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Predicting stock price direction using machine learning models

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Resumo

O presente trabalho visa avaliar a eficiência dos modelos de aprendizagem automática na previsão da direção do preço de ações no dia seguinte, utilizando indicadores técnicos e padrões de vela. Este estudo considerou 440 ações do índice Standard & Poor's 500 e, para cada uma delas, foram desenvolvidos três modelos binários diferentes com base nos seguintes algoritmos de aprendizagem automática: Deep Neural Network, Support Vector Machine, e Random Forest. Além disso, foi criado um naive predictor para ajudar a comparar os resultados dos modelos. Os modelos foram julgados com base na sua precisão e retorno financeiro.

Os resultados mostraram que os modelos de aprendizagem automática alcançaram resultados semelhantes aos do modelo naive e não conseguiram prever com precisão a direção do preço das ações no dia seguinte, utilizando as características selecionadas, indicando que não existe uma relação aparente entre os mesmos.

Palavras-chave: Inteligência Artificial, Aprendizagem Automática, Mercado de Ações, Previsão de Preço.

Classificação JEL:

G17 - Financial Forecasting and Simulation

C88 - Other Computer Software

Abstract

The present work aims to evaluate the efficiency of machine learning models in predicting next-day stock price direction, using technical indicators and candlestick patterns. This study considered 440 stocks from the Standard & Poor's 500 index and for each one of them, three different binary models were developed based on the following machine learning algorithms: Deep Neural Network, Support Vector Machine, and Random Forest. Additionally, a naive predictor was created to help compare the models results. The models were judged based on their accuracy and financial returns.

The results showed that the machine learning models achieved similar results to the naive model and failed to accurately predict the next-day stock price direction using the selected features, indicating that there is no apparent relationship between them.

Keywords: Artificial Intelligence, Machine Learning, Stock Market, Price Prediction.

JEL Classification:

G17 - Financial Forecasting and Simulation

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List of Abbreviations

AI – Artificial Intelligence

ANN – Artificial Neural Network

DNN – Deep Neural Network

DT – Decision Tree

LSTM – Long Short-term Memory

ML – Machine Learning

NN – Neural Network

OHLCV – Open-High-Low-Close-Volume

RF – Random Forest

S&P 500 – Standard & Poor's 500

SVM – Support Vector Machine

Chapter 1: Introduction

The growth of processing power and data availability over recent years has enabled Machine Learning techniques to be successfully applied in a wide range of industries. Stock market price prediction has been an area of significant interest to the research community since an accurate forecast can create an investment opportunity or avoid potential losses.

Predicting stock prices has proven to be a challenging task as market data is frequently associated with hidden relationships and a high degree of uncertainty. Scholars, however, believe that Artificial Intelligence algorithms have made it possible to model some of the non-linearity in the financial markets. While this topic has gained popularity and more studies have been published, many questions remain about those who have been successful. This is because most only study a small number of stocks and rarely show how the results would translate into actual returns in a financial market.

To understand if ML algorithms can successfully forecast the next day stock price direction using technical indicators and candlestick patterns, we selected all the Standard & Poor's 500 constituents that have a historical performance dating back to 2010. Three binary prediction models were developed using these algorithms: Deep Neural Network, Support Vector Machine with a polynomial and a radial basis kernel, Random Forest. Additionally, a naive predictor was created to help compare the models results. The models output predicted whether the stock price would increase or decrease the next day. Based on those predictions, financial returns were calculated and compared between the models and with a buy-and-hold strategy.

The present study is organized into different chapters. Chapter 2 provides context to the findings by reviewing articles with similar themes. Chapter 3 presents the theoretical background that provided the framework for this study's methods. A detailed description of the methodologies used to gather the necessary data and to train the different prediction models is provided in Chapter 4. An analysis of the results obtained by each model is presented and compared in Chapter 5. Lastly, in Chapter 6, general conclusions are derived from the models results.

Chapter 2: Literature Review

2.1. Stock Market

One of the most significant aspects of the current global economy is the stock market, as it can impact the economic progress of many nations and provides new opportunities for business expansion (Casson & Lee, 2011). In the financial market, people can trade publicly traded company shares, giving the buyer ownership of a company. The stock market can be essentially represented by its trends known as bull and bear markets (Edwards et al., 2018). A bull market is often represented by steadily rising prices and represents an investment opportunity, whereas a bear market is characterized by a drop in prices and generally results in possible losses for an investor. A third situation, which can also be considered a market condition, occurs when the prices fluctuate within a defined range. This situation is known as a sideways market.

For each of the market conditions, an investor can take different strategies to gain a financial hedge. A long position is advised in a bullish market, whereas a short position is recommended in a bearish market. When a position is long, the holder who owns the stock stands to gain if the price increases. In a short position, the investor loans the stock from a broker and instantly sells it at the current market price. He then waits for a price decrease to repurchase the stock and returns it to the broker, profiting from the price difference. In the sideways market, investors typically avoid making any kind of investment since there is no apparent trend and the market is perceived as unstable.

A variety of charts are used by traders to assist them in making decisions on the stock market (Folger, 2022). A chart is usually used as a simple visual representation of how a stock's price or volume has changed over time. Line charts display only one specific characteristic of a security asset, often the close price over time, while bar charts and candlestick charts show the open, high, low, and close prices.

In the stock market, indexes are widely used since they represent a segment of the financial market and can help investors track market movements. Nearly 500 of the top United States publicly traded corporations are represented by the S&P 500 index, which places a strong focus on market capitalization. The S&P 500 is regarded as one of the strongest indicators of significant United States stocks as well as the entire equities market due to its depth and diversity (Kenton, 2022). Due to these features, it is frequently used as a benchmark for equity funds (Liang, 1999).

2.2. General Machine Learning

A ML algorithm is a computer procedure that uses incoming data to complete a task without being explicitly programmed to do so. Ultimately, ML seeks to replicate the way humans process sensory information (El Naqa & Murphy, 2015).

ML algorithms are broadly classified into four categories: supervised, unsupervised, semi-supervised and reinforcement. The most widely used methods belong to the supervised learning category. In supervised learning, the training data consists of a set of labeled examples, each with its own set of features and corresponding output (Brownlee, 2020). By using the features and the outputs from one dataset (training data), the algorithm predicts the outputs (labels) for another dataset (test data). A supervised learning problem can be further divided into two categories: regression and classification. Classification problems have discrete output variables, whereas regression problems have continuous output variables. Unlike supervised learning, unsupervised learning involves an unlabeled set of features and attempts to group the data into distinct groups. The dataset in semi-supervised learning contains both labeled and unlabeled samples. An initial model is trained on a few labeled samples before being applied iteratively to a larger set of unlabeled data. In reinforcement learning, after defining a set of rules, the algorithm tries to explore different options and possibilities in order to find an optimal solution (Kaelbling et al., 1996). This procedure is carried out through trial and error.

2.3. Stock Market Prevision Using Machine Learning Models

For a long time, predicting stock prices was considered unachievable. This assumption was supported by the Random Walk Theory (Cootner, 1964) and the Efficient Market Hypothesis (Fama, 1970). The Random Walk Theory states that the price of securities in the stock market evolves randomly. The Efficient Market Hypothesis posits that security prices reflect all available information and therefore, it should be impossible to outperform the overall market. Nonetheless, in recent years, numerous research studies have demonstrated some promise in predicting stock prices by achieving accuracy scores well over the 50% threshold (Ou & Wang, 2009; Chong et al., 2017).

ML approaches have become increasingly popular in estimating asset prices and trends. AI algorithms have made it possible to tackle computationally intensive models that can detect and predict some of the nonlinearity prevalent in financial markets. The research community has shifted its focus to ML models because traditional financial methods used to forecast an asset price, such as the autoregressive method (AR), moving average model (MA), and autoregressive moving average model (ARMA), have proven to have worst performance (Adebiyi et al., 2014) and rely solely on past returns to make a prediction rather than taking advantage of all data available through data mining processes. Not only have they outperformed the classical models on price prediction but also on portfolio management and credit evaluation (Bahrammirzaee, 2010).

The ability of Neural Networks to interpret noisy data has led to its widespread adoption by researchers. Massive amounts of data can be used to train these algorithms, and if they are applied to build DNNs with numerous hidden layers, they may be able to identify more nonlinear relationships in data. The results obtained by using Artificial Neural Networks surpassed those obtained by linear and logical regression models (Altay & Satman, 2005). This algorithm can be traced back to 1988, when White (1988) created a simple ANN to test its efficiency in predicting IBM daily stock returns. His results weren't promising as he couldn't constitute convincing statistical evidence against the Efficient Market Hypothesis.

Fernandez-Rodrıguez et al. (2000) created a simple ANN model solely based on the time series of the Madrid Stock Exchange General Index. The preceding nine days of the index were utilized as inputs, and the output was a buy/sell signal. The study concluded that the NN trading model outperformed a simple buy-and-hold strategy during a bear market and a stable market, but it underperformed the buy-and-hold strategy during a bull market.

Long Short-term Memory neural networks, which are a type of Recurrent Neural Networks, have been increasingly popular in stock price prediction. These networks were developed by Hochreiter and Schmidhuber (1997) in order to improve performance by addressing the vanishing gradient problem that recurrent networks have when dealing with large data sequences. Shad et al. (2018) compared a DNN and an LSTM on stock price prediction, and the findings revealed that these two NNs topologies performed similarly.

The SVM is a different ML technique that has grown in popularity for predicting stock prices and trends. Vapnik (1999) presented this approach with the ability to divide classes by looking for a hyperplane in higher dimensions. Since then, numerous academics assert that they have successfully used it to forecast stock prices. Kim (2003) forecasted the direction of daily stock price change in the Korea Composite Stock Price Index in 2003 using the SVM model and thirteen technical indicators. Many academics cite his work and consider it successful due to its up to 57% accuracy in predicting the test set, which is much higher than the 50% accuracy threshold (Madge & Bhatt, 2015). However, there is no indication in his study of how his forecasts would translate into financial gains. The one thing we can conclude about Kim's work is that the SVM model outperformed a back-propagation neural network (BPN) and the case-based reasoning (CBR) since he compared the results obtained by all these models.

More recently Kara et al. (2011) compared the performance between an ANN and a SVM in predicting the direction of movement in the daily Istanbul Stock Exchange (ISE) National 100 Index. In his work, the ANN attained an average accuracy of 75.65%, significantly better than the 71.52% achieved by the SVM.

Another type of ML algorithm that has been employed in stock price prediction is the Random Forest. Breiman (2001) proposed it and, like the SVM, it has found some success since it avoids the issue of modeling the underlying distribution and instead focuses on producing accurate predictions for some variables given other factors.

Ballings et al. (2015) benchmarked ensemble methods consisting of RF, AdaBoost, and Kernel Factory against single classifier models such as NNs, Logistic Regression, SVM, and K-Nearest Neighbor using data from 5767 publicly listed European companies. The authors used Area Under the Curve (AUC) as a performance measure for predicting long term stock price direction and reported Random Forest as the top algorithm.

The features used in ML methods are another important topic of discussion since they directly impact the model's predictive power. Most of the input features used by researchers in asset price forecast can be categorized into four categories: Open-High-Low-Close-Volume data, technical indicators, fundamental data, and word embeddings. The first category is an aggregated form of market data. The second category is calculated mathematically from the OHLCV data and, examples include the moving average indicator, relative strength index indicator, and percentage price oscillator indicator (Agrawal et al., 2019). The third category is related to the quantitative variables that are assumed to influence the underlying company's intrinsic worth (Huang et al., 2021). The fourth and last category is used for text analysis to represent words, often in the form of a real valued vector (Mohan et al., 2019).

Although less common, candlestick pattern identification has also been used by researchers to predict stock market movements. For DJIA components from 1992 to 2002, Marshall et al. (2006) found that the candlestick charting strategy did not profit under a holding period of 10 days. On the other hand, Goo et al. (2007) found some profitable candlestick chart patterns in 25 Taiwanese companies. The inconsistent results across the literature may be due to differing stock samples.

Chapter 3: Theoretical Framework

3.1. Artificial Neural Network

An ANN is a mathematical model that attempts to replicate the structure and capabilities of biological neural networks. A neuron is the fundamental building block of every NN. Similarities in design between the artificial and the biological neuron can be seen in Figure 3.1. In a biological neuron, information enters the neuron via dendrite, which is processed by the body and transmitted via axon. In an artificial neuron, information enters the body via weighted inputs, then all the weighted inputs are summed together with a bias. At the exit, the previously calculated sum is passed through an activation function. The mathematical formulation of the artificial neuron model below demonstrates its simplicity:

$$\boldsymbol{y} = \boldsymbol{f}\left(\sum_{\boldsymbol{i}=\boldsymbol{0}}^{\boldsymbol{n}} (\boldsymbol{w_i} * \boldsymbol{x_i}) + \boldsymbol{b}\right) \tag{3.1}$$

Where $\boldsymbol{x}$ is the input value, $\boldsymbol{w}$ is the respective weight, $\boldsymbol{b}$ is the bias, $\boldsymbol{f}$ is the activation function and $\boldsymbol{y}$ is the final output value. The characteristics of an artificial neuron are defined by its activation function. The criteria for selecting an activation function are determined by the problem at hand. Sigmoid (σ) and rectified linear (ReLU) are examples of functions that allow to solve non-linear problems.

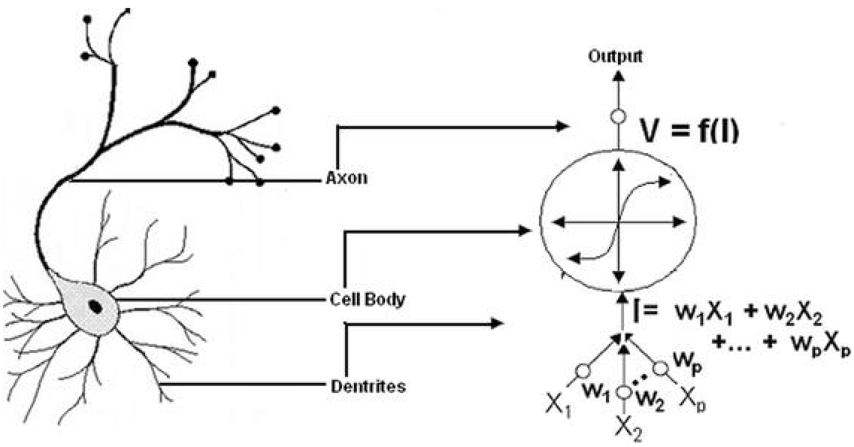

Figure 3.1 - Relation between biological and artificial neurons

The perceptron is considered one of the simplest NN architectures. Containing only a neuron inside a hidden layer, it is only capable of solving linear problems however, a multi-layer perceptron has the capability of solving non-linear complex problems. There are many ways of interconnecting the neurons inside an ANN but the two most known are the feed-forward topology and the recurrent topology. In feed-forward neural networks, information only flows in one direction, from input to output without back loops. On the other hand, recurrent neural networks can not only transmit information in one direction but also backwards. The number of hidden layers in a network must also be considered because it improves a network's representational power and assists in learning highly abstract characteristics. A network with more than one hidden layer is often referred has a DNN.

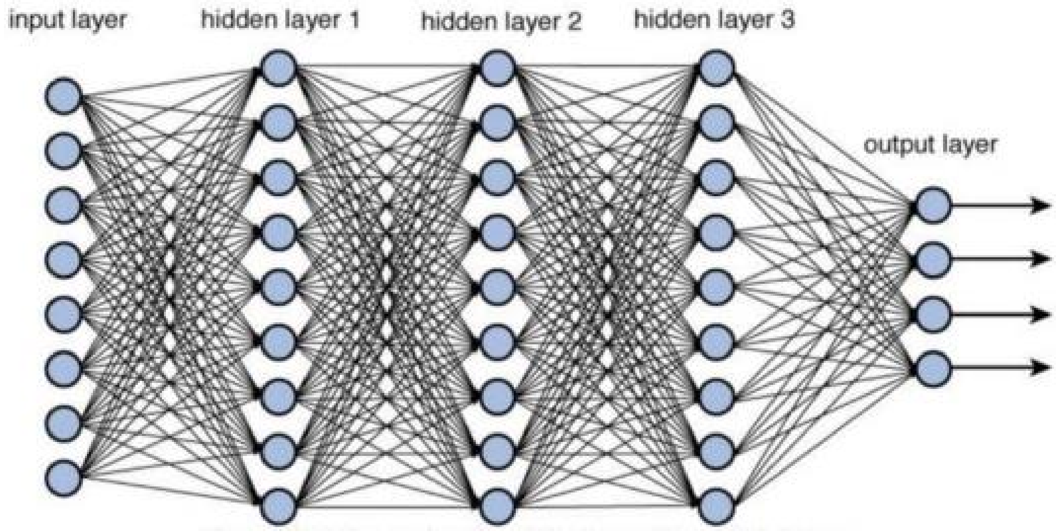

Figure 3.2 - DNN architecture

The training of an ANN can be described in a few steps. First, all the weights are randomly initialized. Then each node receives data through the inputs, calculates the output and progresses it forwards. After a value is calculated from the last node, the result is compared to the actual target in the training data and the error is determined using a loss function. One of the most popular loss functions used to solve binary classification problems is the binary cross-entropy:

$$\boldsymbol{Loss = -\frac{1}{n}\sum_{i=1}^{n} y_{true} \cdot log\left(y_{predicted}\right) + (1 - y_{true}) \cdot log(1 - y_{predicted})} \quad (3.2)$$

Where $\boldsymbol{n}$ is the number of samples (batch), $\boldsymbol{y_{true}}$ the true value and $\boldsymbol{y_{predicted}}$ the predicted value. Finally, using backpropagation, the error is passed through every individual neuron and the gradient is computed with respect to all the weights. Then a step is taken in the opposite direction of the gradient and the size of this step is determined by the learning rate. The use of optimizers like the stochastic gradient descent and the adaptive moment estimation can help prevent the training process from staying in a local minimum. A complete loop over the data using the described procedures is an epoch.

3.2. Support Vector Machine

A SVM is a supervised learning algorithm that can solve regression and classification problems, although it is most commonly used to solve classification problems. In essence, SVM seeks the hyperplane in the original input space capable of correctly separating a given dataset and maximizing the margin between the support vectors and the hyperplane. The hyperplane is a decision boundary that separates classes, and the support vectors are simply the datapoints closer to the hyperplane. These points have a direct impact in the position of the hyperplane.

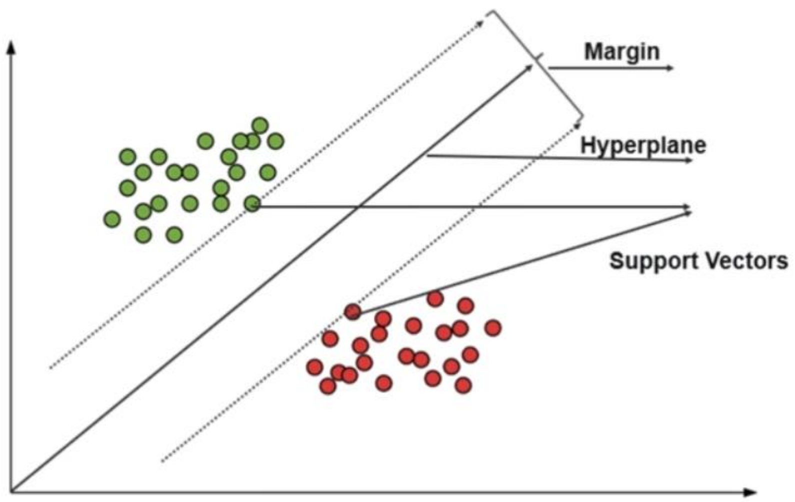

Figure 3.3 - Linear SVM

In addition to solve linear problems, SVMs can perform a non-linear decision boundary by mapping input data onto high-dimensional feature spaces and calculating the largest hyperplane margin in that space. This mapping is induced by the kernel functions method. In figure 3.4 it is possible to observe how this method helps the SVM algorithm to draw a hyperplane between two different classes.

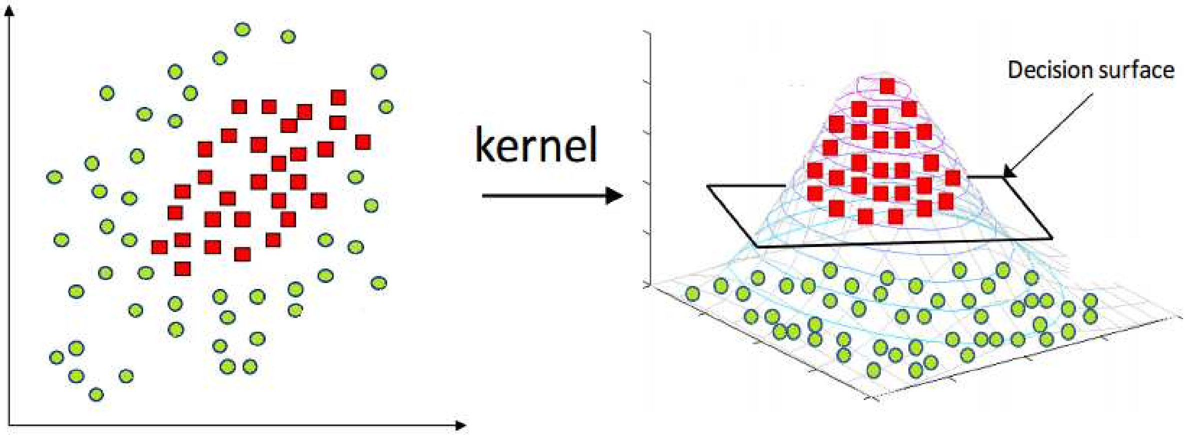

Figure 3.4 - Non-linear SVM using radial basis function kernel

3.3. Decision Tree

The Decision Tree is another supervised learning algorithm with the ability to solve regression and classification problems. It reflects a decision-making process through a tree like structure. The algorithm starts from the root of the tree, which represents the entire data sample population, and progressively splits the dataset into smaller subsets as the tree grows. The outcome is a tree comprising decision nodes and leaf nodes. Decision nodes are sub-nodes that split the data into additional sub-nodes and show a decision to be made. Leaf nodes are nodes that do not split and represent a classification. A branch refers to a subsection of the tree.

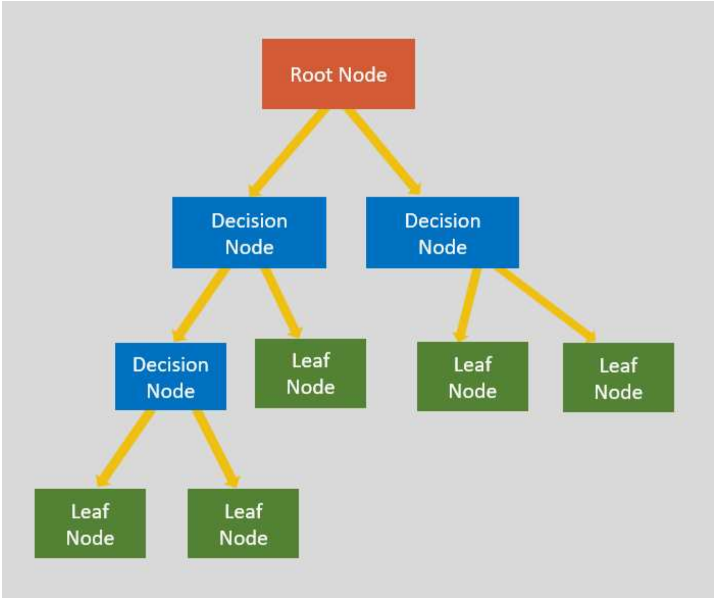

Figure 3.5 - Definitions inside a DT

The tree split decision is based on a specific criteria. The two most common criteria are information gain and gini index. In information gain, the features with the least entropy are selected as the ones that provide the most information about a class. Entropy quantifies the randomness of the information being processed:

$$E = \sum_{i=0}^{c} -p_i \cdot log_2(p_i) \tag{3.3}$$

Where c is the number of different classes in the dataset and p_i the probability of class i and E the calculated entropy. As the gini index quantifies the probability of an element in a dataset being mislabeled if randomly classified, it is the features with the lower gini index that determine the optimal split:

$$G = 1 - \sum_{i=0}^{c} p_i^2 \tag{3.4}$$

3.4. Random Forest

The RF is also a supervised learning algorithm capable of solving regression and classification problems. The algorithm uses the bagging ensemble method to combine multiple DTs in order to get a more accurate prediction. This method allows each individual tree to be trained with a different training subset from the training data and the output is then calculated based on majority voting. Compared to DTs, RFs are slower algorithms that tend to have fewer overfitting problems (Prajwala, 2015). (For more information about the machine learning algorithms consult Burkov, 2019)

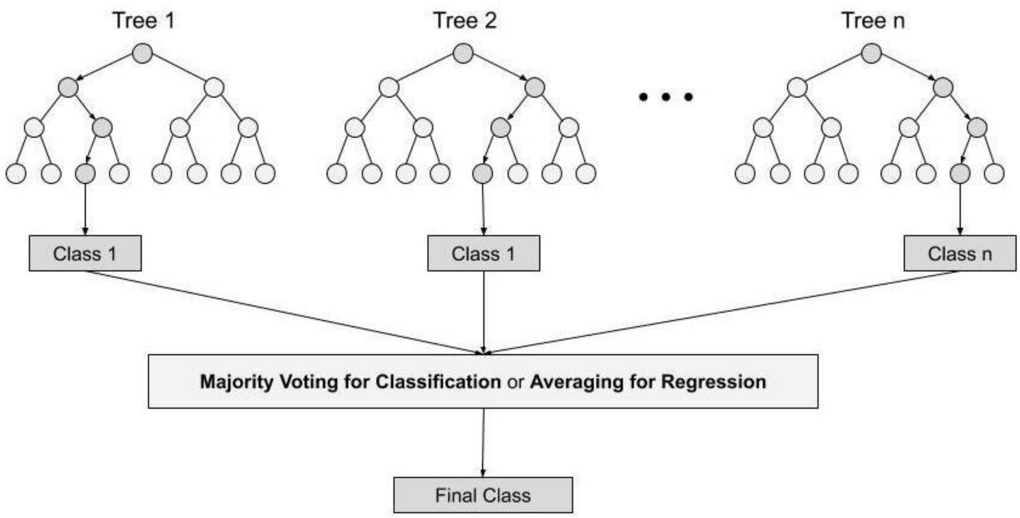

Figure 3.6 - RF overview

Chapter 4: Methodology

4.1. Data

For this study, all data were obtained from https://finance.yahoo.com/ using a data mining program written in Python. This program collected the daily OHLCV historical performance data of each company included in the S&P 500 index from 01-01-2010 through 30-06-2022 (3144 records). These requirements were met by 440 companies in total (Annex A). The distribution of industries among the selected companies is shown in Figure 4.1. The datasets were divided into three subsets: the training set (01-01-2010 through 30-06-2021), the validation set (01-07-2021 through 31-12-2021), and the test set (01-01-2022 through 30-06-2022). During the test set period, the average return was -15.43%, 79.1% of the companies had a negative return (Figure 4.2), and energy was the best performing sector (Figure 4.3).

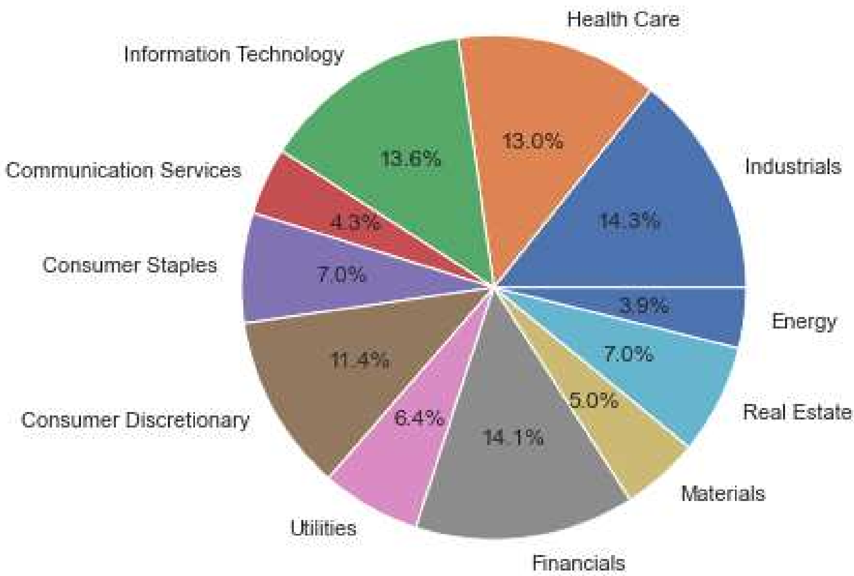

Figure 4.1 - Distribution of industries among the studied companies

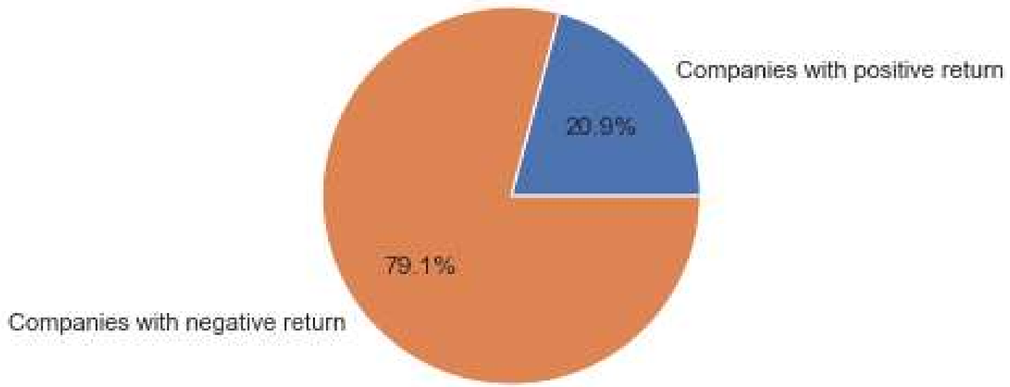

Figure 4.2 - Distribution of companies returns in the test set period

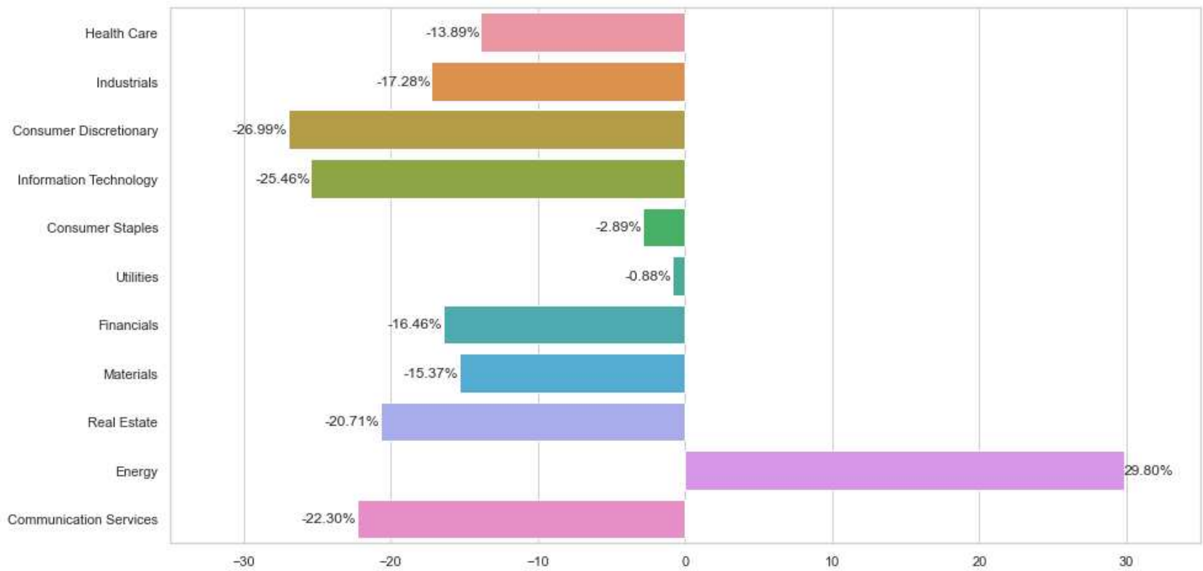

Figure 4.3 - Average return by industry in the test set period

Based on the OHLCV collected data, all technical indicators and candlestick pattern identification variables were calculated with the TA-Lib Python package using a five-day time window. In total, eighteen technical indicators and eighteen candlestick patterns were used as inputs to the ML models (Annex B). Before the training process began, all the technical indicators were standardized:

$$z = \frac{X - \mu}{\sigma} \tag{4.1}$$

Where z is the calculated standardized value, X the observation, μ the mean and σ the standard deviation. Candlestick pattern identification variables were not standardized since they are categorical variables where 0 represents the absence of a pattern, 1 represents the identification of a bullish pattern, and -1 represents the identification of a bearish pattern.

4.2. Training and Tunning

Due to the large number of stocks used in this study, we opted to use grid search with only a few hyperparameter options (Table 4.1). The Scikit-learn Python package was applied to train the SVM and the RF. The Keras Python package was utilized to train the DNN. Regarding the DNN, there were a set of parameters that weren't used in the grid search and in turn had a predefined value (Table 4.2). After the training process was completed for a specific ML model, the validation set accuracy was calculated for all the trained models. The one that achieved the highest accuracy was chosen as the optimal and used to predict the test set. A naive predictor, which predicted randomly if a stock would increase or decrease the next day, was also implemented to help compare the models results.

Table 4.1 - Tunning parameters used for each model during the training phase

Model	Tunning Parameters
Random Forest	{"n_estimators": [100,150,200], "criterion": ["gini", "entropy"]}
Support Vector Machine	{"C": [0.9, 0.95, 1], "kernel": ["rbf", "poly"]}
DNN	{"hidden_layers": [2,3], "layers_neurons": [20,25]}

Table 4.2 - Default parameters used for the DNN during the training phase

Parameter	Value
Batch size	10
Learning Rate	0.001
Number of epochs	40
Hidden layers activation function	ReLU
Output layer activation function	Sigmoid
Loss function	Binary Crossentropy
Optimizer	Adam

Chapter 5: Results

Table 5.1 shows the average accuracy achieved by each ML model and the naive predictor for all the company's stocks during the test period (Annex C). All ML models achieved similar accuracy values and were close to the naive model's value. As a result, the model's inputs provided no insight into the next-day price direction. In addition, Table 5.2 supports this idea since the models achieved an average accuracy close to 50% in each sector.

Table 5.1 - Average accuracy obtained by each model during the test period

	DNN	RF	SVM	Naive
Average Accuracy	50.04%	50.22%	49.21%	50.17%

Table 5.2 - Average accuracy obtained by each model in different sectors during the test period

Sector	DNN	RF	SVM	Naive
Communication Services	51.42%	48.23%	48.75%	51.16%
Consumer Discretionary	50.72%	51.62%	50.03%	50.15%
Consumer Staples	50.29%	50.26%	51.37%	50.69%
Energy	49.61%	46.77%	49.13%	51.16%
Financials	49.21%	49.79%	48.07%	49.63%
Health Care	49.45%	49.40%	48.58%	50.20%
Industrials	50.10%	49.96%	49.40%	50.73%
Information Technology	50.63%	51.72%	48.69%	49.44%
Materials	50.19%	49.03%	49.70%	49.37%
Real Estate	49.71%	51.82%	48.55%	50.13%
Utilities	49.82%	50.23%	50.56%	50.47%

Besides the accuracy values, the returns were also compared between the models and with a buy-and-hold strategy (Annex D). In light of the fact that the ML models outperformed the buy-and-hold strategy (Table 5.3), it is possible to argue that they might be able to anticipate significant market movements. The naive model, however, refutes this idea as it also outperformed the buy-and-hold strategy and its returns are close to those obtained by the other ML models. Furthermore, although almost all models outperformed a buy-and-hold strategy in bearish sectors, none of them outperformed the energy sector which had positive returns (Table 5.4).

Table 5.3 - Average return obtained by each model and the buy-and-hold strategy during the test period

	DNN	RF	SVM	Naive	Buy-and-hold
Average return	-7.34%	-6.85%	-10.04%	-7.14%	-15.43%

Table 5.4 - Average return obtained by each model and the buy-and-hold strategy in different sectors during the test period

Sector	Average DNN Return	Average RF Return	Average SVM Return	Average Naive Return	Average Buy-and-Hold Return
Communication Services	-8.35%	-14.06%	-16.40%	-11.35%	-22.30%
Consumer Discretionary	-10.02%	-10.62%	-13.46%	-14.61%	-26.99%
Consumer Staples	-0.73%	-1.13%	0.92%	3.16%	-2.89%
Energy	21.43%	10.27%	15.54%	21.24%	29.80%
Financials	-11.48%	-7.35%	-13.91%	-9.82%	-16.46%
Health Care	-7.85%	-7.15%	-10.07%	-4.56%	-13.89%
Industrials	-9.54%	-9.42%	-11.48%	-6.62%	-17.28%
Information Technology	-11.74%	-7.05%	-14.67%	-13.46%	-25.46%
Materials	-7.69%	-9.00%	-9.21%	-8.37%	-15.37%
Real Estate	-9.04%	-9.00%	-14.57%	-11.66%	-20.71%
Utilities	0.14%	0.12%	-1.14%	-0.46%	-0.88%

Chapter 6: Conclusion

Predicting stock prices has always interested the research community. As traditional financial models haven't succeeded in this task, many academics have shifted their focus to ML algorithms. Throughout the literature there have been inconsistent results most probably due to different stock samples used in each research.

This study tried to answer some of the questions related to the effectiveness of ML models in predicting stock prices by incorporating different features. The OHLCV data from 440 S&P 500 stocks was used to calculate technical indicators and identify candlestick patterns. Then 3 different types of ML algorithms were trained using that information. The average accuracy and return were calculated for each individual stock during the test set and compared between the models, a naive predictor and a buy-and-hold strategy.

The results observed showed that the average prediction accuracy obtained by each ML model was very similar to the one achieved by the naive model. In terms of average stock returns, the three ML models outperformed the buy-and-hold strategy however the naive predictor delivered comparable results. The model's outperformance was also due to the fact that most stocks had negative returns during the test period. When the models were compared in a sector that yielded positive returns, they underperformed the buy-and-hold strategy.

With all the results taken into account, we can conclude that all the models could not predict the stock price direction effectively. This was not due to the models weak learning capacity, but due to the non-existent relationship between technical indicators and candlestick patterns with the next day's price direction.

This dissertation is relevant in the sense that it provides a clear direction for future research. The focus of researchers should be on discovering features that have not been extensively used in previous studies, which might impact the direction of stock price movement.

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Annexes

Annex A: Table containing the companies used in this study, their symbols and respective sectors

Symbol	Company	Sector
MMM	3M	Industrials
AOS	A. O. Smith	Industrials
ABT	Abbott Laboratories	Health Care
ABMD	Abiomed	Health Care
ACN	Accenture	Information Technology
ATVI	Activision Blizzard	Communication Services
ADM	ADM	Consumer Staples
ADBE	Adobe	Information Technology
AAP	Advance Auto Parts	Consumer Discretionary
AMD	Advanced Micro Devices	Information Technology
AES	AES Corp	Utilities
AFL	Aflac	Financials
A	Agilent Technologies	Health Care
APD	Air Products & Chemicals	Materials
AKAM	Akamai Technologies	Information Technology
ALK	Alaska Air Group	Industrials
ALB	Albemarle Corporation	Materials
ARE	Alexandria Real Estate Equities	Real Estate
ALGN	Align Technology	Health Care
LNT	Alliant Energy	Utilities
ALL	Allstate Corp	Financials
GOOGL	Alphabet (Class A)	Communication Services
GOOG	Alphabet (Class C)	Communication Services
MO	Altria Group	Consumer Staples
AMZN	Amazon	Consumer Discretionary
AEE	Ameren Corp	Utilities
AAL	American Airlines Group	Industrials
AEP	American Electric Power	Utilities
AXP	American Express	Financials
AIG	American International Group	Financials
AMT	American Tower	Real Estate
AWK	American Water Works	Utilities
AMP	Ameriprise Financial	Financials
ABC	AmerisourceBergen	Health Care
AME	Ametek	Industrials
AMGN	Amgen	Health Care
APH	Amphenol	Information Technology
ADI	Analog Devices	Information Technology

ANSS	Ansys	Information Technology
AON	Aon	Financials
APA	APA Corporation	Energy
AAPL	Apple	Information Technology
AMAT	Applied Materials	Information Technology
AJG	Arthur J. Gallagher & Co.	Financials
AIZ	Assurant	Financials
T	AT&T	Communication Services
ATO	Atmos Energy	Utilities
ADSK	Autodesk	Information Technology
ADP	Automatic Data Processing	Information Technology
AZO	AutoZone	Consumer Discretionary
AVB	AvalonBay Communities	Real Estate
AVY	Avery Dennison	Materials
BKR	Baker Hughes	Energy
BALL	Ball Corporation	Consumer Discretionary
BAC	Bank of America	Financials
BBWI	Bath & Body Works Inc.	Consumer Discretionary
BAX	Baxter International	Health Care
BDX	Becton Dickinson	Health Care
BRK-B	Berkshire Hathaway	Financials
BBY	Best Buy	Consumer Discretionary
BIIB	Biogen	Health Care
BIO	Bio-Rad Laboratories	Health Care
TECH	Bio-Techne	Health Care
BLK	BlackRock	Financials
BK	BNY Mellon	Financials
BA	Boeing	Industrials
BKNG	Booking Holdings	Consumer Discretionary
BWA	BorgWarner	Consumer Discretionary
BXP	Boston Properties	Real Estate
BSX	Boston Scientific	Health Care
BMY	Bristol Myers Squibb	Health Care
AVGO	Broadcom	Information Technology
BR	Broadridge Financial Solutions	Information Technology
BRO	Brown & Brown	Financials
BF-B	Brown-Forman	Consumer Staples
CHRW	C. H. Robinson	Industrials
CDNS	Cadence Design Systems	Information Technology
CPB	Campbell Soup	Consumer Staples
COF	Capital One Financial	Financials
CAH	Cardinal Health	Health Care
KMX	CarMax	Consumer Discretionary
CCL	Carnival Corporation	Consumer Discretionary
CAT	Caterpillar	Industrials

CBRE	CBRE	Real Estate
CE	Celanese	Materials
CNC	Centene Corporation	Health Care
CNP	CenterPoint Energy	Utilities
CF	CF Industries	Materials
CRL	Charles River Laboratories	Health Care
SCHW	Charles Schwab Corporation	Financials
CVX	Chevron Corporation	Energy
CMG	Chipotle Mexican Grill	Consumer Discretionary
CB	Chubb	Financials
CHD	Church & Dwight	Consumer Staples
CI	Cigna	Health Care
CINF	Cincinnati Financial	Financials
CTAS	Cintas Corporation	Industrials
CSCO	Cisco Systems	Information Technology
C	Citigroup	Financials
CTXS	Citrix Systems	Information Technology
CLX	Clorox	Consumer Staples
CME	CME Group	Financials
CMS	CMS Energy	Utilities
KO	Coca-Cola Company	Consumer Staples
CTSH	Cognizant Technology Solutions	Information Technology
CL	Colgate-Palmolive	Consumer Staples
CMCSA	Comcast	Communication Services
CMA	Comerica	Financials
CAG	Conagra Brands	Consumer Staples
COP	ConocoPhillips	Energy
ED	Consolidated Edison	Utilities
STZ	Constellation Brands	Consumer Staples
CPRT	Copart	Industrials
GLW	Corning	Information Technology
COST	Costco	Consumer Staples
CTRA	Coterra	Energy
CPT	Camden Property Trust	Real Estate
CCI	Crown Castle	Real Estate
CSGP	CoStar Group Inc.	Real Estate
CSX	CSX	Industrials
CMI	Cummins	Industrials
CVS	CVS Health	Health Care
DHI	D. R. Horton	Consumer Discretionary
DHR	Danaher Corporation	Health Care
DRI	Darden Restaurants	Consumer Discretionary
DVA	DaVita	Health Care
DE	Deere & Co.	Industrials
DAL	Delta Air Lines	Industrials

XRAY	Dentsply Sirona	Health Care
DVN	Devon Energy	Energy
DXCM	DexCom	Health Care
DLR	Digital Realty Trust	Real Estate
DFS	Discover Financial Services	Financials
DISH	Dish Network	Communication Services
DG	Dollar General	Consumer Discretionary
DLTR	Dollar Tree	Consumer Discretionary
D	Dominion Energy	Utilities
DPZ	Domino's Pizza	Consumer Discretionary
DOV	Dover Corporation	Industrials
DTE	DTE Energy	Utilities
DUK	Duke Energy	Utilities
DRE	Duke Realty Corp	Real Estate
DD	DuPont	Materials
DXC	DXC Technology	Information Technology
EMN	Eastman Chemical	Materials
ETN	Eaton Corporation	Industrials
EBAY	eBay	Consumer Discretionary
ECL	Ecolab	Materials
EIX	Edison International	Utilities
EW	Edwards Lifesciences	Health Care
EA	Electronic Arts	Communication Services
LLY	Eli Lilly & Co	Health Care
ELV	Elevance Health Inc.	Health Care
EMR	Emerson Electric Company	Industrials
ETR	Entergy	Utilities
EOG	EOG Resources	Energy
EFX	Equifax	Industrials
EQIX	Equinix	Real Estate
EQR	Equity Residential	Real Estate
ESS	Essex Property Trust	Real Estate
EL	Estee Lauder Companies	Consumer Staples
RE	Everest Re	Financials
EVRG	Evergy	Utilities
ES	Eversource Energy	Utilities
EXC	Exelon	Utilities
EXPE	Expedia Group	Consumer Discretionary
EXPD	Expeditors	Industrials
EXR	Extra Space Storage	Real Estate
XOM	ExxonMobil	Energy
FFIV	F5 Networks	Information Technology
FAST	Fastenal	Industrials
FDS	FactSet Research Systems Inc.	Financials
FRT	Federal Realty Investment Trust	Real Estate

FDX	FedEx	Industrials
FIS	Fidelity National Information Services	Information Technology
FITB	Fifth Third Bancorp	Financials
FE	FirstEnergy	Utilities
FISV	Fiserv	Information Technology
FMC	FMC Corporation	Materials
F	Ford	Consumer Discretionary
FTNT	Fortinet	Information Technology
BEN	Franklin Resources	Financials
FCX	Freeport-McMoRan	Materials
GRMN	Garmin	Consumer Discretionary
IT	Gartner	Information Technology
GD	General Dynamics	Industrials
GE	General Electric	Industrials
GIS	General Mills	Consumer Staples
GPC	Genuine Parts	Consumer Discretionary
GILD	Gilead Sciences	Health Care
GPN	Global Payments	Information Technology
GL	Globe Life	Financials
GS	Goldman Sachs	Financials
HAL	Halliburton	Energy
HAS	Hasbro	Consumer Discretionary
PEAK	Healthpeak Properties	Real Estate
HSIC	Henry Schein	Health Care
HES	Hess Corporation	Energy
HOLX	Hologic	Health Care
HD	Home Depot	Consumer Discretionary
HON	Honeywell	Industrials
HRL	Hormel	Consumer Staples
HST	Host Hotels & Resorts	Real Estate
HWM	Howmet Aerospace	Industrials
HPQ	HP	Information Technology
HUM	Humana	Health Care
HBAN	Huntington Bancshares	Financials
IBM	IBM	Information Technology
IEX	IDEX Corporation	Industrials
IDXX	Idexx Laboratories	Health Care
ITW	Illinois Tool Works	Industrials
ILMN	Illumina	Health Care
INCY	Incyte	Health Care
INTC	Intel	Information Technology
ICE	Intercontinental Exchange	Financials
IFF	International Flavors & Fragrances	Materials
IP	International Paper	Materials
IPG	Interpublic Group	Communication Services

INTU	Intuit	Information Technology
ISRG	Intuitive Surgical	Health Care
IVZ	Invesco	Financials
IRM	Iron Mountain	Real Estate
JBHT	J. B. Hunt	Industrials
JKHY	Jack Henry & Associates	Information Technology
J	Jacobs Engineering Group	Industrials
SJM	JM Smucker	Consumer Staples
JNJ	Johnson & Johnson	Health Care
JCI	Johnson Controls	Industrials
JPM	JPMorgan Chase	Financials
JNPR	Juniper Networks	Information Technology
KDP	Keurig Dr Pepper Inc.	Consumer Staples
K	Kellogg's	Consumer Staples
KEY	KeyCorp	Financials
KMB	Kimberly-Clark	Consumer Staples
KIM	Kimco Realty	Real Estate
KLAC	KLA Corporation	Information Technology
KR	Kroger	Consumer Staples
LHX	L3Harris Technologies	Industrials
LH	LabCorp	Health Care
LRCX	Lam Research	Information Technology
LVS	Las Vegas Sands	Consumer Discretionary
LDOS	Leidos	Industrials
LEN	Lennar	Consumer Discretionary
LNC	Lincoln National	Financials
LIN	Linde	Materials
LYV	Live Nation Entertainment	Communication Services
LKQ	LKQ Corporation	Consumer Discretionary
LMT	Lockheed Martin	Industrials
L	Loews Corporation	Financials
LOW	Lowe's	Consumer Discretionary
LUMN	Lumen Technologies	Communication Services
MTB	M&T Bank	Financials
MRO	Marathon Oil	Energy
MKTX	MarketAxess	Financials
MAR	Marriott International	Consumer Discretionary
MMC	Marsh & McLennan	Financials
MLM	Martin Marietta Materials	Materials
MAS	Masco	Industrials
MA	Mastercard	Information Technology
MTCH	Match Group	Communication Services
MKC	McCormick & Company	Consumer Staples
MCD	McDonald's	Consumer Discretionary
MCK	McKesson Corporation	Health Care

MDT	Medtronic	Health Care
MRK	Merck & Co.	Health Care
MET	MetLife	Financials
MTD	Mettler Toledo	Health Care
MGM	MGM Resorts International	Consumer Discretionary
MCHP	Microchip Technology	Information Technology
MU	Micron Technology	Information Technology
MSFT	Microsoft	Information Technology
MAA	Mid-America Apartments	Real Estate
MOH	Molina Healthcare Inc.	Health Care
MHK	Mohawk Industries	Consumer Discretionary
TAP	Molson Coors Beverage Company	Consumer Staples
MDLZ	Mondelez International	Consumer Staples
MPWR	Monolithic Power Systems	Information Technology
MNST	Monster Beverage	Consumer Staples
MCO	Moody's Corporation	Financials
MS	Morgan Stanley	Financials
MSI	Motorola Solutions	Information Technology
MSCI	MSCI	Financials
NDAQ	Nasdaq	Financials
NDSN	Nordson Corporation	Industrials
NTAP	NetApp	Information Technology
NFLX	Netflix	Communication Services
NWL	Newell Brands	Consumer Discretionary
NEM	Newmont	Materials
NEE	NextEra Energy	Utilities
NKE	Nike	Consumer Discretionary
NI	NiSource	Utilities
NSC	Norfolk Southern	Industrials
NTRS	Northern Trust	Financials
NOC	Northrop Grumman	Industrials
NLOK	NortonLifeLock	Information Technology
NRG	NRG Energy	Utilities
NUE	Nucor	Materials
NVDA	Nvidia	Information Technology
NVR	NVR	Consumer Discretionary
OXY	Occidental Petroleum	Energy
ODFL	Old Dominion Freight Line	Industrials
OMC	Omnicom Group	Communication Services
ON	ON Semiconductor Corporation	Information Technology
OKE	Oneok	Energy
ORCL	Oracle	Information Technology
ORLY	O'Reilly Automotive	Consumer Discretionary
PCAR	Paccar	Industrials
PKG	Packaging Corporation of America	Materials

PARA	Paramount Global Class B	Communication Services
PH	Parker-Hannifin	Industrials
PAYX	Paychex	Information Technology
PNR	Pentair	Industrials
PEP	PepsiCo	Consumer Staples
PKI	PerkinElmer	Health Care
PFE	Pfizer	Health Care
PM	Philip Morris International	Consumer Staples
PNW	Pinnacle West Capital	Utilities
PXD	Pioneer Natural Resources	Energy
PNC	PNC Financial Services	Financials
POOL	Pool Corporation	Consumer Discretionary
PPG	PPG Industries	Materials
PPL	PPL	Utilities
PFG	Principal Financial Group	Financials
PG	Procter & Gamble	Consumer Staples
PGR	Progressive Corporation	Financials
PLD	Prologis	Real Estate
PRU	Prudential Financial	Financials
PTC	PTC	Information Technology
PEG	Public Service Enterprise Group	Utilities
PSA	Public Storage	Real Estate
PHM	PulteGroup	Consumer Discretionary
QCOM	Qualcomm	Information Technology
PWR	Quanta Services	Industrials
DGX	Quest Diagnostics	Health Care
RL	Ralph Lauren Corporation	Consumer Discretionary
RJF	Raymond James Financial	Financials
RTX	Raytheon Technologies	Industrials
O	Realty Income Corporation	Real Estate
REG	Regency Centers	Real Estate
REGN	Regeneron Pharmaceuticals	Health Care
RF	Regions Financial Corporation	Financials
RSG	Republic Services	Industrials
RMD	ResMed	Health Care
RHI	Robert Half International	Industrials
ROK	Rockwell Automation	Industrials
ROL	Rollins	Industrials
ROP	Roper Technologies	Industrials
ROST	Ross Stores	Consumer Discretionary
RCL	Royal Caribbean Group	Consumer Discretionary
SPGI	S&P Global	Financials
CRM	Salesforce	Information Technology
SBAC	SBA Communications	Real Estate
SBNY	Signature Bank	Financials

SLB	Schlumberger	Energy
STX	Seagate Technology	Information Technology
SEE	Sealed Air	Materials
SRE	Sempra Energy	Utilities
SHW	Sherwin-Williams	Materials
SPG	Simon Property Group	Real Estate
SWKS	Skyworks Solutions	Information Technology
SNA	Snap-on	Industrials
SO	Southern Company	Utilities
LUV	Southwest Airlines	Industrials
SWK	Stanley Black & Decker	Industrials
SBUX	Starbucks	Consumer Discretionary
STT	State Street Corporation	Financials
STE	Steris	Health Care
SYK	Stryker Corporation	Health Care
SIVB	SVB Financial	Financials
SNPS	Synopsys	Information Technology
SYY	Sysco	Consumer Staples
TROW	T. Rowe Price	Financials
TTWO	Take-Two Interactive	Communication Services
TPR	Tapestry	Consumer Discretionary
TGT	Target Corporation	Consumer Discretionary
TEL	TE Connectivity	Information Technology
TDY	Teledyne Technologies	Industrials
TFX	Teleflex	Health Care
TER	Teradyne	Information Technology
TXN	Texas Instruments	Information Technology
TXT	Textron	Industrials
COO	The Cooper Companies	Health Care
HIG	The Hartford	Financials
HSY	The Hershey Company	Consumer Staples
MOS	The Mosaic Company	Materials
TRV	The Travelers Companies	Financials
DIS	The Walt Disney Company	Communication Services
TMO	Thermo Fisher Scientific	Health Care
TJX	TJX Companies	Consumer Discretionary
TMUS	T-Mobile US	Communication Services
TSCO	Tractor Supply Company	Consumer Discretionary
TT	Trane Technologies	Industrials
TDG	TransDigm Group	Industrials
TRMB	Trimble	Information Technology
TFC	Truist Financial	Financials
TYL	Tyler Technologies	Information Technology
TSN	Tyson Foods	Consumer Staples
USB	U.S. Bancorp	Financials

UDR	UDR	Real Estate
ULTA	Ulta Beauty	Consumer Discretionary
UNP	Union Pacific	Industrials
UAL	United Airlines	Industrials
UPS	United Parcel Service	Industrials
URI	United Rentals	Industrials
UNH	UnitedHealth Group	Health Care
UHS	Universal Health Services	Health Care
VLO	Valero Energy	Energy
VTR	Ventas	Real Estate
VRSN	Verisign	Information Technology
VRSK	Verisk Analytics	Industrials
VZ	Verizon Communications	Communication Services
VRTX	Vertex Pharmaceuticals	Health Care
VFC	VF Corporation	Consumer Discretionary
VTRS	Viatris	Health Care
V	Visa	Information Technology
VNO	Vornado Realty Trust	Real Estate
VMC	Vulcan Materials	Materials
WRB	W. R. Berkley Corporation	Financials
GWW	W. W. Grainger	Industrials
WAB	Wabtec	Industrials
WBA	Walgreens Boots Alliance	Consumer Staples
WMT	Walmart	Consumer Staples
WM	Waste Management	Industrials
WAT	Waters Corporation	Health Care
WBD	Warner Bros. Discovery Inc. Series A	Communication Services
WEC	WEC Energy Group	Utilities
WFC	Wells Fargo	Financials
WELL	Welltower	Real Estate
WST	West Pharmaceutical Services	Health Care
WDC	Western Digital	Information Technology
WY	Weyerhaeuser	Real Estate
WHR	Whirlpool Corporation	Consumer Discretionary
WMB	Williams Companies	Energy
WTW	Willis Towers Watson Public Limited Company	Financials
WYNN	Wynn Resorts	Consumer Discretionary
XEL	Xcel Energy	Utilities
YUM	Yum! Brands	Consumer Discretionary
ZBRA	Zebra Technologies	Information Technology
ZBH	Zimmer Biomet	Health Care
ZION	Zions Bancorp	Financials

Annex B: Table containing the features used to train the machine learning models

Name	Type
Simple Moving Average	Technical Indicator
Exponential Moving Average	Technical Indicator
Weighted Moving Average	Technical Indicator
Triangular Moving Average	Technical Indicator
Kaufman Adaptive Moving Average	Technical Indicator
Average Directional Movement Index	Technical Indicator
Average Directional Movement Index Rating	Technical Indicator
Aroon Oscillator	Technical Indicator
Commodity Channel Index	Technical Indicator
Chande Momentum Oscillator	Technical Indicator
Directional Movement Index	Technical Indicator
Money Flow Index	Technical Indicator
Momentum	Technical Indicator
Rate of change	Technical Indicator
Relative Strength Index	Technical Indicator
Williams' %R	Technical Indicator
Average True Range	Technical Indicator
Normalized Average True Range	Technical Indicator
Doji	Candlestick Pattern
DragonFly Doji	Candlestick Pattern
Gravestone Doji	Candlestick Pattern
Spinning Top	Candlestick Pattern
Hammer	Candlestick Pattern
Engulfing	Candlestick Pattern
Inverted Hammer	Candlestick Pattern
Piercing	Candlestick Pattern
Morning Star	Candlestick Pattern
Three Advancing White Soldiers	Candlestick Pattern
Hanging Man	Candlestick Pattern
Shooting Star	Candlestick Pattern
Evening Star	Candlestick Pattern
Three Black Crows	Candlestick Pattern
Dark Cloud Cover	Candlestick Pattern
Rising/Falling Three Methods	Candlestick Pattern
Harami	Candlestick Pattern
Takuri	Candlestick Pattern

Annex C: Table containing the average accuracy obtained by each model in the test period

Symbol	Random Forest	Support Vector Machine	Deep Neural Network	Naive
A	55.74%	54.92%	50.00%	50.82%
AAL	54.10%	45.90%	47.54%	55.74%
AAP	52.46%	51.64%	49.18%	50.82%
AAPL	54.92%	51.64%	50.00%	44.26%
ABC	46.72%	47.54%	45.90%	52.46%
ABMD	47.54%	51.64%	50.82%	49.18%
ABT	54.10%	52.46%	50.00%	51.64%
ACN	49.18%	49.18%	45.90%	51.64%
ADBE	54.92%	45.08%	52.46%	61.48%
ADI	50.82%	52.46%	50.82%	43.44%
ADM	42.62%	49.18%	55.74%	57.38%
ADP	57.38%	47.54%	51.64%	54.10%
ADSK	48.36%	40.98%	59.84%	53.28%
AEE	50.82%	49.18%	50.82%	51.64%
AEP	49.18%	59.02%	60.66%	54.10%
AES	42.62%	45.90%	50.00%	53.28%
AFL	44.26%	40.16%	53.28%	42.62%
AIG	47.54%	58.20%	50.00%	47.54%
AIZ	45.08%	52.46%	48.36%	48.36%
AJG	42.62%	46.72%	49.18%	43.44%
AKAM	49.18%	48.36%	47.54%	50.82%
ALB	49.18%	50.00%	46.72%	40.98%
ALGN	41.80%	37.70%	54.92%	54.92%
ALK	44.26%	45.08%	56.56%	53.28%
ALL	51.64%	53.28%	51.64%	49.18%
AMAT	50.00%	47.54%	45.08%	52.46%
AMD	56.56%	50.82%	54.10%	50.00%
AME	49.18%	50.00%	50.00%	54.92%
AMGN	51.64%	52.46%	40.16%	40.98%
AMP	53.28%	48.36%	50.00%	50.00%
AMT	46.72%	45.08%	48.36%	56.56%
AMZN	43.44%	49.18%	42.62%	45.08%
ANSS	55.74%	44.26%	51.64%	51.64%
AON	44.26%	45.90%	48.36%	48.36%
AOS	59.02%	50.82%	54.92%	54.92%
APA	51.64%	52.46%	53.28%	45.08%
APD	46.72%	45.90%	46.72%	51.64%
APH	57.38%	55.74%	50.82%	43.44%
ARE	53.28%	44.26%	43.44%	54.10%
ATO	53.28%	51.64%	52.46%	56.56%
ATVI	49.18%	45.08%	56.56%	52.46%

AVB	47.54%	40.98%	42.62%	54.10%
AVGO	58.20%	48.36%	58.20%	48.36%
AVY	45.90%	40.98%	57.38%	53.28%
AWK	64.75%	49.18%	40.16%	45.90%
AXP	53.28%	53.28%	52.46%	48.36%
AZO	50.82%	54.10%	54.10%	51.64%
BA	42.62%	46.72%	50.82%	47.54%
BAC	57.38%	37.70%	50.82%	52.46%
BALL	50.82%	52.46%	52.46%	52.46%
BAX	50.00%	50.00%	50.00%	57.38%
BBWI	45.08%	40.98%	48.36%	51.64%
BBY	51.64%	47.54%	52.46%	54.92%
BDX	54.92%	50.82%	50.82%	54.92%
BEN	60.66%	46.72%	51.64%	57.38%
BF-B	56.56%	53.28%	54.10%	51.64%
BIIB	45.90%	47.54%	52.46%	56.56%
BIO	50.00%	48.36%	49.18%	50.82%
BK	52.46%	51.64%	50.00%	51.64%
BKNG	47.54%	51.64%	50.00%	54.10%
BKR	48.36%	50.82%	44.26%	62.30%
BLK	48.36%	45.08%	47.54%	50.00%
BMY	47.54%	51.64%	49.18%	58.20%
BR	55.74%	60.66%	54.92%	41.80%
BRK-B	47.54%	54.92%	51.64%	58.20%
BRO	53.28%	50.82%	40.16%	55.74%
BSX	51.64%	57.38%	54.10%	51.64%
BWA	54.10%	47.54%	54.92%	56.56%
BXP	48.36%	45.90%	53.28%	56.56%
C	47.54%	45.08%	54.92%	50.82%
CAG	49.18%	51.64%	46.72%	47.54%
CAH	45.90%	45.90%	46.72%	54.92%
CAT	52.46%	52.46%	45.90%	45.08%
CB	53.28%	50.00%	53.28%	45.08%
CBRE	56.56%	54.92%	44.26%	54.92%
CCI	50.00%	53.28%	45.90%	50.82%
CCL	47.54%	46.72%	58.20%	45.90%
CDNS	50.00%	48.36%	55.74%	54.10%
CE	51.64%	50.00%	50.00%	48.36%
CF	47.54%	52.46%	57.38%	57.38%
CHD	48.36%	45.90%	50.82%	47.54%
CHRW	58.20%	52.46%	50.82%	48.36%
CI	50.82%	46.72%	45.08%	39.34%
CINF	50.00%	52.46%	49.18%	55.74%
CL	52.46%	50.00%	54.92%	54.10%
CLX	48.36%	44.26%	50.82%	57.38%

CMA	44.26%	45.08%	39.34%	48.36%
CMCSA	42.62%	51.64%	54.10%	49.18%
CME	55.74%	49.18%	46.72%	44.26%
CMG	50.82%	52.46%	46.72%	59.02%
CMI	45.90%	50.00%	55.74%	46.72%
CMS	49.18%	51.64%	50.82%	45.08%
CNC	46.72%	41.80%	46.72%	48.36%
CNP	54.10%	56.56%	54.10%	49.18%
COF	50.82%	43.44%	46.72%	45.08%
COO	48.36%	44.26%	53.28%	50.00%
COP	44.26%	51.64%	58.20%	54.10%
COST	51.64%	57.38%	51.64%	50.82%
CPB	57.38%	59.84%	51.64%	49.18%
CPRT	50.82%	50.00%	45.08%	50.82%
CPT	44.26%	41.80%	45.08%	50.00%
CRL	56.56%	48.36%	51.64%	54.92%
CRM	56.56%	51.64%	58.20%	48.36%
CSCO	47.54%	42.62%	46.72%	49.18%
CSGP	43.44%	48.36%	50.82%	47.54%
CSX	48.36%	55.74%	52.46%	45.90%
CTAS	48.36%	50.00%	52.46%	50.00%
CTRA	48.36%	54.10%	58.20%	49.18%
CTSH	40.98%	49.18%	47.54%	50.00%
CTXS	49.18%	40.98%	58.20%	40.98%
CVS	50.00%	50.00%	51.64%	54.10%
CVX	43.44%	50.00%	48.36%	53.28%
D	45.08%	47.54%	46.72%	54.92%
DAL	40.16%	44.26%	53.28%	46.72%
DD	59.02%	63.93%	60.66%	43.44%
DE	51.64%	57.38%	54.10%	53.28%
DFS	54.92%	45.90%	43.44%	47.54%
DG	57.38%	54.10%	50.00%	48.36%
DGX	50.00%	56.56%	54.10%	54.10%
DHI	50.82%	53.28%	56.56%	46.72%
DHR	49.18%	54.10%	61.48%	54.92%
DIS	49.18%	45.90%	55.74%	41.80%
DISH	57.38%	48.36%	55.74%	54.10%
DLR	59.02%	61.48%	49.18%	52.46%
DLTR	57.38%	50.82%	54.92%	57.38%
DOV	54.92%	53.28%	45.90%	48.36%
DPZ	56.56%	54.92%	59.84%	46.72%
DRE	50.82%	45.08%	42.62%	46.72%
DRI	50.00%	54.10%	48.36%	53.28%
DTE	49.18%	60.66%	57.38%	51.64%
DUK	45.90%	49.18%	50.00%	44.26%

DVA	54.92%	54.92%	53.28%	53.28%
DVN	55.74%	50.82%	50.82%	56.56%
DXC	47.54%	50.00%	51.64%	52.46%
DXCM	54.92%	46.72%	47.54%	46.72%
EA	46.72%	43.44%	56.56%	55.74%
EBAY	45.08%	46.72%	50.00%	43.44%
ECL	45.08%	41.80%	40.98%	45.90%
ED	50.00%	43.44%	50.82%	47.54%
EFX	50.00%	49.18%	48.36%	46.72%
EIX	44.26%	56.56%	45.90%	55.74%
EL	46.72%	45.08%	51.64%	50.82%
ELV	51.64%	47.54%	48.36%	40.98%
EMN	53.28%	51.64%	47.54%	50.82%
EMR	51.64%	50.00%	46.72%	43.44%
EOG	46.72%	49.18%	50.82%	53.28%
EQIX	54.92%	53.28%	53.28%	47.54%
EQR	59.02%	54.10%	55.74%	59.84%
ES	47.54%	55.74%	46.72%	48.36%
ESS	54.92%	55.74%	48.36%	51.64%
ETN	46.72%	53.28%	50.00%	48.36%
ETR	53.28%	53.28%	56.56%	43.44%
EVRG	49.18%	50.82%	42.62%	49.18%
EW	59.84%	49.18%	53.28%	42.62%
EXC	45.08%	44.26%	50.00%	47.54%
EXPD	45.08%	44.26%	47.54%	51.64%
EXPE	49.18%	57.38%	57.38%	55.74%
EXR	45.08%	42.62%	57.38%	42.62%
F	54.92%	43.44%	51.64%	50.00%
FAST	54.10%	51.64%	45.08%	54.10%
FCX	52.46%	52.46%	54.10%	50.00%
FDS	55.74%	52.46%	45.90%	52.46%
FDX	52.46%	55.74%	58.20%	57.38%
FE	50.82%	51.64%	49.18%	50.82%
FFIV	52.46%	50.00%	54.10%	54.92%
FIS	45.90%	46.72%	45.90%	52.46%
FISV	58.20%	49.18%	54.92%	53.28%
FITB	49.18%	46.72%	44.26%	47.54%
FMC	50.82%	47.54%	50.82%	48.36%
FRT	51.64%	51.64%	52.46%	50.82%
FTNT	50.82%	46.72%	50.82%	53.28%
GD	49.18%	48.36%	52.46%	53.28%
GE	47.54%	48.36%	43.44%	54.92%
GILD	47.54%	50.00%	45.08%	50.00%
GIS	50.00%	50.82%	50.00%	54.10%
GL	55.74%	50.00%	54.10%	51.64%

GLW	47.54%	42.62%	49.18%	47.54%
GOOG	51.64%	50.00%	54.10%	51.64%
GOOGL	45.90%	50.82%	45.90%	46.72%
GPC	53.28%	54.10%	49.18%	48.36%
GPN	55.74%	51.64%	52.46%	51.64%
GRMN	48.36%	43.44%	45.90%	55.74%
GS	50.82%	44.26%	54.92%	53.28%
GWW	52.46%	52.46%	46.72%	51.64%
HAL	46.72%	37.70%	52.46%	47.54%
HAS	53.28%	50.00%	45.08%	48.36%
HBAN	51.64%	43.44%	57.38%	50.82%
HD	54.92%	47.54%	47.54%	46.72%
HES	48.36%	52.46%	45.90%	41.80%
HIG	49.18%	47.54%	45.08%	45.90%
HOLX	48.36%	39.34%	40.16%	48.36%
HON	46.72%	45.08%	52.46%	50.00%
HPQ	53.28%	45.08%	40.16%	47.54%
HRL	53.28%	48.36%	49.18%	45.90%
HSIC	49.18%	47.54%	52.46%	45.90%
HST	51.64%	54.92%	51.64%	50.82%
HSY	54.92%	49.18%	44.26%	49.18%
HUM	40.16%	45.08%	44.26%	50.00%
HWM	50.82%	44.26%	51.64%	54.10%
IBM	45.08%	43.44%	43.44%	46.72%
ICE	51.64%	53.28%	47.54%	52.46%
IDXX	40.16%	41.80%	40.16%	54.92%
IEX	51.64%	47.54%	56.56%	45.90%
IFF	49.18%	49.18%	55.74%	45.90%
ILMN	51.64%	45.08%	48.36%	48.36%
INCY	50.82%	47.54%	51.64%	49.18%
INTC	47.54%	48.36%	45.08%	49.18%
INTU	48.36%	50.82%	55.74%	50.00%
IP	42.62%	49.18%	60.66%	53.28%
IPG	41.80%	39.34%	49.18%	56.56%
IRM	51.64%	54.92%	50.82%	54.10%
ISRG	45.08%	49.18%	44.26%	45.90%
IT	52.46%	52.46%	51.64%	45.08%
ITW	51.64%	50.82%	46.72%	36.89%
IVZ	53.28%	51.64%	51.64%	45.08%
J	47.54%	50.82%	55.74%	54.92%
JBHT	55.74%	52.46%	49.18%	49.18%
JCI	48.36%	43.44%	50.00%	46.72%
JKHY	51.64%	49.18%	41.80%	43.44%
JNJ	58.20%	49.18%	50.00%	50.00%
JNPR	45.90%	47.54%	44.26%	53.28%

JPM	45.08%	48.36%	47.54%	54.92%
K	49.18%	51.64%	54.92%	44.26%
KDP	52.46%	54.10%	49.18%	52.46%
KEY	50.00%	46.72%	51.64%	43.44%
KIM	54.92%	50.82%	55.74%	45.90%
KLAC	62.30%	49.18%	59.84%	50.82%
KMB	41.80%	50.00%	49.18%	46.72%
KMX	53.28%	46.72%	45.90%	54.92%
KO	46.72%	52.46%	44.26%	51.64%
KR	54.10%	52.46%	46.72%	50.00%
L	51.64%	51.64%	49.18%	46.72%
LDOS	52.46%	54.10%	45.90%	45.90%
LEN	49.18%	54.10%	46.72%	43.44%
LH	52.46%	51.64%	53.28%	46.72%
LHX	51.64%	48.36%	54.10%	53.28%
LIN	47.54%	57.38%	55.74%	50.82%
LKQ	59.02%	59.02%	55.74%	54.92%
LLY	37.70%	47.54%	53.28%	48.36%
LMT	48.36%	51.64%	49.18%	50.00%
LNC	43.44%	38.52%	43.44%	40.16%
LNT	54.10%	52.46%	45.90%	54.92%
LOW	54.10%	54.10%	46.72%	52.46%
LRCX	54.92%	53.28%	50.00%	49.18%
LUMN	43.44%	54.92%	44.26%	55.74%
LUV	50.82%	50.82%	52.46%	43.44%
LVS	49.18%	51.64%	52.46%	41.80%
LYV	54.92%	54.92%	53.28%	46.72%
MA	60.66%	50.00%	58.20%	53.28%
MAA	59.02%	38.52%	39.34%	51.64%
MAR	47.54%	47.54%	48.36%	49.18%
MAS	54.92%	44.26%	41.80%	51.64%
MCD	58.20%	41.80%	48.36%	54.92%
MCHP	50.82%	47.54%	47.54%	58.20%
MCK	50.82%	50.00%	41.80%	54.92%
MCO	45.08%	50.82%	50.82%	49.18%
MDLZ	50.00%	53.28%	49.18%	51.64%
MDT	54.10%	48.36%	46.72%	47.54%
MET	49.18%	41.80%	50.82%	49.18%
MGM	56.56%	47.54%	54.10%	53.28%
MHK	36.07%	43.44%	41.80%	48.36%
MKC	40.16%	47.54%	48.36%	52.46%
MKTX	46.72%	41.80%	45.08%	39.34%
MLM	57.38%	51.64%	49.18%	48.36%
MMC	48.36%	51.64%	45.90%	36.89%
MMM	46.72%	46.72%	53.28%	47.54%

MNST	58.20%	54.10%	54.10%	45.08%
MO	48.36%	56.56%	57.38%	52.46%
MOH	45.90%	46.72%	50.00%	45.90%
MOS	54.10%	53.28%	47.54%	48.36%
MPWR	54.92%	49.18%	45.90%	55.74%
MRK	50.82%	54.10%	58.20%	45.90%
MRO	45.08%	50.00%	54.92%	40.98%
MS	42.62%	49.18%	51.64%	53.28%
MSCI	46.72%	44.26%	46.72%	57.38%
MSFT	54.10%	50.00%	46.72%	49.18%
MSI	51.64%	51.64%	48.36%	55.74%
MTB	44.26%	50.82%	46.72%	54.10%
MTCH	52.46%	48.36%	57.38%	49.18%
MTD	50.00%	48.36%	47.54%	47.54%
MU	54.92%	44.26%	40.16%	54.10%
NDAQ	47.54%	43.44%	48.36%	46.72%
NDSN	54.92%	58.20%	59.02%	59.84%
NEE	57.38%	38.52%	43.44%	49.18%
NEM	49.18%	51.64%	45.08%	51.64%
NFLX	45.90%	45.90%	41.80%	53.28%
NI	42.62%	51.64%	47.54%	51.64%
NKE	56.56%	54.92%	59.02%	46.72%
NLOK	45.08%	51.64%	54.10%	40.16%
NOC	50.00%	54.92%	53.28%	58.20%
NRG	48.36%	44.26%	45.08%	49.18%
NSC	43.44%	49.18%	53.28%	50.82%
NTAP	50.00%	43.44%	39.34%	45.90%
NTRS	50.82%	45.90%	48.36%	52.46%
NUE	49.18%	50.00%	45.90%	46.72%
NVDA	50.82%	54.10%	50.82%	45.08%
NVR	59.02%	52.46%	50.82%	48.36%
NWL	59.02%	45.90%	47.54%	49.18%
O	59.02%	50.82%	53.28%	48.36%
ODFL	50.82%	42.62%	42.62%	54.10%
OKE	50.82%	50.82%	50.00%	54.92%
OMC	48.36%	50.00%	51.64%	50.00%
ON	53.28%	55.74%	46.72%	45.08%
ORCL	52.46%	44.26%	50.00%	49.18%
ORLY	49.18%	50.82%	48.36%	45.08%
OXY	52.46%	51.64%	54.92%	50.00%
PARA	49.18%	50.82%	49.18%	50.00%
PAYX	50.00%	45.90%	53.28%	45.90%
PCAR	49.18%	45.08%	53.28%	46.72%
PEAK	55.74%	48.36%	54.92%	40.16%
PEG	54.10%	49.18%	51.64%	54.92%

PEP	48.36%	51.64%	50.00%	50.82%
PFE	45.08%	45.08%	42.62%	47.54%
PFG	50.00%	50.00%	51.64%	49.18%
PG	50.82%	54.92%	46.72%	50.00%
PGR	50.00%	43.44%	50.82%	53.28%
PH	51.64%	48.36%	45.08%	54.10%
PHM	56.56%	52.46%	59.84%	44.26%
PKG	44.26%	46.72%	46.72%	50.82%
PKI	49.18%	51.64%	46.72%	51.64%
PLD	46.72%	34.43%	49.18%	50.82%
PM	50.82%	47.54%	49.18%	53.28%
PNC	49.18%	44.26%	53.28%	52.46%
PNR	52.46%	47.54%	59.02%	54.10%
PNW	52.46%	49.18%	45.08%	44.26%
POOL	53.28%	57.38%	60.66%	54.10%
PPG	39.34%	43.44%	47.54%	47.54%
PPL	48.36%	51.64%	54.92%	47.54%
PRU	52.46%	47.54%	41.80%	48.36%
PSA	63.11%	50.00%	49.18%	46.72%
PTC	37.70%	43.44%	54.10%	45.90%
PWR	49.18%	48.36%	44.26%	46.72%
PXD	42.62%	43.44%	40.98%	47.54%
QCOM	57.38%	51.64%	52.46%	51.64%
RCL	49.18%	43.44%	51.64%	48.36%
RE	50.82%	49.18%	51.64%	50.82%
REG	54.92%	42.62%	49.18%	49.18%
REGN	52.46%	54.92%	50.00%	54.10%
RF	52.46%	50.82%	47.54%	43.44%
RHI	46.72%	48.36%	49.18%	53.28%
RJF	50.00%	45.08%	49.18%	51.64%
RL	50.82%	59.84%	54.10%	52.46%
RMD	43.44%	55.74%	47.54%	46.72%
ROK	49.18%	43.44%	48.36%	53.28%
ROL	51.64%	54.92%	48.36%	44.26%
ROP	45.08%	44.26%	44.26%	45.90%
ROST	47.54%	39.34%	45.08%	49.18%
RSG	54.10%	50.00%	41.80%	52.46%
RTX	50.00%	49.18%	40.16%	47.54%
SBAC	45.90%	44.26%	47.54%	50.00%
SBNY	53.28%	48.36%	54.10%	47.54%
SBUX	53.28%	50.82%	50.82%	50.82%
SCHW	50.00%	46.72%	47.54%	47.54%
SEE	54.10%	54.10%	52.46%	54.92%
SHW	44.26%	45.08%	42.62%	51.64%
SIVB	50.00%	47.54%	50.82%	54.10%

SJM	52.46%	46.72%	45.08%	48.36%
SLB	45.90%	47.54%	52.46%	54.92%
SNA	48.36%	45.08%	42.62%	52.46%
SNPS	51.64%	54.10%	50.00%	50.82%
SO	53.28%	54.10%	59.84%	53.28%
SPG	48.36%	51.64%	55.74%	45.90%
SPGI	51.64%	54.92%	48.36%	42.62%
SRE	48.36%	47.54%	45.90%	51.64%
STE	48.36%	48.36%	49.18%	54.10%
STT	48.36%	54.92%	45.08%	46.72%
STX	53.28%	47.54%	55.74%	50.82%
STZ	53.28%	58.20%	54.10%	56.56%
SWK	45.08%	41.80%	45.90%	54.92%
SWKS	46.72%	45.08%	47.54%	48.36%
SYK	50.82%	50.00%	51.64%	52.46%
SYY	54.92%	54.10%	54.10%	45.90%
T	45.90%	49.18%	52.46%	46.72%
TAP	46.72%	53.28%	45.08%	49.18%
TDG	46.72%	47.54%	47.54%	49.18%
TDY	47.54%	53.28%	50.82%	49.18%
TECH	45.90%	43.44%	55.74%	56.56%
TEL	56.56%	50.00%	54.10%	45.90%
TER	49.18%	43.44%	54.92%	48.36%
TFC	49.18%	47.54%	48.36%	55.74%
TFX	50.82%	45.08%	58.20%	50.00%
TGT	44.26%	47.54%	50.00%	42.62%
TJX	54.92%	58.20%	52.46%	54.92%
TMO	50.82%	45.08%	49.18%	53.28%
TMUS	53.28%	47.54%	50.00%	52.46%
TPR	52.46%	52.46%	49.18%	51.64%
TRMB	52.46%	41.80%	49.18%	45.08%
TROW	43.44%	44.26%	47.54%	53.28%
TRV	52.46%	59.02%	51.64%	50.82%
TSCO	51.64%	46.72%	46.72%	57.38%
TSN	50.00%	46.72%	53.28%	53.28%
TT	47.54%	45.08%	59.02%	56.56%
TTWO	42.62%	43.44%	48.36%	50.82%
TXN	55.74%	53.28%	56.56%	44.26%
TXT	53.28%	55.74%	59.02%	49.18%
TYL	53.28%	56.56%	52.46%	52.46%
UAL	53.28%	53.28%	45.08%	61.48%
UDR	51.64%	50.82%	48.36%	50.82%
UHS	55.74%	53.28%	54.10%	48.36%
ULTA	51.64%	50.82%	48.36%	51.64%
UNH	46.72%	48.36%	45.08%	43.44%

UNP	48.36%	54.10%	47.54%	50.00%
UPS	48.36%	49.18%	53.28%	59.02%
URI	54.10%	50.00%	54.92%	49.18%
USB	41.80%	43.44%	47.54%	54.92%
V	55.74%	54.10%	51.64%	50.00%
VFC	46.72%	46.72%	45.90%	45.08%
VLO	44.26%	50.00%	44.26%	52.46%
VMC	45.90%	45.08%	42.62%	45.90%
VNO	50.00%	49.18%	53.28%	40.16%
VRSK	52.46%	48.36%	50.00%	53.28%
VRSN	48.36%	43.44%	45.90%	55.74%
VRTX	52.46%	42.62%	43.44%	55.74%
VTR	48.36%	49.18%	52.46%	57.38%
VTRS	55.74%	44.26%	44.26%	56.56%
VZ	48.36%	52.46%	48.36%	55.74%
WAB	44.26%	50.00%	54.10%	46.72%
WAT	39.34%	56.56%	49.18%	37.70%
WBA	49.18%	51.64%	50.82%	48.36%
WBD	47.54%	54.10%	52.46%	53.28%
WDC	48.36%	50.00%	50.00%	47.54%
WEC	51.64%	47.54%	49.18%	52.46%
WELL	51.64%	54.10%	50.00%	49.18%
WFC	46.72%	51.64%	53.28%	45.08%
WHR	54.10%	50.00%	54.10%	45.90%
WM	53.28%	46.72%	51.64%	50.82%
WMB	35.25%	43.44%	42.62%	54.10%
WMT	49.18%	50.82%	45.90%	53.28%
WRB	50.00%	44.26%	48.36%	60.66%
WST	43.44%	44.26%	44.26%	51.64%
WTW	50.82%	48.36%	54.10%	49.18%
WY	48.36%	41.80%	47.54%	46.72%
WYNN	52.46%	50.82%	50.00%	44.26%
XEL	51.64%	53.28%	51.64%	54.92%
XOM	45.08%	49.18%	40.98%	51.64%
XRAY	50.00%	46.72%	53.28%	47.54%
YUM	50.00%	40.98%	45.90%	49.18%
ZBH	45.90%	43.44%	56.56%	50.82%
ZBRA	45.90%	47.54%	51.64%	41.80%
ZION	57.38%	48.36%	52.46%	56.56%

Annex D: Table containing the average accuracy obtained by each model and the buy-and-hold strategy in the test period

symbol	Random Forest	Support Vector Machine	Deep Neural Network	Naive	Buy-and-hold
A	-0.44%	-10.32%	-10.11%	-8.00%	-24.65%
AAL	-1.85%	-35.69%	-32.30%	6.08%	-30.51%
AAP	-1.26%	-7.00%	-15.93%	-10.34%	-25.37%
AAPL	-0.17%	0.10%	-17.78%	-21.94%	-23.50%
ABC	0.42%	8.85%	2.56%	13.38%	8.26%
ABMD	-26.87%	-12.12%	-24.06%	-17.22%	-29.98%
ABT	-16.51%	-10.79%	-17.97%	-4.66%	-21.53%
ACN	-13.80%	-25.03%	-13.57%	-15.71%	-31.29%
ADBE	2.67%	-23.62%	-6.84%	22.94%	-34.71%
ADI	-6.62%	-12.97%	-0.85%	-26.47%	-16.87%
ADM	-0.11%	11.76%	7.18%	17.50%	13.77%
ADP	13.39%	-17.85%	-5.66%	3.16%	-13.04%
ADSK	-22.24%	-36.36%	8.28%	-6.43%	-37.67%
AEE	2.57%	-4.44%	0.49%	-0.80%	1.20%
AEP	2.28%	10.83%	13.94%	8.23%	7.63%
AES	-23.74%	-11.96%	-7.39%	-4.24%	-16.49%
AFL	-3.77%	-12.84%	5.06%	-5.85%	-4.82%
AIG	-21.56%	13.78%	0.00%	-12.41%	-11.48%
AIZ	1.06%	12.73%	3.85%	-2.50%	9.34%
AJG	-7.29%	-6.50%	-2.03%	-7.56%	-2.11%
AKAM	-8.04%	-18.03%	-14.25%	-7.49%	-21.60%
ALB	-9.28%	-11.76%	-13.20%	-29.57%	-10.47%
ALGN	-50.99%	-54.60%	-13.39%	-18.03%	-62.63%
ALK	-36.23%	-21.88%	-6.94%	-2.00%	-25.13%
ALL	10.13%	2.60%	-4.42%	0.33%	6.05%
AMAT	-24.25%	-40.31%	-46.54%	-13.71%	-42.51%
AMD	8.68%	-17.04%	-8.07%	-33.86%	-48.09%
AME	-15.35%	-7.05%	-17.56%	4.13%	-23.06%
AMGN	3.88%	10.56%	1.97%	-3.53%	8.27%
AMP	0.35%	-19.30%	-10.36%	-22.61%	-21.12%
AMT	-13.10%	-10.86%	-15.49%	-1.89%	-11.60%
AMZN	-39.42%	-14.14%	-29.20%	-31.24%	-36.08%
ANSS	10.77%	-37.22%	-15.02%	-11.87%	-38.95%
AON	-5.23%	-7.11%	-15.28%	-16.81%	-8.31%
AOS	1.72%	-23.21%	-8.92%	-13.43%	-34.43%
APA	18.20%	30.24%	81.22%	-2.67%	28.65%
APD	-16.40%	-19.26%	-11.15%	0.20%	-17.81%
APH	-4.43%	-11.16%	-20.12%	-30.43%	-25.58%
ARE	-22.49%	-28.04%	-30.17%	-12.17%	-34.25%
ATO	-1.32%	6.53%	2.60%	12.98%	5.61%

ATVI	-0.76%	18.94%	2.88%	18.45%	15.63%
AVB	-24.10%	-25.06%	-22.52%	-15.45%	-22.78%
AVGO	5.86%	-15.43%	-4.30%	-18.28%	-26.07%
AVY	-17.74%	-21.71%	8.21%	-8.94%	-22.20%
AWK	11.42%	-16.41%	-26.06%	-17.71%	-20.81%
AXP	3.44%	3.15%	0.40%	-3.07%	-17.09%
AZO	-4.87%	4.64%	5.87%	11.46%	4.64%
BA	-36.07%	-30.64%	-16.06%	-40.47%	-33.39%
BAC	-5.54%	-34.92%	-15.30%	-18.24%	-31.01%
BALL	-12.44%	-7.04%	-17.43%	-6.66%	-26.71%
BAX	-16.66%	-23.16%	-10.41%	-9.49%	-24.24%
BBWI	-50.30%	-64.24%	-43.09%	-40.22%	-62.08%
BBY	-19.65%	-26.45%	-5.19%	-11.91%	-34.24%
BDX	14.10%	1.52%	4.45%	-1.39%	0.93%
BEN	-4.17%	-28.02%	-5.44%	3.28%	-30.35%
BF-B	0.90%	-5.11%	-0.92%	15.98%	-0.94%
BIIB	-16.87%	-4.62%	2.35%	18.19%	-15.94%
BIO	-12.30%	-23.42%	-12.25%	-11.59%	-32.55%
BK	9.10%	-6.15%	-21.85%	-17.77%	-27.52%
BKNG	-17.50%	-4.63%	-18.87%	-7.12%	-26.45%
BKR	-1.61%	0.33%	-9.97%	61.36%	18.33%
BLK	-19.91%	-27.77%	-25.98%	-29.42%	-32.22%
BMY	15.18%	14.53%	5.18%	25.66%	26.50%
BR	3.07%	15.99%	2.51%	-20.40%	-20.48%
BRK-B	-6.39%	-0.96%	-0.68%	5.81%	-9.08%
BRO	6.22%	1.73%	-25.36%	-3.74%	-15.69%
BSX	7.90%	1.01%	11.84%	10.75%	-12.34%
BWA	-5.63%	-28.14%	-8.97%	-10.02%	-22.24%
BXP	-20.04%	-30.64%	-13.87%	-4.89%	-24.95%
C	-12.99%	-18.80%	-5.53%	-20.91%	-25.36%
CAG	-6.64%	5.05%	7.64%	0.08%	0.79%
CAH	-3.96%	-4.00%	0.47%	-2.17%	3.23%
CAT	-1.12%	7.47%	-18.56%	-15.32%	-11.36%
CB	8.53%	-1.11%	3.75%	-1.66%	1.22%
CBRE	-2.32%	-19.20%	-33.51%	-18.27%	-32.20%
CCI	-16.68%	-4.43%	-15.31%	-9.41%	-19.46%
CCL	-50.58%	-46.88%	5.40%	-52.28%	-58.57%
CDNS	-8.68%	-7.22%	22.17%	-5.36%	-17.60%
CE	1.07%	-10.69%	-18.32%	-24.21%	-28.52%
CF	0.00%	7.75%	45.26%	23.11%	22.35%
CHD	-1.90%	1.46%	9.19%	5.22%	-9.19%
CHRW	31.66%	0.43%	-9.18%	-5.53%	-5.98%
CI	5.01%	6.66%	6.43%	-9.21%	14.15%
CINF	12.98%	3.70%	-4.76%	16.24%	4.23%
CL	-6.71%	-8.47%	1.58%	7.48%	-5.82%

CLX	-20.32%	-27.77%	-12.69%	5.29%	-20.23%
CMA	-24.34%	-22.38%	-30.60%	-16.07%	-14.24%
CMCSA	-18.70%	-17.41%	5.09%	-20.75%	-22.49%
CME	6.49%	-6.42%	-14.90%	-17.19%	-8.56%
CMG	6.01%	10.23%	-18.93%	12.06%	-23.81%
CMI	-20.41%	-14.36%	-13.21%	-9.15%	-11.74%
CMS	4.88%	-2.14%	0.68%	1.12%	2.77%
CNC	0.00%	-4.59%	-18.84%	-10.40%	2.77%
CNP	7.70%	11.62%	19.28%	8.65%	5.43%
COF	-28.26%	-32.15%	-30.44%	-35.11%	-28.81%
COO	-15.14%	-22.80%	-12.26%	-15.65%	-24.64%
COP	4.87%	7.87%	33.02%	41.83%	23.98%
COST	-2.17%	1.92%	-23.65%	-4.65%	-17.09%
CPB	10.84%	23.67%	6.87%	5.84%	10.65%
CPRT	-15.16%	-18.54%	-24.29%	-22.73%	-25.77%
CPT	-17.99%	-28.51%	-25.19%	-9.51%	-24.10%
CRL	-14.61%	-35.11%	-5.33%	-5.13%	-39.39%
CRM	-1.60%	-12.53%	0.25%	-8.78%	-33.21%
CSCO	-27.74%	-35.74%	-26.81%	-27.21%	-32.11%
CSGP	-33.89%	-11.13%	-13.80%	-31.62%	-23.63%
CSX	-18.52%	-6.14%	-8.47%	-11.01%	-21.47%
CTAS	-10.09%	-8.57%	-3.73%	-9.49%	-12.18%
CTRA	8.34%	28.80%	48.15%	32.51%	36.48%
CTSH	-12.01%	-7.66%	-12.03%	-10.67%	-23.55%
CTXS	12.60%	3.04%	12.55%	-13.89%	-1.45%
CVS	-2.82%	-9.17%	-3.87%	-0.90%	-10.38%
CVX	1.91%	22.29%	19.61%	17.63%	23.24%
D	-2.45%	-7.30%	-6.27%	6.60%	0.86%
DAL	-23.91%	-25.68%	-4.19%	-18.84%	-26.43%
DD	-5.56%	21.51%	31.34%	-22.26%	-30.16%
DE	-20.13%	-6.90%	-15.24%	-10.87%	-14.13%
DFS	2.51%	-19.52%	-27.15%	-5.36%	-19.43%
DG	37.74%	18.66%	5.67%	-3.59%	4.91%
DGX	-11.29%	7.96%	9.65%	5.15%	-16.27%
DHI	-13.93%	-17.01%	-27.03%	-24.53%	-37.29%
DHR	-22.22%	-3.88%	3.53%	-9.49%	-19.92%
DIS	-25.44%	-33.63%	-13.28%	-34.72%	-38.98%
DISH	5.31%	-27.86%	-38.05%	-30.54%	-46.17%
DLR	8.69%	-6.47%	-25.62%	-7.61%	-27.24%
DLTR	30.33%	-1.06%	30.96%	9.32%	10.68%
DOV	-11.73%	-10.49%	-31.99%	-2.07%	-32.00%
DPZ	0.27%	-4.00%	16.19%	-22.58%	-29.68%
DRE	-5.47%	-13.09%	-9.29%	-5.11%	-14.27%
DRI	-17.42%	5.14%	-1.03%	-9.47%	-23.46%
DTE	2.49%	18.07%	14.49%	-8.03%	5.76%

DUK	5.49%	-2.43%	10.16%	-8.18%	2.44%
DVA	4.70%	-7.48%	-2.29%	3.41%	-29.43%
DVN	54.61%	21.30%	30.25%	37.69%	22.49%
DXC	-16.66%	-15.00%	-6.72%	7.82%	-8.13%
DXCM	-19.38%	-36.42%	-47.68%	-23.88%	-42.05%
EA	-6.20%	-15.04%	6.72%	0.03%	-8.98%
EBAY	-33.46%	-32.45%	-26.38%	-29.65%	-36.12%
ECL	-26.70%	-32.88%	-34.80%	-27.44%	-33.22%
ED	7.69%	0.26%	6.00%	3.52%	11.27%
EFX	-15.59%	-19.59%	-15.57%	-15.87%	-36.56%
EIX	-17.80%	-3.64%	0.77%	-4.17%	-6.89%
EL	-23.57%	-36.43%	-9.15%	-3.81%	-30.60%
ELV	9.83%	-2.13%	-0.33%	-8.61%	4.46%
EMN	-22.55%	-16.33%	-9.10%	-7.50%	-23.76%
EMR	-0.02%	0.46%	-9.29%	-15.78%	-12.26%
EOG	24.68%	23.68%	11.29%	16.33%	24.20%
EQIX	8.33%	-6.56%	-2.85%	-25.54%	-22.32%
EQR	-3.46%	-13.26%	0.96%	2.17%	-20.49%
ES	-5.49%	-1.21%	-10.35%	-13.08%	-6.34%
ESS	-7.90%	-13.49%	-16.84%	-11.70%	-25.86%
ETN	-11.65%	-16.59%	-4.34%	-21.56%	-24.54%
ETR	3.55%	9.11%	13.86%	-16.23%	0.26%
EVRG	2.22%	-1.70%	-10.50%	0.13%	-4.40%
EW	1.79%	-19.78%	-7.79%	-23.62%	-25.18%
EXC	-8.40%	-6.91%	10.31%	-11.30%	8.93%
EXPD	-26.03%	-25.03%	-15.78%	-13.95%	-25.03%
EXPE	-15.01%	10.71%	6.59%	-32.11%	-48.11%
EXR	-21.85%	-22.02%	16.24%	-10.12%	-22.02%
F	-21.10%	-32.85%	-14.50%	-17.86%	-47.08%
FAST	-1.03%	-6.37%	-23.62%	2.48%	-19.80%
FCX	14.71%	-3.70%	-7.98%	-2.95%	-26.98%
FDS	-9.18%	-11.09%	-15.59%	-12.71%	-19.52%
FDX	9.91%	17.15%	26.56%	16.39%	-9.57%
FE	-6.32%	-3.05%	-4.35%	-8.37%	-7.30%
FFIV	-18.31%	-6.97%	-4.86%	-20.13%	-37.08%
FIS	-10.74%	-6.55%	-19.27%	-11.24%	-16.96%
FISV	8.60%	-12.03%	-2.57%	9.94%	-15.54%
FITB	-7.63%	-14.43%	-21.07%	-17.61%	-23.42%
FMC	11.27%	-6.71%	0.25%	-2.68%	-1.75%
FRT	-17.06%	-14.15%	-12.54%	-10.47%	-29.10%
FTNT	-14.04%	-14.19%	-11.03%	25.91%	-14.19%
GD	6.52%	11.03%	20.41%	9.09%	5.70%
GE	-5.92%	-8.41%	-19.69%	-23.36%	-33.82%
GILD	-17.84%	-9.18%	-14.81%	-5.26%	-13.92%
GIS	1.72%	3.13%	12.50%	16.36%	11.09%

GL	1.67%	-7.07%	8.63%	5.16%	3.16%
GLW	-14.52%	-22.40%	-6.28%	-21.50%	-12.93%
GOOG	-7.73%	-21.85%	-5.49%	-17.22%	-22.62%
GOOGL	-23.37%	-15.54%	-22.79%	-16.85%	-22.96%
GPC	4.01%	5.54%	-2.41%	3.74%	-3.20%
GPN	-5.60%	-16.99%	7.47%	-7.70%	-20.42%
GRMN	-20.35%	-28.65%	-29.74%	-9.13%	-25.85%
GS	2.74%	-28.31%	-10.76%	6.96%	-23.28%
GWW	5.76%	-0.95%	-4.64%	0.75%	-11.03%
HAL	-1.11%	-28.60%	31.35%	23.12%	34.14%
HAS	-2.10%	-12.51%	-19.59%	-15.99%	-17.89%
HBAN	-1.46%	-26.42%	-11.08%	-4.69%	-22.53%
HD	-2.73%	-20.74%	-22.83%	-21.40%	-32.98%
HES	16.55%	36.31%	2.12%	1.28%	42.38%
HIG	0.25%	-0.99%	-7.06%	-7.06%	-6.59%
HOLX	14.06%	-14.19%	-15.81%	4.31%	-3.76%
HON	-12.36%	-17.10%	5.26%	-9.55%	-16.25%
HPQ	7.80%	-13.22%	-24.70%	-16.15%	-11.60%
HRL	4.59%	1.59%	1.31%	0.86%	-2.38%
HSIC	-5.58%	-1.89%	3.79%	-3.68%	0.28%
HST	0.61%	10.02%	3.97%	-7.66%	-11.10%
HSY	18.06%	7.18%	3.71%	9.46%	13.30%
HUM	-3.14%	7.90%	-20.33%	13.32%	0.62%
HWM	3.24%	-9.26%	7.08%	7.70%	-3.12%
IBM	-8.38%	-5.30%	-1.71%	-0.67%	3.43%
ICE	-5.03%	-17.40%	-23.51%	-12.34%	-28.03%
IDXX	-48.97%	-43.11%	-49.16%	1.84%	-43.23%
IEX	-16.18%	-21.64%	-0.73%	-15.13%	-21.51%
IFF	-20.61%	-14.27%	-6.51%	-21.48%	-21.28%
ILMN	-26.88%	-49.58%	-50.52%	-29.43%	-51.05%
INCY	4.62%	-1.24%	-3.87%	4.92%	2.60%
INTC	-33.09%	-15.06%	-31.27%	0.59%	-29.92%
INTU	-24.04%	-26.58%	-2.44%	-11.93%	-38.29%
IP	-19.62%	-2.82%	5.15%	2.11%	-9.30%
IPG	-26.59%	-41.48%	0.10%	-14.10%	-27.12%
IRM	-0.11%	10.15%	-1.52%	14.44%	-6.12%
ISRG	-35.84%	-32.33%	-47.66%	-27.79%	-43.73%
IT	-25.11%	-23.42%	-25.35%	-26.35%	-25.41%
ITW	-15.40%	-12.51%	-14.63%	-33.02%	-25.75%
IVZ	-15.05%	-29.40%	-20.43%	-24.25%	-29.33%
J	-10.02%	-14.38%	0.52%	-11.12%	-10.90%
JBHT	-5.86%	-15.74%	-13.72%	-8.52%	-22.07%
JCI	-31.68%	-40.17%	-20.25%	-27.90%	-38.65%
JKHY	15.14%	9.86%	-0.29%	-11.20%	6.19%
JNJ	4.64%	2.54%	2.19%	-4.52%	3.18%

JNPR	-12.98%	-18.33%	-24.20%	-10.81%	-18.58%
JPM	-18.07%	-17.76%	-20.23%	-12.52%	-28.70%
K	4.45%	15.25%	18.51%	7.94%	10.73%
KDP	-4.76%	-1.92%	2.49%	-4.73%	-2.81%
KEY	-14.10%	-26.18%	3.12%	-16.99%	-25.83%
KIM	-4.87%	-8.63%	4.76%	-17.72%	-17.90%
KLAC	30.00%	-8.53%	18.50%	-15.67%	-26.32%
KMB	-10.06%	-4.87%	-14.05%	-10.46%	-5.74%
KMX	1.38%	-24.60%	-22.33%	12.41%	-26.33%
KO	4.04%	12.15%	3.53%	-0.68%	5.78%
KR	0.00%	-2.43%	-10.69%	2.98%	6.46%
L	4.81%	7.61%	-2.76%	-4.48%	1.62%
LDOS	3.50%	9.88%	-7.99%	6.03%	10.07%
LEN	-30.06%	-17.95%	-27.29%	-26.70%	-37.72%
LH	-11.73%	-18.79%	-7.21%	-9.64%	-19.51%
LHX	9.94%	9.08%	6.88%	13.23%	12.40%
LIN	-15.79%	10.86%	0.74%	4.35%	-13.95%
LKQ	16.52%	22.10%	-5.60%	15.88%	-16.16%
LLY	0.46%	-3.51%	25.94%	12.93%	18.87%
LMT	-6.38%	10.03%	1.50%	10.80%	18.21%
LNC	-18.50%	-41.73%	-31.33%	-44.44%	-32.16%
LNT	5.92%	13.61%	-4.31%	9.37%	-4.73%
LOW	5.02%	-7.21%	-35.78%	-17.76%	-31.08%
LRCX	-10.71%	-8.55%	-20.37%	-31.38%	-41.13%
LUMN	-10.57%	-1.84%	-20.34%	17.51%	-11.50%
LUV	-21.64%	-13.49%	1.78%	-26.31%	-17.77%
LVS	-5.27%	2.75%	14.40%	-30.40%	-13.49%
LYV	9.14%	12.03%	7.58%	-16.93%	-30.66%
MA	12.94%	-9.98%	5.80%	-5.33%	-13.04%
MAA	6.59%	-27.66%	-23.92%	-8.16%	-23.41%
MAR	-5.16%	-20.46%	-2.88%	-11.11%	-15.97%
MAS	-7.86%	-24.21%	-28.06%	-5.39%	-27.33%
MCD	4.39%	-12.27%	-4.96%	-0.02%	-7.76%
MCHP	-8.32%	-24.81%	-23.14%	-6.51%	-34.03%
MCK	19.03%	20.21%	11.11%	15.10%	32.23%
MCO	-35.29%	-27.92%	-6.77%	-9.03%	-29.11%
MDLZ	-11.83%	-3.33%	-5.66%	0.32%	-5.94%
MDT	0.04%	-14.25%	-12.50%	-4.14%	-14.78%
MET	15.18%	-18.55%	1.35%	-9.57%	-0.47%
MGM	-7.13%	-39.79%	0.00%	5.97%	-35.86%
MHK	-52.45%	-32.28%	-33.38%	-30.61%	-31.24%
MKC	-14.67%	3.02%	-14.25%	20.07%	-10.63%
MKTX	-33.26%	-34.74%	-29.07%	-42.75%	-34.36%
MLM	-2.92%	-11.47%	-23.65%	-24.81%	-31.60%
MMC	-5.12%	-5.12%	-5.72%	-12.94%	-7.30%

MMM	-19.64%	-29.28%	-13.08%	-17.16%	-26.99%
MNST	30.02%	15.52%	10.30%	-9.04%	-3.30%
MO	-17.59%	-7.29%	3.60%	-0.95%	-12.95%
MOH	-7.61%	-3.83%	-6.32%	-4.39%	-11.09%
MOS	22.14%	10.11%	-9.91%	3.76%	19.78%
MPWR	16.00%	-21.76%	-25.91%	11.76%	-20.70%
MRK	12.84%	8.97%	19.81%	-0.68%	20.35%
MRO	-19.84%	8.00%	19.04%	-3.71%	35.09%
MS	-21.08%	-13.31%	1.11%	-9.62%	-21.96%
MSCI	-27.03%	-29.17%	-25.80%	-10.08%	-30.28%
MSFT	-2.38%	-10.57%	-15.55%	-9.38%	-22.25%
MSI	-11.24%	-6.92%	-16.84%	-10.19%	-21.58%
MTB	-7.41%	7.03%	-7.34%	21.44%	2.58%
MTCH	-13.97%	-38.71%	-1.54%	-27.25%	-47.04%
MTD	-18.32%	-30.69%	-25.36%	-4.07%	-31.58%
MU	-2.44%	-27.74%	-48.12%	-11.10%	-41.49%
NDAQ	-13.55%	-24.52%	-14.83%	-13.72%	-24.40%
NDSN	12.60%	8.58%	20.32%	4.48%	-19.56%
NEE	14.24%	-31.36%	-22.40%	-2.47%	-17.08%
NEM	-8.01%	-5.45%	-4.73%	7.06%	1.66%
NFLX	-66.83%	-61.79%	-67.79%	-43.28%	-70.14%
NI	-1.63%	8.22%	-6.79%	9.67%	7.05%
NKE	-16.61%	-10.70%	-5.16%	-25.66%	-37.30%
NLOK	-6.70%	-0.94%	3.16%	-15.94%	-15.31%
NOC	-9.55%	11.49%	12.92%	39.26%	19.79%
NRG	-17.08%	-18.07%	-20.73%	-14.85%	-11.96%
NSC	-19.08%	-12.48%	-14.43%	-5.00%	-22.31%
NTAP	-18.82%	-28.52%	-33.67%	-17.48%	-29.26%
NTRS	-8.09%	-22.62%	-12.12%	-1.96%	-18.19%
NUE	7.78%	1.54%	-17.15%	-4.99%	-6.01%
NVDA	-26.97%	-7.21%	-31.40%	-39.05%	-48.40%
NVR	-1.47%	-19.94%	-17.00%	-31.00%	-31.11%
NWL	14.69%	-5.35%	16.60%	-9.69%	-12.75%
O	4.35%	-1.38%	0.45%	0.15%	-2.58%
ODFL	-6.55%	-24.85%	-26.30%	-16.05%	-26.30%
OKE	2.41%	-7.32%	4.98%	13.44%	-6.43%
OMC	-23.66%	-7.87%	12.09%	-1.06%	-14.31%
ON	0.00%	26.11%	-25.84%	-29.48%	-27.15%
ORCL	-2.48%	-26.22%	-5.97%	-11.02%	-21.26%
ORLY	-2.81%	0.70%	0.00%	-2.86%	-8.45%
OXY	62.28%	58.49%	83.44%	40.76%	90.28%
PARA	-8.72%	-21.25%	-17.32%	-16.40%	-22.21%
PAYX	0.00%	-9.12%	-0.89%	-12.41%	-14.62%
PCAR	-6.60%	-5.87%	18.19%	-5.73%	-6.05%
PEAK	-5.85%	-28.48%	9.99%	-22.80%	-28.48%

PEG	1.57%	4.35%	6.86%	5.13%	-5.37%
PEP	0.27%	8.47%	-1.79%	4.31%	-3.61%
PFE	-11.81%	-20.51%	-25.62%	-12.11%	-10.08%
PFG	2.96%	-4.64%	-2.36%	-13.95%	-8.03%
PG	-13.30%	4.50%	-9.91%	-10.58%	-12.71%
PGR	3.17%	-11.39%	6.53%	8.91%	11.41%
PH	-4.70%	-20.17%	-22.70%	-2.33%	-21.73%
PHM	-12.49%	5.40%	24.07%	-27.59%	-29.42%
PKG	-7.92%	6.11%	1.56%	12.93%	3.20%
PKI	-14.34%	-10.96%	-22.93%	-9.73%	-25.97%
PLD	-28.11%	-40.14%	-1.20%	-22.94%	-28.25%
PM	2.03%	-0.45%	-4.17%	11.86%	5.37%
PNC	-14.43%	-27.45%	-0.49%	-4.70%	-24.42%
PNR	-28.56%	-37.66%	-3.98%	-9.82%	-35.61%
PNW	5.99%	-4.28%	-3.87%	-7.56%	3.60%
POOL	-17.50%	-1.74%	-3.15%	-13.55%	-36.40%
PPG	-38.88%	-34.56%	-26.06%	-30.16%	-31.30%
PPL	-2.11%	-2.44%	6.22%	-6.31%	-10.22%
PRU	1.96%	-9.32%	-25.70%	-21.16%	-12.36%
PSA	11.65%	-1.83%	8.95%	-11.27%	-14.84%
PTC	-27.20%	-12.36%	2.04%	-10.66%	-12.91%
PWR	7.73%	-1.71%	-5.24%	-9.22%	6.66%
PXD	-7.32%	-7.79%	-12.45%	1.78%	21.02%
QCOM	-5.23%	-4.42%	-6.92%	-7.69%	-30.06%
RCL	-42.73%	-58.31%	-20.53%	-55.17%	-55.44%
RE	10.39%	3.81%	4.37%	12.79%	2.11%
REG	-2.58%	-18.28%	-17.99%	-8.24%	-20.69%
REGN	11.35%	5.98%	2.54%	2.47%	-4.70%
RF	4.22%	-11.91%	-29.86%	-15.15%	-15.13%
RHI	-24.76%	-18.59%	-25.43%	-18.00%	-31.00%
RJF	-5.85%	-26.69%	-22.10%	-2.38%	-12.28%
RL	-21.88%	-4.57%	-5.69%	-5.96%	-24.31%
RMD	-22.22%	22.08%	-7.81%	-16.28%	-17.96%
ROK	-28.47%	-37.23%	-30.77%	-6.67%	-41.95%
ROL	6.14%	0.50%	-5.06%	-8.50%	4.08%
ROP	-18.34%	-22.59%	-18.26%	-12.58%	-17.14%
ROST	-25.73%	-37.69%	-11.90%	-13.89%	-36.54%
RSG	7.58%	-3.72%	-11.17%	4.56%	-3.84%
RTX	1.70%	-2.82%	-15.17%	4.68%	7.28%
SBAC	-3.40%	-6.21%	1.84%	-13.15%	-16.49%
SBNY	-23.37%	-38.38%	-12.19%	-29.85%	-43.79%
SBUX	-5.62%	-13.96%	-5.36%	-11.94%	-34.50%
SCHW	-7.29%	-17.06%	-19.13%	-16.97%	-25.82%
SEE	11.69%	-12.17%	-13.04%	-2.75%	-12.26%
SHW	-30.85%	-28.79%	-36.81%	-12.06%	-33.53%

SIVB	-26.90%	-33.37%	-11.92%	-8.64%	-41.50%
SJM	6.09%	-14.39%	-10.95%	-4.75%	-4.46%
SLB	-8.23%	1.51%	15.06%	13.96%	14.06%
SNA	-7.89%	-8.89%	-19.87%	-3.58%	-6.77%
SNPS	5.45%	11.05%	-3.99%	-1.52%	-15.24%
SO	0.68%	1.82%	12.21%	8.80%	3.67%
SPG	-38.57%	-33.60%	-5.08%	-34.84%	-39.33%
SPGI	-11.38%	-5.74%	-20.52%	-33.29%	-27.40%
SRE	6.02%	-3.91%	1.46%	14.38%	13.88%
STE	2.48%	-1.81%	-4.92%	-10.73%	-14.12%
STT	-23.22%	0.42%	-31.12%	-25.49%	-32.15%
STX	-14.75%	-23.56%	-7.52%	-29.31%	-36.83%
STZ	14.55%	17.32%	14.46%	22.97%	-3.63%
SWK	-37.73%	-49.29%	-31.92%	-15.15%	-42.94%
SWKS	-30.55%	-39.97%	-37.80%	-30.25%	-41.25%
SYK	-10.23%	-18.78%	1.53%	-4.47%	-25.70%
SYY	8.14%	9.91%	12.40%	-4.00%	8.04%
T	-2.76%	-2.83%	8.09%	-6.49%	9.08%
TAP	6.10%	14.68%	2.74%	8.27%	16.92%
TDG	-15.68%	-14.11%	-16.92%	-14.35%	-18.08%
TDY	-6.45%	6.17%	-13.32%	-14.53%	-15.93%
TECH	-29.64%	-26.88%	1.21%	0.99%	-28.56%
TEL	-8.39%	-28.97%	-8.72%	-28.81%	-29.88%
TER	-15.82%	-23.91%	-6.76%	-42.83%	-45.67%
TFC	-7.91%	-18.23%	-13.70%	1.54%	-21.52%
TFX	-3.84%	-23.69%	1.91%	-9.23%	-23.27%
TGT	-45.98%	-29.21%	-13.49%	-36.92%	-38.82%
TJX	-2.64%	3.66%	-4.63%	1.72%	-24.43%
TMO	-0.88%	-13.73%	-14.68%	-9.20%	-16.90%
TMUS	20.07%	13.55%	17.41%	9.23%	17.43%
TPR	28.78%	3.18%	-5.07%	-25.62%	-23.52%
TRMB	-13.58%	-31.82%	-23.27%	-15.19%	-31.82%
TROW	-40.75%	-39.47%	-33.58%	-18.75%	-40.64%
TRV	5.05%	13.74%	-3.01%	-10.69%	6.45%
TSCO	-9.30%	-13.99%	-11.37%	9.88%	-17.04%
TSN	-1.69%	-2.88%	5.21%	3.10%	-1.71%
TT	-21.46%	-33.37%	-1.02%	0.36%	-33.24%
TTWO	-26.95%	-30.47%	-8.89%	-4.71%	-29.72%
TXN	-4.64%	-3.32%	2.36%	-12.94%	-19.84%
TXT	-0.69%	4.34%	9.38%	-13.00%	-21.52%
TYL	2.96%	8.26%	-17.92%	-10.15%	-35.99%
UAL	9.14%	13.80%	-24.92%	39.64%	-21.57%
UDR	-4.93%	-21.57%	-17.52%	-15.64%	-22.72%
UHS	10.64%	-0.15%	2.96%	-12.92%	-18.77%
ULTA	7.47%	19.29%	-17.36%	8.17%	-5.22%

UNH	-1.89%	1.02%	1.71%	-5.09%	2.67%
UNP	1.16%	1.75%	-14.97%	-10.37%	-13.97%
UPS	-17.29%	-13.13%	-4.97%	-2.67%	-15.16%
URI	-7.75%	-13.60%	-15.07%	-13.70%	-27.09%
USB	-19.07%	-19.90%	-6.85%	10.14%	-19.47%
V	8.59%	-12.65%	-3.57%	9.67%	-9.90%
VFC	-23.53%	-39.81%	-27.72%	-23.28%	-38.76%
VLO	16.16%	35.52%	2.09%	14.45%	41.11%
VMC	-23.77%	-28.02%	-29.24%	-15.96%	-31.08%
VNO	-20.17%	-20.18%	-21.19%	-33.02%	-33.85%
VRSK	-9.54%	-16.73%	-11.48%	1.04%	-22.71%
VRSN	-9.15%	-27.58%	-33.43%	-17.31%	-34.05%
VRTX	24.22%	-0.75%	5.48%	23.95%	25.98%
VTR	-8.58%	1.94%	0.29%	16.80%	-0.71%
VTRS	4.73%	-13.42%	-19.12%	15.98%	-23.93%
VZ	-3.49%	6.86%	1.75%	9.72%	-2.86%
WAB	-22.80%	-7.79%	0.00%	-2.25%	-10.47%
WAT	-20.76%	6.62%	-3.44%	-29.21%	-9.60%
WBA	-16.98%	-13.27%	-10.10%	-11.92%	-22.97%
WBD	-35.87%	-25.44%	-24.87%	-20.19%	-48.01%
WDC	-19.34%	-4.04%	-17.56%	-20.43%	-31.14%
WEC	-2.45%	-3.83%	-0.17%	6.55%	3.35%
WELL	14.84%	0.84%	6.36%	-5.95%	-2.72%
WFC	-16.69%	-1.98%	-4.86%	-29.00%	-21.72%
WHR	-12.41%	-15.70%	-10.71%	-25.95%	-32.21%
WM	0.00%	-7.06%	2.98%	0.97%	-7.06%
WMB	-6.70%	5.04%	2.60%	22.19%	18.91%
WMT	5.43%	0.42%	-17.89%	-2.43%	-15.71%
WRB	7.43%	-1.75%	4.64%	28.40%	24.40%
WST	-28.51%	-32.83%	-29.89%	-9.51%	-32.83%
WTW	-12.84%	-5.85%	3.49%	-7.73%	-15.15%
WY	-10.45%	-19.80%	-8.55%	-19.79%	-18.56%
WYNN	-8.48%	-3.27%	-19.54%	-31.84%	-33.92%
XEL	7.52%	8.86%	7.70%	15.33%	3.34%
XOM	9.32%	28.48%	2.57%	29.08%	38.68%
XRAY	-14.73%	-14.12%	-10.44%	-15.25%	-36.03%
YUM	-10.76%	-28.31%	-14.74%	-7.68%	-16.63%
ZBH	-14.76%	-15.59%	2.96%	-12.08%	-15.01%
ZBRA	-35.47%	-36.85%	-21.89%	-47.18%	-48.91%
ZION	12.65%	-18.68%	-15.21%	10.96%	-19.10%