Automated Trading System for Stock Index Using LSTM Neural Networks and Risk Management

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***Abstract*—Financial time series predictions are a challenge due to their nonlinear and chaotic nature. In recent decades, many researchers and investors have studied methods to improve quantitative analysis. In the field of artificial intelligence, sophisticated machine learning techniques, such as deep learning showed better performance. In this paper, an automated trading system is built to predict future trends of stock index prices. Using an LSTM-based agent to learn temporal patterns in the data, the algorithm triggers automatic trades according to the historical data, technical analysis indicators, and risk management. The results demonstrate that the proposed method, called LSTM-RMODV, shows better performance when compared with other methods, including the buy-and-hold technique. The proposed method also works in bear or bull market conditions, showing a rate over net income based on invested capital of 228.94%. That is, despite the low accuracy, the algorithm is capable of generating consistent profits when all the transaction costs are considered.**

***Index Terms*—Deep learning, Long short-term memory, Automated trading system, Risk management**

I. Introduction

Financial market forecasting is considered one of the most important economic fields and has attracted increasing attention from researchers and practitioners [1], [2]. In a stable economy, fixed-income funds and savings accounts are becoming less attractive due to a drop in real interest rates [3]. On the other hand, financial markets have attracted increasing attention since these investments tend to be more profitable than traditional ones. In addition, trading has become popular as a result of the associated profit potential [4].

However, this type of market represents a real challenge and methods to address these markets are at the forefront of current research. That is, financial variables are affected by several aspects resulting in complex behavior, such as different seasonal patterns, barely addressed by classical statistical models. In contrast, machine learning (ML) methods have shown better results in recent decades due to their ability to handle nonlinear variables issue [2].

In this context, two major approaches for information treatment are commonly used to analyze financial assets: fundamental and technical analysis, known as qualitative and quantitative methods, respectively [5]. Typically, fundamental analysis studies the fundamental factors that are related to a pretended investment when selecting a portfolio. Technical analysis indicates trade points; that is, buy and sell signals from assets.

Technical analysis (TA) theory, based on [6], is the study of price action. The forecast uses a graphical tool added to the price and volume information assets. According to the author, technical analysts, also known as graphic analysts, believe that anything that can probably affect the market price is absolutely reflected in the price. In this case, there are three statements based on the TA assumptions: (a) the price discounts everything, (b) prices move in trends, and (c) historical behaviors repeat themselves. Therefore, fundamental analysts study the causes of market movements, while technical analysis studies the effects. Understanding why oscillations occur has gained minimal importance [6]. Furthermore, the most dramatic cases of bull and bear markets in history began with little or no change in fundamentals. When the fundamentals appeared, the trend was already well established [6].

Recently, many TA studies proposed methods for time series forecasting as a support system for decision making [7]. The two main methods are statistical, also called econometric, and artificial intelligence (AI), such as artificial neural networks (ANN), ML, and soft computing (SC).

In the TA field, AI has shown efficient performance. Initiated by the well established ANN introduced by [8], new approaches have been proposed to solve the many issues found in structures that contain only one hidden layer. Improvements, such as those achieved through recurrent neural networks (RNN) have solved part of the overfitting problem, but it is not enough. Other issues concerning error, such as vanishing gradient, remain [9]. Therefore, more sophisticated techniques from ML, such as deep learning (DL), have been proposed to

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handle these problems [10]–[14]. The long short-term memory (LSTM) DL approach has become one of the main tools for financial time series forecasting among ML models [10]. This is due to the technique's ability to learn features from many hidden layers and memorize these patterns to use in the future [9].

The objective of this paper is to build and evaluate an algorithm constructed using computational intelligence for forecasting trend directions in Bovespa mini index (WIN). The model is based on the LSTM deep learning technique, and has the capacity to make a profit. The main contribution of this work, in addition to applying DL, is considering the transition cost and managing risk through trading strategies.

The remainder of this paper is organized as follows: Section II presents an overview of related works. Section III describes the model structure and Section IV presents the experimental results. Finally, Section V concludes this paper and discusses directions for future research.

II. Background and Related Work

Computer technology improvements have affected the markets in many ways. For example, to introduction of the electronic trading system, previously handled manually among financial market brokers [15]. In addition, the present capacity offered by computational systems and extensive financial data significantly benefited financial time series forecasting [16].

However, financial time series dynamics characterized by nonlinearity present challenges to the building of forecasting models [2], [17]. So, in recent decades, numerous studies have suggested ways to predict financial time series [7]. Indeed, technical features, such as noisy, nonparametric, and a chaotic nature, occur because financial prices are affected by different reasons and many macro-economic factors [18]. Hence, forecasting accuracy has become a huge challenge and of great interest to investors.

Traditional statistical methods commonly assume that time series are generated from a linear process and make predictions for future values [5], [19]. On the other hand, AI techniques, such as SC, have been applied with success because they can capture nonlinear behavior among the relevant factors [20]. One of the most widespread AI technique for predicting is the use of ANN. The first study on the applicability of this approach to financial markets was prepared by [8]. Based on this research, several studies have emerged and broadened the horizons of price and movement forecasts for capital market assets [4], [7], [18], [21]–[24].

Nevertheless, ANN models have limitations [21] that have spurred the development and application of new ML techniques to solve these issues. The model's shortcoming main suffered is overfitting, the major drawback of the risk minimization principle [25].

Deep network techniques have been applied with relative success to financial market prediction [26] as have other ML methods [27]. In addition to AI's ability to capture nonlinear relations among relevant issues without prior knowledge [20], another relevant factor is the lower computational cost of this method [27]. Among the models that have applied ML, [28]–[33], have received more attention and are related to this paper.

Advanced AI models, such as DL, have attracted attention by using LSTM. RNN have shown proprieties that can learn a large quantity of temporal data [13] in hidden layers [14]. Introduced by [9], LSTM is an improvement on recurrent networks.

Neural networks were created with the goal of representing the human brain mathematically. Their structure contains units called neurons, similar to the human biological system. The existing interactions between neurons, responsible for information transmission, are represented by activation functions. Traditionally, ANN have connections in a single direction RNNs, however, have the capability to backflow information [10].

When inferring about a certain situation, the human brain recurs from a preexisting memory about the context. An ANN also needs this recursive ability. However, it is a challenge for RNNs, which suffer from a large amount of data. In this case, error signals tend to miss with a short-term memory, creating the vanishing gradient effect [9].

Therefore, a novel recurrent network architecture with an appropriate gradient-based capability to handle this error backflow was presented in [9]. The model architecture has LSTM and the capability to learn time intervals over 1,000 steps, even in cases of noisy and incompressible input sequences. This new approach, called memory cell, passes information through gate units, and a constant error flow avoids vanishing gradient between the steps. In addition to the input and output gates, the forget gate unit is responsible for retraining or forgetting the necessary information about the current stage, see Figure 1.

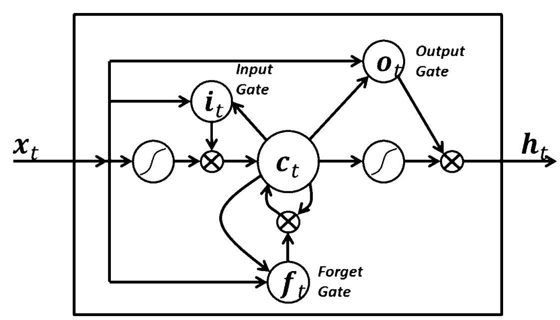

Fig. 1: Architecture of long short-term memory [9].

In practical terms, the forecasting model constructed in [10] is based on ML and LSTM techniques for day trading where the position is finished in the same trading day. The evaluation model was compared with ML traditional algorithms and other well-established investment strategies. Thus, the experimental results showed that the proposed model achieved good accuracy and created profit.

The proposed LSTM in [11] contributed to an automated algorithm of the decision-making process. The model executes sequential decisions using 1 minute candles from financial time series. To avoid overfitting, the most popular regularization dropout technique was chosen. The experimental results in all three simulation systems exhibited the capability to yield profits.

In addition to the benefits of this technique, other studies, such as [12], [13] combined the use of LSTM with technical indicators to improve the results. The indicators added in [13] model reduced the influence of noise in the market, characteristic of this type of temporal series. The results reveal the significant contribution of the proposed method.

An automated trading system model based on LSTM is proposed to predict price movements in stock index futures. Additionally, trading strategies such as risk management (RM), take profit (TP), and stop loss (SL) are implemented to avoid erroneous entries. This component represents the most significant contribution of this study because trading strategy is rarely explored by researchers while, in practice, it is the most important factor for investors making trading decisions.

If this evaluation is not applied, it is difficult to know that the proposed model works in the real world. As suggested by [34], perhaps, many failed models could exist in the literature because the models are not evaluated in the real market. The next section explains the methodology applied in this paper.

III. Methodology

The conceptual model was elaborated from [2], since the model's structure is compatible with the foundations of [5], [35]. Figure 2 shows the steps of this model.

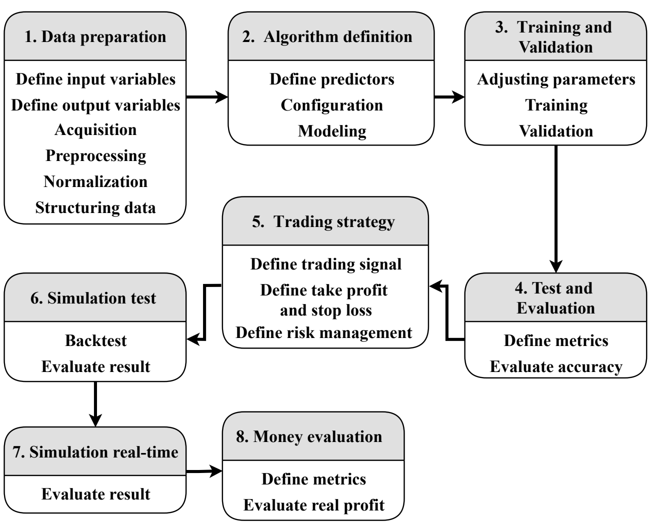

Fig. 2: Conceptual model steps [2].

The first step is composed of preparing data for the learning process. In this part, input and output variables, data acquisition, pre-processing, normalization, and structuring data were defined [2]. The second phase involves defining the algorithms for the forecasting and training models. The third phase is related to training and validation, which involves executing the training in order to learn the features of the historical data and validate these data. Better validation requires adjusting the training parameters. With training finished, the next step executes the test and measures the accuracy by defined metrics. The existing literature has addressed the method up to stage four, but few researchers have gone beyond this point [2], [7], [34], and an analysis beyond stage four is the main contribution of this paper. The successful intelligent method depends on the trading rules set in the fifth phase. Opening a position trade based only on predicted values can lead to false entries. That is, a poorly managed output point can result in less profitable operations, as will be shown in the experimental results. This structure handles all situations to avoid an unnecessarily drop in profit. The next phase is the simulation test applying the trading strategy with historical data, a process called backtesting, and then measuring the results obtained. In step seven, the test is repeated but in an environment containing a demo account to test the model in the real-time market without real money. Finally, the last phase evaluates the performance of the trading system in terms of making profits in the real market [2]. This is one of the most important phases as it provides information to ensure that the proposed automated trading system can produce profits in the real world.

The proposed method was based on a multi-layer LSTM network for a forecast horizon of 3 candles of 5 minutes each, referring to the Bovespa mini index future. This choice was made because the LSTM technique, as previously mentioned, provides better results than an RNN, which suffers from vanishing gradient [9] problems. In turn, stock indexes represent the most used databases in forecasting with ML applications [30]. Thus, based on the proposed conceptual model, Figure 3 represents the architecture applied in the proposed model, and the steps are explained in the following sections.

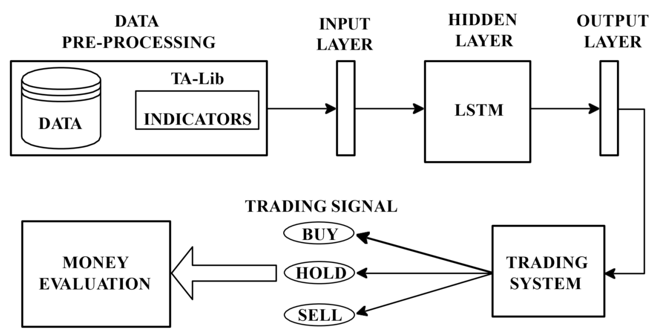

Fig. 3: Model architecture.

A. Data Preparation

The structure of this phase is composed, first, by historical prices in the candlesticks format originating in Japan [36]. Each candle contains price information about open, high, low, close, and financial volume (OHLCV) granulated to 5 minutes. Thus, the historical data cover the period from January 2016 to December 2018, totaling 79,867 data separated into 85% for the training process and 15% for testing. Then, the period from January 2019 to December 2019 was used to evaluate the financial profit. Figure 4 represents all those cited in the approach.

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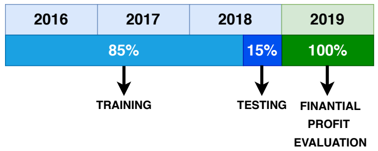

Fig. 4: Training and testing approach.

In addition to OHLCV, the model used 108 technical indicators (TI) as input variables, commonly used in TA [6], and different periods aiming to include short and long price oscillations. The TI choice is due to empirical methods based on previous knowledge about the market. After data acquisition, as [5] indicates, the data are normalized properly and the reverse process is employed for forecasting.

The indicators can be extracted in two ways: (a) through the trading platform or (b) using a tool called TA-Lib[1]. This paper uses the second option because the first has higher computational cost that can result in an order delay process.

B. Long Short-term Memory

Predictor algorithm is based on an LSTM network and its structure is developed through TensorFlow[2] using Keras[3] interface. The architecture receives a matrix of 20 x 113 normalized data information for the input layer. This dataset represents 20 historical data with the respective OHLCV and TI.

Moreover, the hidden layer is composed of 4 LSTM layers interspersed with 4 dropout layers, the most used regularization technique for training since it avoids overfitting [11], and 1 fully connected (FC) layer. Finally, the output layer provided the price forecasting. Figure 5 shows the input, hidden, and output layers, where *n* represents the neurons used and *r* the dropout rate.

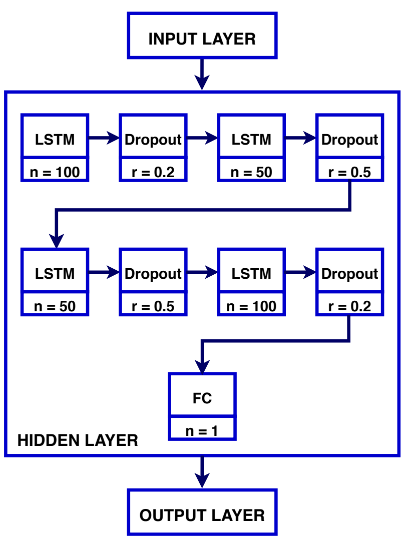

Fig. 5: LSTM model architecture.

[1]http://ta-lib.org/
[2]https://www.tensorflow.org
[3]https://keras.io

C. Metrics

Metrics evaluation of forecasting models was used to measure the performance of the algorithm prediction [10]. Similarly, metrics of accuracy, precision, recall, and F-measure were used in this study and shown in Equations 1 to 4, respectively.

$$A = \frac{t_p + t_n}{t_p + f_p + t_n + f_n} \tag{1}$$

$$P = \frac{t_p}{t_p + f_p} \tag{2}$$

$$R = \frac{t_p}{t_p + f_n} \tag{3}$$

$$F = 2\frac{P * R}{P + R} \tag{4}$$

where t_p, t_n, f_p, and f_n represents true positive, true negative, false positive, and false negative, in this order. Those values can be obtained from correct and incorrect predictions in a positive and negative class.

D. Automated Trading System

This section explains the whole trading strategy. This includes the RM that represents the SL and the minimum necessary variation of the forecasting horizon to open a position. This section also shows the rules for entering and closing position trades. Therefore, the major contribution of this paper is presented by the parameter approach to the model's profitability.

MetaTrader 5[4] platform was used in this phase. This automated trading system (ATS) receives the forecasting horizon from the output layer and processes the information for execution in an order.

First, the SL parameter is set to 200, in the cases where it is applied. So, after the ATS executes an entry operation, an SL is generated at the same time. This means that if the price direction goes against the prediction, the position is automatically closing when counting 200 negative points of WIN.

The SL trading strategy was used to avoid a high drawdown in each operation. This strategy was useful in cases of atypical market movements caused by macro-economic factors, such as breaking news and catastrophes. This trading strategy also avoids the phenomenon known as breaking account. Have been reported a lot of investor robots, that besides not be profitable, can breakdown the investor account in a single day. The lack of an SL strategy is one of the reasons for this outcome.

On the other hand, the TP was set to 400 points. Also known as stop gain, this parameter is frequently used by traders in their operations in order to realize a profit from each operation. Additionally, it helps to avoid that price market changes and entire positive points are given back, which is the worst scenario.

Five setups of LSTM models were built for evaluation in this paper. For classification as a buy or sell signal, the first two compare the value of the forecasting horizon with the last

[4]https://www.metatrader5.com/

close candle. Case forecast horizon is higher than last close price, a buy signal is generated. In contrast, if the forecast horizon is lower than close price, a sell signal is given.

RM was applied in all three of the last models. The base RM used from this point is based on the forecast horizon for which 3 classes are defined: a) buy signal (long) if the prediction is greater than 0.2%, Equation 5; b) sell signal (short) if it is less than 0.2%, Equation 6; and c) hold for intermediate values.

$$P_{t+3} - P_t \geq 0.2\% P_t \tag{5}$$

$$P_{t+3} - P_t \leq -0.2\% P_t \tag{6}$$

where P_{t+3} is the forecast horizon and P_t is the close price.

Thus, the five models are:

- **LSTM-N** used a naive strategy based on the forecasting; that is, open a position on the current market price and close 3 consolidated candles ahead through market order. Figure 6 shows the LSTM-N strategy.

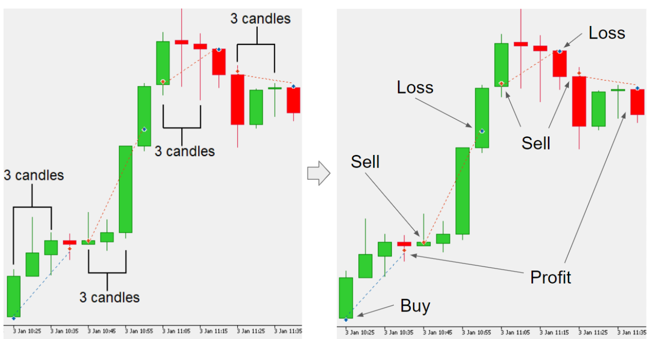

Fig. 6: LSTM-N strategy.

- **LSTM-PH** was entirely based on the forecasting horizon and used the price prediction as TP and SL. So, if the trading signal is buy, the model sets a positive value for TP and the negative value for SL. For a sell signal, the opposite is true. This strategy is illustrated in Figure 7.

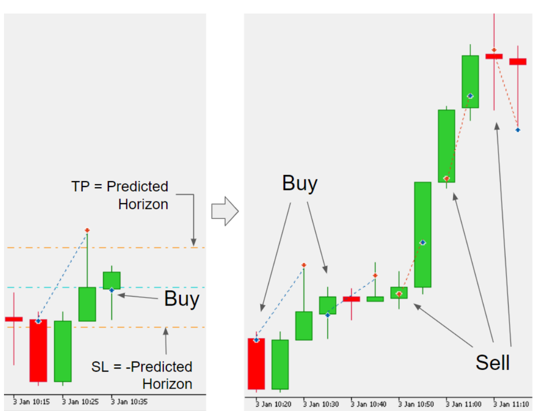

Fig. 7: LSTM-PH strategy.

- **LSTM-RMO** used an RM strategy, and considered a target of open operations as 400 TP and 200 SL points. LSTM-RMO strategy is illustrated in Figure 8.

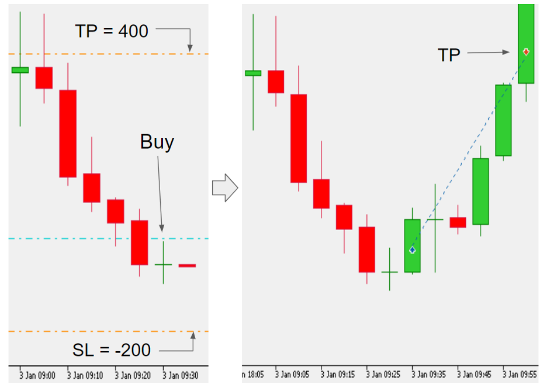

Fig. 8: LSTM-RMO strategy.

- **LSTM-RMOD** used LSTM-RMO strategy and a daily RM transaction; that is, in case of daily accumulated points is upper than 1,000 TP or under 400 SL, the robot shuts down and reboots the next day.
- **LSTM-RMODV** model was based on an important TA widely used by big market players known as big sharks. That analysis is the Volume Weighted Average Price (VWAP) indicator, and this TI is not in the TA-Lib library. Therefore, it is added at this stage to measure the financial impact. So, in the LSTM-RMODV, if a buy signal is under VWAP, no operation is done, but if a buy signal is above this, the operation is normally executed. In the same way, if a sell signal is above VWAP, no operation is done, but if a sell signal is under this, the operation is normally executed. This happens because the traders believe that if the price market is higher than VWAP, the big players are interested in the bull market. On the other hand, if the price market is lower than VWAP, there are big players interested in a bear market. The LSTM-RMODV strategy is illustrated in Figure 9.

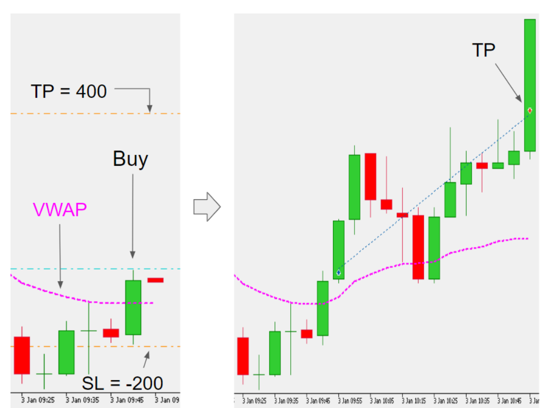

Fig. 9: LSTM-RMODV strategy.

E. Financial Evaluation

Since only the high accuracy rate in financial forecasting does not define a successful model, this section proves how financial evaluation based on market knowledge is useful for practical investors.

When trading ends, profitability is measured by the difference between the opening and closing price. Knowing the profit value, the next step is to calculate the transaction costs based the operated contracts, Equation 7 illustrates this formula. Finally, it is possible to deduct 20% of income tax from net income [37] to find the resulting profit.

$$R = p \times 0.2 \times c \tag{7}$$

where R is the financial result, p represents accumulated points, the leverage factor parameter is 0.2, and c is the number of used contracts.

Additionally, the Sharpe ratio is widely used as a performance evaluation for investment funds [38], and this measure can be applied to evaluate this type of market [39]. Its representation is shown in Equation 8.

$$\textit{Sharpe ratio}_i = \frac{\gamma_i - \gamma_f}{\sigma_i} \tag{8}$$

where γ_i represents the expect return, and γ_f is the risk free return in the market, which is the excess return of the strategy. The denominator σ_i is the standard deviation of the return.

IV. Experimental Results

The results from the five model's testing steps are evaluated and explained in this section. The metrics applied according to Section III-C are presented in Table I. Those metrics are from the algorithm prediction performance and report how well it works as a prediction model. Because the positive and negative class values were extremely close, this paper chose to demonstrate the negative class values only.

Thus, based on these results, it is possible to infer that the best model was the LSTM-N, exhibiting the best accuracy, precision, and F-measure while the LSTM-RMODV exhibited just the best recall. Moreover, comparing the models that used RM, when using daily RM, the exposed risk was reduced and, additionally, VWAP TI avoided false positives and false negatives. Therefore, these models improved metric values and highlighted the LSTM-RMODV as the best model related to RM.

TABLE I: Model metrics

LSTM Models	Accuracy	Precision	Recall	F-measure
LSTM-N	**0.504**	**0.503**	0.549	**0.525**
LSTM-PH	0.441	0.433	0.461	0.446
LSTM-RMO	0.354	0.367	0.528	0.433
LSTM-RMOD	0.363	0.367	0.529	0.433
LSTM-RMODV	0.388	0.381	**0.636**	0.477

However, an interesting perspective is highlighted by the financial metrics represented in Table II. LSTM-N had the major accumulated points and the biggest drawdown – that represents the largest drop in the asset in a given period – and number of operations. When observing the numbers, it is possible to conclude that LSTM-N demands many trades to significantly accumulate points, which also increases the risk noted by high drawdown. All this effort results in a number of accumulated points close to LSTM-RMODV but with more resources; that is, providing a comparative scenario, drawdown, and number of operations was less than 6 times and 8 times, respectively, in the case of LSTM-RMODV.

Furthermore, the worst case scenario is represented by LSTM-PH, proving that using the forecast only can be a problem in practice, contributing to the RM usefulness. So, except by accumulated points, illustrated in Figure 10, high values from other metrics can bring negative impacts on the financial evaluation.

TABLE II: Financial metrics

LSTM Models	Accumulated points	Drawdown	Number of operations
LSTM-N	**14,865**	17,250	5,227
LSTM-PH	-18,075	18,075	4,644
LSTM-RMO	500	12,650	1,364
LSTM-RMOD	8,720	5,750	905
LSTM-RMODV	**14,145**	**2,760**	**647**

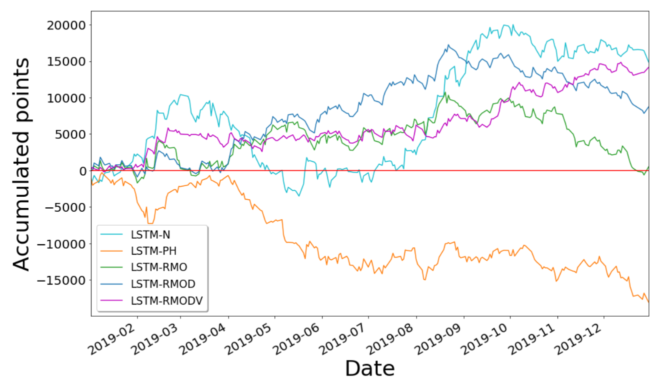

Fig. 10: LSTM-RMODV - Accumulated points in 2019.

For proof, the financial evaluation was calculated for each case, and the profit results are shown in Table III. Based on these results, it is clear that LSTM-N is not the best option given the profitability. Instead, the best one is LSTM-RMODV. Financial metrics values are the key to financial evaluation and represent the most important analysis bacause the proposed model must result in profit in the real world.

First, it was possible to calculate initial invested capital with drawdown and the number of operations. Then, the number of operations is the basis for transaction cost. Finally, the result shown in the third column of Table III, discounted the transaction cost and the income tax rate and generated the profit. The value is presented in the last column and Figure 11 illustrates the profit from the five models.

As previously mentioned and seen now, the LSTM-N model is not the best in terms of profit. One reason is the high number of operations that increased the transaction cost. Additionally, the model shows the best positive return among the other five models, but near LSTM-RMODV, when considerate the costs, the LSTM-N result is not the biggest of them.

Considering the invested capital, the risk-return of the LSTM-N model is not well accepted by investors. Instead, LSTM-RMODV is more attractive. That is, the ratio between profit and invested capital is 0.04 in LSTM-N while it is 2.28 in LSTM-RMODV. Although the LSTM-RMODV Sharpe ratio was 0.082, the traders need lower invested capital for higher financial returns. This analysis is important to investors because the LSTM-RMODV is risky but also highly profitable. Moreover, since the LSTM-PH had negative accumulated points, it also became the worst case.

TABLE III: Financial evaluation

LSTM Models	Invested capital	Result	Transaction costs	Profit
LSTM-N	6,063.50	2,973.00	2,613.50	287.60
LSTM-PH	5,937.00	-3,615.00	2,322.00	-4,749.60
LSTM-RMO	3,212.00	100.00	682.00	-465.60
LSTM-RMOD	1,602.50	1,744.00	452.50	1033.20
LSTM-RMODV	**875.50**	2,829.00	323.50	**2,004.40**
Income tax over net revenue = 20%				

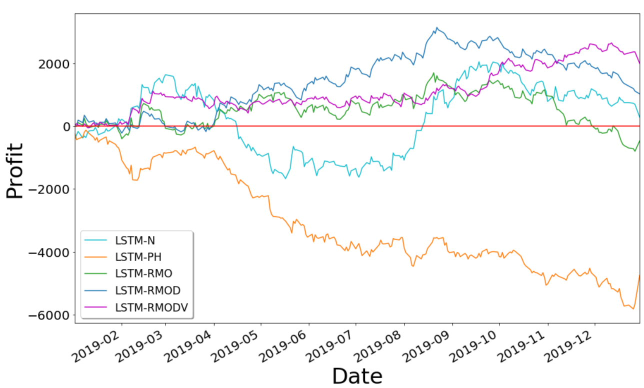

Fig. 11: LSTM-RMODV - Profit in 2019.

Therefore, to improve the study, Table IV shows five simulated scenarios based on the number of operated contracts. It was used to compare the LSTM-RMODV with the well-known the buy-and-hold (B&H) technique – buying and holding a trade with the aim that the value will increase naturally over time.

Thus, the same invested capital was considered in two types of scenarios. For B&H, a growth rate of 30% represents the benchmark profit based on the development of Ibovespa during the test period, 2019. Those results are compared with the data of the success model to find the risk-return relationships.

The evidence is based on the total empirical results, and in fact, the risk-return from a day-trading strategy is worth it. Furthermore, the model has a rate over net income and invested capital of 228.94% while the B&H shows just 30%. This is possible due to the high leverage characteristic of future contracts. Table IV also reveals that the ratio between both strategies is 7.7.

TABLE IV: Simulated leverage LSTM-RMODV versus B&H

Number of contracts	Invested capital	Benchmark annual valuation	Profit B&H	Profit LSTM-RMODV
1	875.50	1,138.15	262.00	2,004.40
5	4,377.50	5,690.75	1,309.98	10,022.00
10	8,755.00	11,381.50	2,619.96	20,044.00
50	43,775.00	56,907.50	13,099.78	100,220.00
100	87,550.00	113,815.00	26,199.56	200,440.00
Ratio LSTM-RMODV:B&H = 7.7				

V. Conclusion

In this paper, an ATS based on DL was proposed for operations in WIN. Five models were developed to compare different trading strategies and the application of appropriate RM. The results of the intelligent algorithms were compared with the B&H technique. The main contribution of this work is the financial evaluation and the normally used metrics to measure the model's performance. The study's analysis showed the high profitability of the LSTM-RMODV even without high accuracy. This result was possible considering the appropriated RM based on the prior knowledge of the market. When the best model was compared to B&H, it proved to be much better, achieving a ratio 7.7 times more profitable than B&H considering all the transaction costs, including income rate over day trade.

As expected, the empirical results show the importance of the RM for ATS. It was possible to observe that the first and second models that did not apply that RM showed the worst profitable results. Additionally, the third model shows the inefficacy of simple RM. However, the results increase at the same rate as the RM improves. That theory can be proven through the results of the LSTM-RMOD and LSTM-RMODV model. Furthermore, prior knowledge about the market is important when building successful models. Technical knowledge is not enough in this field due to the improvements using VWAP in the last model, LSTM-RMODV.

Thus, this paper shows how the proposed ATS works and can result in profits in the real environment considering total costs.

For future works, another model containing more sophisticated layers will be proposed to improve accuracy, precision, recall, and F-measure. Additionally, this study has proven that the RM is the difference between profit and loss. Therefore, using an intelligent model based on reinforcement learning will return interesting results for financial markets.

Other trading strategies such as the breakeven and trailing stop, will be implemented and tested using another time series from a mature market, for example, the S&P500.

Acknowledgements

This research was supported by the Brazilian Coordination of Improvement of Higher Level Personnel (CAPES).

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