "Providing a new approach to active portfolio management and smart stock trading with emphasis on feature selection attitude" in this study, they tried to implement an active portfolio management approach, a method for smart trading based on price Stocks are expected to offer a specific four-year period. Returns from the portfolios of genetic algorithms based on genetic algorithms and proximity to the nearest neighbor based on genetic algorithms and the portfolio of purchases and maintenance as a representative of the passive management approach The portfolio was calculated in each of the four years. The portfolio obtained from the neural network method based on genetic algorithm has the highest efficiency in the four-year period, which shows the superiority of the active portfolio management approach over the passive portfolio management approach. Anzaei and Niko Maram 1399 in a study on "Designing a model for determining stock trading strategies with a futures-based approach, fundamental analysis, engineering features and machine learning algorithms" in his research using a model consisting of futures research, fundamental analysis, rules Trading Experts and machine learning algorithms offer a model for adopting appropriate trading strategies. First, using the opinion of experts and futures research, scenarios for the stock market are designed and by performing a fundamental analysis, a portfolio consisting of six shares is formed. In the next stage, using 7 machine learning algorithms and data of selected companies in the period 1393 to 1398, modeling is done to predict the price trend of each selected share. Model input variables include technical indicators, technical rules, sign reading rules and stock trading data. The results show that using the proposed model for investing in the stock market creates higher returns than the stock market index and using trading strategies based on light gradient amplification (LGBM) algorithm signals higher returns compared to buy-hold and technical strategies for the portfolio. Offers selected stocks .Amiri et al. 2016 in their research on "Introducing a smart trading model in financial markets based on genetic algorithm, fuzzy logic and neural network" in this study have tried to identify the turning points in financial markets, intelligent trading system Establish the known rules of technical analysis and use the three tools of genetic algorithm, fuzzy logic and neural network. And used genetic algorithms to optimize technical rules due to computational complexity. Fuzzy logic was also used to identify the current market position in the present study. Because depending on the specific type of market (trendy or neutral) a set of rules will be selected. In the end, the signals generated by each of the rules with the help of the element neural network will be a single result (buy, sell or hold). The results show a statistically significant difference between buying and holding a share and the system. There are suggested deals in this research. In other words, their proposed system has a very high profitability potential. Raee and Hosseini 1394 in their research entitled "Comparison of sales returns based on technical indicators and fuzzy logic and the combined method of genetic algorithm - fuzzy logic" in this study using technical analysis indicators and fuzzy logic decision making and optimization methods and decision making The fuzzy genetic combination method has been used to make sales decisions. The study period was from the beginning of 2008 to the end of 2012 and was 4 years of training and one year of testing. The sample included 50 listed companies. Samples were filtered based on the performance of technical indicators during the test period. Companies were selected as the final sample whose technical indicators did not differ significantly during the years of training. Thus, based on historical information and training course, suitable indicators for determining higher efficiency were determined and in the fuzzy method based on conventional trading rules and in the fuzzy genetic method based on learning trading rules, extraction and trading were performed according to signal strength. The fuzzy and fuzzy genetic method is more efficient and significant than the purchase and maintenance method. Tehrani and Abbasi in 2008 in a study entitled "Application of artificial neural networks in stock trading scheduling: with a technical analysis approach" in his research, the ability of artificial neural networks (ANN) to improve the effectiveness of technical analysis indicators in predicting trend signs They checked the stock price. The results of the models, based on a sample of 50 companies listed on the Tehran Stock Exchange, showed that artificial neural networks have the ability to predict the signs of a change in the short-term trend of stock prices in the Tehran Stock Exchange. In the bullish market, after deducting transaction costs, there is no significant difference between the efficiency of the artificial neural network model, the method of purchase and maintenance and the most profitable technical indicators. However, in the downtrend market, the efficiency of the artificial neural network model is higher than the efficiency of the purchase and maintenance method, although in the downtrend, the trend indices (moving average) gained the highest returns.

According to the research background, it can be said that different methods have been used to optimize the portfolio and reduce the risk of the investment portfolio. Therefore, there is no comprehensive model that simultaneously addresses the combined learning methods for stock selection and training and the GA genetic algorithm for stock portfolio optimization. Therefore, in this article, using homogeneous and inhomogeneous learning models such as SVM, DT, NB, KNN, MLP neural network and weighted average, Iran Stock Exchange data during the years 1390 to the end of 1394 and the genetic algorithm to test the data. And stock portfolio optimization has been used with the aim of increasing the stock portfolio return and reducing the stock portfolio risk of Iran Stock Exchange during the years 1395 to 1399.

3. Research methodology

As mentioned, the main purpose of this article is to provide a stock portfolio design model, which is done in two steps. In the first step, using a combined model from a series of machine learning models to select superior stocks and use usage data. It is based on a timing approach and is optimized using the genetic algorithm. It selects investment options and in the next step, the genetic algorithm is used to determine the weight of each of the selected stocks in the portfolio. To do this, the trend of each stock must first be predicted by the proposed research model, which is a homogeneous and heterogeneous two-level model. Daily sales of shares to be taken. The method is that after classifying the process of all assets, one by one, only those who most likely gave the signal to buy and maintain, are eligible to participate in the next step and those who at the end of each day or week or month signal They have been sold out of the portfolio if they are in the portfolio, otherwise no action will be taken on them. Figure (1) shows a general model of the proposed timing model in which hybrid machine learning models are used to determine the signal to buy or sell.

The general model of the machine learning block to predict the future performance of each company in the next day is shown in Figure (2). Input characteristics To predict the return (trend) of each company in the next day, different characteristics are used (the mentioned items are independent variables in our research):

In this method, the teaching of the homogeneous and heterogeneous two-level HHEL model will be based on four types of input data (technical, fundamental, macro and time series variables) which are shown in Table (1).

Figure 1: General Market Timing Model Proposed.

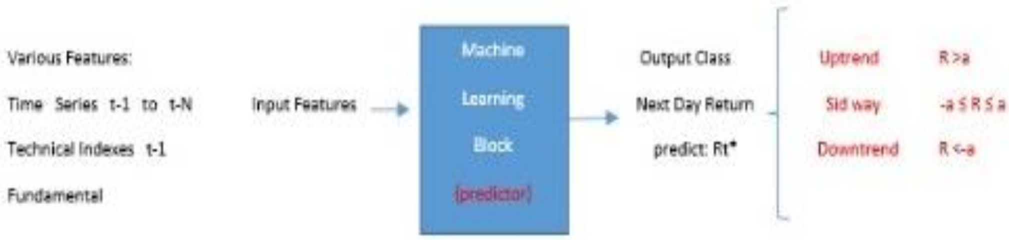


Figure 2: The overall structure of each company's market trend forecast.

Table (1) Features used to teach the HHEL model

Feature category	Types of features used in the model
Technical	RSI,MACD, ROC ,PDMA,PDEMA,PDLMA
Fundamental	Closing price, trading volume, number of buyers, number of trades, value of daily trades, day value of the company, number of shares of the company, price in favor of each share
Macroeconomic	Old design day coin price, Imam design daily coin price, gold day price, dollar day price, euro day price, daily index price, daily oil price
time series	Return (price) of each company in the last 10 days leading up to the current day

It is worth mentioning that in this study, we used the Bagging method to teach the model, both at the level of samples by 10% and at the level of features by 50%. This method uses homogeneous basic models, they are trained independently of each other and in parallel. In this method, the whole set of training is divided into a number of distinct categories and only a percentage of the total set of data is used to teach each basic learner. In this way, L models of the same basic learning model are trained using different datasets, and as a result, aggregating their results can reduce prediction error. The collective learning machine is divided into homogeneous and inhomogeneous categories based on the homogeneity or heterogeneity of the basic learning models. In heterogeneous methods, L different learning models (support vector machine, decision tree, K-nearest neighbor, MLP neural network, Bayesian network) are used as basic learning models. Whereas in homogeneous methods, the same type of base wind deflector (eg backup vector machine) with L model number is used. In this research, we intend to use a combined two-level homogeneous-heterogeneous collective learning method as shown in Figure (3) to predict the market trend of each company. In this method, we use 5 different learning models (support vector machine with different kernels, decision tree, K-nearest neighbor algorithm, MLP neural network, NB.) As heterogeneous basic models of collective learning in the first level and to improve the accuracy of methods. Bases such as decision tree, Bayesian, etc. The use of combined methods or homogeneous collective methods has been suggested. ,1999)

The proposed HHEL model consists of 5 learners that each lever in the model has a weight and is composed of several bass levers. To determine the best output can be obtained from the model, we specify. A possible solution to the problem can be seen in Table (2) .

Table (2) is a possible solution to the HHEL model optimization problem

Ws vm	W DT	W NB	WK NN	WM LP	NBLs vm	NBL DT	NBL NB	NBLK NN	NBL MLP

0<W<1

5<NBL<50

NBL = Number of base launchers per lender

W = Lerner weight

Optimal adjustment of free parameters of the proposed model using genetic algorithm

In the proposed model, we use the genetic algorithm to optimize the free variables of the model, such as the weight coefficients that are given to each algorithm in the model and the number of base learners that are assigned to each learner for training. To optimize the free parameters of the proposed model, the genetic algorithm is used on the training data set. It is necessary to specify the free parameters of the genetic algorithm in the first step. In order to implement the hyper trading system, the model parameters for the proposed algorithm are presented in Table (3).

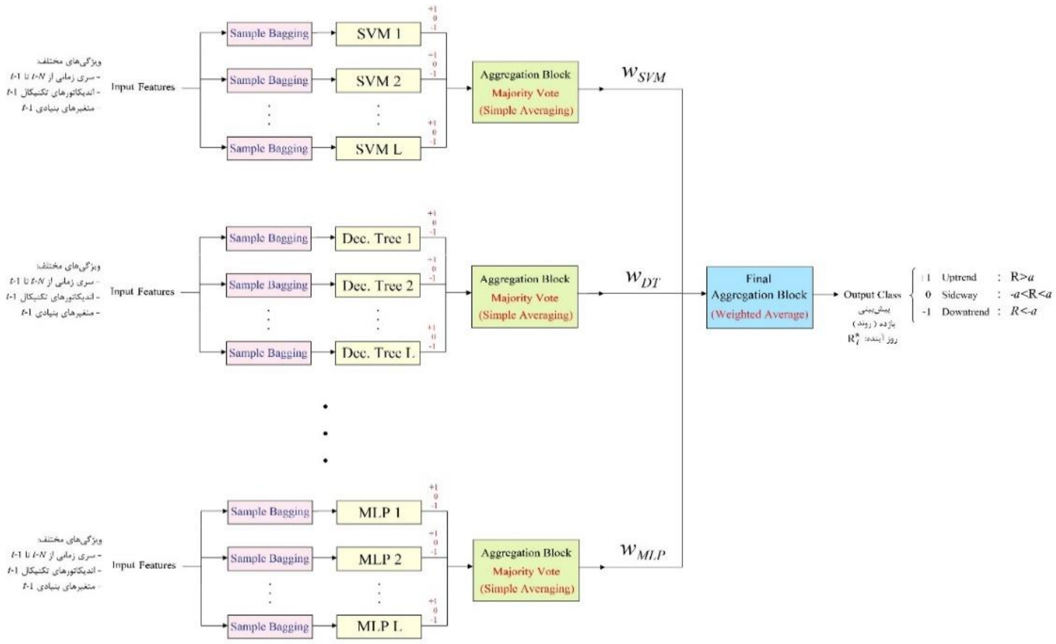


Figure 3: Proposed collective learning model to predict the market trend of each company.

Table No. (3) Set the hyper parameters of the proposed algorithm

Number of repetitions	MAXITER	150
population	POPSIZE	30
PRECOMBINATION	PRECOMBINATION	0.1
PCCROSSOVER	P Crossover	0.5
PMUTATIN	P mutation	0.4

PRECOMBINATION+PCCROSSOVER+PMUTATIN=1

To evaluate any possible solution to the problem in the genetic algorithm, a fitting function or an evaluation criterion is used, which can be seen in the following equation. The weight of each of the parameters of the objective function or genetic fitness used in optimizing the HHEL model is such that the weight of the sensitivity coefficient is 25%, the weight of the specificity coefficient is 25% and the weight of the accuracy coefficient is 50%.

Fitness = W1sensivity + W2 specificity + W3 Accuracy

Classify the trend of each share

After optimizing the free parameters of our model by genetic algorithm and determining the best weights for each Lerner (W) and the best number of Bass Learners (NBL) for each Lerner. Determined to decide whether to buy, sell or hold a share. So, for example, we have n to DT, none of which are superior to each other. Finally, we calculate their majority vote, which is finally the DT output, which we multiply by the total weight of DT. We do this for all learners. . Finally, we take the answer of every 5 Learners from that weighted average.

majority vote DT * WDT = Final result of DT

majority vote KNN*WKNN = Final result of KNN
majority vote SVM*WSVM = Final result of SVM
majority vote NB*WNB = Final result of NB
majority vote MLP* WMLP = Final result of MLP
∑ final results / ∑W

➢ The second stage of portfolio adjustment

In the next step, the goal is to define the ratio of capital allocated to each asset. To perform this step, the same optimal set of assets in the Markowitz model can be obtained using a single-objective formula (Jobst, Horniman, Lucas, & Mitra, 2001).

$$\underset{w_i,\dots,w_n}{Min}\ \lambda\left[\sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}\right] - (1-\lambda)\left[\sum_{i=1}^{n} w_i \mu_i\right],$$

$$\text{Subject to: } \begin{cases} \sum_{i=1}^{n} w_i = 1 \\ 0 \le w_i \le 1, \forall\, i = 1,\dots,n, \end{cases}$$

where λ = the coefficient of risk aversion.

In this regard, the variable that represents the investor risk aversion (λ) is introduced to the model as a factor to describe his behavior in relation to risk investment options. Used for weighting selected stocks is shown as minimizing investor risk preferences, ie in this function, the Landa coefficient is tried to be minimized each time the investor's selected stocks are weighed. Results of optimization of free parameters of the proposed homogeneous and heterogeneous two-level model using genetic algorithm on training data in this method we have 30 solutions or (population number) in the genetic algorithm, each of which must be updated in 150 repetitions. In other words, we evaluate 150 * 30 = 4500 solutions in this method and to update the population from We use three operators, each with the probabilities specified in Table 3. Then, by performing the genetic algorithm on the test data, the results are shown in Diagram No. (1)

Fitness = W1sensivity + W2 specificity + W3 Accuracy

The results of weight optimization and the number of bass launchers used in the model are shown in Figure 1.

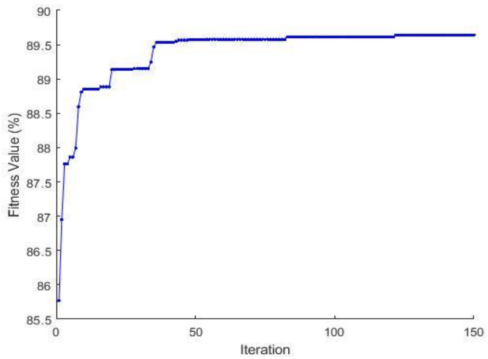


Diagram No. (1) Convergence of Genetic Algorithm for Optimizing Weight and Number of Base Learners in HHEL Model

The result of optimizing the free parameters of the HHEL model with the genetic algorithm shows that by what weight each Lerner in the general model can be integrated in a heterogeneous state. In the table below, the weights are shown with W and also shown in the model Suggestion for each lener A few bass leaners can optimize the model. It has been shown that MLP with 32 bass levers has the greatest effect on model optimization and knn, dt with the lowest bass learner optimize the final model. Adjusting these parameters has a significant effect on system performance. The table of optimization results for the weight of each leaner and the number of bass levers used for each leaner with the genetic algorithm is shown in Table (4).

Table No. (4) Results of optimizing the weight of each leaner and the number of bass levers used for each leaner with the algorithm

Weight Learners					Number of base learner				
wsvm	w DT	WNB	WKNN	WMLP	NBL SVM	NBL DT	NBL NB	NBL KNN	NBL MLP
0.2157	0.9622	0.4465	0.5627	0.9886	21	16	22	16	32

The next step after optimizing the model with genetic algorithm is to detect the trend of each share by the model, which should be done on the training data, and after checking the validity of the model results, test it on the test data and adjust the case portfolio daily. Use.

Trading system test results Market trend classification results using homogeneous and heterogeneous two-tier model

The proposed model is used on test data. We intend to measure the accuracy of trend detection by the HHEL model on test data so that we can use the model to use in daily portfolio reset. Table 5 shows the confusion Matrix of test data and compares the output of the proposed research model with the actual labeling of the data.

Table No. 5 confusion Matrix table for test data

HHEL PRIDICTION / Data lable	Up trend	sid way	down trend
Up trend	54266	6050	933
Side way	3196	118434	897
down trend	4902	10270	30219

Row I and column j are test samples that really belonged to class i, and the proposed HHEL model recognized them in class j. The main diameter of this matrix is the test samples that the system correctly identified. The i-th rows are the number of instances that are really class i, and the sum of the j-column values are the number of instances that the HHEL model has detected in the j-th class.

As can be seen from Table 5, the error rate in determining the share trend for test data is very low, so the model is valid in terms of accuracy and coverage and can be used in daily portfolio adjustment. The final results of the model validation on The test data show that the high accuracy and reliability of the trend of each share by the proposed model.

After optimizing the weight and number of base learners in the proposed model by genetic algorithm, one of the research hypotheses should be examined. According to the model evaluation result, the HHEL model can be used to predict the stock trend. Therefore, we must measure its generalizability for test data. Hypothesis 1) The proposed HHEL timing model performs better than each of the base leners for timing and market forecasting in terms of accuracy and sensitivity. According to the model evaluation result, the HHEL model can be used to predict the stock trend. Therefore, we must measure its generalizability for test data.

Fitness = W1 Sensivity + W2 Specificity + W3 Accuracy

Table No. 5: Comparison of the results of market classification evaluation criteria based on HHEL approach with test data

Ascending	Sise way	Descending	Evaluation criteria
98.9997	84.5714	95.2155	Specificity
66.403	96.6864	88.5567	sensivity
92.5296	91.0525	92.4286	Accuracy

Table No. 6 HHEL model validation on test data and comparison with other machine learning methods

Accuracy			sensiviity			specificity			parametrs
93.47	91.14	92.57	88.78	96.65	66.57	95.17	84.79	99	The average of each class
92.3977			84.0073			92.9935			Average values
1.2			15.67			7.48			Standard deviation

Table No. 7 Comparative results of the performance of the proposed research model (HHEL) With other share trend classification models

معیار ارزیابی / الگوریتم	Avg specificity	vgSensivity	Avg Accuracy
SVM	66.66	33.33	51.12
DT	84.41	66.11	80.79
NB	84.24	64.81	78.14
KNN	63.79	30.46	50.64
MLP	75.5	58.64	67.45
HHEL	92.92	83.88	92.34

According to the number table 7, the results show that the use of homogeneous and heterogeneous two-level model has an accuracy of 92.34%, a sensitivity of 83.88% and a specificity of 92.92%. And their performance evaluation criteria are very different from other comparative models and are preferable to using each of the leners individually to classify the share trend. This is done on test data and the model results are compared with the actual results. Figure 4 shows the results of the table above.

Results of the second stage of daily portfolio adjustment by genetic algorithm

The objective function in the genetic algorithm used in the daily portfolio adjustment phase to weigh selected stocks appears to minimize investor risk preferences. In other words, in this function, the Landa coefficient is tried to be minimized each time the investor's selected stocks are weighed. Diagram No. (2) shows the convergence of the genetic algorithm for optimizing the weight of the selected stocks in the portfolio with the mentioned objective function.

From the beginning of 2016 to the end of 2013, the daily portfolio adjustment test data was performed and the results of the average weight considered for each of the 208 companies showed that the daily portfolios are shown in the Figure 5.

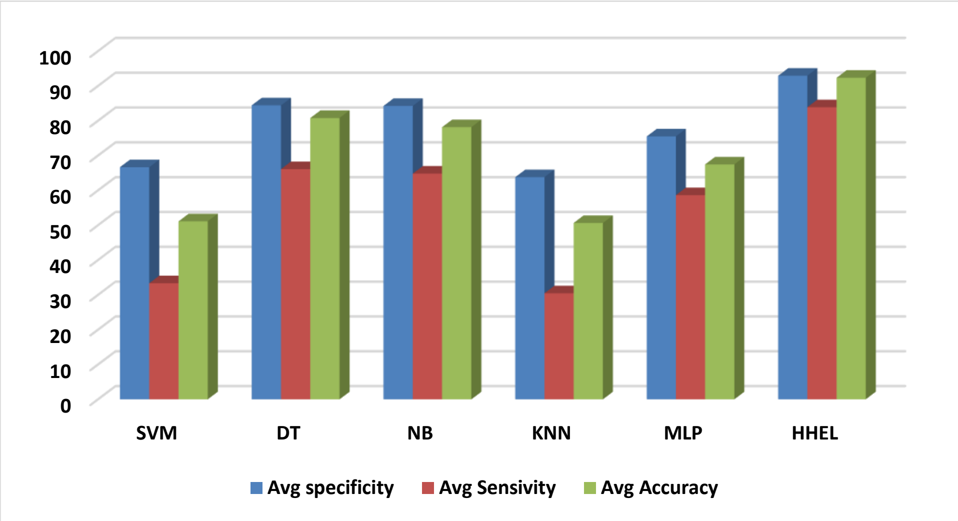


Figure 4 Comparing the performance of forecasting models with the proposed research model(HHEL)

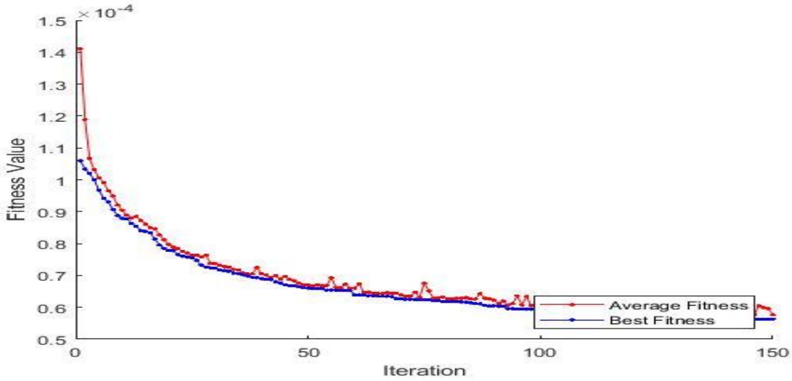


Diagram No. (2) Convergence of Genetic Algorithm for Optimizing the Weight of Selected Stocks in the Portfolio

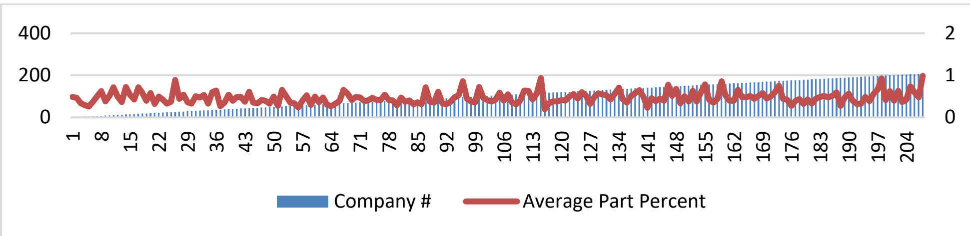
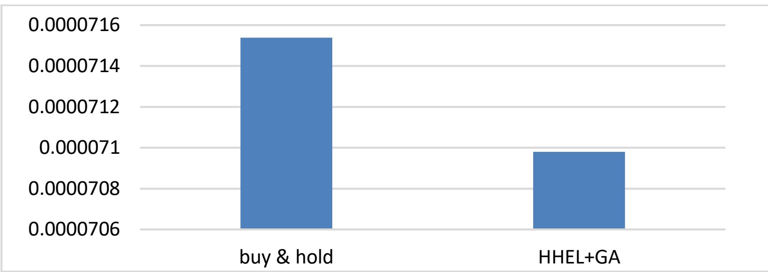


Figure 5 Average weight of each of the 208 companies in daily portfolios with the HHEL + GA (MV) model

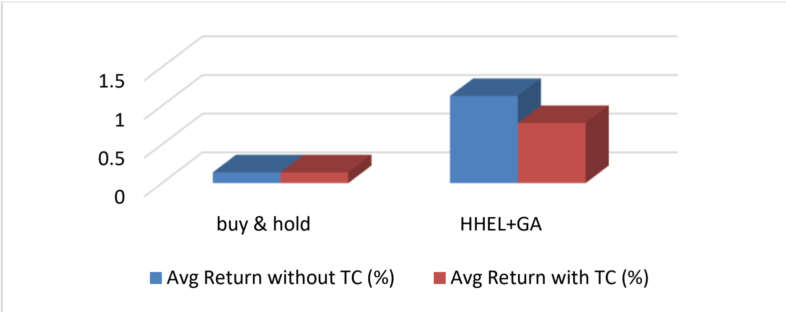
Results of the second hypothesis

1) The basket designed with the market scheduling approach using the homogeneous and heterogeneous two-level combined model HHEL and the genetic algorithm has a better performance than the basket designed with the purchase and maintenance approach.



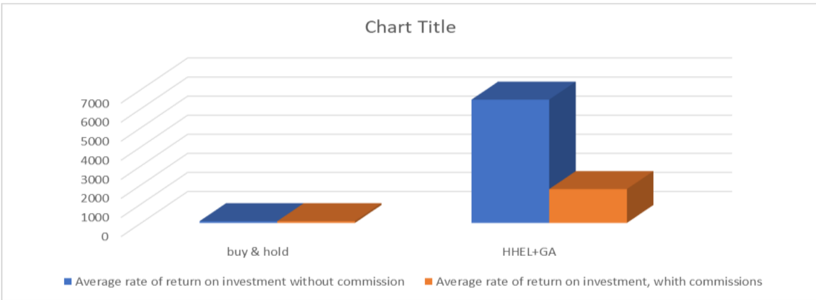
Criteria for comparing two portfolios	buy & hold	HHEL+GA
Avg Risk (%)	7.153	7.098

Figure 6 Comparison of the average purchase and maintenance portfolio risk with the proposed portfolio for test data



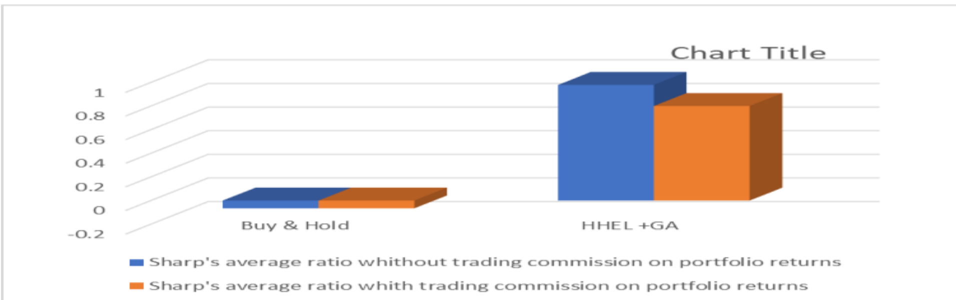
Criteria for comparing two portfolios	buy & hold	HHEL+GA
Avg Return without TC (%)	0.138939412	1.12608
Avg Return without TC (%)	0.138939412	0.776256

Figure 7 Comparison of the Avg Return buy & hold portfolio with the proposed portfolio for test data



Criteria for comparing two portfolios	buy & hold	HHEL+GA
Average rate of return on investment without commission	91.65	6462.469
Average rate of return on investment, including commissions	91.65	1773.741

Table No. 8 Comparison of the rate of return on investment of the research portfolio (HHEL+ GA) buy and hold portfolio



Criteria for comparing two portfolios	Buy & Hold	HHEL +GA
Sharp's average ratio whithout trading commission on portfolio returns	-0.06584182	0.978953
Sharp's average ratio whith trading commission on portfolio returns	-0.06584182	0.800278

Table No. 10 Comparison of the rate of Sharp's average ratio of the research portfolio (HHEL + GA) buy and hold portfolio

Comparison of results with previous research

In a comparative method, we compared the results of this study with similar studies. It was observed that in a study conducted by Philip Dias Pava et al., In 2018, they used the svm + mv and svm + 1 / n methods to form a portfolio and daily trading decision criteria. However, in this study, we used a ensemble homogeneous and heterogeneous method to increase the accuracy of the model to classify the trend of each share instead of svm. And it was observed that the validation results of the model show the superiority of this model over non-ensemble. In this study, we developed ensemble machine learning models to achieve a better model for decision-making in day-to-day transactions. Also, for comparison, we performed this model with the market value weighting method and with the equal value method and the results show the superiority of our model in forming a daily basket by weighting method with a single-objective function based on Markowitz, which is done with a genetic algorithm. It was observed that the homogeneous and heterogeneous hybrid model responds better to the share trend classification than the SVM model. In another article by Sadeghi et al.

In 2021 in their research aimed at optimizing forex market investment strategies, a hybrid technique based on EmcSVM and fuzzy NSGA-II to classify efficient trends and trades in the Forex markets. presents. Initially, EmcSVM is used to predict and classify future market trends into uptrend, sideways and downtrends. Then, NSGA-II is applied to optimize the meta-parameters of the proposed fuzzy trading system, including various AND-OR Buy / Sell technical rules for uptrends. In the table above, the results of the models of both studies are compared with the results of this study. The results indicate that the proposed research model is more accurate than comparative models .In Figure 9, the performance of the proposed model is compared with the research model of Philip Dias Pava 2018 and Sadeghi 2021.

Also, in Table No. 6, the performance of the model in terms of accuracy and recognizability has been compared with the research models of Philip Dias Pava 2018 and Sadeghi 2021, and in Table No. 7, the results of this research have been compared with other studies.

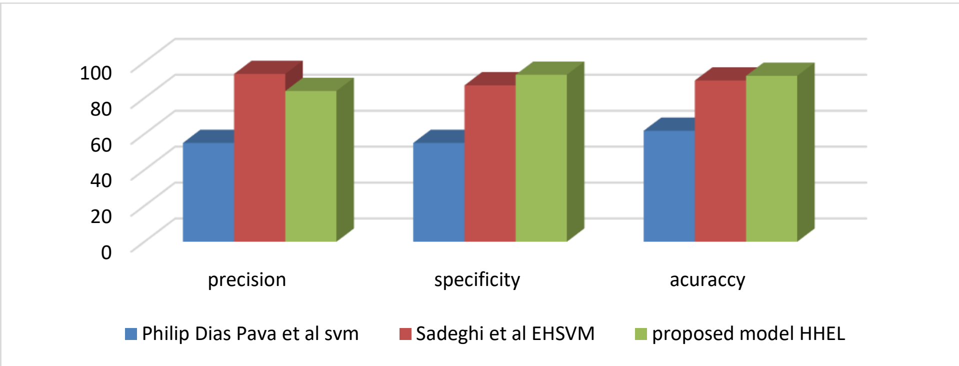


Figure 9: Comparing the performance of the proposed model with comparative models

Table 6 :Comparison table of combined model results to classify the trend of each share with comparative models

	Philip Dias Pava et al	Sadeghi et al	proposed model
	svm	EHSVM	HHEL
Sensivicity	54.97	93.4	84.0073
Specificity	70.29	87.04	92.99
Accuracy	61.73	89.72	92.39

Table 7: Comparative table of the performance of the proposed model for basket formation with comparative models

	Paiva, F. D et all 2018	Proposed research method	Proposed research method
	svm+mv without TC	HHEL+MV(GA)without TC	HHEL+MV(GA)with TC
ROI	3809.9	6462.468912	1773.74146

5. Conclusion

In this paper, using a timing strategy and using homogeneous and heterogeneous ensemble learning methods, a buy, hold and sell signal was received for all available stocks and a market forecast based on ascending, neutral or descending trend based on fundamental characteristics was obtained, Technical, macro and time series of each company in the 10 days leading up to the current day. Based on this, from the data of 480 companies listed on the Tehran Stock Exchange, 208 companies were selected as active companies that had sufficient information between 2011 and 2021. For teaching data by two-level collective learning machine (HHEL) and predicting market trends based on timing strategy, data from 5 years 1390 to 1394 have been used, and Genetic algorithms were used to test the data as stock portfolio optimization based on maximizing stock portfolio returns and minimizing investment portfolio risk and were compared with the same buy & hold strategy. The proposed homogeneous and heterogeneous two-level HHEL model compared to other comparative models for classification of share trends such as SVM support vector machine and DT decision tree, NB, NL, MLP, KNN with Accuracy 92.34% and Sensitivity coefficient 83.88% and the specificity coefficient (Specificity) 92.92 has the highest accuracy and precision and recall. Therefore, the results showed that ensemble models are more suitable for prediction than traditional or non-hybrid models and have more predictive power. Artificial intelligence and machine learning systems can help fund managers manage risk, especially for market timers. Also, the ensemble learning approach in the final decision has reduced the error, so it is suggested that market timers use this model in their predictions to timing the market. Also, the use of genetic and nature-inspired algorithms in forecasting related to financial issues and capital markets can help to improve the performance of the model to an acceptable extent. Also, the research model proposed for daily portfolio formation (HHEL + GA) will help to increase the return by 63% and the return on investment to be 70 times higher and the Sharp ratio to be 14 times higher without considering the commission and having a portfolio with controlled risk. And after reviewing, it was found that the return and the rate of return on investment and the Sharp ratio, even with the calculation of transaction fees, are 8, 19 and 12 times higher than the purchase and maintenance strategy, respectively. The proposed two-level homogeneous and heterogeneous ensemble model in the classification of trend per share compared to the model used in the classification of trend per share by Philip Dias Pava 2018 has 29.0.3, 22.7 and 30.66 times the higher accuracy and precision and recall. Also, the proposed method for daily portfolio adjustment (HHEL + GA) had a return of 1.96 times higher and a higher 0.46 higher return than the existing methods of Philip Dias Pava et al. 2018 (SVM + MV). In order to improve the article, it is suggested to use different machine learning methods to predict stock prices and select active listed companies. New meta-innovative algorithms are also proposed to achieve higher portfolio returns with lower risk.

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نقش زمان بندی بازار در توسعه محصولات مالی

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چکیده

تحقیقات توسعه محصولات مالی جدید در بازار سرمایه چند ده ای است که بسیار مورد توجه قرار گرفته است و یکی از مصولات مالی در بازار سرمایه استفاده مدل های نوین در پیش بینی روند بازار برای کنترل ریسک و افزایش بازده است.که میتواند مورد استفاده زمان سنجان بازار نیز قرار گیردو در این راستا زمان سنجان بازار با افزودن سیستم زمان بندی بازار به فرآیند تعیین و تخصیص گزینه های سـرمایه گـذاری با تعیین زمان ورود و خروج به موقع ریسک سرمایه گذاری را کاهش داده و باعث حفظ ارزش پرتفومی شوند.اما از انجا که استراتژی‌های زمان‌بندی موفق بازار به توانایی پیش‌بینی برتر بستگی دارد لذا در این مقاله با استفاده از رویکرد زمان سنجی بازار محصولی جدید در حوزه ی پیش بینی روند بازار سرمایه جهت کنترل ریسک و افزایش بازده سرمایه گذاری ارائه شده برای این کار با یک روش یادگیری جمعی دو سطحی همگن و غیر همگن(HHEL) به ارائه سیگنال خرید، نگهداری و فروش و پیش‌بینی بازار بر اساس ویژگی‌های بنیادی ویژگی‌های فنی و سری زمانی بازدهی هر شرکت در ۱۰ روز منتهی به روز جاری پرداخته شده است. بر این اساس ، ۲۰۸ شرکت که به عنوان شرکت‌های فعال بین سال‌های ۱۳۹۰ تا ۱۳۹۹ بودند، انتخاب شدند. از داده های ۵ سال اول با استفاده از روش بگینگ جهت آموزش مدل استفاده شده و مدل با استفاده از الگوریتم ژنتیک (GA) جهت افزایش دقت و کارایی بهینه گشته است و برای تست مدل پیشنهادی از ان در تشکیل سبد سهام به منظور تعیین گزینه های سرمایه گذاری استفاده شده و از الگوریتم ژنتیک (GA)به منزله بهینه‌سازی سبد سهام بر اساس بیشینه سازی بازده سبد سهام و کمینه سازی ریسک سبد سهام سرمایه‌گذاری استفاده و در نهایت بازده و ریسک سبد سرمایه گذاری بدست آمده با استراتژی خرید و نگهداری مقایسه شده است. نتایج نشان داد مدل پیش بینی پیشنهادی نسبت به سایر مدل های مقایسه ای با دقت (Accuracy) ۹۲.۳۴ درصد و حساسیت(Sensivity) ۸۳.۸۸ درصد و ضریب تشخیص پذیری(Specificity) ۹۲.۹۲ دارای بالاتریت دقت و صحت و تشخیص پذیری نسبت به سایر مدل های مقایسه ای میباشد و همچنین میانگین خطا در طبقه بندی روند توسط مدل ترکیبی دو سطحی همگن و ناهمگن نسبت به سایر مدل های مقایسه ای کمتر بو ده است.و نیز الگوی پیشنهادی جهت تشکیل پرتفو روزانه و وزن دهی روزانه سهام های منتخب (HHEL +GA) در مقایسه با استراتژی خرید و نگهداری به افزایش بازدهی ۶۳ درصدی و نرخ بازگشت سرمایه به مراتب ۷۰ برابر بیشتر و نسبت شارپ به مراتب ۱۴ برابر بالاتر بدون احتساب کارمزد و داشتن یک پرتفو با ریسک کنترل شده کمک نماید

کلمات کلیدی: محصول مالی ،بهینه‌سازی سبد سهام، زمان سنجی بازار ، مدل ترکیبی (جمعی) یادگیر ی ماشین