Expert Systems With Applications 233 (2023) 120840

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Practical machine learning: Forecasting daily financial markets directions ☆

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ARTICLE INFO

Keywords:
Financial time series prediction
Machine learning
Stock markets
Developing markets

ABSTRACT

Financial time series prediction has many applications in economics, but producing profitable strategies certainly has a special place among them, a daunting challenge. Statistical and machine learning techniques are intensively researched in the search for a holy grail of stock markets forecasting. However, it is not clear to prospecting researchers how good those popular models are regarding useful predictions on a real scenario. This paper contributes to that discussion, providing decisive evidences contrary to the use of basic out-of-the-box models, specifically Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF) and Naive-Bayes (NB). Results consider optimistic and unreal variables often found in literature, as well as a more close-to-real simulation of the models usage. Specifically, current day closing prices direction forecasting results are contrasted with those on next day forecasts. As expected, when forecasting the current day, accuracy is almost perfect. However, when used to forecast next day closing direction, with a strict data separation policy and without direction or snooping bias, ANN, SVM, RF and NB produce results essentially equal to random guessing. The main achieved result is the demonstration of how a machine learning approach would fare in a support decision system for forecasting short-term future market direction, regardless of the level of market development, considering more than 100 securities in a 10 years period. Consequences for algorithmic trading relate to discouraging usage of the considered models as implemented here. On a more abstract sense, this paper presents more evidence to the Efficient Market Hypothesis (EMH).

1. Introduction

The Efficient Market Hypothesis (EMH) states it is impossible to consistently predict stock prices and beat the market, as theorized by Malkiel and Fama (1970). That classic text affirms that, at an equilibrium state, the prices reflect all available information, reacting almost instantly on any new data that could eventually be used to make some prediction about prices. The subject attracts a lot of academia and professional attention due to its possibilities of high returns and financial risk protection (Ballings, den Poel, Hespeels, & Gryp, 2015, p. 7046). However, twenty years after Malkiel and Fama (1970), the EMH is not accepted as refused, as stated by Fama (1991) in a work which updates the hypothesis forms, examines some attempts to refute it and finally keeps it as valid (Fama, 1991, p. 1609). Up to this day, financial markets prediction is still a prolific research topic.

The price returns from stock markets, consonant with the EMH arguments, behave as a Random Walk model (Patel, Shah, Thakkar, & Kotecha, 2015b, p. 2162). In this case, the returns are generated by a stochastic process (Araújo, Oliveira, & Meira, 2015, p.4082), being unpredictable, a problem known as Random Walk Dilemma (RWD). The "model" term refers to the price generation process, which is obviously unknown and sought by traders. Models capable of predicting price values or movements may lead to high returns and hedging protection (Ballings et al., 2015, p.7046). Beyond an investment channel, stock markets are primary indicators of economic conditions of countries (Göçken, Özçalıcı, Boru, & Dosdoğru, 2016, p.320). Therefore, accurate predictions lead not only to potential profits but also to powerful decision tools about sovereign economy. In this context, Podsiadlo and Rybinski (2016, p. 219) state that wrong economic decisions can be catastrophic for individuals as well as whole nations, highlighting the importance of stock markets predictions.

Because of their importance for the economy, financial markets attract research on risk and decision support systems (Hsu, Lessmann, Sung, Ma, & Johnson, 2016, p. 215). Predictive algorithms are explored on financial time series and show some forecasting potential on stock prices (Ballings et al., 2015, p.7046). Among common algorithms, previous literature works with linear models, such as Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH), and non-linear models, such as Artificial Neural Network

☆ This document was a collaborative effort.

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https://doi.org/10.1016/j.eswa.2023.120840
Received 29 July 2020; Received in revised form 14 April 2023; Accepted 11 June 2023
Available online 25 June 2023

(ANN) and Support Vector Machine (SVM) (Chen, Xiao, Sun, & Wu, 2017; Gerlein, McGinnity, Belatreche, & Coleman, 2016; Zhang, Lin, & Shang, 2017).

Among the prediction techniques, technical and fundamental analyses deserve attention, due to their popularity among practitioners. Cavalcante, Brasileiro, Souza, Nobrega, and Oliveira (2016, p.194) observe that fundamental analysis studies economic factors influencing market movements, evaluating companies performances, for example, through financial reports (Barak, Arjmand, & Ortobelli, 2017, p. 90). On the other hand, technical analysis seeks indicators of repeating patterns, using them to define which operations can be profitable (Chen, Cheng, & Tsai, 2014, pp. 329–330). This broad classification of prediction techniques is also used by Xiao, Xiao, Lu, and Wang (2013). However, those authors recognize that the knowledge of facts with the potential to influence market prices, such as politics, macro and microeconomics, which are fundamentalist indicators, is not always readily available (Xiao et al., 2013, p. 96). Therefore, many fund managers place great importance on technical analysis indicators, as observed by Hudson, McGroarty, and Urquhart (2017, p. 136), because they are generally calculated directly from prices, as stated by Sobreiro et al. (2016, pp. 88–89).

However, correct prices or movements prediction is a challenging task. The random walk character of stock prices was empirically confirmed by some studies, as stated by Timmermann and Granger (2004, p. 15). Modeled as time series, stock prices exhibit irregular movements and tendencies (Dash & Dash, 2016, p.43), non-linearities, discontinuities, interactions with political and economic events and relation with the behavior of markets participants (Göçken et al., 2016, p. 320). Therefore, forecasting methods capable of capturing non-linear relationships obtain superior results in financial markets applications (Reboredo, Matías, & Garcia-Rubio, 2012, p. 246) when compared with linear methods (Zhang et al., 2017, p. 162). Some of those non-linear techniques are studied as a group called machine learning.

According to the definition of Xiao et al. (2013, pp. 99–100), learning systems generally try to extract patterns from a training data set. Intense computational tools used to this end are grouped as machine learning algorithms or models. They are commonly categorized as classifiers, such as SVM, or regressors, such as Support Vector Regression (SVR). Both categories are used in stock prices time series predictions. As examples, Kumar, Meghwani, and Thakur (2016) apply SVM and ANN as classifiers of the direction taken by international markets indexes and Henrique, Sobreiro, and Kimura (2018), by their turn, use SVR to predict the values of international markets indexes. In this context, Gerlein et al. (2016, p.193) state that machine learning techniques show impressive results when applied not only to time series, but also to other areas, such as document analysis, astronomy and biology.

As commented before, stock prices time series forecasting constitutes a formidable task. Because of that, it has become a common practice to utilize those data series to measure performance and accuracy of machine learning techniques, as studied by Hsu et al. (2016, p. 215). That review analyzed works with high reported predictive accuracies, suggesting papers with profitable forecasting models, contrary to the evidences of the EMH. As an example, Patel et al. (2015b) combine SVR with other models and technical analysis indicators to predict stock market indexes. They conclude there is predictive power at a significant level in their approach. Dash and Dash (2016) also combine machine learning and technical analysis indicators and ANN to develop a model to buy and sell stock market indexes. They conclude ANN achieves superior performance for indexes forecasting.

Despite the difficulties of obtaining precise predictions about stock prices, this research area has grown in popularity in recent years, as introduced by Narayan and Sharma (2016, p. 105). This is related to the plain availability of data generated by current technology (Dash & Dash, 2016, p. 43). The research aiming consistent profits from financial markets using the literature on machine learning actually searches for evidences contrary to the EMH (Hsu et al., 2016, pp. 215–216), being relevant for the scientific community. This paper contributes to the literature of stock markets prediction using machine learning methods applied to different markets. Specifically, ANN, SVM, Naive-Bayes (NB) and Random Forest (RF) are used to forecast indexes and stock prices directions, consonant with the approach followed by Patel, Shah, Thakkar, and Kotecha (2015a), but extending the authors' work to various markets with different characteristics, a larger stocks database, using a more robust scheme for partitioning data and, more importantly, evaluating predictions for the next day direction under next-to-real conditions. It is desired that the results cast some reflections on the usage of machine learning basic models in financial time series from stock markets.

Most studies of stock prices prediction using machine learning are conducted with developed markets data, as stated by Chen, Leung, and Daouk (2003, p. 901) and Atsalakis and Valavanis (2009, p. 5933). However, trading on developing markets, such as Brazil, Russia, India, China and South Africa, the economic block known as BRICS, might contribute to mitigate portfolio risk (Sobreiro et al., 2016, pp.86–87). In a previous work on ANN, Cao, Leggio, and Schniederjans (2005, p.2510) point that difficulties on obtaining profits from developed markets may signify that those have attained a certain level of efficiency where no more profits are possible by using such predictive techniques. Therefore, machine learning prediction tools on developing markets may exhibit different results for profitability and also diminish a gap on the related literature. In fact, Kumar and Thenmozhi (2014, p. 289) state developing markets are more predictable than the developed ones. The current paper presents results on both markets.

Beyond new results on the daily direction forecasts of more than 110 financial securities from 10 international markets, both developing and developed, obtained with four prediction techniques, our paper brings three more advancements, specially regarding the highly cited Patel et al. (2015a) and Kara, Boyacioglu, and Baykan (2011). The first advancement settles an important misconception on the dependent variable of the models. Although results reported by Patel et al. (2015a) and Kara et al. (2011) entice the reader for profitable opportunities, they are virtually unattainable in practical trading. Forecasting daily closing prices directions using data calculated with those very same closing prices, by using technical analysis, is surely important for academic research on prediction methods evaluation and comparisons, but brings no real value for a trader who already knows closing prices at the end of the trading day. Fund managers and traders might benefit more on direction predictions for future days, for instance, the closing prices direction of the next day given the prices today. In this context, this paper contrasts the performance of machine learning forecasting techniques for the current day as well as the next day, evaluating the usefulness of those methods for prospecting traders.

The second advance of this paper relates to how data is separated in each phase of the machine learning experiments. Patel et al. (2015a) and Kara et al. (2011) propose interesting considerations on keeping the samples from each year proportional to each other as well as the number of days of bullish or bearish closing. However, their data partitioning scheme allows for reusage of parametrization data on out-of-sample tests, which could compromise results. As a benchmark for comparisons, our paper firstly uses the very same partitioning rules proposed by Patel et al. (2015a) and Kara et al. (2011). However, when experimenting on the next day closing price direction, the current paper applies a more rigid partitioning data scheme, making impossible any data reusage in any phase of calculations. It must be stressed that this scenario mimics a real application of machine learning for prices direction forecasting: defining a dependent variable useful for trading strategies (the next day price direction) and independent variables made of current day prices actually known before a trading decision is made. Finally, the third advancement brought by this paper is comparing not only continuous and discrete technical analysis indicators as independent variables, as done by Patel et al. (2015a), but also mixing simultaneously both kinds as inputs to the forecasting algorithms.

The main objective of this paper is to provide a more robust answer to the question of how useful are machine learning techniques, in their basic algorithmic forms, for predicting stock and indexes prices daily direction and, subsequently, building profitable trading strategies. Summarizing the key contributions, this paper bases its answer to the proposed research question by considering 10 different markets, being 5 from developed countries and 5 from developing countries, gathering data on 10 stocks from the largest capitalization companies from each market as well as each market index. The dependent variables are not only the current daily closing price directions (which serve as a benchmark for comparing results of previous works as well as the performance of models when using continuous, discrete and both forms of technical analysis indicators as inputs), but also the next day closing price direction. Adding to those results, experiments also consider possible persistence on forecasting power by setting the closing price of two days ahead as the dependent variable. Momentum effects are also considered by applying a threshold for prediction. As stated before, the out-of-sample tests are conducted on a rigid premise of not using data already considered on parametrizations or training, which guarantees robust results.

Although not conclusive about the EMH, which is not directly tested by any methods presented here, the current paper adds to evidences in favor of it. Results, as shown below, indicate the tested basic out-of-the-box algorithms of the machine learning literature have no predictive ability at all over financial markets regarding the next-day closing prices. Even the safer approach of forecasting only when prices vary more than a certain threshold, known as momentum strategy, results in no foreseeable gain in trading strategies. Those results are the same for both developing and developed countries, considering popular technical analysis indicators as independent variables in their continuous, discrete or both forms simultaneously. Albeit inconclusive about the EMH, the results that follow discourage further research on ANN, SVM, NB and RF as tools for the next day price direction forecasting, at least considering their basic textbook forms. Therefore, improvements to the models, combinations or even hybridization are mandatory for building feasible decision support systems for market direction.

For reporting the research, the paper is organized as follows. Section 2 provides a brief overview of the models considered in this paper as well as how they are commonly applied on the literature of machine learning financial forecasting applications. Next, on Section 3, it is laid down the data separation schemes, as well as input variable forms considerations and the objects of forecasts. Following on, Section 4 reports results from all scenarios proposed, highlighting accuracy and their statistical significance. Finally, Section 5 states main results and suggests future research directions.

2. Brief literature review

The following paragraphs are dedicated to briefly review and contextualize machine learning applications to financial time series forecasting. Section 2.1 provides a quick overview of the machine learning and statistical methods applied in this research. How those techniques are currently used in forecasting financial markets is briefly reviewed in Section 2.2. The objective of presenting the models' usage in that section is to show how their basic forms are still subject of research, without a clear answer regarding their effectiveness for predicting markets directions or prices. As stated before, this paper aims to contribute to that discussion. For a more comprehensive, in-depth and objective literature review, please refer to Henrique, Sobreiro, and Kimura (2019).

2.1. Machine learning classifiers

Based on the Bayes' Theorem, the Naive-Bayes classifier is more of a statistical approach, with no parametrization required, than a novel machine learning technique. However, due to its popularity and common insertion as a machine learning model, as done by Patel et al. (2015a), this paper considers results from Naive-Bayes forecasting of closing prices direction. The Bayes' Theorem, stated as $P(y|\mathbf{x}) = \frac{P(\mathbf{x}|y)P(y)}{P(\mathbf{x})}$, provides calculations for the probability of *a posteriori* classification of a sample in a y class given the data characteristics, written as a vector $\mathbf{x}$.

The vector $\mathbf{x}$ represents the selected independent variables, characteristics of each sample that will be used for the classification in one y class. In the forecasting problem at hand, for each daily price direction, $x_1, x_2, \dots, x_n$ are Technical Analysis (TA) indicators values and y is either UP or DOWN. As such, the probability $P(y|\mathbf{x})$ are estimated by training data, as in Patel et al. (2015a, p. 264). The model assumes conditional independence on $x_1, x_2, \dots, x_n$ values. Therefore, $P(\mathbf{x}|y_i) = P(x_1|y_i)P(x_2|y_i)...P(x_n|y_i) = \prod_{k=1}^{n} P(x_k|y_i)$. Following Patel et al. (2015a, p. 265), $P(x_k|y_i)$ is calculated by its frequency of occurrence on training data. Closing daily prices are classified as UP (higher close price than the day before) or DW (lower close price than the day before). An UP day, for instance, would receive that label if $P(\mathbf{x}|y_{up})P(y_{up}) > P(\mathbf{x}|y_{dw})P(y_{dw})$.

Dating from 1964 (Zhang, Patuwo, & Hu, 1998, pp. 36–37), ANNs were originally designed to mimic neurological systems. Representing neurons from the brain, the nodes which compose the network are interconnected to receive, modify and transmit signals to each other (Yoon, Swales Jr, & Margavio, 1993, pp.52–53). Connections between the layers have specific weighting values, calculated with training data, similar to a learning process. ANNs handle non-linearities and have great capacity for generalizations, as demonstrated by Hornik (1991), Hornik, Stinchcombe, and White (1989). They are a popular and dominant tool in finance and economic modeling (Zhong & Enke, 2017, p.127).

The works of Kara et al. (2011) and Patel et al. (2015a) utilize an ANN model called feed-forward, in which all neurons in a layer are connected to the neurons of the next layer, transmitting the information processed according to a transfer function. Each neuron in the first layer receives all characteristic of the vector $\mathbf{x}$ of inputs $x_1, x_2, \dots, x_m$, TA indicators values in this paper, execute a transformation and pass to the next layer, which can be the output itself, that is, the classification of an observation (Laboissiere, Fernandes, & Lage, 2015, p. 67). In this paper, observations are daily prices directions and they are classified either as UP or DOWN. Normally, ANNs are composed of one input layer, one or more hidden layers and an output (Kumar & Thenmozhi, 2014, p. 291). Each of those layers has a number of neurons. There is no established method for defining a structure for layers and the number of neurons, as concluded by Atsalakis and Valavanis (2009, p.5938).

The ANN model considered by this paper follows Kara et al. (2011) and Patel et al. (2015a), using only one hidden layer with n neurons. Interconnections are weighted by $\mathbf{w}$ and each optimal w_m is obtained by Gradient Descent with momentum, by which at each k interaction, the weight vector $\mathbf{w}(k)$ is updated according to the gradient of the minimum squared classification errors $E(k)$ (Yu & Chen, 1997, p. 518). The weights update follows $\Delta\mathbf{w}(k) = lr[-\nabla E(k)] + mc\Delta\mathbf{w}(k-1)$, in which $0 < mc < 1$ is the momentum constant and lr the learning rate. Those parameters are optimized with parametrization data (Rodríguez-González, García-Crespo, Colomo-Palacios, Iglesias, & Gómez-Berbís, 2011, p.11493).

During the weights update process, the momentum constant mc controls the fraction of previous weights to be added in the current weights, minimizing prediction errors with parametrization data (Kumar & Thenmozhi, 2014, p.291). Each of those interactions is called an epoch, ep, and a maximum number of them is fixed to assure convergence. It must be noted that the maximum number of epochs is also a parameter sought by optimization. Finally, the model must specify a transfer function $\varphi(\cdot)$ in $y_k = \varphi\left(\sum_{i=1}^{m} w_i x_i\right)$, which represents the classification of an observation by the ANN. Following Kara et al. (2011) and Patel et al. (2015a), the selected transfer function is the hyperbolic tangent sigmoid given by $tanh(u) = \frac{e^u - e^{-u}}{e^u + e^{-u}}$. In the output of the model, the logistic function $f(u) = \frac{1}{1+e^{-u}}$ standardize the classification of an UP or a DW prediction for the closing price.

Results obtained by ANN classifications are commonly compared to those obtained by SVM, introduced by Vapnik (1995). SVM is based on a structural risk minimization principle (Cao, 2003; Kim, 2003, p. 321, p.308), meaning the learning process involves estimating a function for minimizing the classification error superior limit (Chen & Hao, 2017; Yu, Chen, Wang, & Lai, 2009, p. 88,p. 341). It maps the input variables $\mathbf{x}^T = \{x_1, x_2, \dots, x_m\}$ of an observation $\mathbf{x}$, with m dimensions and of difficult classification, to a space of a higher number of dimensions m_z, where a simpler linear model for classification is sought (Kim, 2003, p.307–308). In this case, m is the number of TA indicators. Mathematically, the SVM model maps $\mathbf{x}$ as $\phi(\cdot) : \mathbb{R}^m \rightarrow \mathbb{R}^{m_z}$ and seeks a class separation hyperplane given by $\mathbf{w}^T\phi(\mathbf{x}) + b = 0$, in which $\mathbf{w}$ is a vector of weights and b is a constant (Huang, Nakamori, & Wang, 2005; Kumar & Thenmozhi, 2014; Son, Noh, & Lee, 2012, p.2514, p. 11609, p. 294).

According to Huang et al. (2005, p. 2514), the optimal hyperplane for separating the classes, in this case UP and DW days, must obey conditions of $y_k[\mathbf{w}^T\phi(\mathbf{x}_k) + b] \geq 1$ and the distance between the hyperplane and an observation k is given by $\left|\mathbf{w}^T\phi(\mathbf{x}_k) + b\right| / \|\mathbf{w}\|^2$. The following calculations aim to maximize the margin $\|\mathbf{w}\|$ of the separating hyperplane (Żbikowski, 2015, p.1798). For that optimal hyperplane, ξ is introduced as a tolerable classification error, following the notation of Yu et al. (2009, p.89), for writing the objective function $\min\phi(\mathbf{w}, b, \xi) = \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{k=1}^{N}\xi_k$, with conditions given by $y_k[\mathbf{w}^T\phi(\mathbf{x}_k) + b] \geq 1 - \xi_k$. The parameter $\mathbf{C}$ is a constant for controlling the margins of the hyperplane and classification errors of training data. This minimization problem can be solved with the introduction of Lagrange's multipliers, as pointed by Vapnik (1995), a strategy for finding maxima and minima under established conditions. Applying non-negative multipliers α and β, the minimization problem can be stated as Equation $\min\phi(\mathbf{w}, b, \xi) = \mathcal{L} =$
$\frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{k=1}^{N}\xi_k - \sum_{k=1}^{N}\alpha_k\left[y_k(\mathbf{w}^T\phi(\mathbf{x}_k) + b) - 1 + \xi_k\right] - \sum_{k=1}^{N}\beta_k\xi_k$, under conditions given by $\beta_k\xi_k = 0$ and $\alpha_k\left[y_k(\mathbf{w}^T\phi(x_k) + b) - 1 + \xi_k\right] = 0$.

For solving that particular minimization problem, Karush (1939) and Kuhn and Tucker (1951) show how to generalize the Lagrange method. For the purposes of this brief review, it is important to register that the solution involves the introduction of kernel functions in the form $K(\mathbf{t}, \mathbf{u}) = \phi(\mathbf{t})^T\phi(\mathbf{u})$, which make solutions possible without specifying the $\phi(\cdot) : \mathbb{R}^m \rightarrow \mathbb{R}^{m_z}$ mapping. Common kernel functions in the literature are radial, $K(\mathbf{t}, \mathbf{u}) = e^{-\gamma\|\mathbf{t}-\mathbf{u}\|^2}$, and polynomial functions, $K(\mathbf{t}, \mathbf{u}) = (\mathbf{t} \cdot \mathbf{u} + 1)^d$.

Another popular machine learning classifier, RF is based on decision trees, or binary trees, which are built using training data sampled by bootstraping. A decision tree, formally defined as Classification and Regression Tree (CART) (Breiman, 2001), categorizes each sample based on the best choice of its variables. Specifically, a quantity of variables are taken and the best division is used to create a binary partition (Ballings et al., 2015, p.7049) and this processes is repeated until all partitions are of unitary size, which is the classification given by the CART. For the purposes of this research, each sample is a daily price direction classification and its variables are the associated TA indicators. A number of decision trees is called a RF, and the classification is given by the consensus of its trees. As pointed by Kumar et al. (2016, p.3), there are two parameters which need to be optimized for a RF classifier: how many variables are considered in each division for individual trees and the number of trees in a forest. Those parameters are obtained with training data.

2.2. Previous works

One of the most cited early papers on artificial intelligence applied to forecast financial markets is the work of Kamstra and Donaldson (1996). The authors contrast the forecasting of volatility by GARCH with results obtained by ANN. The superiority of ANN is clearly shown mainly by its ability to approximate non-linear functions. In a later paper, Donaldson and Kamstra (1999) confirm that methods capable of handling non-linearities provide superior results when compared with linear models. On another hand, SVM, which is credited to Vapnik (1995), is later considered in the work of Kim (2003) to predict the daily direction of the Korean KOSPI index. In order to improve results, Pai and Lin (2005) combine SVM with ARIMA attempting to capture both linear and non-linear characteristics of time series.

A few years after the groundbreaking work of Vapnik (1995), SVM became a novelty as benchmark for other models. Huang et al. (2005), for example, compare SVM with Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA) and Elman Backpropagation Neural Network (EBNN), with better market direction forecasting with the use of SVM. Regarding comparisons, two works are worth mentioning. Kara et al. (2011) evaluate daily direction forecasting results obtained with basic forms of ANN and SVM, using a historical price database of 10 years of the Turkish market. Later, Patel et al. (2015a) propose a similar work, adding RF and NB classifiers. Both works use TA indicators as inputs to the models and apply them to forecast the current day closing price/value direction prediction. Up until recently, basic models are still used in forecasting time series, as in the work with ANN models conducted by Chen et al. (2018) and the forecasts with SVM using Bitcoin data conducted by Souza et al. (2019), or the comparisons proposed by Park, Lee, Lee, et al. (2019). A more advanced approach to neural networks, called Deep Neural Network (DNN), is examined by Zhong and Enke (2019) with slightly better results than common basic ANNs.

Some approaches seek to improve basic models by combining them with other techniques, although it is not obvious if basic forms of classifiers would work in real market conditions. A variant of SVM called SVR, used not as a classifier but as a value predictor model, is used by Huang and Tsai (2009) over samples mapped in clusters according to their similarities with Self-Organizing Feature Map (SOFM) (Huang & Tsai, 2009, p. 1531). In turn, Guo et al. (2018) and Rustam and Kintandani (2019) propose distinct optimization schemes with Particle Swarm Optimization (PSO). Finally, Henrique et al. (2018) apply SVR with TA indicators to forecast securities prices in High Frequency Trading (HFT) and, also working in high frequency data, Yang et al. (2020) apply SVM to forecast volatility.

Preparations before using a classifier model, called pre-processing, is exemplified by Kim and Han (2000) and Hassan, Nath, and Kirley (2007), attempting to reduce variables dimensionality. They use Genetic Algorithm (GA) prior to training the ANN. In a different approach, the two most used models of machine learning in financial time series prediction, ANN and SVM, are combined in a single forecasting framework by Cao and Wang (2019). Similarly, ANN, GA and SVR are put together on two different approaches by Jujie and Danfeng (2018), improving results when compared to the use of the basic models separately.

Other authors propose a modification on the algorithms themselves, like Yu et al. (2009). That paper improves the original SVM model regarding computational costs and generalization capabilities, calling the new model Least Squares Support Vector Machine (LSSVM). As another example of model improvement, Chen et al. (2003) incorporate Bayesian probabilities to better deal with outliers, hence creating Probabilistic Neural Network (PNN). Improvements to the basic RF model are described and explored by Basak, Kar, Saha, Khaidem, and Dey (2019). Enhanced learning schemes are implemented in ANN by Selvamuthu, Kumar, and Mishra (2019).

Table 1
Parameters for all classification models considered and their values ranges.

Parameters	Values
n.	10; 20; 30;…; 100.
ep.	1000; 2000;…; 10000.
mc.	0.1; 0.2;…; 0.9.
lr.	0.1; 0.2;…; 0.9.
C.	0.5; 1.0; 5.0; 10.0; 100.0.
γ.	0.5; 1.0; 1.5;…; 10.0.
d.	1; 2; 3; 4.
$Trees$.	10; 20; 30;…; 200.

The most recent approaches of applying machine learning methods to forecast financial markets instruments involve combination and hybridization of basic models. For instance, Chen and Chen (2016) apply a visual pattern recognition system and GA. Zhong and Enke (2017) process the input variables with Principal Component Analysis (PCA) before using them on ANN models. On a similar fashion, PCA and ANN are also explored together by Islam, Al-Shaikhli, Nor, and Tumian (2019). As an example of a hybrid approach, Chen and Hao (2017) combine SVM and k-Nearest Neighbors (kNN) into a model with inputs subject to a measure of information gain, seeking better prediction performance. Zhang, Teng, and Chen (2019), on the other hand, hybridize SVR with an optimization algorithm called Firefly. Finally, Ren, Wu, and Liu (2018) consider sentiment analysis data with SVM to seek accurate direction forecasting.

3. Methods

As briefly reviewed in Section 2.1, most classifiers have specific parameters to be optimized, which is achieved with parametrization data. Therefore, parametrizing the models means searching for the best parameters which result in the most accurate classification, given previously classified observations. In this specific work, observations mean the daily closing price directions. After parameters optimization, models are trained with training data, selected to tune the models to specific classification conditions, represented by previously labeled observations, following a supervised learning framework. Finally, test data are used to forecast daily direction of closing prices, following the works of Kara et al. (2011) and Patel et al. (2015a), with subtle, albeit important, differences described next. It needs to be stressed that previous classifications of test data are unknown by the models.

As previously described, the totality of data selected for research is divided into three sets, called parametrization, training and testing observations. Kara et al. (2011) and Patel et al. (2015a) innovate in guaranteeing all three sets contain proportional samples by year. In the same fashion, the authors recommend that the UP and DOWN days are made proportional across every considered year. The current work, in all its experiments, follows this recommendation strictly. Specifically, 20% of total data is sampled, on the conditions described above, to compose the parametrization data set. This set is further divided into two equal sub-sets: 10% destined to search for the best parameters to classify more accurately as possible the second 10% half of the parametrization set. Table 1 shows the parameters for all the considered models and their respective values range.

After determining optimal values for each parameter in Table 1, the classification models are trained on previously labeled data. This paper applies two distinct methods of separating training and testing data. The first method, proposed after Kara et al. (2011) and Patel et al. (2015a), involves partitioning all available data, including those observations already used for parametrizing the models, into two halves. In this scheme, 50% of total data is destined to training the classifiers and the other 50% are used for testing purposes. It is crucial to point out that this particular partitioning proposal might make use of a subset of observations in more than one phase of the experiments. More specifically, a sample used to seek optimal parameters, following Kara et al. (2011) and Patel et al. (2015a), may also be used to train and even test models.

The above data partitioning scheme might lead to a problem known as data snooping bias, which refers to using information for forecasting that would be unavailable at the time of predictions, if they were made in a real scenario. In this case, the model could be tested on observations that were already used for model training. To account for this problem and make predictions closer to real applications, this paper also applies a rigid data separating scheme. In this regard, all available data are divided into three non-overlapping groups: 20% for parametrization, 60% for training and 20% for testing and evaluation. Naturally, the samples available for testing are reduced when compared to the previous scheme, but this latter approach guarantees a more accurate simulation in real markets conditions.

Predictions evaluations, on all data sets, are done by accuracy and *F-measure*, following Patel et al. (2015a). Computing True Positives (TP), False Positives (FP), True Negatives (TN) and False Negatives (FN), the accuracy is given by $\frac{TP+TN}{TP+FP+TN+FN}$. For statistical significance evaluation of different results, McNemar tests are employed, following Kim (2003), Kim and Han (2000), Yu et al. (2009) and Podsiadlo and Rybinski (2016). The tests are built by pairing the forecasting results for each pair of classifiers and testing the χ^2 symmetry. Statistical significance is then given by the resulting *p-values*.

Regarding data, 10 financial markets are selected, 5 developed markets and 5 developing markets. Developed markets considered are from USA, United Kingdom, Japan, Germany and Canada. The developing markets are from Brazil, Russia, India, China and South Africa (BRICS block). From each market, the 10 largest capitalization stocks from each index are selected, along with the main market index. For the Indian market, both BSESN and NIFTY100 indexes are selected in order to obtain results comparable to those of Patel et al. (2015a). Therefore, a total of 111 securities are selected to evaluate the classifiers regarding daily market direction, as listed in Tables 2 and 3.

Daily quotes range from January 2, 2007 to June 16, 2017, except for those cases involving more recent initial stock offerings, like Facebook (FB) or Google (GOOGL). Data were obtained from *Reuters*©, except S&P500 quotes, obtained from *Yahoo!Finance*©. A pre-processing step is taken regarding missing quotes: they are replaced by the previous day prices. However, as this paper uses daily quotes from volatile, big capitalization stocks, those situations are rare exceptions. It should be noted that Kara et al. (2011) and Patel et al. (2015a) do not specify how they proceed in those cases.

As predicting variables, common TA indicators, the same selected by Kara et al. (2011) and Patel et al. (2015a), are used as attributes of each observation. They are used both as continuous and discrete values. Continuous values refer to TA numerical values, calculated by historical past prices. Discrete values refer to trend indications interpretations, such as uptrend or downtrend. As previously discussed, Patel et al. (2015a) compare results between the two approaches and the current paper includes a third possibility: using continuous and discrete values simultaneously. Therefore, TA indicators used as independent variables are: Simple Moving Average (SMA), Weighted Moving Average (WMA), Exponential Moving Average (EMA), *Momentum*, William R%, Moving Average Convergence Divergence (MACD), Relative Strength Indicator (RSI), Accumulation/Distribution Oscillator (ADO) and Commodity Channel Index (CCI), all calculated considering the daily closing prices. As previously stated, the dependent variable is the direction of daily closing prices, either upwards or downwards.

4. Results and analysis

Results are divided into two distinct experiments. The first subsection that follows analyses results obtained using the same framework as Kara et al. (2011) and Patel et al. (2015a). In this first case, the forecasting variable is the current day closing price direction and

Table 2
Stocks and market indexes selected from developed countries. Securities are represented by respective tickers.

Country/Market:	USA	U.K.	Japan	Germany	Canada
Index:	S&P500.	FTSE100.	NIKKEI400.	DAX.	S&P/TSX.
Stocks:	AMZN.	AZN.	6178.	ADSGn.	BAMa.
	APPL.	BATS.	6758.	ALVG.	BCE.
	BRKb.	BLT.	7182.	BASFn.	BNS.
	FB.	BP.	7201.	BAYGn.	CNR.
	GOOG.	GSK.	8306.	BEIG.	ENB.
	GOOGL.	HSBA.	8316.	BMWG.	RY.
	JNJ.	RDSa.	8411.	CBKG.	SMO.
	JPM.	RDSb.	9432.	CONG.	SU.
	MSFT.	ULVR.	9437.	DAIGn.	TD.
	XOM.	VOD.	9501.	DB1Gn.	TRP.

Note: GOOGL and GOOG are stocks from the same company (*Alphabet Inc.*). The first has corresponding voting rights in stockholders assemblies. Both are traded separately in *NASDAQ*.

Table 3
Stocks and market indexes selected from developing countries (BRICS). Securities are represented by respective tickers.

Country/Market:	Brazil	Russia	India	China	S. Africa
Index:	IBOV.	RST.	BSESN, NIFTY100.	SSEC.	JTOPI.
Stocks:	ABEV3.	GAZP.	HDBK.	600 028.	AMSJ.
	BBAS3.	GMKN.	HDFC.	600 519.	ANGJ.
	BBDC3.	LKOH.	HLL.	601 288.	APNJ.
	BBDC4.	MGNT.	INFY.	601 318.	BGAJ.
	ITUB4.	NVTK.	KTKM.	601 328.	BIDJ.
	PETR3.	ROSN.	MRTI.	601 398.	BILJ.
	PETR4.	SBER.	ONGC.	601 628.	BTIJ.
	SANB11.	SBERp.	RELI.	601 857.	BVTJ.
	VALE3.	SNGS.	SBI.	601 939.	CFRJ.
	VALE5.	SNGSp.	TCS.	601 988.	DSYJ.

Table 4
Forecasting performance measures for current price direction. Data from AMZN testing dataset. Ac.: accuracy. F-M.: F-measure.

Model	Time (ms)	Continuous Variables		Discrete Variables		All Variables	
		Ac. (%)	F-M. (%)	Ac. (%)	F-M. (%)	Ac. (%)	F-M. (%)
ANN.	773.46	74.88	75.24	51.39	52.84	65.53	65.53
SVM.†	004.35	87.01	87.15	100.00	100.00	100.00	100.00
SVM.‡	001.40	82.84	82.84	100.00	100.00	100.00	100.00
RF.	002.82	90.27	90.27	100.00	100.00	100.00	100.00
NB.	002.92	60.04	60.03	99.30	99.31	99.07	99.07

Note: †: Radial kernel. ‡: Polynomial kernel. Considering the following hardware: Intel® Xeon® with 80 processors CPU E5-4610 v3@1.70 GHz and 500GB RAM, operating system *Red Hat*® 4.8.5-4 with Linux kernel 3.10.

the data partitioning scheme of parametrization, training and testing observations sets allows for data reuse, as previously described. The second sub-section considers the more rigid approach of partitioning data and the forecasts of only the next day closing price directions, simulating more realistic trading conditions.

4.1. Forecasting the current day price direction

Calculating predictions for the current market close price may be useful basically to compare the general accuracy of models and computational performance. In this regard, the first experiment relates computing costs, measured in time consumed executing the classification algorithm for all models and variables considerations, involving only one stock, Amazon (AMZN), to illustrate basic models' behavior. The accuracy and time results are shown in Table 4. It can be observed that ANN has the biggest computational cost (processing time), followed by SVM with radial kernel, NB and RF. SVM with polynomial kernel shows the best performance, keeping as high accuracy as other models, but registering considerably less time to be executed.

Performance measures shown in Table 4 correspond to only one specific stock, to illustrate general accuracy and computational costs of each model. However, to make it possible more general conclusions, all the following results correspond to the complete selection of stocks and indexes described in Section 3. To save space and make discussions more concise, accuracy results are shown aggregated as means for each market. In this fashion, the classification accuracies for the current day closing price direction forecasting, considering only the test data set from stocks, are calculated for each model, resulting in very high rates. For instance, accuracy results obtained by SVM with polynomial kernel, the best performing model of Table 4, are shown in Table 5. The other models' accuracies are similarly high, but they are omitted in order to save space.

All results considering current day closing price forecasts exhibit accuracies above the 50% expected from a theoretical random model. Notably, NB displays less accuracy compared to the other models when only continuous TA indicators are considered as inputs. However, when discrete indicators are used, NB gets as accurate as the other models. In contrast, SVM with polynomial kernel shows superior predictive performance over other models. In some cases, specially with only discrete TA indicators used as inputs, the model does not misclassify a single sample. Similar observations can be made from the direction forecasting results over market indexes. For instance, Table 6 shows almost perfect accuracies for forecasting current day closing market indexes using SVM with polynomial kernel.

Considering all results from models, there seems to be no difference in classifiers behavior when applied to stock prices or indexes, regarding predictions for the daily direction. Also, no differences are apparent regarding the development of a given market. Therefore, as observed in any of the mentioned tables, developing markets do not indicate more inefficiencies opportunities to be explored, at least by the basic

Table 5
Forecasting accuracies considering the current closing price prediction of stocks over test data for the SVM model with polynomial kernel. Results expressed as means.

Market	Continuous Variables		Discrete Variables		All Variables	
	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)
USA.	82.71	82.76	100.00	100.00	100.00	100.00
U.K.	83.62	83.62	100.00	100.00	100.00	100.00
Japan.	84.33	84.35	100.00	100.00	99.94	99.94
Germany.	83.90	83.91	100.00	100.00	100.00	100.00
Canada.	84.11	84.11	100.00	100.00	100.00	100.00
Brazil.	84.49	84.50	100.00	100.00	100.00	100.00
Russia.	83.70	83.71	100.00	100.00	100.00	100.00
India.	83.80	83.82	100.00	100.00	100.00	100.00
China.	84.07	84.08	100.00	100.00	100.00	100.00
S. Africa.	84.19	84.22	99.91	99.92	100.00	100.00

Table 6
Forecasting accuracies considering the current closing direction prediction of market indexes over test data for the SVM model with polynomial kernel. Results expressed as means.

Market	Continuous variables		Discrete variables		All variables	
	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)
S&P500.	81.67	81.67	100.00	100.00	100.00	100.00
FTSE100.	83.73	83.74	100.00	100.00	100.00	100.00
NIKKEY400.	83.58	83.73	100.00	100.00	100.00	100.00
DAX.	82.96	83.00	100.00	100.00	100.00	100.00
S&P/TSX	83.75	83.77	100.00	100.00	100.00	100.00
IBOV.	83.35	83.35	100.00	100.00	100.00	100.00
RTS.	86.16	86.16	100.00	100.00	100.00	100.00
NIFTY100.	83.99	83.99	100.00	100.00	100.00	100.00
SSEC.	82.16	82.15	100.00	100.00	100.00	100.00
JTOPI.	84.79	84.82	100.00	100.00	100.00	100.00

Table 7
McNemar's tests for the SVM model with polynomial kernel using each form of input variables from TA.

Index	Variables	Discrete	All
S&P500.	Continuous.	230.004 [***]	230.004 [***]
	Discrete.		0
FTSE100.	Continuous.	209.005 [***]	208.005 [***]
	Discrete.		0
NIKKEY400.	Continuous.	65.015 [***]	65.015 [***]
	Discrete.		0
DAX.	Continuous.	221.004 [***]	221.004 [***]
	Discrete.		0
S&P/TSX.	Continuous.	208.005 [***]	208.005 [***]
	Discrete.		0
IBOV.	Continuous.	210.005 [***]	210.005 [***]
	Discrete.		0
RTS.	Continuous.	175.006 [***]	172.051 [***]
	Discrete.		0
NIFTY100.	Continuous.	202.005 [***]	202.005 [***]
	Discrete.		0
BSESN.	Continuous.	207.005 [***]	207.005 [***]
	Discrete.		0
SSEC.	Continuous.	221.004 [***]	221.004 [***]
	Discrete.		0
JTOPI.	Continuous.	193.005 [***]	193.005 [***]
	Discrete.		0

Note: Zero means distributions are so similar that the test is not possible at all. When possible, *p-values* are given between brackets and denoted by ***: $< 10^{-10}$; **: $< 10^{-6}$; *: $< 10^{-3}$.

classifiers methods considered in this paper. Another important result from the comparison proposed on the current closing price forecasting is the low performance of the ANN described in Section 2.1. That was observed in all experiments ran in this paper, with results similar to the one-stock case reported in Table 4. Compared to RF or NB, neural networks are of complex implementation and lead to less accurate forecasting than other simpler models. When possible, considering classifiers in their basic forms, SVM with polynomial kernel would be the more efficient choice for practical implementations.

In order to evaluate the statistical significance of the above results, specially when considering the possible predicting variables forms, McNemar's tests are conducted for all models. As examples, tests results for SVM with polynomial kernel forecastings of current closing value directions of markets indexes are displayed by Table 7. In order to evaluate the hypothesis of the distributions of forecasts being different from one another, *p-values* are considered. In the current case of Table 7, all distributions of forecasts are different when discrete or continuous forms of TA indicators are used. Therefore, there is a significant difference between current day direction forecastings by SVM polynomial when used as inputs discrete or continuous TA indicators. With those results in mind, SVM is greatly benefited by the use of discrete forms of TA indicators, as observed by the results of Table 6. Those comments also apply to ANN, RF and NB models, as well as the SVM with radial kernel. Because their respective tables are very similar to Table 7, they are omitted from this paper. It should be noted, however, no significant improvement in results are observed when both forms of TA indicators are used.[1]

Above results are similar to those obtained by Patel et al. (2015a), that is, direction forecasting accuracy is generally improved by the use of TA indicators in their discrete forms, considering the predictions for the current day closing direction, applying ANN, RF, NB and SVM, both radial and polynomial kernels. It remains to be tested, considering only discrete variables as inputs to the models, which classifier obtains the best results. Again, McNemar's tests are designed to compare differences between forecasting distributions, evaluated by the *p-values*. In order to save space, only the results for the S&P500 are displayed in Table 8. Analyzing the *p-values*, there are no evidences of differing results between RF, NB and SVM models regarding forecasts of the close value of indexes for the current day. However, as explicit by Table 8,

[1] McNemar's tests for ANN forecasts exhibit significant *p-values* for all cases, but with no conclusive improvement.

Table 8
McNemar's test for S&P500 index over current day closing direction forecasting.

Model	SVM radial	SVM polynomial	ANN	NB
RF.	0	0	778.001 [***]	1.333 [0.248]
SVM Radial.		0	778.001 [***]	1.333 [0.248]
SVM Polynomial.			778.001 [***]	1.333 [0.248]
ANN.				769.063 [***]

Note: Zero means distributions are so similar that the test is not possible at all. When possible, *p-values* are given between brackets and denoted by ***: $< 10^{-10}$; **: $< 10^{-6}$; *: $< 10^{-3}$.

Table 9
Performance measures obtained by Patel et al. (2015a) using as input trend indicators from TA (discrete form).

Security	ANN		SVM		RF		NB	
	Ac. (%)	F-M. (%)	Ac. (%)	F-M. (%)	Ac. (%)	F-M. (%)	Ac. (%)	F-M. (%)
BSESN.	86.69	87.21	88.69	88.95	89.59	89.85	89.84	90.26
NIFTY.	87.24	87.70	89.09	89.35	89.52	89.77	89.52	89.90
Reliance.	87.09	87.48	90.72	90.80	90.79	90.87	92.22	92.34
Infosys.	85.72	86.15	88.80	88.98	90.01	90.17	89.19	89.50

Note: Ac.: Accuracy; F-M.: *F-Measure*. Patel et al. (2015a) do not specify which SVM kernel (radial or polynomial) is used for tests.

Table 10
Performance measures using as input trend indicators from TA (discrete form) for selected Indian securities.

Security	ANN		SVM radial		SVM polin.		RF		NB	
	Ac. (%)	F-M. (%)	Ac. (%)	F-M. (%)	Ac. (%)	F-M. (%)	Ac. (%)	F-M. (%)	Ac. (%)	F-M. (%)
BSESN.	84.80	85.77	100.00	100.00	100.00	100.00	100.00	100.00	99.53	99.53
NIFTY.	35.16	35.34	100.00	100.00	100.00	100.00	100.00	100.00	98.98	98.98
Reliance.	22.23	21.68	100.00	100.00	100.00	100.00	100.00	100.00	99.14	99.14
Infosys.	23.53	23.53	100.00	100.00	100.00	100.00	100.00	100.00	99.37	99.37

Note: Ac.: Accuracy; F-M.: *F-Measure*.

Table 11
Forecasting accuracies considering the next day closing price prediction of stocks over test data for the SVM model with polynomial kernel. Results expressed as means.

Market	Continuous Variables		Discrete Variables		All Variables	
	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)
USA.	52.30	52.67	51.11	50.91	51.26	51.17
U.K.	49.71	50.19	50.60	51.05	50.99	51.17
Japan.	51.76	51.76	50.32	50.38	51.16	51.22
Germany.	50.64	50.85	50.39	50.42	50.25	50.25
Canada.	53.08	52.75	51.31	50.87	51.29	51.14
Brazil.	49.78	49.53	50.79	50.71	50.66	50.72
Russia.	50.56	50.76	50.18	50.23	49.54	49.52
India.	50.58	50.59	50.39	50.49	49.98	49.99
China.	50.06	50.28	51.15	51.19	51.12	51.16
S. Africa.	51.40	51.32	51.17	50.90	51.88	51.82

forecasts produced by ANN are significantly different from the other models, meaning neural networks were less accurate than RF, NB and SVM in the cases reported in this paper.

The work of Patel et al. (2015a) reports accuracies between 86% and 92% for ANN, SVM, RF and NB models for two stocks (RELI and INFY) and two Indian market indexes (BSESN and NIFTY). Those results are summarized in Table 9. To make results comparable, those same securities have their respective measures, on the conditions of this paper, shown in Table 10. It can be readily seen that this paper reports better results for almost all cases, exceptions being when ANN is used to predict current day closing values for RELI, INFY and NIFTY. A possible cause is the mismatch on the historical periods: Patel et al. (2015a) work with data from January 2003 to December 2012.

It needs to be stressed that results from this section might be incoherent with real applications. They are obtained by models which might be incorrectly parametrized and trained, following Kara et al. (2011) and Patel et al. (2015a) approach for data reuse possibilities, as described in Section 3. To make a point showing how basic classifiers and machine learning methods behave forecasting market direction on real applications, the next results consider the rigid scheme of partitioning data as previously described. Also, forecasting current closing prices using as inputs TA indicators calculated from those very same close prices has questionable usefulness, limited to the comparisons made so far. The reason is a data snooping paradox, meaning a model that uses presently unavailable information to make a forecast. As used in this sub-section, models require the closing price, obviously available only at market close, rendering classifiers output of close direction useless. Therefore, the following results account for predictions for the next day closing prices.

4.2. Forecasting the next day direction

The accuracy measures of SVM with polynomial kernel forecasting the next day closing direction for the stocks described in Section 3 are shown in Table 11. Those results are obtained over the test data set, considering the rigid partitioning scheme described in Section 3, which makes samples reuse impossible. Therefore, the conditions of the forecasts presented in the following paragraphs are close to real applications of machine learning classifiers on forecasts of market direction. Similarly to the previous sub-section, the following results consider TA indicators in continuous, discrete and both forms.

Unlike when predicting current day price close, machine learning techniques applied to the next day close prices do not present any predictive power in the conditions described in Section 3. In fact,

Table 12
Forecasting accuracies considering the next day closing direction prediction of market indexes over test data for the SVM model with polynomial kernel. Results expressed as means.

Market	Continuous Variables		Discrete Variables		All Variables	
	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)
S&P500.	55.78	49.12	53.92	52.62	53.73	52.16
FTSE100.	51.55	–	53.75	53.99	51.55	51.44
NIKKEY400.	54.91	–	52.60	52.07	57.23	56.96
DAX.	53.60	51.43	53.24	52.65	53.78	53.20
S&P/TSX.	55.13	53.51	53.66	52.18	51.28	49.64
IBOV.	53.25	52.24	56.22	55.69	59.18	59.04
RTS.	51.66	51.08	52.95	52.67	50.92	50.72
NIFTY100.	55.37	46.95	56.11	55.33	55.37	55.02
BSESN.	51.29	51.23	55.35	55.33	52.58	52.55
SSEC.	51.41	51.09	50.66	50.54	47.65	47.34
JTOPI.	51.48	51.08	50.55	50.31	49.08	49.04

Table 13
McNemar's tests between next day close forecast distributions given by each model and predictions of a random model. Input variables are TA indicators in discrete form.

Index	SVM Radial	SVM Polynomial	ANN	RF	NB
S&P500.	2.372 [0.124]	1.213 [0.271]	4.996 [0.025]	3.321 [0.068]	0.035 [0.852]
FTSE100.	2.201 [0.138]	6.416 [0.011]	2.385 [0.122]	5.306 [0.021]	0.678 [0.410]
NIKKEY400.	1.870 [0.171]	0	0.719 [0.396]	0	0
DAX.	0.520 [0.471]	0.524 [0.469]	0.445 [0.505]	2.458 [0.117]	0
S&P/TSX.	4.861 [0.027]	4.891 [0.027]	11.404 [*]	6.416 [0.011]	3.668 [0.055]
IBOV.	9.927 [0.002]	3.679 [0.055]	1.327 [0.249]	4.516 [0.034]	1.047 [0.306]
RTS.	0.560 [0.454]	2.207 [0.137]	1.012 [0.314]	1.633 [0.201]	0.879 [0.349]
NIFTY100.	8.141 [0.004]	6.062 [0.014]	8.694 [0.003]	6.289 [0.012]	1.556 [0.212]
BSESN.	0.091 [0.763]	2.157 [0.142]	0	1.487 [0.223]	0.013 [0.908]
SSEC.	0.190 [0.663]	1.945 [0.163]	0.445 [0.505]	0.034 [0.853]	0.243 [0.622]
JTOPI.	0.055 [0.815]	0	0.174 [0.677]	0.361 [0.548]	0.804 [0.370]

Note: Zero means distributions are so similar the test is impossible, *p-values* are given by brackets and denoted by ***: $< 10^{-10}$; **: $< 10^{-6}$; *: $< 10^{-3}$.

Table 14
Forecasting accuracies considering the next day direction prediction of stocks over test data for the SVM model, with polynomial kernel, considering the application of a threshold of price variation for forecast validity. Results expressed as means.

Market	Continuous Variables		Discrete Variables		All Variables	
	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)
USA.	49.83	49.52	49.68	49.72	50.55	50.68
U.K.	49.97	49.58	50.38	50.60	50.70	50.90
Japan.	49.74	49.98	49.71	49.43	48.33	48.32
Germany.	52.59	52.59	49.76	49.72	50.53	50.51
Canada.	52.11	51.82	51.42	51.19	52.04	52.00
Brazil.	51.90	51.88	49.83	49.93	51.62	51.59
Russia.	51.64	50.97	51.61	51.38	51.45	51.37
India.	50.25	50.76	52.54	52.73	52.01	52.23
China.	51.97	52.12	50.59	50.65	50.70	50.74
S. Africa.	50.06	50.70	51.15	51.01	52.67	52.73

for most securities considered in Table 11, accuracy attained by the classifications is very close to the theoretical 50% of a random classifier. Measures are so low that, for some cases, it is impossible to mathematically calculate a *F-Measure*. Likewise, accuracy measures for the next day close price direction forecasts using ANN, RF, NB and SVM radial follow the same random pattern and, therefore, are omitted. Those unfortunate results also appear when data are composed of market indexes, as exposed by Table 12 for the SVM polynomial case. Overall, accuracy is close to random either for stocks or indexes, without any apparent difference regarding developed or developing markets.

In order to highlight the randomness of forecasting results regarding next day direction, McNemar's tests are run comparing predictions distributions given by each model to random predictions of 50% probabilities. Results for market indexes are given by Table 13 (tests results for stocks, which present similar numbers, are omitted to save space). Input variables considered are of discrete form, which should yield the bests results according to Section 4.1. As seen from *p-values* of Table 13, the null hypothesis cannot be rejected in practically all cases, exception being ANN applied to forecast S&P/TSX index next day direction. However, the corresponding accuracy in this case is only 50,55%. This means an edge in forecasting ability attained by the ANN model of only 0,55% over a random model in a total of 1300 days, discouraging any practical implementation.[2]

Seeking improvements to models accuracy, some authors apply filters to data before using prediction models. For instance, Pei, Wang, and Fang (2017) seek neural networks predictions of prices smoothed by moving averages. Also applying neural networks, Laboissiere et al. (2015) forecast *maxima* and *minima* of stock prices. In the same spirit, the following results report SVM polynomial forecasting accuracy of next day directions, but under a price range threshold. In other words, a constraint is considered: models are only run over observations for which the previous day has a given price range larger than a fixed threshold. That procedure aims to capture those periods with presumably stronger trends, which could be more evident to the models. Considering half the historical daily variation as threshold for each security, accuracy results are shown in Table 14.

[2] In order to vary the dependent variable, experiments also tested forecast accuracy for two and five days ahead. The results are very similar to those presented in Section 4.2 and, therefore, omitted.

Table 15
Forecasting accuracies considering the next day direction prediction of stocks over test data for the SVM model with polynomial, considering the application of a threshold of price variation for forecast validity. Results expressed as means.

Market	Continuous Variables		Discrete Variables		All Variables	
	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)	Accuracy (%)	*F-Measure* (%)
S&P500.	55.45	63.94	56.09	56.72	55.45	54.95
FTSE100.	51.74	52.82	52.33	53.12	51.74	51.80
NIKKEY400.	50.00	–	50.00	50.00	44.34	43.10
DAX.	54.68	–	52.63	51.99	51.75	51.50
S&P/TSX.	51.04	50.79	50.74	50.38	49.55	49.03
IBOV.	51.30	50.47	53.60	52.77	51.87	51.30
RTS.	51.59	51.59	48.12	48.11	52.46	52.48
NIFTY100.	58.41	56.64	55.35	54.32	54.74	54.12
SSEC.	59.18	59.01	54.43	53.20	54.75	53.39
JTOPI.	56.00	56.34	50.86	50.86	49.71	49.37

Note: "-" denotes an error rate so high that makes the indicator calculations impossible.

Table 16
McNemar's tests between next day direction forecast distributions given by each model, under a price range threshold, and predictions of a random model. Input variables are TA indicators in discrete form.

Index	SVM radial	SVM polynomial	ANN	RF	NB
S&P500.	1.837 [0.175]	0.844 [0.358]	3.141 [0.076]	0.500 [0.480]	4.792 [0.029]
FTSE100.	1.120 [0.290]	0.736 [0.391]	0.379 [0.538]	0.764 [0.382]	0.155 [0.693]
NIKKEY400.	0.706 [0.401]	0	0	0.327 [0.568]	0
DAX.	4.440 [0.035]	8.257 [0.004]	0.255 [0.614]	3.883 [0.049]	1.980 [0.159]
S&P/TSX.	0.155 [0.693]	1.455 [0.228]	0	2.485 [0.115]	0.092 [0.762]
IBOV.	1.760 [0.185]	2.154 [0.142]	2.021 [0.155]	3.484 [0.062]	1.735 [0.188]
RTS.	0.379 [0.538]	0.387 [0.534]	0.042 [0.837]	1.315 [0.251]	1.375 [0.241]
NIFTY100.	1.516 [0.218]	1.010 [0.315]	0.147 [0.702]	1.455 [0.228]	0.158 [0.691]
BSESN.	0	1.398 [0.237]	0.621 [0.431]	2.206 [0.137]	1.903 [0.168]
SSEC.	2.890 [0.089]	2.695 [0.101]	4.040 [0.044]	2.021 [0.155]	1.075 [0.300]
JTOPI.	0.490 [0.484]	0.260 [0.610]	0.090 [0.764]	0.180 [0.672]	0.010 [0.920]

As noted from the table, even forecasting daily direction only for days with stronger previous daily price range does not make results better than a theoretical random model. Those experiments consider only observations not filtered by threshold, that is, all samples with a daily price range smaller than half historical range are discarded. That procedure is applied to all data sets, being parametrization, train and test set. This surely reduces the total data available for each security, but is a valid attempt to isolate days with above than average trend strength. Application of that strategy for market indexes yield similar results, as shown by Table 15. The same experiments were run for ANN, RF, NB and SVM radial with very similar results.

As explicit by results of this sub-section, no improvement is observed in the application of the price range *minimum* constraint strategy over developing markets stocks or indexes. As done before, McNemar's tests are run pairing forecasting results from the models constrained (with discrete TA indicators as input) and results from a random model. Tests results, shown in Table 16, do not give evidence for null rejection of similarity between distributions of forecasts from ANN, SVM, RF and NB and those from the random model.

5. Conclusion

Financial time series prediction is a very hot research topic, not only for academic (Chen & Hao, 2017, p. 340) purposes but also for obvious economic reasons (Rodríguez-González et al., 2011, p. 1148). As those series are noisy, chaotic and non-linear in nature (Chang, Liu, Lin, Fan, & Ng, 2009; Tay & Cao, 2001, p. 309; p.6889), scientific and professional researches are increasingly exploring methods capable of handling these characteristics, such as machine learning models. Therefore, those systems find large applications field on predictive and profitable approaches (Zhong & Enke, 2017, p.128). In this context, the above paragraphs register how ANN, SVM, RF and NB are used in forecasting market price/value direction on a daily basis, for a range of 10 distinct markets, including 11 securities from each. As input variables, TA indicators are selected from specialized literature, considering continuous values, discrete trend indicators as well as both forms together. Also, two different frameworks are considered: forecasting the current day close direction allowing for data reuse, following Kara et al. (2011) and Patel et al. (2015a); and next day close direction, with strict data separation scheme, following Henrique et al. (2019).

Using any of the considered models, as strictly described on Section 2.1, it is plainly possible to obtain accurate predictions on close price/value directions for the current day, after market close. Any form of TA indicators used as inputs is sufficient to produce high performance results for that case, being the discrete form the best choice. In this framework, as with Kara et al. (2011) and Patel et al. (2015a), there is no clear accuracy advantage on the choice of SVM, RF or NB, except that SVM with polynomial *kernel* has the least computational cost. However, the results indicate, with statistical significance, that ANN forecasts are less accurate than the others. Also, following results from previous studies, the use of TA discrete trend indicators improves results. It is crucial, however, to note that those results are of limited relevance in practice, given that the forecasts of close price direction are made after the market closes.

Aiming to produce results of practical relevance and academic consistency, next day price direction forecasts are considered in Section 4.2. Experiments follow recommendations given by Henrique et al. (2019). The conclusions are very distinct from when current day price directions were forecast. In fact, keeping a strict policy allowing no data reuse and no data snooping bias, the models considered in this paper, that is, basic statistical and machine learning approaches, are virtually useless in providing useful information for trading decisions regarding next day direction. Specifically, the results presented in this paper show they are no better than random models with 50% probabilities of direction choosing. That harsh conclusion applies to both developing and developed markets, as well as stocks and indexes. Keeping constant the proportion of days of up and down directions, as well as the available years in the parametrization, training and testing data sets, help making sure the models are not biased towards major uptrends or downtrends periods; however, the results are far from positive.

The major conclusion is that the out-of-the-box statistical and machine learning models of ANN, SVM, RF and NB are unable to forecast next day closing price or value direction of financial markets whatsoever. Not even considering potentially less developed markets, as those of the BRICS block. As shown in Section 4, next day direction forecasting with those models is essentially the same as random guessing in the long run and, as such, discourages any practical applications. It should be noted, however, that results consider historical daily prices and forecasting accuracy may improve with the use of higher sampling frequencies. That is a theme for future studies. Another limitation of the current work is that it only covers high capitalization securities from each market. Future research might explore forecasting capabilities over small caps.

This paper does not cover discussions regarding trust in artificial intelligence and machine learning systems, a trendy research topic (Schmidt, Biessmann, & Teubner, 2020). In our approach, we assumed a user would always decide to follow the machine learning recommendation of the price direction forecast. However, future studies could consider user input when the system is known to be inaccurate, as done by Gomez, Unberath, and Huang (2023). That is, combining human expertise and intelligent systems recommendations might lead to profitable strategies, provided trust is correctly calibrated. This subject of trust and human-machine teaming is beyond the scope of this paper, but the reader can refer to the work of Glikson and Woolley (2020) for a comprehensive survey on trust in artificial intelligence systems.

Similar to trust, we did not consider any consequences of forecasting financial markets prices and indexes with respect to fairness or ethics, recent hot research themes. Although our focus was on accuracy of basic machine learning models, a broader discussion might include the ethics of applying such systems to trading strategies (Cooper, Davis, Kumiega, & Van Vliet, 2020). Also, in our practical experiments, there are no considerations about how a user would use direction forecasting information in light of perceived fairness of machine learning systems. For example, Makhlouf, Zhioua, and Palamidessi (2021) provide a structured list of fairness notions and guidance on how fairness could be addressed in forecasting systems. Therefore, future works should consider how the perception of fairness might influence the reliance on machine learning forecasting systems. Angerschmid, Zhou, Theuermann, Chen, and Holzinger (2022), for example, conduct experiments to show how explanations and introduced fairness can affect trust and perceived fairness of an artificial intelligent system recommendation.

In conclusion, future research should refrain from using ANN, SVM, RF and NB out-of-the-box models in their pure form and invest time in searching for improvements in their inner workings, hybridizing and combining them. Also, special care should be applied to make sure tests are snooping bias free and results are given with statistical significance. Considering to be a well-known problem in machine learning applications, future works should take every caution on separating data for testing purposes in order to guarantee statistical validity.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

References

Angerschmid, A., Zhou, J., Theuermann, K., Chen, F., & Holzinger, A. (2022). Fairness and explanation in AI-informed decision making. *Machine Learning and Knowledge Extraction*, *4*(2), 556–579.

Araújo, R., Oliveira, A. L., & Meira, S. (2015). A hybrid model for high-frequency stock market forecasting. *Expert Systems with Applications*, *42*(8), 4081–4096.

Atsalakis, G. S., & Valavanis, K. P. (2009). Surveying stock market forecasting techniques–Part II: Soft computing methods. *Expert Systems with Applications*, *36*(3), 5932–5941.

Ballings, M., den Poel, D. V., Hespeels, N., & Gryp, R. (2015). Evaluating multiple classifiers for stock price direction prediction. *Expert Systems with Applications*, *42*(20), 7046–7056.

Barak, S., Arjmand, A., & Ortobelli, S. (2017). Fusion of multiple diverse predictors in stock market. *Information Fusion*, *36*(1), 90–102.

Basak, S., Kar, S., Saha, S., Khaidem, L., & Dey, S. R. (2019). Predicting the direction of stock market prices using tree-based classifiers. *The North American Journal of Economics and Finance*, *47*(1), 552–567.

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32.

Cao, L. (2003). Support vector machines experts for time series forecasting. *Neurocomputing*, *51*(1), 321–339.

Cao, Q., Leggio, K. B., & Schniederjans, M. J. (2005). A comparison between fama and French's model and artificial neural networks in predicting the Chinese stock market. *Computers & Operations Research*, *32*(10), 2499–2512.

Cao, J., & Wang, J. (2019). Stock price forecasting model based on modified convolution neural network and financial time series analysis. *International Journal of Communication Systems*, Article e3987.

Cavalcante, R. C., Brasileiro, R. C., Souza, V. L., Nobrega, J. P., & Oliveira, A. L. (2016). Computational intelligence and financial markets: A survey and future directions. *Expert Systems with Applications*, *55*(1), 194–211.

Chang, P.-C., Liu, C.-H., Lin, J.-L., Fan, C.-Y., & Ng, C. S. (2009). A neural network with a case based dynamic window for stock trading prediction. *Expert Systems with Applications*, *36*(3, Part 2), 6889–6898.

Chen, T.-l., & Chen, F.-y. (2016). An intelligent pattern recognition model for supporting investment decisions in stock market. *Information Sciences*, *346*(1), 261–274.

Chen, Y.-S., Cheng, C.-H., & Tsai, W.-L. (2014). Modeling fitting-function-based fuzzy time series patterns for evolving stock index forecasting. *Applied Intelligence*, *41*(2), 327–347.

Chen, Y., & Hao, Y. (2017). A feature weighted support vector machine and K-nearest neighbor algorithm for stock market indices prediction. *Expert Systems with Applications*, *80*(1), 340–355.

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 & Operations Research*, *30*(6), 901–923.

Chen, L., Qiao, Z., Wang, M., Wang, C., Du, R., & Stanley, H. E. (2018). Which artificial intelligence algorithm better predicts the Chinese stock market? *IEEE Access*, *6*, 48625–48633.

Chen, H., Xiao, K., Sun, J., & Wu, S. (2017). A double-layer neural network framework for high-frequency forecasting. *ACM Transactions on Management Information Systems (TMIS)*, *7*(4), 11:2–11:17.

Cooper, R., Davis, M., Kumiega, A., & Van Vliet, B. (2020). Ethics for automated financial markets. In L. San-Jose, J. L. Retolaza, & L. van Liedekerke (Eds.), *Handbook on ethics in finance* (pp. 1–18). Cham: Springer International Publishing.

Dash, R., & Dash, P. K. (2016). A hybrid stock trading framework integrating technical analysis with machine learning techniques. *The Journal of Finance and Data Science*, *2*(1), 42–57.

Donaldson, R. G., & Kamstra, M. (1999). Neural network forecast combining with interaction effects. *Journal of the Franklin Institute*, *336*(2), 227–236.

Fama, E. F. (1991). Efficient capital markets: II. *The Journal of Finance*, *46*(5), 1575–1617.

Gerlein, E. A., McGinnity, M., Belatreche, A., & Coleman, S. (2016). Evaluating machine learning classification for financial trading: An empirical approach. *Expert Systems with Applications*, *54*(1), 193–207.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627–660.

Göçken, M., Özçalıcı, M., Boru, A., & Dosdoğru, A. T. (2016). Integrating metaheuristics and artificial neural networks for improved stock price prediction. *Expert Systems with Applications*, *44*(1), 320–331.

Gomez, C., Unberath, M., & Huang, C.-M. (2023). Mitigating knowledge imbalance in AI-advised decision-making through collaborative user involvement. *International Journal of Human-Computer Studies*, *172*, Article 102977.

Guo, Y., Han, S., Shen, C., Li, Y., Yin, X., & Bai, Y. (2018). An adaptive SVR for high-frequency stock price forecasting. *IEEE Access*, *6*(1), 11397–11404.

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. (2018). Stock price prediction using support vector regression on daily and up to the minute prices. *The Journal of Finance and Data Science*, *4*(3), 183–201.

Henrique, B. M., Sobreiro, V. A., & Kimura, H. (2019). Literature review: Machine learning techniques applied to financial market prediction. *Expert Systems with Applications*, *124*(1), 226–251.

Hornik, K. (1991). Approximation capabilities of multilayer feedforward networks. *Neural Networks*, *4*(2), 251–257.

Hornik, K., Stinchcombe, M., & White, H. (1989). Multilayer feedforward networks are universal approximators. *Neural Networks*, *2*(5), 359–366.

Hsu, M.-W., Lessmann, S., Sung, M.-C., Ma, T., & Johnson, J. E. (2016). Bridging the divide in financial market forecasting: Machine learners *vs.* financial economists. *Expert Systems with Applications*, *61*(1), 215–234.

Huang, W., Nakamori, Y., & Wang, S.-Y. (2005). Forecasting stock market movement direction with support vector machine. *Computers & Operations Research*, *32*(10), 2513–2522.

Huang, C.-L., & Tsai, C.-Y. (2009). A hybrid SOFM-SVR with a filter-based feature selection for stock market forecasting. *Expert Systems with Applications*, *36*(2), 1529–1539.

Hudson, R., McGroarty, F., & Urquhart, A. (2017). Sampling frequency and the performance of different types of technical trading rules. *Finance Research Letters*, *22*(1), 136–139.

Islam, M. R., Al-Shaikhli, I. F., Nor, R. M., & Tumian, A. (2019). Neural network and principle component analysis based numerical data analysis for stock market prediction with machine learning techniques. *Journal of Computational and Theoretical Nanoscience*, *16*(3), 806–812.

Jujie, W., & Danfeng, Q. (2018). An experimental investigation of two hybrid frameworks for stock index prediction using neural network and support vector regression. *Economic Computation and Economic Cybernetics Studies and Research*, *52*(4), 193–210.

Kamstra, M., & Donaldson, G. (1996). Forecasting combined with neural networks. *Journal of Forecast*, *15*(1), 49–61.

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.

Karush, W. (1939). Minima of functions of several variables with inequalities as side conditions. (Master's thesis), University of Chicago.

Kim, K. (2003). Financial time series forecasting using support vector machines. *Neurocomputing*, *55*(1–2), 307–319.

Kim, K.-j., & Han, I. (2000). Genetic algorithms approach to feature discretization in artificial neural networks for the prediction of stock price index. *Expert Systems with Applications*, *19*(2), 125–132.

Kuhn, H., & Tucker, A. (1951). Proceedings of 2nd berkeley symposium. (pp. 481–492).

Kumar, D., Meghwani, S. S., & Thakur, M. (2016). Proximal support vector machine based hybrid prediction models for trend forecasting in financial markets. *Journal of Computer Science*, *17*(1), 1–13.

Kumar, M., & Thenmozhi, M. (2014). Forecasting stock index returns using ARIMA-SVM, ARIMA-ANN, and ARIMA-random forest hybrid models. *International Journal of Banking, Accounting and Finance*, *5*(3), 284–308.

Laboissiere, L. A., Fernandes, R. A., & Lage, G. G. (2015). Maximum and minimum stock price forecasting of Brazilian power distribution companies based on artificial neural networks. *Applied Soft Computing*, *35*(1), 66–74.

Makhlouf, K., Zhioua, S., & Palamidessi, C. (2021). Machine learning fairness notions: Bridging the gap with real-world applications. *Information Processing & Management*, *58*(5), Article 102642.

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.

Narayan, P. K., & Sharma, S. S. (2016). Intraday return predictability, portfolio maximisation, and hedging. *Emerging Markets Review*, *28*(1), 105–116.

Pai, P.-F., & Lin, C.-S. (2005). A hybrid ARIMA and support vector machines model in stock price forecasting. *Omega*, *33*(6), 497–505.

Park, M., Lee, M. L., Lee, J., et al. (2019). Predicting stock market indices using classification tools. *Asian Economic and Financial Review*, *9*(2), 243–256.

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

Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015b). Predicting stock market index using fusion of machine learning techniques. *Expert Systems with Applications*, *42*(4), 2162–2172.

Pei, A., Wang, J., & Fang, W. (2017). Predicting agent-based financial time series model on lattice fractal with random Legendre neural network. *Soft Computing*, *21*(7), 1693–1708.

Podsiadlo, M., & Rybinski, H. (2016). Financial time series forecasting using rough sets with time-weighted rule voting. *Expert Systems with Applications*, *66*(1), 219–233.

Reboredo, J. C., Matías, J. M., & Garcia-Rubio, R. (2012). Nonlinearity in forecasting of high-frequency stock returns. *Computational Economics*, *40*(3), 245–264.

Ren, R., Wu, D. D., & Liu, T. (2018). Forecasting stock market movement direction using sentiment analysis and support vector machine. *IEEE Systems Journal*, (99), 1–11.

Rodríguez-González, A., García-Crespo, Á., Colomo-Palacios, R., Iglesias, F. G., & Gómez-Berbís, J. M. (2011). CAST: Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator. *Expert Systems with Applications*, *38*(9), 11489–11500.

Rustam, Z., & Kintandani, P. (2019). Application of support vector regression in Indonesian stock price prediction with feature selection using particle swarm optimisation. *Modelling and Simulation in Engineering*, *2019*.

Schmidt, P., Biessmann, F., & Teubner, T. (2020). Transparency and trust in artificial intelligence systems. *Journal of Decision Systems*, *29*(4), 260–278.

Selvamuthu, D., Kumar, V., & Mishra, A. (2019). Indian stock market prediction using artificial neural networks on tick data. *Financial Innovation*, *5*(1), 12 pages.

Sobreiro, V. A., da Costa, T. R. C. C., Nazário, R. T. F., e Silva, J. L., Moreira, E. A., Lima Filho, M. C., et al. (2016). The profitability of moving average trading rules in BRICS and emerging stock markets. *The North American Journal of Economics and Finance*, *38*(1), 86–101.

Son, Y., Noh, D.-j., & Lee, J. (2012). Forecasting trends of high-frequency KOSPI200 index data using learning classifiers. *Expert Systems with Applications*, *39*(14), 11607–11615.

Souza, M. J. S., Almudhaf, F. W., Henrique, B. M., Negredo, A. B. S., Ramos, D. G. F., Sobreiro, V. A., et al. (2019). Can artificial intelligence enhance the bitcoin bonanza?. *The Journal of Finance and Data Science*.

Tay, F. E., & Cao, L. (2001). Application of support vector machines in financial time series forecasting. *Omega*, *29*(4), 309–317.

Timmermann, A., & Granger, C. W. (2004). Efficient market hypothesis and forecasting. *International Journal of Forecasting*, *20*(1), 15–27.

Vapnik, V. (1995). *The nature of statistical learning theory*. New York: Springer.

Xiao, Y., Xiao, J., Lu, F., & Wang, S. (2013). Ensemble ANNs-PSO-GA approach for day-ahead stock E-exchange prices forecasting. *International Journal of Computational Intelligence Systems*, *6*(1), 96–114.

Yang, R., Yu, L., Zhao, Y., Yu, H., Xu, G., Wu, Y., et al. (2020). Big data analytics for financial market volatility forecast based on support vector machine. *International Journal of Information Management*, *50*(1), 452–462.

Yoon, Y., Swales Jr, G., & Margavio, T. M. (1993). A comparison of discriminant analysis versus artificial neural networks. *Journal of the Operational Research Society*, *44*(1), 51–60.

Yu, X.-H., & Chen, G.-A. (1997). Efficient backpropagation learning using optimal learning rate and momentum. *Neural Networks*, *10*(3), 517–527.

Yu, L., Chen, H., Wang, S., & Lai, K. K. (2009). Evolving least squares support vector machines for stock market trend mining. *IEEE Transactions on Evolutionary Computation*, *13*(1), 87–102.

Żbikowski, K. (2015). Using volume weighted support vector machines with walk forward testing and feature selection for the purpose of creating stock trading strategy. *Expert Systems with Applications*, *42*(4), 1797–1805.

Zhang, N., Lin, A., & Shang, P. (2017). Multidimensional k-nearest neighbor model based on EEMD for financial time series forecasting. *Physica A: Statistical Mechanics and its Applications*, *477*(1), 161–173.

Zhang, G., Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, *14*(1), 35–62.

Zhang, J., Teng, Y.-F., & Chen, W. (2019). Support vector regression with modified firefly algorithm for stock price forecasting. *Applied Intelligence*, *49*(5), 1658.

Zhong, X., & Enke, D. (2017). Forecasting daily stock market return using dimensionality reduction. *Expert Systems with Applications*, *67*(1), 126–139.

Zhong, X., & Enke, D. (2019). Predicting the daily return direction of the stock market using hybrid machine learning algorithms. *Financial Innovation*, *5*(1), 4.

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