International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2020, 10(1), 59-66.

Investment Performance of Machine Learning: Analysis of S&P 500 Index

Chia-Cheng Chen[1], Chun-Hung Chen[2], Ting-Yin Liu[3]*

[1]Department of Finance, Ling Tung University of Science and Technology, Taichung, Taiwan, [2]Department of Finance, National Yunlin University of Science and Technology, Doulium, Yunlin County, Taiwan, [3]Department of Business Affairs, Mingdao High School, Taichung, Taiwan. *Email: tingyin.liu.713@gmail.com

Received: 02 October 2019 **Accepted:** 05 December 2019 **DOI:** https://doi.org/10.32479/ijefi.8925

ABSTRACT

This study aims to explore the prediction of S&P 500 stock price movement and conduct an analysis of its investment performance. Based on the S&P 500 index, the study compares three machine learning models: Artificial neural networks (ANN), support vector machines (SVM), and random forest. With a performance evaluation of S&P 500 index historical data spanning from 2014 to 2018, we find: (1) By overall performance measures, machine learning models outperform benchmark market index. (2) By risk-adjusted measures, the empirical results suggest that Random Forest generates the best performance, followed by SVM and ANN.

Keywords: Artificial Neural Network, Support Vector Machines, Random Forest, Machine Learning, Investment Performance
JEL Classifications: C11, C15, C53, G17

1. INTRODUCTION

In recent years, deep learning, machine learning, and artificial intelligence (AI) are mainstream. Despite the fact that there have been a number of empirical researches conducted on machine learning to predict share price movement (Ciner, 2019; Du, 2018; Long et al., 2019; Hiransha et al., 2018; Yang et al., 2019), attention has been paid majorly to the prediction efficacy of machine learning rather and little on the aspects of performance and risk measurement. Therefore, this study aims to fill the gap and delve into the financial evaluation of machine learning applications in the S&P 500.

Stock market price movement prediction has to confront the strongest rejection from the academic paradigm of efficient market hypothesis states that prices of stocks are informationally efficient which means that it is impossible to predict stock prices based on the trading data (Malkiel and Fama, 1970). However, more recent results show that, if the information obtained from stock prices is pre-processed efficiently and appropriate algorithms are applied then the trend of stock or stock price index may be predictable (Patel et al., 2015). The new discovery can greatly benefit market practitioners because accurate predictions of the movement of stock price indexes are very important for developing effective market trading strategies (Leung et al., 2000).

The main objective of the research is to input the results of ten technical analysis indicators into artificial neural networks (ANN), support vector machines (SVM), and Random Forest models to predict stock price movement and evaluate investment performance and risk measurement. In the circumstance, the machine learning models buy stocks when predicting a rise and short stocks when predicting a decline in prices. Based on the S&P 500 (GSPC) Index from 2014 to 2018, this research compares the investment performance among the machine learning models.

The remainder of this paper are organized as follows. Section 2 provides a brief overview of the theoretical literature. Section 3 describes the research data. Section 4 provides the prediction models and risk-adjusted measures used in this study. Section 5 reports the empirical results from the comparative analysis. Finally, Section 6 contains the concluding remarks.

2. LITERATURE REVIEW

For a long time, it was impossible that changes in the prices of stocks can be forecastable. Predicting returns in the stock market is usually posed as a forecasting problem where prices are predicted. Intrinsic volatility in the stock market across the globe makes the task of prediction challenging. Stock prediction and selection have long been identified as an important but challenging topic in the research area of financial market analysis (Du, 2018; Henrique et al., 2019; Long et al., 2019). In this section, we focus the review of previous studies on ANN, SVM, and random forest applied to stock market prediction and investment performance.

To quest the future features of stock markets, various forecasting algorithms have been employed, of which, computational intelligence (CI) (or AI) has become increasingly dominant due to its powerful learning capability and high prediction accuracy. Typical CI techniques in stock market prediction (for stock prices, stock returns, market indexes, etc.) are ANNs (Du, 2018; Kim and Shin, 2007; Qiu et al., 2016; Xi et al., 2014) and SVMs (Kazem et al., 2013; Li et al., 2014; Li et al., 2015; Yang et al., 2019).

ANN and SVM have been demonstrated to provide promising results in predict the stock price return (Henrique et al., 2019; Huang and Liu, 2019; Kara et al., 2011; Khan et al., 2016; Patel et al., 2015; Zhang et al., 2019). Hassan et al. (2007) propose and implement a fusion model by combining the Hidden Markov Model (HMM), ANN and Genetic Algorithms (GA) to forecast financial market behavior. Using ANN, the daily stock prices are transformed into independent sets of values that become an input to HMM. Forecasts are obtained for a number of securities in the IT sector and are compared with a conventional forecast method.

Wang et al. (2016) are developed and combined a hybrid v-support vector regression (SVR) model with principal component analysis and brainstorm optimization for stock price index forecasting. Numerical results indicate that the developed hybrid model is not only simple but also able to satisfactorily approximate the actual CSI300stock price index, and it can be an effective tool in stock market mining and analysis. Yang et al. (2019) predict stock market price with a forecasting model based on chaotic mapping, firefly algorithm, and SVR. Compared with genetic algorithm-based SVR (SVR-GA), chaotic genetic algorithm-based SVR (SVR-CGA), firefly-based SVR (SVR-FA), ANNs and adaptive neuro-fuzzy inference systems, the proposed model performs best based on two error measures, namely mean squared error and mean absolute percent error.

Gupta et al. (2018) use quantile random forests to study the predictive value of various consumption-based and income-based inequality measures across the quantiles of the conditional distribution of stock returns. Results suggest that the inequality measures have predictive value for stock returns in sample, but do not systematically predict stock returns out of the sample. Ciner (2019) show that when the random forest method, which accounts for both linear and nonlinear dynamics, is used for regression, industry returns indeed contain significant out of sample forecasting power for the market index return. Basak et al. (2018) develop an experimental framework for the classification problem which predicts whether stock prices will increase or decrease with respect to the price prevailing n days earlier. Two algorithms, Random Forests, and gradient boosted decision trees facilitate this connection by using ensembles of decision trees.

Khan et al. (2016) employ several algorithms in stock prediction such as SVM, ANN, linear discriminant analysis, linear regression, K-NN, and Naïve Bayesian Classifier to approach the subject of predictability with greater accuracy. Chatzis et al. (2018) leverage the merits of a series of techniques including classification trees, SVM, random forests, neural networks, extreme gradient boosting, and deep neural networks and find significant evidence of interdependence and cross-contagion effects among stock, bond and currency markets.

3. RESEARCH DATA

The data used in this paper all come from yahoo finance (https://finance.yahoo.com/). We collect 1258 S&P 500 (GSPC) Index samples from the yahoo finance over January 2014 to December 2018 period. These data form our entire data set. Percentage-wise increase and decrease cases of each year in the entire data set are shown in Table 1.

There are some technical indicators through which one can predict the future movement of stocks. Here in this study, a total of ten technical indicators as employed in Kara et al. (2011) are used. These indicators are shown in Table 2.

In the research, we input the results of ten technical analysis indicators into ANN, SVM and Random Forest models to predict stock price movement. In the circumstance in which the transaction costs are calculated, the machine learning models buy stocks when predicting a rise and short stocks when predicting a decline in prices. Based on the S&P 500 (GSPC) Index, the research compares the investment efficiency between the machine learning models.

Table 1: The number of increase and decrease cases percentage in each year in the entire data set of the S&P 500 index

Year	Increase	%	Decrease	%	Total
2014	144	57	108	43	252
2015	119	47	133	53	252
2016	132	52	120	48	252
2017	143	57	108	43	251
2018	132	53	119	47	251
Total	670	53	588	47	1258

Table 2: Selected technical indicators and their formulas

Name of indicators	Formulas
SMA (10-day)	$\dfrac{C_t + C_{t-1} + \cdots + C_{t-9}}{10}$
WMA (10-day)	$\dfrac{((n) \times C_t + (n-1) \times C_{t-1} + \cdots + C_{t-9})}{(n + (n-1) + \cdots + 1)}$
Momentum	$C_t - C_{t-n}$
Stochastic K%	$\dfrac{C_t - LL_{t-n}}{HH_{t-n} - LL_{t-n}} \times 100$
Stochastic D%	$\dfrac{\sum_{i=0}^{n-1} K_{t-i}\%}{n}$
Relative strength index (RSI)	$100 - \dfrac{100}{1 + \left(\sum_{i=0}^{n-1} Up_{t-i} / n\right) / \left(\sum_{i=0}^{n-1} Dw_{t-i} / n\right)}$
MACD	$MACD(n)_{t-1} + \dfrac{2}{n+1} \times (DIFF_t - MACD(n)_{t-1})$
Larry William's R%	$\dfrac{H_n - C_t}{H_n - L_n} \times 100$
A/D oscillator	$\dfrac{H_t - C_{t-1}}{H_t - L_t}$
Commodity channel index (CCI)	$\dfrac{M_t - SM_t}{0.015 D_t}$

C_t is the closing price, L_t is the low price, H_t is the high price at time t, $DIFF_t = EMA(12)_t - EMA(26)_t$, EMA is exponential moving average, $EMA(k)_t = EMA(k)_{t-1} + \alpha \times (C_t - EMA(k)_{t-1})$, α is a smoothing factor, $\alpha = \frac{2}{k+1}$, k is time period of k day exponential moving average, LL_t and HH_t mean lowest low and highest high in the last t days, respectively. $M_t = \frac{H_t + L_t + C_t}{3}$, $SM_t = \frac{\left(\sum_{i=1}^{n} M_{t-i+1}\right)}{n}$, $D_t = \frac{\left(\sum_{i=1}^{n} | M_{t-i+1} - SM_t |\right)}{n}$, UP_t means upward price change while DW_t is the downward price change at time t

4. PREDICTION MODELS AND RISK-ADJUSTED MEASURES

4.1. Prediction Models

4.1.1. ANN

The ANNs are non-linear models that make use of a structure capable to represent arbitrary complex non-linear processes that relate the inputs and outputs of any system (Chatzis et al., 2018; Chen et al., 2003; Hassan et al., 2007; Henrique et al., 2019; Huang and Liu, 2019; Kara et al., 2011; Khan et al., 2016; Leung et al., 2000; Olson and Mossman, 2003; Patel et al., 2015). ANN represents one widely used soft computing technique for stock market forecasting. ANN has demonstrated capability in financial modeling and prediction (Huang and Liu, 2019; Kara et al., 2011; Leung et al., 2000; Olson and Mossman, 2003; Patel et al., 2015).

In this study, a three-layered feedforward ANN model was structured to predict the stock price index movement. This ANN model consists of an input layer, a hidden layer and an output layer, each of which is connected to the other. The ANN architecture is defined by the way in which the neurons are interconnected. The network is fed with a set of input-output pairs and is trained to reproduce the output. The number of neurons (hn) in the hidden layer, the value of learning rate (lr), momentum constant (mc) and the number of iterations (ep) are ANN model parameters that must be efficiently determined. Inputs for the network were ten technical indicators that were represented by ten neurons in the input layer. The architecture of the three-layered feedforward ANN is illustrated in Figure 1. The investment performance of ANN prediction model are summarized in Table 3.

4.1.2. SVM

In machine learning, SVM are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. SVM emerged from research in statistical learning theory on how to regulate generalization and find an optimal trade-off between structural complexity and empirical risk. SVMs classify points by assigning them to one of two disjoint half-spaces, either in the pattern space or in a higher-dimensional feature space. One of the most popular SVM classifiers is the "maximum margin" one, which aims to minimize an upper bound on the generalization error through maximizing the margin between two disjoint half-planes (Burges, 1998; Cortes and Vapnik, 1995; Patel et al., 2015). A SVM is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. In two dimensional space, this hyperplane is a line dividing a plane into two parts wherein each class lay on either side (Bhatia and Madaan, 2018).

The main idea of a SVM is to construct a hyperplane as the decision surface such that the margin of separation between positive and negative examples is maximized (Xu et al., 2009). The equation of the hyperplane can be given as:

$$\omega^T + b = 0 \tag{1}$$

The margin is width is $2/\|\omega\|$ and the learning problem is equivalent to unconstrained optimization problem over ω.

$$\min \omega^2 + C \sum_{y}^{N} \max(0, 1 - y_i f(x_i)) \tag{2}$$

SVM are highly effective in high dimensional spaces but under perform when target classes (for classification problems) are overlapping i.e. kernel functions need to be used.

The architecture of SVM is illustrated in Figure 2. The investment performance of SVM prediction model is summarized in Table 3.

4.1.3. Random forest

Random Forest is an ensemble, data-miner which uses "deep" (unpruned) decision trees as base learners. It is a modification of applying to bag to multiple classifications and regression trees, and averaging the predictions of the approximately uncorrelated trees to yield the final estimate. Random Forest model was unable to show any clear patterns in the data through variable importance plots and did not show any significant improvement in performance in comparison to generalized linear models (Bhatia and Madaan, 2018). Decision tree learning is one of the most popular techniques for classification. Its classification accuracy is comparable with other classification methods, and it is very efficient.

Figure 1: Architecture of artificial neural networks

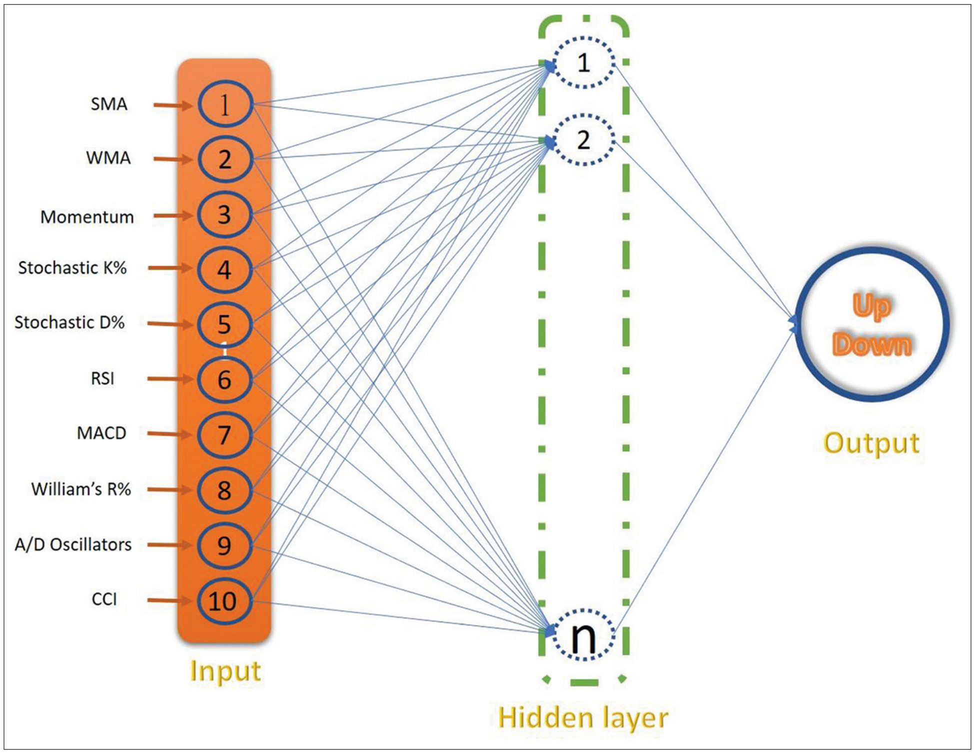
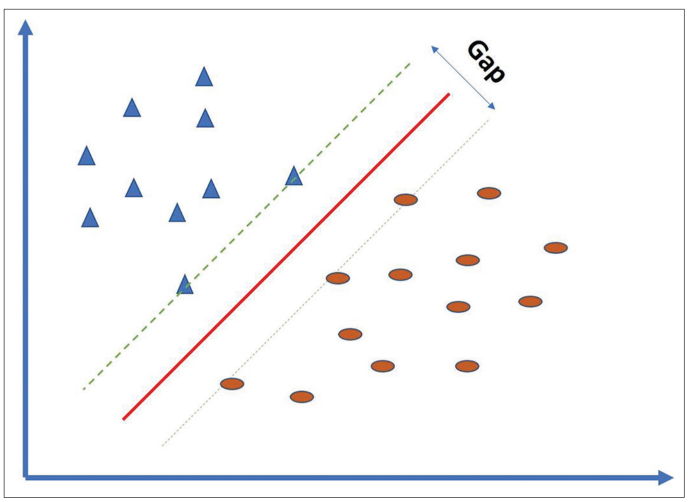


Figure 2: Architecture of support-vector machines



Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classification. It uses decision tree as the base learner of the ensemble. The idea of ensemble learning is that a single classifier is not sufficient for determining class of test data. Reason being, based on sample data, classifier is not able to distinguish between noise and pattern. So it performs sampling with replacement such that given n trees to be learnt are based on these data set samples. After creation of n trees, when testing data is used, the decision which majority of trees come up with is considered as the final output. This also avoids problem of over-fitting. The investment performance of random forests prediction model is summarized in Table 3.

Table 3: Annual returns of three prediction model with benchmark

Prediction models	2014	2015	2016	2017	2018	5 years
GSPC (Benchmark)	12.28	−1.03	12.34	17.95	−5.69	35.85
ANN	−7.00	28.81	9.09	2.29	25.87	59.06
SVM	25.91	4.54	17.49	22.71	13.90	84.55
Random forest	25.31	31.96	15.11	24.12	−9.14	87.36

ANN is the artificial neural network, SVM is the support vector machines, TREE is the random forest, GSPC is the S&P 500 index, it's also benchmark in the study

5. EXPERIMENTAL RESULTS AND ANALYSIS

The research empirically examines the financial performance of machine learning through performance measures, such as Jensen's Alpha, Sharpe ratio, Treynor ratio, information ratio, and Modigliani ratio. Our experimental results are based on data retrieved from the S&P 500 Index (from 2014 to 2018). The empirical results are presented firstly by descriptive statistics, followed by an annual evaluation analysis, and concluded with overall performance comparison among machine learning models.

5.1. Descriptive Statistics

The analysis of the overall performance of ANN, SVM, and Random Forest models is undertaken base on the benchmarks indices, the S&P 500 Index (GSPC). The descriptive statistics of the daily returns for the benchmark indices, and for the three machine learning models are reported in Table 4. Figure 3 is the daily return chart of machine learning models and GSPC from 2014 to 2018.

Figure 3: Daily return of machine learning with GSPC benchmark investment performance

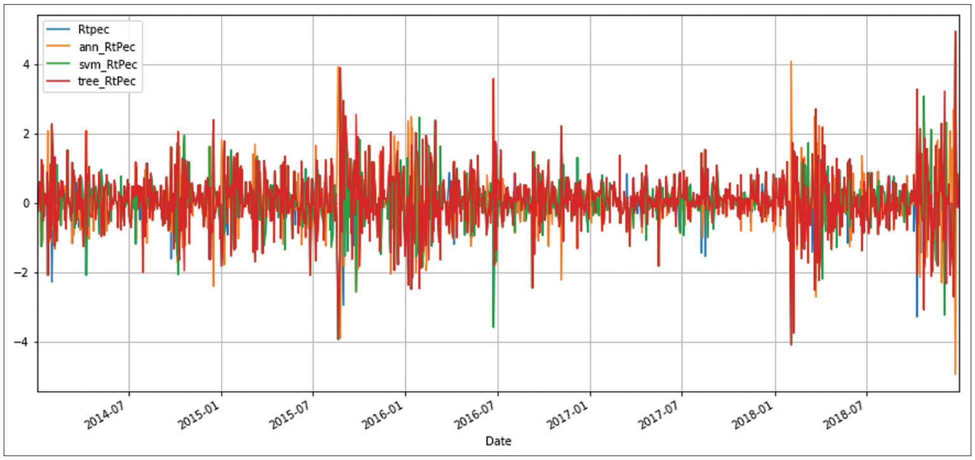


Figure 4: Cumulative return of machine learning with S&P 500 index benchmark investment performance

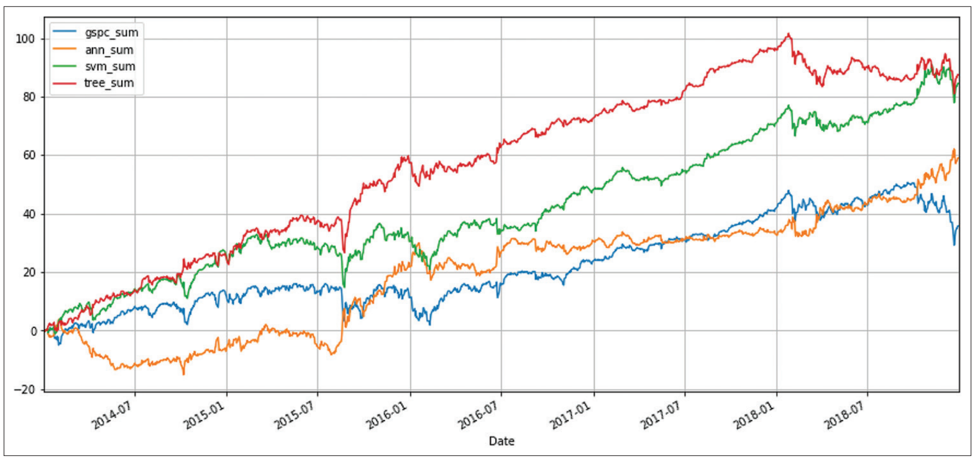


Table 4: Descriptive statistics of daily returns

Indicators	ANN	SVM	TREE	GSPC (benchmark)
MAX	4.0979	4.9593	4.9593	4.9593
MIN	−4.9593	−4.0979	−4.0979	−4.0979
STD	0.8320	0.8306	0.8304	0.8328
MEAN	0.0469	0.0672	0.0694	0.0285
Median	0.0352	0.0695	0.0621	0.0381

ANN is an artificial neural network, SVM is the support vector machines, TREE is the random forest, GSPC is the S&P 500 index, it's also a benchmark in the study

As presented in Table 4 and Figure 3, our proposed machine learning models generate significantly higher mean returns. In terms of average daily return, SVM and random forest generate 2 times higher returns than GSPC (benchmark); with ANN of 1.5 times. Among the machine learning models, the results indicate that the order of investment performance excellence can be put down as follows: SVM, random forest, and ANN.

For the entire sample period, the cumulative returns of ANN, SVM, and Random Forest are respectively of 59.06%, 84.55%, and 87.36% in Figure 4. By annual data, our machine learning models are particularly impressive during the bear markets. Specifically, in 2015 with a market return of −1.03%, ANN, SVM, and random forest are respectively of 28.81%, 4.54%, and 31.96%. Likewise, in 2018 with a market return of −5.69%, ANN and SVM are respectively of 25.87% and 13.90%. Overall, our empirical results suggest machine learning is promising for higher cumulative returns in the S&P 500 index applications.

5.2. Risk-adjusted Measures

5.2.1. Sharpe ratio

The Sharpe ratio is used to help investors understand the return of an investment compared to its risk. The ratio is the average return earned in excess of the risk-free rate per unit of volatility or total risk. Subtracting the risk-free rate from the mean return allows an investor to better isolate the profits associated with risk-taking activities. Generally, the greater the value of the Sharpe ratio, the more attractive the risk-adjusted return. In particular, a negative Sharpe ratio indicates a situation of "anti-skill," since the performance of the riskless asset is clearly superior.

According to Table 5, it is evident from the empirical results presented in proposed machine learning models outperform the benchmark. More specifically, the Sharpe ratios of GSPC in 2015 and 2018 produce negative values, indicating no investment worth. The Sharpe ratios of ANN, SVM, and random forest are almost positive for all 5 years and outperform that of GSPC. In short, the Sharpe ratio of ANN, SVM, and Random Forest all exceed that of the GSPC benchmark index.

5.2.2. Information ratio

The information ratio measures the risk-adjusted returns of a financial asset or stock relative to a certain benchmark. This ratio aims to show excess returns relative to the benchmark, as well as the consistency in generating the excess returns. The consistency of generating excess returns is measured by the tracking error.

Although originally referred to by Treynor and Black (1973) as the "appraisal ratio," the information ratio is the ratio of relative returns to relative risk, and whilst the Sharpe ratio examines the returns relative to a riskless asset, the information ratio is based upon returns relative to a risky benchmark.

In Table 6, a comparison of machine learning models' performance during these 5 years manifests that SVM and random forest have higher information ratios, with the values respectively of 0.0619 and 0.0471. ANN has the lowest, with the values respectively of 0.0138.

5.2.3. Tracking error

Tracking errors are calculated as the relative standard deviation of returns between a stock and a benchmark. A tracking error is a useful performance measure relative to a benchmark since it is measured in units of asset returns. The comparative empirical tracking errors of the machine learning models with respect to the benchmark indices are reported in Table 7.

Concretely speaking, we found that the graver the machine learning models' tracking errors are, the better the investment performances turn out. For instance, the returns of ANN in 2015 and 2018 are 28.81% and 25.87%. Their tracking errors are 1.5608 and 1.7589. The results justify the value of active management by machine learning compared to passive index tracking.

5.3. Overall Performance Comparison

5.3.1. Jensen's alpha

Jensen's alpha is an absolute measure of performance. It was developed by American economist Michael Jensen in 1968 (Jensen, 1968). It is given by the annualized return of the stock, deducted the yield of an investment without risk, minus the return of the benchmark multiplied by the stock's beta during the same period. Jensen's alpha gives the excess return obtained when deviating from the benchmark (Jensen, 1972).

The magnitude of Jensen's alpha depends on two key variables: the return of the benchmark and the beta. This indicator represents the part of the mean return of the stock that cannot be explained by the systematic risk exposure to market variations.

As it is an absolute measure, it does not reflect completely the risk of the stock. It is then generally easier for a more risky stock to exhibit a greater Jensen's alpha than for a less risky stock. It should be then applied to the homogenous class of assets. Moreover, the validity of this measure depends crucially on the hypothesis that the beta of the stock is stationary. The validity of this hypothesis has to be tested before focusing on the value of this indicator (Grinblatt and Titman, 1987; 1989; 1992).

The Jensen's alpha provides quite a robust measure of the abnormal returns that are generated by the stock as compared to a passive combination of the risk-free asset and a market index with exactly the same risk characteristics as the stock.

Table 8 shows that Jensen's Alphas of the machine learning models are positive, transpiring that their investment performances are better than that of the benchmark index. Therefore, the sequence of investment performance excellence can be put down as follows: Random Forest, SVM, and ANN.

5.3.2. Beta and Treynor ratio

The beta is a measurement of its volatility of returns relative to the entire market. It is used as a measure of risk and is an integral part of the capital asset pricing model. An index with a higher beta has greater risk and also greater expected returns.

The Treynor ratio, also known as the reward-to-volatility ratio, is a performance metric for determining how much excess return was generated for each unit of risk taken on by a stock. Excess return in this sense refers to the return earned above the return that could have been earned in a risk-free investment. Risk in the Treynor ratio refers to systematic risk as measured by a stock's beta. Beta measures the tendency of a stock's return to change in response to changes in return for the overall market. The higher the Treynor ratio, the better the performance of the stock under analysis.

In Tables 8 and 9, we can see that ANN generates the greater return, which reaches 59.06%, and yet, its beta is −0.2784 and the resulting Treynor ratio is −0.1876. The reason behind it's

Table 5: Sharpe ratio index

Year	GSPC	ANN	SVM	TREE
2014	0.0629	−0.0444	0.1399	0.1366
2015	−0.0081	0.1136	0.0144	0.1266
2016	0.0556	0.0398	0.0807	0.0691
2017	0.1631	0.0144	0.2100	0.2242
2018	−0.0239	0.0939	0.0489	−0.0368
5 years	0.0301	0.0523	0.0768	0.0795

ANN: Artificial neural network, SVM: Support vector machines

Table 6: Information ratio

Year	ANN	SVM	TREE
2014	−0.0662	0.0895	0.0618
2015	0.0758	0.0353	0.1392
2016	−0.0101	0.0377	0.0117
2017	−0.1054	0.0459	0.0527
2018	0.0715	0.0913	−0.0131
5 years	0.0138	0.0619	0.0471

ANN: Artificial neural network, SVM: Support vector machines

Table 7: Tracking error

Year	ANN	SVM	TREE
2014	1.1553	0.6039	0.8358
2015	1.5608	0.6267	0.9400
2016	1.2652	0.5418	0.9335
2017	0.5915	0.4127	0.4658
2018	1.7589	0.8551	1.0462
5 years	1.3307	0.6253	0.8693

ANN: Artificial neural network, SVM: Support vector machines

Table 8: Index of risk-adjusted return based on volatility

Indicators	ANN	SVM	TREE	GSPC
5 Y return	59.06	84.55	87.36	35.85
Sharpe ratio	0.0523	0.0768	0.0795	0.0301
Jensen's alpha	0.0549	0.0468	0.0566	
Beta	−0.2784	0.7153	0.4520	
Treynor ratio	−0.1876	0.1070	0.1753	
Information ratio	0.0138	0.0619	0.0471	
Modigliani ratio (M2)	0.0469	0.0670	0.0692	0.0285

ANN: Artificial neural network, SVM: Support vector machines

Table 9: Treynor ratio

Year	ANN	SVM	TREE
2014	0.1413	0.2186	0.4438
2015	−0.4039	0.0181	0.2358
2016	−0.2056	0.1030	0.1969
2017	0.6295	0.4075	0.5906
2018	−0.2631	0.0716	−0.0701
5 years	−0.1876	0.1070	0.1753

ANN: Artificial neural network, SVM: Support vector machines

beta's negative value is that machine learning models' primary function is to predict stock price movement and buy stocks when prices rise and short stocks when prices fall. It aims to benefit both from rising and falling, and thus, its nature resembles active management funds rather than tracking the index. In particular, when markets are most down and corrected predicted by ANN, the returns of ANN strategy will inverse with market returns and generate negative covariance between ANN and market index. In addition to ANN whose beta turns out to be negative, the betas of SVM and random forest fall between zero and one, manifesting that although they are less volatile than the market, their investment performances prove to be more outstanding than that of a benchmark index.

5.3.3. Modigliani ratio

The Modigliani risk ratio, often called M2, measures the return provided by an investment in the context of the risk involved. It was developed by Franco Modigliani and Leah Modigliani in the year 1997.

Modigliani and Modigliani (1997) believed that an ordinary investor would find it easier to understand the Modigliani measure compared to Sharpe ratio. The reason behind this was that their measure is expressed in percentage points. It shows how well the investor is rewarded for taking a certain amount of risk, relative to the benchmark and the risk free rate.

In general, the riskier an investment is, the less inclined investors will be to put their money into it. So riskier investments have to offer a higher potential return - that is, deliver a greater profit if the investment succeeds. In simple words, it measures the returns of an investment index or stock for the amount of risk taken relative to some benchmark index.

In terms of Sharpe ratio, Treynor ratio, Information ratio and Modigliani ratio, the three prediction models all excel benchmark index. Among them, SVM and Random Forest outperform ANN.

In brief, conclusions can be elicited from results above that, firstly, the three machine learning models all exhibit better investment performance than the S&P 500 index in terms of higher excess returns or less beta volatility. Among them, In terms of average daily return, SVM and Random Forest generate 2 times higher returns than GSPC (benchmark); with ANN of 1.5 times. For risk-adjusted performance measures, such as the Shape ratio, Jensen's alpha, information ratio, and Modigliani ratio, machine learning models surpass the benchmark index. Moreover, among the three machine learning models, Random Forest generates the best performance, followed by SVM, and ANN coming in last.

6. CONCLUSIONS AND REMARKS

The task-focused in this paper is an analysis of the investment performance of machine learning models. The investment performance of three models namely ANN, SVM, and random forest are compared based on 5 years (2014-2018) of historical data of the S&P 500 (GSPC) Index.

Experiments show that our proposed machine learning models generate significantly higher mean returns. In terms of average daily return, SVM and random forest generate 2 times higher returns than GSPC (benchmark); with ANN of 1.5 times. Among the machine learning models, the results indicate that the order of investment performance excellence can be put down as follows: SVM, random forest, and ANN.

For the entire sample period, the cumulative returns of ANN, SVM, and Random Forest are respectively of 59.06%, 84.55%, and 87.36%. Specifically, in 2015 with a market return of −1.03%, ANN, SVM, and Random Forest are respectively of 28.81%, 4.54%, and 31.96%. Likewise, in 2018 with a market return of −5.69%, ANN and SVM are respectively of 25.87% and 13.90%. Overall, our empirical results suggest machine learning is promising for higher cumulative returns in the S&P 500 index applications.

Jensen's alphas of all three machine learning models produce positive values, indicating that their investment performances surpass that of the benchmark index. Therefore, the sequence of investment performance excellence can be put down as follows: Random Forest, SVM, and ANN.

The foremost object of machine learning models is to predict stock price movement and buy stocks when prices rise and short stocks when prices fall, hoping to obtain profits both from rising and falling. Therefore, it bears a resemblance to active management funds rather than tracking the index, which accounts for their beta's negative values and lucrative performance. With regard to the Sharpe ratio, Treynor ratio, Information ratio, and Modigliani ratio, the three prediction models all excel benchmark index.

To sum up, machine learning models exceed benchmark index in investment performance. Among the machine learning models, Random Forest generates the best performance, followed by SVM and ANN.

REFERENCES

Basak, S., Kar, S., Saha, S., Khaidem, L., Dey, S.R. (2018), Predicting the direction of stock market prices using tree-based classifiers. The North American Journal of Economics and Finance, 47, 552-567.

Bhatia, M., Madaan, A. (2018), Stock portfolio performance by weighted stock selection. Expert Systems with Applications, 113, 161-185.

Burges, C.J. (1998), A tutorial on support vector machines for pattern recognition. Data Mining Knowledge Discovery, 2(2), 121-167.

Chatzis, S.P., Siakoulis, V., Petropoulos, A., Stavroulakis, E., Vlachogiannakis, N. (2018), Forecasting stock market crisis events using deep and statistical machine learning techniques. Expert Systems with Applications, 112, 353-371.

Chen, A.S., Leung, M.T., Daouk, H. (2003), Application of neural networks to an emerging financial market: Forecasting and trading the Taiwan stock index. Computers and Operations Research, 30(6), 901-923.

Ciner, C. (2019), Do industry returns predict the stock market? A reprise using the random forest. The Quarterly Review of Economics and Finance, 72, 152-158.

Cortes, C., Vapnik, V. (1995), Support-vector networks. Machine Learning, 20(3), 273-297.

Du, Y. (2018), Application and Analysis of Forecasting Stock Price Index Based on Combination of ARIMA Model and BP Neural Network. Paper Presented at the 2018 Chinese Control And Decision Conference. Shenyang, China: IEEE.

Grinblatt, M., Titman, S. (1987), The relation between mean-variance efficiency and arbitrage pricing. Journal of Business, 60, 97-112.

Grinblatt, M., Titman, S. (1989), Portfolio performance evaluation: Old issues and new insights. The Review of Financial Studies, 2(3), 393-421.

Grinblatt, M., Titman, S. (1992), The persistence of mutual fund performance. The Journal of Finance, 47(5), 1977-1984.

Gupta, R., Pierdzioch, C., Vivian, A.J., Wohar, M.E. (2018), The predictive value of inequality measures for stock returns: An analysis of long-span UK data using quantile random forests. Finance Research Letters, 13, 315-322.

Hassan, M.R., Nath, B., Kirley, M. (2007), A fusion model of HMM, ANN and GA for stock market forecasting. Expert Systems with Applications, 33(1), 171-180.

Henrique, B.M., Sobreiro, V.A., Kimura, H. (2019), Literature review: Machine learning techniques applied to financial market prediction. Expert Systems with Applications, 124, 226-251.

Hiransha, M., Gopalakrishnan, E.A., Menon, V.K., Soman, K.P. (2018), NSE stock market prediction using deep-learning models. Procedia Computer Science, 132, 1351-1362.

Huang, C.S., Liu, Y.S. (2019), Machine learning on stock price movement forecast: The sample of the Taiwan stock exchange. International Journal of Economics and Financial Issues, 9(2), 189-201.

Jensen, M.C. (1968), The performance of mutual funds in the period 1945-1964. The Journal of Finance, 23(2), 389-416.

Jensen, M.C. (1972), Optimal utilization of market forecasts and the evaluation of investment performance. In: Szego, G.P., Shell, K., editors. Mathematical Methods in Finance. Amsterdam: North-Holland Publishing Company.

Kara, Y., Boyacioglu, M.A., Baykan, Ö.K. (2011), Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul stock exchange. Expert Systems with Applications, 38(5), 5311-5319.

Kazem, A., Sharifi, E., Hussain, F.K., Saberi, M., Hussain, O.K. (2013), Support vector regression with chaos-based firefly algorithm for stock market price forecasting. Applied Soft Computing, 13(2), 947-958.

Khan, W., Ghazanfar, M., Asam, M., Iqbal, A., Ahmad, S., Khan, J.A. (2016), Predicting trend in stock market exchange using machine learning classifiers. Science International, 28(2), 1-11.

Kim, H.J., Shin, K.S. (2007), A hybrid approach based on neural networks and genetic algorithms for detecting temporal patterns in stock markets. Applied Soft Computing, 7(2), 569-576.

Leung, M.T., Daouk, H., Chen, A.S. (2000), Forecasting stock indices: A comparison of classification and level estimation models. International Journal of Forecasting, 16(2), 173-190.

Li, X., Xie, H., Chen, L., Wang, J., Deng, X. (2014), News impact on stock price return via sentiment analysis. Knowledge-Based Systems, 69, 14-23.

Li, X., Xie, H., Song, Y., Zhu, S., Li, Q., Wang, F.L. (2015), Does summarization help stock prediction? A news impact analysis. IEEE Intelligent Systems, 30(3), 26-34.

Long, W., Lu, Z., Cui, L. (2019), Deep learning-based feature engineering for stock price movement prediction. Knowledge-Based Systems, 164, 163-173.

Malkiel, B.G., Fama, E.F. (1970), Efficient capital markets: A review of theory and empirical work. The Journal of Finance, 25(2), 383-417.

Modigliani, F., Modigliani, L. (1997), Risk-adjusted performance. Journal of Portfolio Management, 23(2), 45.

Olson, D., Mossman, C. (2003), Neural network forecasts of Canadian stock returns using accounting ratios. International Journal of Forecasting, 19(3), 453-465.

Patel, J., Shah, S., Thakkar, P., Kotecha, K. (2015), Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques. Expert Systems with Applications, 42(1), 259-268.

Qiu, M., Song, Y., Akagi, F. (2016), Application of artificial neural network for the prediction of stock market returns: The case of the Japanese stock market. Chaos, Solitons and Fractals, 85, 1-7.

Treynor, J.L., Black, F. (1973), How to use security analysis to improve portfolio selection. The Journal of Business, 46(1), 66-86.

Wang, J., Hou, R., Wang, C., Shen, L. (2016), Improved v-support vector regression model based on variable selection and brain storm optimization for stock price forecasting. Applied Soft Computing, 49, 164-178.

Xi, L., Muzhou, H., Lee, M.H., Li, J., Wei, D., Hai, H., Wu, Y. (2014), A new constructive neural network method for noise processing and its application on stock market prediction. Applied Soft Computing, 15, 57-66.

Xu, X., Zhou, C., Wang, Z. (2009), Credit scoring algorithm based on link analysis ranking with support vector machine. Expert Systems with Applications, 36, 2625-2632.

Yang, F., Chen, Z., Li, J., Tang, L. (2019), A novel hybrid stock selection method with stock prediction. Applied Soft Computing, 80, 820-831.

Zhang, K., Zhong, G., Dong, J., Wang, S., Wang, Y. (2019), Stock market prediction based on generative adversarial network. Procedia Computer Science, 147, 400-406.