MACHINE LEARNING METHOD FOR RETURN DIRECTION FORECASTING OF EXCHANGE TRADED FUNDS USING CLASSIFICATION AND REGRESSION MODELS

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ABSTRACT

This article aims to propose and apply a machine learning method to analyze the direction of returns from Exchange Traded Funds (ETFs) using the historical return data of its components, helping to make investment strategy decisions through a trading algorithm. In methodological terms, regression and classification models were applied, using standard datasets from Brazilian and American markets, in addition to algorithmic error metrics. In terms of research results, they were analyzed and compared to those of the Naïve forecast and the returns obtained by the buy & hold technique in the same period of time. In terms of risk and return, the models mostly performed better than the control metrics, with emphasis on the linear regression model and the classification models by logistic regression, support vector machine (using the LinearSVC model), Gaussian Naive Bayes and K-Nearest Neighbors, where in certain datasets the returns exceeded by two times and the Sharpe ratio by up to four times those of the buy & hold control model.

Keywords: Securities Analysis. Financial Market. Artificial Intelligence.

1. INTRODUCTION

The growth of investors on the Brazilian stock exchange is evident, from approximately 500,000 investors at the end of 2011 to more than 3.2 million investors at the end of the first half of 2021 (B3 BOLSA BRASIL BALCAO, 2021), driving numerous discussions and studies on the subject for attracting interest from the population. This growth creates demands for financial products.

As a result, asset analysis and asset pricing modeling in financial markets is one of the challenges of today. Involving Artificial Intelligence (AI), as this is an area in research and in its early stages, it is necessary to carry out experiments and tests to evaluate the reliability of such computational methods for the pricing and forecasting of these financial assets. These types of models, when implemented, tested and proven, can result in a tool for asset management, which can be applied by both ordinary people and large capital managers in order to generate more income and also portfolio protection (DAVENPORT; BEAN, 2021; NATARAJAN, 2021).

It is estimated that between 60-73% of trades on American stock exchanges are already automated (MORDOR INTELLIGENCE, 2021). Such automatons make use of pre-established parameters in programmed code to identify patterns based on various elements of analysis, such as: historical prices, moving averages, trend indicators, candlestick patterns, volatility, volume and for more advanced algorithms: news and sentiment of the environment related to social networks (BHARATHI; GEETHA, 2017).

Investment strategies fall into two categories, technical and fundamental. Technical analysis aims to follow graphical indicators and find patterns within the trading environment, making use of charts, indicators such as RSI (Relative Strength Index), moving averages, trend
lines, among other techniques (PRING, 2014). With regard to fundamental analysis, it aims to use indicators of the financial health of companies in search of companies that have growth potential and/or are discounted from their real market value (GRAHAM; DODD, 2008).

Recent analyses indicate that random investment strategies have better long-term performance than strategies propagated by both technical and fundamental analysts, in addition to presenting lower cost to the investor, they bring less risk linked to operations. While in the short term they can perform better than random strategies, technical and fundamental strategies have greater risk and costs linked to its operations (BIONDO; PLUCHINO; RAPISARDA; HELBING, 2013).

The financial market fluctuates and is non-linear, predicting fluctuations with accuracy is a difficult task to perform. The forecasting capabilities use methods that are constantly being updated and improved, based on iterative systems, financial engineering, analysis of historical data, as well as trial and error. Considering this, the application of asset trading algorithms was researched with the use of Artificial Intelligence, focused on Supervised Learning.

The purpose of this article is to use the historical prices of stocks that compose the Exchange Traded Funds (ETFs) to predict the ETF returns direction for the next day, applying buy or sell orders according to the forecast made by each model implemented. By comparing the computational performance of the proposed models based on a well-established model based on the Random Walk Hypothesis, it is possible to evaluate the computational and predictive performance of each method. Among the models will be evaluated using algorithmic error metrics and risk/return calculation. The financial return of each model is compared to the return of the technique of buying and holding the same assets during the same period of time, aiming to select the most consistent machine learning model.

2. PREDICTION MODELS AND FINANCIAL CONCEPTS

In this study we used ten machine learning models, which are: Linear Regression, Ridge Regression, Logistic Regression, Support Vector Machine (SVM), Linear Support Vector Machine (LinearSVM), K-Nearest Neighbour (KNN), Gaussian Naïve Bayes (GaussianNB), Random Forest, Extreme Gradient Boosting (XGBoost) and Light Gradient Boosting Machine (LightGBM). Both XGBoost and LightGBM were used to regression and classification tasks, totalling twelve different prediction tasks. (KUMAR et al, 2018; NABIPOUR et al, 2020; YANG et al, 2021; ASHFAQ; NAWAZ; ILYAS, 2021).

2.1. Linear Regression

The linear regression model, also known as Ordinary Least Squares (OLS) is a simple and common model for prediction which can be noted on the equation (1) in Table 1. The goal of the model is to establish a relationship between multiple variables \( x_n \) with the response variable \( y \) utilizing it to learn the weights \( \beta_n \) that describes the relationship between the variables, then being able to predict future response variables with the new given dataset (RASCHKA; MIRJALILI, 2017; MÜLLER; GUIDO, 2017).

2.2. Ridge Regression

The ridge regression model is a variation of linear regression which goes through the process of regularization called L2 norm, to ensure the best trade-off between bias and variance for the data through the \( \beta \) coefficients. The main goal of the L2 regularization is to use the lowest possible values for the \( \beta \) coefficients and lower the overfitting of the data (MASÍS, 2021; MÜLLER; GUIDO, 2017).
2.3. Logistic Regression

The logistic regression model, despite its name, is used for binary classification tasks. It takes a weighted combination of the input values $x_n$ and passes it through a sigmoid function, mapping the multiple variables $x_n$ to a response variable $y$ being either 0 or 1. (ZHENG; CASARI, 2018). As well as the ridge regression, the logistic regression model uses the L2 regularization. The goal of the model is to classify the input values according to the probability of the response variable to match a negative (0) or positive (1) value. Being a multivariate problem, the model uses the concept of one-vs-rest (OVR) to overcome the limitation of two classes of the model by training a separate model for each class predicted whether an observation is the same class or not, making it a binary classification problem. It assumes that each classification problem is independent. The equation of the model is expressed in (2) in Table 1 (ALBON, 2018; MASÍS, 2021).

2.4. Support Vector Machines (SVC and LinearSVC)

The support vector machine models are classifiers that work maximizing the distance between the two categories in a projected $n$-dimensional space, separating it by a $n-1$ hyperplane called support vector. The data is classified binarily, being implemented by the models that use similar approaches but with a library variation for its kernel, being SVC having the linear kernel implemented by the terms of libsvm library and LinearSVC implemented in terms of liblinear. The function used to maximize the margins is expressed in (3) in Table 1, where the SVC model uses feature engineering with the Radial Basis Function (RBF) Kernel, expressed in (4) in Table 1, on the $\phi(x)$ function to transform the data from linear to non-linear shifting into $\phi(x) = [x^1, x^2, ... x^n]$, making it a non-linear output. The LinearSVC model makes use of a linear function to the Kernel (ZHENG; CASARI, 2018; MÜLLER; GUIDO, 2017; RASCHKA; MIRJALILI, 2017; ALBON, 2018; AUFFARTH, 2021).

2.5. K-Nearest Neighbors (KNN)

The K-Nearest Neighbors model is a simple classifier that doesn’t learn a function to describe the behaviour of the data, instead, it memorizes the training dataset and make assumptions to classify the data according to the proximity of the values. $K$ is the number of the neighbour values defined to make the classifying judgement of the algorithm. It works by collecting the $K$ most similar values between a new data point and all known instances in the dataset and voting for the most frequent label nearby the new data point. The function that describes the model is expressed in (5) in Table 1 (MÜLLER; GUIDO, 2017; MASÍS, 2021; RASCHKA; MIRJALILI, 2017; ALBON, 2018; AUFFARTH, 2021).

2.6. Gaussian Naïve Bayes (GaussianNB)

The Gaussian naïve Bayes model uses the Bayes theorem expressed in (6) in Table 1 for conditional probabilities to classify data. It considers that the values are continuous and have a normal (gaussian) distribution, as expressed in (7) in Table 1. The model assumes that the features are independent of each other, which impedes dramatically the capacity of prediction for not usually being the case, unless the assumption is correct (MÜLLER; GUIDO, 2017; MASÍS, 2021; ALBON, 2018).
2.7. Random Forest

The random forest model is an ensemble of multiple decision trees that takes decisions averaging the prediction results of the trees (also called voting). The random forest is less susceptible to a data overfit due to its utilization of subsets of data for each tree node, resulting in a powerful model which does not take decisions based on the whole dataset, therefore, reducing the high variance of the results (MASÍS, 2021; MÜLLER; GUIDO, 2017; RASCHKA; MIRJALILI, 2017).

2.8. Extreme Gradient Boosting (XGBoost)

The XGBoost model is an ensemble of multiple decision trees with the same principles of the random forest model, but distributing the trees level-wise. The model is commonly known for its speed and performance towards other models. The model computes each tree to incrementally reduce the error. It uses two rigorous techniques called Quantile Sketch for sampling and Split Finding for grouping sparse resources (AUFFARTH, 2021; MASÍS, 2021).

2.9. Light Gradient Boosting Machine (LGBM)

The LightGBM model is also an ensemble of multiple decision trees. It differs from the XGBoost model distributing its trees in a leaf-wise manner. It also is different due to the use of Gradient-Based One-Side Sampling (GOSS) for sampling and Exclusive Feature Bundling (EFB) for grouping the sparse resources (AUFFARTH, 2021; MASÍS, 2021).

| Table 1 – Models expressions |
|-------------------------------|
| Linear Regression            | \( y = \beta_0 * x_0 + \beta_1 * x_1 + \cdots + \beta_n * x_n = \sum_{i=0}^{n} \beta_i x_i \) (1) |
| Logistic Regression          | \( P(y_i = 1|X) = \frac{1}{1 + e^{-(\beta_0 x_0 + \beta_1 x_1)}} \) (2) |
| Support Vector Machines      | \( y = \beta^T \phi(x) + b \) (3) |
| RBF Kernel                   | \( k_{rbf}(x_1, x_2) = \exp (\gamma \|x_1 - x_2\|^2) \) (4) |
| K-Nearest Neighbors          | \( Y(x) = \frac{1}{k} \sum_{x_i \in N_k(x)} y_i \) (5) |
| Bayes Theorem                | \( P(y|x_1, \cdots, x_j) = \frac{P(y) \prod_{i=1}^{j} P(x_i|y)}{P(x_1, \cdots, x_j)} \) (6) |
| Normal distribution          | \( p(x_j|y) = \frac{1}{\sqrt{2\pi \sigma_y^2}} e^{-\frac{(x_j - \mu_y)^2}{2\sigma_y^2}} \) (7) |

Source: Author.

2.10. Correlation and Covariance

In financial engineering, it is necessary the comprehension of the covariance (8) and correlation (9) concepts. These instruments are widely used in statistics and regression analysis. Both metrics measure the relationship between two financial assets. The covariance measures
to how extent two variables change together while the correlation measures the strength of the relationship between the two variables. The expressions for both concepts are in Table 2 (FRANKE; HÄRDLE; HAFNER, 2008; BENNINGA, 2014).

Table 2 – Covariance and correlation expressions

|                | Expression                                                                 |
|----------------|-----------------------------------------------------------------------------|
| Covariance     | \[ cov(x, y) = \frac{1}{N} \sum_{t=1}^{N} (r_x(t) - \bar{r}_x)(r_y(t) - \bar{r}_y) \] (8) |
| Correlation    | \[ corr(x, y) = \frac{cov(x, y)}{\sigma_x \sigma_y} \] (9)                  |

Source: Author.

The presentation of all these concepts has the objective to find an applicability of financial market data using financial engineering to understand them and make them usable in machine learning models towards forecasting. The proposed models have a great capacity to generate useful results in several areas. The composition of multiple models adds to the decision-making in the field of asset trading because they have different techniques and approaches to the data provided, thus, the composition of models can be an auxiliary tool in quantitative analysis when properly implemented. The composition also allows the models to have their performance compared to each other, allowing the behaviours of each approach to be perceived in the same given dataset.

3. PROPOSED METHODOLOGY

Two base indexes were selected for the study of each model. The Ibovespa index, represented by the BOVA11 ETF, and the S&P500 index, represented by the SPY ETF, which are respectively Brazilian and American indexes and ETFs. To ensure the applicability of the models, the stocks from the 12 largest companies that compose each index, which contained their stocks traded on the stock exchange since 01/01/2012 were selected, with the objective of predicting each ETF return direction for the next trading day using it’s 12 components historical data as input.

The programming environment was the Integrated Development Environment (IDE) Anaconda, using the source code editing program Visual Studio Code, and the Python 3.6.5 programming language. Application Programming Interfaces (APIs) were used to assist in the application, manipulation, visualization and evaluation of each method, scikit-learn, lightgbm, xgboost, yfinance, pandas, numpy and matplotlib.

All data was obtained through Yahoo Finance (yfinance). The obtained data was the daily closing prices between the dates 01/01/2012 and 25/01/2022, here shown as in the format dd/mm/yyyy, containing 2496 trading days in the Brazilian dataset and 2533 trading days in the American dataset.

The selected stocks for the Ibovespa index were: Vale (VALE3), Petróleo Brasileiro - Petrobras (PETR4 and PETR3), Itaú Unibanco (ITUB4), Banco Bradesco (BBDC4), B3 – Brasil Bolsa Balcão (B3SA3), Ambev (ABEV3), JBS (JBSS3), WEG (WEGE3), Suzano (SUZB3), Itaúsa (ITSA4) and Banco do Brasil (BBAS3). The selected stocks represent around 50% of the BOVA11 ETF portfolio. The price evolution of the selected Brazilian stocks in the analyzed period is shown in Figure 1.
The selected stocks for the S&P500 index were: Apple (AAPL), Microsoft (MSFT), Amazon (AMZN), Alphabet* (former GOOGLE) (GOOGL and GOOG), Procter & Gamble (PG), Tesla (TSLA), Bank of America (BAC), Nvidia (NVDA), Johnson & Johnson (JNJ), UnitedHealth Group (UNH) and JPMorgan Chase (JPM). The selected stocks represent around 50% of the SPY ETF portfolio. The price evolution of the selected American stocks in the analyzed period is shown in Figure 2.

The relationship between the selected stocks and their respective ETFs can be noted in the Tables 3 and 4, containing the correlation matrices.
To facilitate the fitting of the data in the models, data processing and assuring robustness to the algorithm, the daily closing prices data obtained were pre-processed calculating the daily logarithmic return for each asset, since by nature machine learning algorithms are not good extrapolating. Using the log() and diff() numpy functions, the log returns can be obtained and then added to a new column of the dataset called LogReturn. The logarithmic returns make the dataset more stationary than previously, being more useable within the algorithms. The log returns $r_t$ can be expressed by the difference between the log prices $p_t$ in the equation (10) (TSAY, 2005).

$$r_t = p_t - p_{t-1}$$

(10)

Where the non-log return $R_t$ is expressed by the equation (11) (TSAY, 2005).

$$R_t = \frac{p_t}{p_{t-1}} - 1$$

(11)

For visualization purposes, the scatter plot of the returns of the ETFs BOVA11 and SPY were plotted in Figure 3, in order to verify the correlation of the returns of each index of the proposed datasets. The histograms demonstrate the distribution of the returns of each ETF, while the scatter plots relate the returns of each ETF on both axes, where a straight line would represent a perfect correlation between the assets (TSAY, 2005; BENNINGA, 2014; BROOKS, 2008).
The returns of each ETF were plotted, being presented in the Figure 4, to present the distribution of its returns through the analysed period, as well as the volatility clustering, a financial phenomenon that occurs and demonstrates that high volatility moments come followed by high volatility moments and low volatility moments come followed by low volatility moments (TSAY, 2005; BROOKS, 2008).

The datasets are then divided into two parts, considering the last thousand (1000) trading days, the data used for testing in each algorithm, leaving 1496 and 1533 trading days for training the Brazilian and American datasets respectively, guaranteeing a division around 60/40% for the training and testing periods. The algorithms consider an investment of 100% of
the capital in the case of a purchase, as well as a total zero position when the sale is indicated, in order to use the value 0 as a risk-free return in the calculation of the Sharpe index.

The regression and classification models provided by the scikit-learn, lightgbm and xgboost APIs are used to analyze all available data up to time step (t) in order to predict the direction of the return for step (t+1). The input data are the logarithmic returns of the 12 Brazilian stocks selected for the Brazilian ETF and of the 12 American stocks selected for the American ETF. The models analyze the same input data, that is, the same dataset is provided for each model, allowing to analyze the prediction behaviour of each model under the same standard dataset.

In order to train the algorithms, the ETF returns of each day, are assigned to the returns of the previous day of the 12 component stocks, allowing the model to establish a relationship between the returns of the components in the time step (t), and the ETF return obtained in the time step (t+1). In order to assign the values of the actual returns of the ETF in (t+1) to the returns of the components in (t), the dataset table is manipulated, so that the input data is in the same row of the result output as shown in Table 5. By making this association, the algorithms do the learning in the training period, allowing them to establish relationships by obtaining both input (x) and output (y) values. In the testing period, obtaining only the input values (x), the models use the learning done to deliver the output values (y), which are the predictions.

Table 5 - Stock returns in time period t associated with ETF return in time period t+1

| Time period | Input (x) Stock 1 | Stock 2 | ... | Stock 12 | Output (y) ETF return for next day |
|-------------|------------------|--------|-----|----------|----------------------------------|
| t           | Return(t)        | Return(t) | ... | Return(t) | Return(t+1)                      |
| t+1         | Return(t+1)      | Return(t+1) | ... | Return(t+1) | Return(t+2)                      |
| t+2         | Return(t+2)      | Return(t+1) | ... | Return(t+2) | Return(t+3)                      |
| ...         | ...               | ...               | ... | ...               | ...                              |
| t+n         | Return(t+n)      | Return(t+n) | ... | Return(t+n) | Return(t+n+1)                    |

Source: Author.

According to each model technique, the ETF returns for the following day (t+1) are classified binarily (0,1) representing the return direction prediction in the time period (t). If the return predicted is above zero, the data classify them as 1 and if is below zero as 0.

The classifications, being binary, are assigned to a new column called Position. The position also indicates the buying or selling of the asset for the end of the present day (t), and can then be used to compute the return obtained by the algorithm on the next day (t+1), since they are listed in the same row of the table, according to Table 6, which demonstrates the operation of the algorithm.

Table 6 - Column Position and algorithm return obtained based on the model prediction

| Time period | Input (x) Stock returns Stock 1 Stock 2 ... Stock 12 | Output (y) ETF return for next day Pred_Ret(t+1) | Position | ETF real return for next day Real_Ret(t+1) | Algorithm return Position*Real_Ret(t+1) |
|-------------|-----------------------------------------------|-----------------------------------------------|----------|------------------------------------------|---------------------------------------|
| t           | Ret(t)                                        | Pred_Ret(t+1)                                | (0,1)    | Real_Ret(t+1)                            | Position*Real_Ret(t+1)               |
| t+1         | Ret(t+1)                                      | Pred_Ret(t+2)                                | (0,1)    | Real_Ret(t+2)                            | Position*Real_Ret(t+2)               |
| t+2         | Ret(t+2)                                      | Pred_Ret(t+3)                                | (0,1)    | Real_Ret(t+3)                            | Position*Real_Ret(t+3)               |
| ...         | ...                                           | ...                                           | ...      | ...                                      | ...                                  |
| t+n         | Ret(t+n)                                      | Pred_Ret(t+n+1)                              | (0,1)    | Real_Ret(t+n+1)                          | Position*Real_Ret(t+n+1)              |

Source: Author.
Observing Table 6, it can be related that in the test period, given the input values (x), which are the stock returns on the present day (t), the algorithm predicts the return direction of the ETF (y) in the next day (t+1). If, for example, in period (t), given the values (x), the algorithm predicted that (y > 0), then the Position column receives value = 1, and this value is multiplied by the actual return of the ETF for the next day, which is in the same row, thus allowing the real return obtained to be stored and accounted through the column Algorithm Return. The total return of each model is obtained with the sum of all values in the Algorithm Return column in Table 6.

3.1. Regression models

Regression models using the input values (x) of period (t), look for the predictions for the actual value of the ETF return (y) at (t+1) and after that then classify them binarily (0,1). Importing the returns data from the ETF and its components, the methods are implemented by calling the LinearRegression, Ridge, XGBRegressor and LGBMRegressor machine learning models corresponding to the linear regression, ridge regression, extreme gradient boosting and light gradient boosting machine models respectively, through the scikit-learn, xgboost and lightgbm libraries.

3.2. Classification models

The classification models use the input values (x) and seek to predict the direction of the ETF return (y) at (t+1) by classifying them in a binary way (0,1) according to their sign. Importing the returns data from the ETF and its components, the models are implemented by calling the LogisticRegression, SVC, LinearSVC, RandomForestClassifier, XGBClassifier, LGBMClassifier, KNeighborsClassifier and GaussianNB learning models, corresponding to the classifiers: logistic regression, support vector machines (SVC and LinearSVC), random forest, extreme gradient boosting, light gradient boosting machine, Kth Nearest Neighbors and Gaussian Naive Bayes, respectively, via the scikit-learn, xgboost and lightgbm libraries.

Unlike regression methods, some of the classification methods have regularization (C) or random state parameters that need to be specified to guarantee an optimization of the classification.

The values assigned to the parameters are generalized for models that use the regularization parameter C at C=10, defined by experimentation, and the value for random initial state at random_state=0, for the random forest classifier. The reason for specifying the random_state parameter prevents the model from finding different results each time the code is run, since its decision processes are random, it allows stability in decisions with the same dataset. It is worth mentioning that the parameter can be changed, which may result in better classifications by the model using different states that suitably fit each data set, but for the purpose of comparative analysis, the state is kept the same in all data sets. The KNN model was not parameterized, using as default the number of neighbors k = 5.

3.3. Implementation of evaluation metrics

The returns of the ETFs buy & hold technique are computed by adding the logarithmic returns over the entire period of analysis, that is, considering the purchase at the beginning of the period and the sale of assets at the end of the period, thus allowing to establish a comparison between the returns obtained by the multiple negotiations carried out by the implemented models.
The real returns are converted to Booleans in order to be compared with the predicted return directions to measure the classification accuracy of the models implemented.

3.3.1. Naïve Forecast

The naïve forecast model is implemented, considering the previous day’s closing price as the best forecast for the present day. The returns of the previous day (t-1) of the ETF under analysis are considered as the expected returns for the ETF on the present day (t) by modifying the columns of the data set according to Table 7.

| Time period | ETF       | Forecast              |
|-------------|-----------|-----------------------|
| t           | Return(t) | Return(t-1)           |
| t+1         | Return(t+1)| Return(t)            |
| t+2         | Return(t+2)| Return(t+1)         |
| …           | …         | …                     |
| t+n         | Return(t+n)| Return(t+n-1)      |

Table 7 - Naïve Forecast structure

Source: Author.

The Forecast column is created to store the ETF return data with a delay of one day, resulting in a missing value for the ETF return for the component returns in the first time step, thus not being considered the first step of the set of data. The model also establishes a referential comparison for the errors and scores. In relation of the returns obtained, they will be compared to the returns obtained by the models and the buy & hold technique.

3.3.2. Statistical Metrics

The Sharpe ratio was calculated for each method using the data from the periods it had the assets purchased, considering the risk-free rate $r_F$ as 0, because all computed trading is considered as an investment of 100% of the capital involved, or, with 100% of cash capital. The Sharpe index is presented in equation (12).

$$\text{Sharpe Index} = \frac{R_A - r_F}{\sigma_A}$$

The Sharpe indexes are calculated using the accumulated return $R_A$ obtained by the models and the standard deviation of the values of the asset $\sigma_A$ on the days when the algorithm bought it, not considering the values for the non-traded days, allowing to visualize the behaviour of the risk according to the trading decision of each algorithm. Tests were scored on the model’s ability to predict against actual data and on their ability to classify the data.

The regressive models were also evaluated for the ability to predict the actual values for returns, which is outside the scope of the research, since the predictive capabilities of the returns directions are the objective.

Using the metrics section of the scikit-learn API, the functions are imported and implemented using the values obtained in the training and tests of each model to calculate the errors.

The application of the models considers that assets are actively traded in buy or sell operations, with the objective of generating more return to the trader by targeting asset low days and only trading on days with a positive expected return. In the following chapter, it is possible
to visualize the performance of each method in the datasets by observing the returns obtained, as well as the notion of risk linked to the return of each method, being able to classify them as more or less profitable and safe than the technique of buy & hold. As for the algorithmic errors, the errors of the models can be compared to the errors of the naïve forecast, allowing to verify the computational efficiency individually for each model.

4. EXPERIMENTAL RESULTS

The tables 8 and 9 present the results obtained in the reference models for comparison with the results obtained in the implemented models.

| Table 8 - Buy & Hold returns for each ETF |
|------------------------------------------|
| **Buy & Hold**                            |
| BOVA11 | SPY |
| Train log return | 0.2581 | 0.7455 |
| Test log return | 0.3411 | 0.4789 |
| Train standard deviation | 0.0146 | 0.0077 |
| Test standard deviation | 0.0181 | 0.0132 |
| Train Sharpe index | 0.0118 | 0.0633 |
| Test Sharpe index | 0.0188 | 0.0362 |

Source: Author

| Table 9 - Naïve forecast metrics |
|----------------------------------|
| **Naïve Forecast**               |
| BOVA11 | SPY |
| Train log return | -0.1667 | 0.2520 |
| Test log return | 0.1575 | 0.5467 |
| Train standard deviation | 0.0098 | 0.0050 |
| Test standard deviation | 0.0116 | 0.0085 |
| Train Sharpe index | -0.0114 | 0.0328 |
| Test Sharpe index | 0.0136 | 0.0645 |

ERRORS AND SCORES

| Train MSE | 5.71E-04 | 2.40E-04 |
| Test MSE | 7.81E-04 | 4.28E-04 |
| Train RMSE | 2.39E-02 | 1.55E-02 |
| Test RMSE | 2.80E-02 | 2.07E-02 |
| Train MAE | 1.68E-02 | 9.73E-03 |
| Test MAE | 1.80E-02 | 1.23E-02 |
| Train Accuracy | 0.4906 | 0.4768 |
| Test Accuracy | 0.4690 | 0.5000 |
| Train Precision | 0.4900 | 0.5226 |
| Test Precision | 0.4933 | 0.5560 |
| Train F1 score | 0.4903 | 0.5229 |
| Test F1 score | 0.4928 | 0.5560 |
| Train ROC-AUC | 0.4906 | 0.4719 |
| Test ROC-AUC | 0.4678 | 0.4919 |

Source: Author
The logarithmic returns of the training and test periods (Train and Test log return) obtained by the buy & hold technique (Table 8) are evaluated in terms of their magnitude, with a higher number representing more profitability. The data obtained are suitable for both sets of data within the period of time, thus noting that the technique allows for an attractive return, especially in relation to the returns of the American ETF, which are higher in both periods, allowing to visualize that there is a greater linearity of growth in the shares of its composition, while the shares that make up the Brazilian ETF have a lower return, despite being linked to a greater risk due to the characteristics of the Brazilian stock market. The higher Brazilian market risks are shown through the Sharpe indices, being 5 times lower than the American in the training period. The standard deviations also show the great variation in the prices of Brazilian assets, characterizing them as up to twice as volatile as those of American assets.

The most important data provided by Tables 8 and 9 are the values obtained for the test period, as it is the validation period. The main information obtained from the results in these tables are the logarithmic returns and the Sharpe index of the test period, being respectively 34.11% and 0.0188 for the BOVA11 ETF, and, 47.89% and 0.0633 for the SPY ETF. Error data are considerable, when compared to the errors obtained by the proposed models to become a relevant metric for comparison. Tables 10, 11 and 12 present the results obtained for the proposed models for comparison with the results obtained in the control methods, in Tables 8 and 9, and also for comparison between models and datasets.

**Table 10 - Regression models results**

|                     | Linear Regression | Ridge Regression | XGBoost Regression | LGBM Regression |
|---------------------|-------------------|------------------|--------------------|-----------------|
|                     | BOVA11  | SPY     | BOVA11  | SPY     | BOVA11  | SPY     | BOVA11  | SPY     |
| Train log return    | 0.8667  | 0.9841  | 0.5116  | 0.7377  | 8.1935  | 4.5489  | 7.7680  | 4.3051  |
| Test log return     | 0.7984  | 0.7590  | 0.4543  | 0.6359  | 0.2675  | 0.1404  | -0.2062 | 0.0702  |
| Train standard deviation | 0.0111 | 0.0069  | 0.0118  | 0.0077  | 0.0089  | 0.0046  | 0.0091  | 0.0047  |
| Test standard deviation | 0.0128 | 0.0107  | 0.0148  | 0.0123  | 0.0134  | 0.0183  | 0.0152  | 0.0098  |
| Train Sharpe index  | 0.0525  | 0.0927  | 0.0289  | 0.0626  | 0.6176  | 0.0102  | 0.5725  | 0.5998  |
| Test Sharpe index   | 0.0626  | 0.0712  | 0.0307  | 0.0516  | 0.0200  | 0.0138  | -0.0136 | 0.0071  |

**ERRORS**

|                     | Train MSE  | Test MSE  | Train RMSE | Test RMSE | Train MAE | Test MAE | Train Accuracy | Test Accuracy | Train Classification Accuracy | Test Classification Accuracy |
|---------------------|------------|-----------|------------|-----------|-----------|----------|----------------|---------------|-----------------------------|-------------------------------|
| BOVA11 SPY          | 2.11E-04   | 3.27E-04  | 4.55E-03   | 6.48E-03  | 5.09E-02  | 5.90E-02 | 0.0063         | 0.0046        | 0.5043                      | 0.5095                     |

Source: Author

Once the errors data is obtained from the regression models implemented, it is possible to evaluate them quantitatively when comparing with the values of the naïve forecast in Table 9. When observing the errors MSE, RMSE and MAE, the computational efficiency of the regression models is noted, all values being lower than those of the control model, with the valid mention of the linear and ridge regression models, which obtained much lower results than the naïve prediction in the American dataset.
Table 11 - Classification models results (part 1)

|                     | Logistic Regression | SVM (SVC) | SVM (LinearSVC) | Random Forest |
|---------------------|---------------------|-----------|-----------------|---------------|
| BOVA11 SPY          | BOVA11 SPY          | BOVA11 SPY| BOVA11 SPY      | BOVA11 SPY    |
| Train log return    | 0.6767              | 0.7220    | 4.1192          | 2.6827        |
| Test log return     | 0.8020              | 0.6847    | 0.5165          | 0.2816        |
| Train standard deviation | 0.0103 | 0.0075 | 0.0098 | 0.0059 |
| Test standard deviation | 0.0136 | 0.0117 | 0.0145 | 0.0116 |
| Train Sharpe index  | 0.0439              | 0.0627    | 0.2806          | 0.2991        |
| Test Sharpe index   | 0.0592              | 0.0584    | 0.0358          | 0.0243        |

SCORSES

|                     | Train Accuracy | Test Accuracy | Train Precision | Test Precision | Train F1 score | Test F1 score | Train ROC-AUC | Test ROC-AUC |
|---------------------|----------------|---------------|-----------------|----------------|----------------|---------------|---------------|--------------|
| BOVA11 SPY          | 0.5284         | 0.5315        | 0.5287          | 0.5553         | 0.5175         | 0.5456        | 0.5284        | 0.5313       |
|                      | 0.5470         | 0.5566        | 0.5496          | 0.5646         | 0.6998         | 0.7013        | 0.5025        | 0.5038       |
|                    0.7398 | 0.5175         | 0.7652        | 0.5412          | 0.6998         | 0.5338         | 0.5338        | 0.7397        | 0.5017       |
|                    0.7604 | 0.5135         | 0.7237        | 0.5571          | 0.7259         | 0.6042         | 0.5025        | 0.7444        | 0.4925       |
|                    0.5378 | 0.5335         | 0.5378        | 0.5562          | 0.8065         | 0.5519         | 0.5328        | 0.5378        | 0.4925       |
|                    0.5620 | 0.5475         | 0.5613        | 0.5631          | 0.5309         | 0.6848         | 0.5009        | 0.5236        | 0.4925       |
|                    0.9980 | 0.5265         | 0.9980        | 0.5532          | 0.6976         | 0.5284         | 0.5276        | 1.0000        | 0.4941       |
|                    1.0000 | 0.5075         | 1.0000        | 0.5578          | 0.9980         | 0.5788         | 0.5788        | 0.9980        | 0.4941       |

Table 12 - Classification models results (part 2)

|                     | XGBoost Classifier | LGBM Classifier | KNN | Gaussian NB |
|---------------------|--------------------|-----------------|-----|-------------|
| BOVA11 SPY          | BOVA11 SPY         | BOVA11 SPY      | BOVA11 SPY | BOVA11 SPY |
| Train log return    | 8.2498             | 4.5750          | 8.2498 | 4.5488      |
| Test log return     | 0.3578             | 0.3604          | 0.2296 | 0.4813      |
| Train standard deviation | 0.0089 | 0.0046 | 0.0089 | 0.0046      |
| Test standard deviation | 0.0134 | 0.0104 | 0.0128 | 0.0097      |
| Train F1 score      | 0.6233             | 0.6537          | 0.6233 | 0.6521      |
| Test F1 score       | 0.0268             | 0.0345          | 0.0180 | 0.0497      |

SCORES

|                     | Train Accuracy | Test Accuracy | Train Precision | Test Precision | Train F1 score | Test F1 score | Train ROC-AUC | Test ROC-AUC |
|---------------------|----------------|---------------|-----------------|----------------|----------------|---------------|---------------|--------------|
| BOVA11 SPY          | 0.9980         | 1.0000        | 0.9980          | 0.9980         | 0.9980         | 0.9980        | 0.9980        | 0.9980       |
|                      | 1.0000         | 0.9980        | 0.9980          | 0.9980         | 0.9980         | 0.9980        | 0.9980        | 0.9980       |
|                    0.9997 | 0.9976         | 0.9976        | 0.9976          | 0.9976         | 0.9976         | 0.9976        | 0.9976        | 0.9976       |
|                    0.6997 | 0.7089         | 0.7092        | 0.7092          | 0.7092         | 0.7092         | 0.7092        | 0.7092        | 0.7092       |
|                    0.6906 | 0.7012         | 0.7012        | 0.7012          | 0.7012         | 0.7012         | 0.7012        | 0.7012        | 0.7012       |
|                    0.4455 | 0.5643         | 0.5654        | 0.5654          | 0.5654         | 0.5654         | 0.5654        | 0.5654        | 0.5654       |
|                    0.5165 | 0.5865         | 0.5726        | 0.5726          | 0.5726         | 0.5726         | 0.5726        | 0.5726        | 0.5726       |
|                    0.4945 | 0.5865         | 0.5726        | 0.5726          | 0.5726         | 0.5726         | 0.5726        | 0.5726        | 0.5726       |
|                    0.5285 | 0.5668         | 0.5707        | 0.5707          | 0.5707         | 0.5707         | 0.5707        | 0.5707        | 0.5707       |
|                    0.4733 | 0.6414         | 0.5689        | 0.5689          | 0.5689         | 0.5689         | 0.5689        | 0.5689        | 0.5689       |
|                    0.4533 | 0.6211         | 0.4618        | 0.4618          | 0.4618         | 0.4618         | 0.4618        | 0.4618        | 0.4618       |
|                    0.1708 | 0.6211         | 0.4618        | 0.4618          | 0.4618         | 0.4618         | 0.4618        | 0.4618        | 0.4618       |

Source: Author

Some models make predictions with high accuracy in the training period that can be visualized by the Training Accuracy, where the XGBoost, LGBM models for both regression and classification tasks and the Random Forest classification model reached a score of 1 or close to 1, guaranteeing returns close to home of 824% within 1496 days for the Brazilian dataset, and of 457% within 1533 days for the American dataset.

With the errors and scores of all the models presented, the models can be compared, being able to notice the similarity between the approaches of some methods. In the regression models, a better performance is perceived in terms of error values when compared to those obtained by the naïve forecast, remaining lower in all parameters corresponding to the respective datasets. The values of the classification models scores show superior results in all categories when compared to the naïve forecast, with the exception of the Gaussian Naïve Bayes model, which presented a lower result in the F1 score, in the Brazilian dataset. These results denote a numerical and algorithmic efficiency of the models in relation to the computational capacity, since there are fewer errors and more scores in the tested models than in the naïve forecast.
The accuracy score is impractical for comparing regression and classification models, for this, the predicted values in the regressive models were converted to Boolean values in terms of the binary classification of the return direction predicted, being presented as Classification Accuracy in Table 10, allowing comparison with the Accuracy values in Tables 11 and 12 of the classification models. So, considering the prediction accuracy for all models, the regression models presented similar results to the classification models, being evidenced the ineffectiveness of the XGBoost and LightGBM models for the regression tasks, which presented results substantially inferior to the naïve forecast especially in the American dataset. The rest of the models ensured greater accuracy than the naïve forecast in all datasets.

Looking forward to ensure comprehension and data visualization, the graphs plotted in bars in Figures 5, 6, 7 and 8 present the most relevant data for the analyses, where Figures 5 and 6 present respectively the returns and the Sharpe indices obtained for each model, Figure 7 presents the results for the mean absolute errors in the regression models, and Figure 8 presents a comparison between the models regarding the accuracy in the classification of the returns direction.

Figure 5 – Return of the buy & hold and the models in the validation period

![Graph showing returns of models](image)

Source: Author

The logarithmic returns plotted in Figure 5 present the performance of each model within the testing period, evidencing the effectiveness of each model in predicting the direction of future returns with the data provided. The effectiveness of models in the American dataset in predicting the direction of ETF SPY returns, where linear and ridge regression models and logistic, linear support vector classifier and Gaussian Naive Bayes classification models showed substantially higher returns than those of the buy & hold technique.

As for the effectiveness of the models in the Brazilian dataset regarding the prediction of the returns direction of the ETF BOVA11, only three of the twelve models showed returns
lower than the buy & hold technique, models which all make use of decision trees, XGBoost for regression, LightGBM for regression and classification (the only model to present a negative return). Linear regression and logistic models, linear support vector classifier and K-nearest neighbors obtained returns of more than twice the buy & hold in the BOVA11 ETF.

Figure 6 – Sharpe index of the buy & hold and the models in the validation period

![Sharpe Index Chart]

Source: Author

Sharpe ratios measure excess return per unit of risk, in this case, the higher its value, the better, indicating that there is less risk linked to the period in which the asset was in the portfolio. The Gaussian Naive Bayes model presented a value four times higher than the buy & hold. This index indicates that in addition to obtaining superior returns, some models also allow risk reduction.
The mean absolute errors (MAE) shown in Figure 7 measure the deviations between predicted and actual values for each model and dataset. It is noted that regression models have a smaller error than the control model of the naïve forecast, denoting superior numerical efficiency, since the predicted values are smaller.

Figure 8 – Classification accuracy score of the models
For the real evaluation of all models regarding the classification, the score given for the classification accuracy of the models is taken into account, being presented in Tables 9, 11 and 12 as Test Accuracy and in Table 10 as Test Classification Accuracy. The score from 0 to 1 evaluates the model's data classification. The accuracy score of the models is understood as 1 corresponds to all predictions made being correct and 0 being all predictions incorrect. Figure 8 presents the accuracy scores for each model. Decision trees regression models (XGBoost and LightGBM) scored below the naive prediction in the American dataset.

Notably, the models perform slightly above 50% in terms of classification accuracy, which is a result that may suggest the discarding of the methods. These results become relevant when relating the accuracy of the models (Figure 7) to the returns (Figure 5) and Sharpe indices (Figure 6) obtained. These relations allow a quantitative analysis of the accuracy in regards of the decision making. When the models were wrong in ordering to buy, they obtained low losses of returns and when they were wrong when ordering to sell, they only failed to win.

With the tables and figures the models are allowed to be compared in terms of the returns, risks, errors and effectiveness in the classification of the data. It is possible to take conclusions regarding the models individually and the research carried out as a whole, aiming to be used as aid tools for decision making in the asset trading or even in an automated way within the trading environment.

5. CONCLUSIONS

The results obtained with the machine learning models analyzed the returns direction of Exchange Traded Funds (ETFs), and allowed the visualization of the models in action using the data provided, helping in decision making in trading strategies of assets through algorithms. At a first moment, the results of the models' scores, shows the effectiveness of some models in the classification of the returns directions. During the training period, the effectiveness of the models that use of decision trees (Random Forest, XGBoost and LightGBM) is visible, denoting a possible overfitting of the data. Overfitting that was not justified when observing the accuracy scores of the models used for classification in the training period, remaining stable like the rest of the classification models, slightly above 0.5. The overfitting is justified for the data obtained in the XGBoost and LightGBM models when used for regression, as they have a high accuracy score in the training period and average or poor performance of both models in terms of obtaining returns.

The generalized score of 0.5 in the accuracy of the models can be understood differently by observing the information provided in Figures 5 and 6 (models returns and Sharpe indices). Concluding, although all models are close to the classification accuracy of 50%, the models that obtained returns and Sharpe indices higher than the buy & hold and naïve forecast were able to avoid large returns losses. This means that when the models were wrong in ordering the purchase of the asset, they obtained minimal negative returns, and when they were wrong in ordering the sale, they just stopped winning, evidencing the correctness of the trading timing of the models that presented considerable returns (linear regression, logistic and LinearSVC).

The numerical errors evaluated by the error metrics MSE, RMSE and MAE, with emphasis on the regression models (Table 10), showed a positive performance, being lower than the reference model of the naïve forecast (Table 9), as well as the data obtained for the classification models (Tables 11 and 12), which reached values higher than the reference in the accuracy, precision, F1 and ROC and AUC scores, demonstrating the numerical efficiency of the models. Given the above, the models presented numerical capacity superior to the control model in general.

When evaluating the returns obtained and relating them to the Sharpe ratios, it was possible to select some models that performed better in each data set. Regarding the returns
obtained in the Brazilian dataset, eight of the twelve selected models stand out, which obtained better results both in the risk management and in the returns obtained. It is necessary to mention the LinearSVC, Logistic Regressor and Linear Regressor models, which obtained the highest returns from both datasets, surpassing by more than twice the buy & hold returns in the Brazilian data set, as well as presenting a Sharpe index up to three times higher. As for the American dataset, six models presented returns and Sharpe indices higher than those of the buy & hold, with real returns (outside the logarithmic base) exceeding 113% in the linear regression model. The returns are modest when compared to the Brazilian dataset, this is also due to the fact that the buy & hold technique performs better in the US market in terms of returns, showing greater linearity and growth of the companies that compose the SPY ETF. Having demonstrated the difficulty of the models to perform better in the American market, it can also be justified by Table 8 and Figures 3 and 4, which demonstrate lower volatility (variation in returns) and an increased growth linearity than in the Brazilian market.

The main results showed that machine learning is a valid tool for forecasting financial data, and can assist in decision making in trading assets in the financial market. The prediction of the direction of returns guaranteed to most models a higher return than the buy & hold, also demonstrating smaller algorithmic errors and higher scores, in addition to risk reduction in regard of the control data. The algorithms were able to identify behavior patterns with a confidence level above 50%, since this degree can be further increased using more input data so that the algorithm takes into account variables of greater relevance, in addition to a better individual parameterization and an adequate data treatment for each model, being necessary empirical evaluations in order to perceive the performance of the algorithm.

The models that obtained returns and accuracies lower than the control data (XGBoost and LightGBM) can be improved with an adequate data treatment for the models, in addition to a better parameterization in order to find an optimal value so that they become tools that also obtain higher returns than control as well as linear, logistic and linearSVC models. The low performance of these models in this study does not classify them as unsuitable tools, but tools that need a better implementation, where their performance is tied to the parameters and data provided.

For future research, it is recommended to include data from financial indicators, interest rates, data from technical analysis of assets, trading volumes, data from foreign markets, commodities, inclusion of analysis of social networks regarding assets in companies, being able to link all these variables in an Artificial Neural Network (ANN) in order to verify the possibility of increasing the accuracy of the predictions.

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APPENDIX

APPENDIX A – Source code of data extraction and treatment, implementation of tested models and control.

The source code is published in GITHUB and the access is public. The URL is <https://github.com/RaphaelPiovezan/ETF-direction-prediction/>.