IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received September 30, 2020, accepted October 3, 2020, date of publication October 12, 2020, date of current version October 21, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3030226

Stock Market Forecasting Using Deep Learning and Technical Analysis: A Systematic Review

AUDELIANO WOLIAN LI AND GUILHERME SOUSA BASTOS, (Member, IEEE)
Institute of Systems Engineering and Information Technology, Federal University of Itajubá, Itajubá 37500-903, Brazil

Corresponding author: Audeliano Wolian Li (audeliano@unifei.edu.br)

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

ABSTRACT Stock market forecasting is one of the biggest challenges in the financial market since its time series has a complex, noisy, chaotic, dynamic, volatile, and non-parametric nature. However, due to computing development, an intelligent model can help investors and professional analysts reduce the risk of their investments. As Deep Learning models have been extensively studied in recent years, several studies have explored these techniques to predict stock prices using historical data and technical indicators. However, as the objective is to generate forecasts for the financial market, it is essential to validate the model through profitability metrics and model performance. Therefore, this systematic review focuses on Deep Learning models implemented for stock market forecasting using technical analysis. Discussions were made based on four main points of view: predictor techniques, trading strategies, profitability metrics, and risk management. This study showed that the LSTM technique is widely applied in this scenario (73.5%). This work significant contribution is to highlight some limitations found in the literature, such as only 35.3% of the studies analysed profitability, and only two articles implemented risk management. Therefore, despite the widely explored theme, there are still interesting open areas for research and development.

INDEX TERMS Deep learning, profitability metrics, risk management, stock market forecasting, systematic review, technical analysis, technical indicators.

I. INTRODUCTION

Asset prices forecasting for stock market is a very difficult and complicated task [1] since several micro and macroeconomic attributes and characteristics influence the price formation, such as political events, news, company balance sheets, among others [2]. These factors contribute to the nonlinear and non-stationary characteristics presented by the market, favoring the proposed task complexity [3], [4].

Therefore, the studies of these influences are made through market analysis, and their main objective is to predict future directions to assist decision making based on market behavior [5]. The literature presents two main approaches: Fundamental Analysis (FA) and Technical Analysis (TA). Both have the same primary objective, and the difference is the information set used for forecasting and decision making. The first focuses on studying company data and seeks to determine whether it has growth potential in the medium to long term [6].

The associate editor coordinating the review of this manuscript and approving it for publication was Wei Liu.

In contrast, TA does not consider the company data, since investors who use this approach believe that information capable of moving the market is absorbed and reflected in the share price [7]. In other words, company balance sheets, accounting scandals, financial crises, or any relevant information capable of generating volatility in an asset is reflected in their price. Therefore, it is possible to avoid the FA data, which are often subjective, to identify patterns present in the asset graph through this strategy type.

Technical analysts make extensive use of Technical Indicators (TI) and candlestick pattern analysis to assist in price movement forecast. Several scientific articles used price information (Open, High, Low, Close prices – OHLC), trading volume, and indicators set as model input based on these techniques. However, when modeling these analyses, two different approaches are used; the works that used TIs generally adopted regression techniques [8]–[10] and those that analysed candlestick patterns adopted image processing techniques [11]–[13].

A computational intelligence techniques survey for forecasting prices in the stock market was proposed by Kumar *et al.* [14] and the authors identified that TIs play an

essential role; however, identifying an adequate TIs set is still an open problem.

Regarding works based on statistical methods, several authors stated that they did not perform efficiently and generated inferior results to models based on artificial intelligence (AI) [15]–[18], as statistical techniques treat financial time series as linear systems. Additionally, the survey of Cavalcante *et al.* [5] stated that some financial time series characteristics are responsible for the difficult task of forecasting compared to other time series. Thus, traditional statistical methods are not effectively applied to the economic context.

White [19] was the pioneer in implementing an artificial neural network (ANN) for financial market forecasting. The author used the daily prices of IBM company as a database. As it was just an initial study, it did not achieve the expected results. It highlighted the difficulties encountered, such as the overfitting problem and low complexity of the neural network, since only a few entries and one hidden layer were used. It was also mentioned possible future works, such as adding a higher number of features in the ANN, working with different forecasting horizons, and evaluating model profitability.

Besides, Cavalcante *et al.* [5] selected publications on computational intelligence from 2009 to 2015 and noted that ANNs were widely used and highlighted Deep Learning (DL) as future work. Then, the survey of Kumar *et al.* [14] presented works that addressed computational intelligence and explored publications from 2016 to 2019, that is, a continuation of the previous work. They highlighted several hybrid implementations and some based on ANN, fuzzy, and DL.

Additionally, Gandhmal and Kumar [20] and Nti *et al.* [21] noted that ANNs were widely used and performed better than fuzzy, support vector machine (SVM) and decision trees since ANNs had more significant potential for generalization. Besides that, Fawaz *et al.* [22] concluded that DL techniques were able to achieve performance similar to the state-of-the-art for time series classification.

TA is often used for investments with a shorter horizon, trend forecasts, and reversal points identification [5]. Therefore, the timeframe used for model training must be taken into account. The vast majority of previous works used daily candles for a one-day forecast horizon or more. In the review by Nti *et al.* [21], the 81 publications using TA only 5 worked with intraday candles, showing a differential potential for future works.

The justification for the lack of research that explores smaller timeframes can be either positive (a study yet to be explored) or negative (not showing exciting results). However, it is possible to justify, in principle, the advantage of using a smaller graphic period through the work of Kumar *et al.* [14], which presented the instances number of each reviewed articles and the one with the highest number was 4818, between the years 1986 and 2005, that is, 267 instances per year on average. As for training, DL models require large data volumes, and this amount of daily candles is relatively small. However, when training with intraday data, the 267 annual instances increase to 28836, considering 9 hours of trading and a 5-minute timeframe.

Sezer *et al.* [23] conducted a DL techniques survey for forecasting financial time series and concluded that recurrent neural networks (RNN) are the most explored by researchers. However, in their review, the authors did not limit the entry attributes set and used FA data, news, price history, market behavior, and TIs. The work focus was to present and analyse the techniques used, including the performance criteria and platforms adopted.

Nowadays, with the development of natural language processing (NLP) and the large volume of news available, sentiment analysis has been applied with relative success in the financial market [24]. Several works use news information together with historical prices for forecasts and have shown results superior to models that use only OHLCV [25]–[27].

Cavalcante *et al.* [5] identified the works generally did not use trading strategies. Also, they did not evaluate the profitability, reinforcing the conclusion of White [19] and the affirmation of Vanstone and Finnie [6], which say there is much research that does not validate the profitability, resulting in several inconsistent models in the long term. Thus, these issues have generated the greatest contribution of Cavalcante *et al.* [5] work, which added two final phases for the financial forecasting standard methodology: trading strategy and profitability evaluation.

To reinforce the need for this new methodology is possible to cite the Nazário *et al.* [28] work, which analysed 85 articles and only 31 used some trading strategy. Also, Wang *et al.* [10] identified that the metrics used for Machine Learning (ML) models have a low correlation with financial metrics, reinforcing the great importance of a completely autonomous system for correct financial validation.

Finally, this systematic review aims to gather and analyse existing articles in the literature, focusing on DL techniques for forecasting prices in the stock market, highlighting the accuracy and profitability metrics used to validate the model and trading strategies adopted.

II. RESEARCH METHODOLOGY

Kitchenham and Charters [29] presented a guide for preparing a systematic review and emphasized that the objective is to identify, evaluate, and discuss relevant works to answer the research questions. Also, they stated that a review of the literature needs to be complete and fair, otherwise it has little scientific value.

A systematic review has some advantages, such as research with less biased results through a well-defined methodology. In the case of quantitative studies, the data can be combined using meta-analytic techniques, thus increasing the probability of detecting new insights.

Therefore, given the information collected, the criteria adopted in this work are justified and the methodology used for this systematic review will be detailed below.

To select the main publications to be used in this work, some strict criteria must be respected and follow a well-defined research protocol. Three steps were proposed by [29] for the development of a systematic review: 1) planning, 2) conducting, and 3) analysis of results.

A. PLANNING THE REVIEW

Therefore, the first stage must bring some questions to be answered at the end of the systematic review and the inclusion, exclusion, and quality criteria. The defined questions are listed in the Table 1.

TABLE 1. Research questions.

ID	Research Question (RQ)
RQ1	Which DL techniques are mostly used to forecast prices in the stock market?
RQ2	Which markets and timeframes are most used for price prediction?
RQ3	What are the metrics used to validate the performance of the proposed model?
RQ4	The works using automated trading systems, which the methods employed?
RQ5	What are the metrics used for profitability evaluation?

The inclusion (IC), exclusion (EC) and quality (QC) criteria are presented in Tables 2, 3 and 4, respectively.

TABLE 2. Inclusion criteria.

Criteria	Description
IC1	Research that addresses the intraday timeframe.
IC2	Works that use trading system.
IC3	Works that use risk management or trading strategy.
IC4	Works using DL as the main technique.

TABLE 3. Exclusion criteria.

Criteria	Description
EC1	Works focused on portfolio management.
EC2	Works focused on fundamental analysis.
EC3	Works focused only on sentiment analysis.
EC4	The work was not published in the English language.

TABLE 4. Quality criteria.

Criteria	Description
QC1	Are the research objectives clear?
QC2	Is the methodology applied adequately?
QC3	Are the results clearly explained?
QC4	The development work is presented in fluid form?
QC5	Are the introduction, results, and conclusion related?
QC6	Is the publication a complete work?

B. CONDUCTING THE REVIEW

The second stage consists of extracting the relevant publications for the systematic review and selecting the works based on the criteria previously defined.

Thus, the Scopus platform was used to extract publications, as it is a reference in academia [30], and the Web of Science (WoS) database was also added to complement the previous platform since it is one of the oldest [31]. In addition, the IEEE Xplore database was also used, as it is a platform widely used in the engineering area. As keywords for the search descriptors were used "*Stock Market*", "*Deep Learning*", "*Forecasting*" and "*Technical Analysis*". In order to cover the largest number of articles related to the themes, probable variations were also used for this selection. Thus, the search string used was:

(("Stock Market") ***OR*** *("Stock Index")* ***OR*** *("Financial Market")* ***OR*** *("Future Market")* ***OR*** *("Equity Market")* ***OR*** *("Share Market")* ***OR*** *("Stock Exchange")* ***OR*** *(Finance)* ***OR*** *("Foreign Exchange"))* ***AND*** *(("Deep Learning"))* ***AND*** *(("Technical Analysis")* ***OR*** *("Graphical Analysis")* ***OR*** *("Technical Indicators")* ***OR*** *("Candlestick Analysis")* ***OR*** *("Candlestick Technique")* ***OR*** *("Charting Technique")* ***OR*** *("Quantitative Analysis"))* ***AND*** *(("Forecasting")* ***OR*** *("Predict")* ***OR*** *("Forecast")).*

In relation to Scopus, each search was set to select these terms only on keywords, abstract, and title documents. Additionally, as a limiter for data collection, "articles", "congresses" and "reviews" were used. For the other databases, it was decided not to impose limitations due to the limited number of publications.

The publications on each platform based on the keywords were made on May 3, 2020, totaling 111 articles. It is possible to observe a significant number of documents present in Scopus concerning the platforms WoS and IEEE Xplore: 82, 18, and 11, respectively.

With the aid of the Start software,[1] a tool developed especially for systematic reviews and based on the work proposed by [32], it was possible to remove duplicate publications, resulting in 84 articles. After reading the abstract (and other sections, when necessary), the inclusion and exclusion criteria were applied, resulting in 46 documents.

Among the 46 studies, only published in the English language and available through consultation by Capes Portal for periodicals[2] were used, leaving 37 publications.

Finally, the integral reading was made of the remaining articles, excluding those that did not fit quality criteria. Besides, works belonging to the same authors and developed as a continuation of the study, the complete work was considered. In this way, three publications were excluded and the remaining 34 will be analysed in the next step. Figure 1, based on [33], illustrates the number of articles separated during the described process.

After a complete reading of the publications selected, Table 5 was filled with all relevant information for each work. Such as the market, period, and timeframe used. The attributes extracted for training/testing the proposed forecast model, the predictor name, and which DL technique used.

[1] http://lapes.dc.ufscar.br/tools/start_tool
[2] http://www.periodicos.capes.gov.br

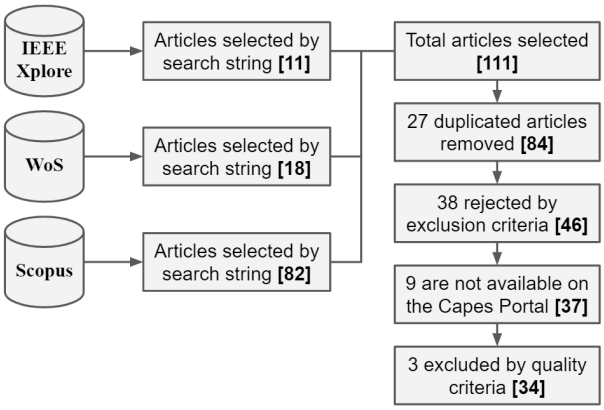

FIGURE 1. Number of articles separated during the conducting stage.

Techniques to compare results, which are measured using accuracy or profitability metrics; it was also analysed whether the authors used trading strategies and risk management.

C. ANALYSIS OF RESULTS

The third and final step consists of analysing the selected articles, separating them in predictor techniques, implemented trading strategies, profitability metrics, and risk management.

1) ANALYSIS BASED ON PREDICTOR TECHNIQUES

This subsection aims to analyse techniques based on forecasting stock market prices or trends. Once the focus of the work is DL techniques, the analysis will cover deep neural network (DNN), convolutional neural network (CNN), long short-term memory (LSTM), hybrid algorithms, and others.

Comparative studies were done by [39], demonstrating that TIs improved the ML model prediction. In the proposed work, several TIs were generated through 1-hour intraday data and a 24-hour forecast window. During the pre-processing step, the data were normalized and an autocorrelation function was used to select only the relevant input data, resulting in 9 TIs. Then, 14 ML models, including CNNs, were implemented and the results obtained by the authors demonstrated that the TIs inclusion increased the next day price forecast accuracy.

A different model was proposed by [52], which uses a CNN network with graph theory implemented. Two models were proposed for tests and comparisons, the first based on correlation and the second on causality. Besides, an ML predictor with linear regression and another using ARIMA also served to compare the results of root-mean-square error (RMSE), mean absolute percentage error (MAPE) e mean absolute error (MAE). The results showed that the proposed model presented smaller errors than traditional techniques, but did not perform tests with a simple CNN network or an LSTM network.

On the other hand, Sezer and Ozbayoglu [55] implemented a CNN network and used several models to compare the work developed performance, including an LSTM network. The significant difference lies in creating a 15 $\times$ 15 matrix formed by 15 TIs and 15 different periods, resulting in CNN input like an image. Finally, they obtained accuracy, precision, and profitability superior to the comparative models. However, Sim *et al.* [56] proposed a similar CNN but using the information of 1-minute. In the experimental tests, CNN showed better results than ANN and SVM, but when varying the amount of TIs, there were no improvements in results.

Unlike most published works, Wang *et al.* [10] proposed a new predictor model based on a one-dimensional CNN (1D CNN) capable of extracting data characteristics; that is, it is not necessary to create TIs. Also, to classify the market as upward, downward, or consolidating, they used a function based on closing price and volatility.

Regarding the works that implemented the LSTM technique, which are more than half of the analysed publications, some approached the pre-processing, results comparisons, and accuracy metrics in similar ways. The authors by [40], [43], [44], [47], [53] used asset prices and TIs as network attributes, and the data were normalized to feed the model input based on the LSTM network. Among them, only Qiu *et al.* [53] proposed a new model: a combination of LSTM and GRU (Gated Recurrent Unit), to explore LSTM ability to process sequential data and the simplicity of GRU, reducing training time and computational cost.

In contrast, the works developed by [38], [41], [54] opted to use standardization in the pre-processing stage. Also, Chen *et al.* [38] proposed a predictive model based on LSTM with Attention Mechanism (AM) and Market Vector (MV), with the MV being responsible for capturing correlations between assets. The results showed that this predictor obtained the smallest errors, being more effective than the commonly implemented LSTM with TIs. In turn, JuHyok *et al.* [41] used 16 candlesticks patterns modeled in the TI format to feed an LSTM network, performing better than a CNN.

AutoSLSTM was developed by [35], which had as its first layer an LSTM network with autoencoder followed by two other simple LSTM layers. The autoencoder technique proved to be very useful in reducing input data noise, resulting in minor errors concerning a simple LSTM network and a traditional MLP. During the tests, the forecast horizon was varied between 1, 5, and 10 days. There were concluded that the higher the parameter value, the more error is accumulated. Moreover, Labiad *et al.* [44] also obtained precision values that decreased with the increase of the forecast horizon, 10, 30, and 60-minutes.

A model with two layers of LSTM stacked and generated 400 characteristics based on market information was proposed by [37]. However, for training, only 250 were randomly selected. Thus, a different attribute set was selected for each new training, resulting in different training data. In contrast, Agrawal *et al.* [34] developed an optimized LSTM, and through the correlation-tensor technique, adaptive TIs were generated, resulting in better accuracy and lower MSE.

Reference [45] used OHLCV information to generate 4 TIs and feed the input of an ARIMA model, then the

TABLE 5. Analysed articles.

ID	Author(s)	Market	Period	Time-frame	Attributes	Predictor	Comparisons	Performance Metrics	Profitability Metrics	Trading Strategy
1	[34]	Indian	2016 - 2018	Daily	OHLCV + 2 TIs	Optimal LSTM	MLP, ELSTM, LR, SVM	Accuracy, MSE	—	Yes
2	[35]	Bahrain	2010 - 2018	Daily	Close + 2 TIs	AutoSLSTM: LSTM autoencoder	LSTM, MLP	MAE, RMSE, R^2	—	—
3	[36]	Crypto-currencies	2018 - 2019	M1	18 TIs	CLSTM: CNN + LSTM	CNN, MLP, RBFNN	Accuracy, Statistical validations	—	Yes
4	[37]	American	2014	M5	OHLCV + 12 TIs	LSTM	Ridge regression, Lasso regression	AUC, ROC	—	Yes
5	[38]	Chinese	2004 - 2018	Daily	OHLCV + 14 TIs	LSTM with Attention and Market Vector	LSTM with varied setups	MAE, MSE	—	—
6	[39]	Belgian	2014 - 2018	H1	9 TIs	2NN, CNN, 2CNN, ResNet and 2CNN_NN	2NN, CNN, 2CNN, ResNet and 2CNN_NN	RMSE, MAE, PCC, Diebold-Mariano	—	—
7	[40]	American	2014 - 2019	Daily	OHLCV + 3 TIs	LSTM	B&H, MACD	MSE	Yes	Yes
8	[41]	Chinese and American	1987 - 2018	Daily	16 candles patterns + 10 TIs	LSTM	SVM, MLP, CNN	Accuracy, Precision, Recall, F1 Score	—	Yes
9	[42]	Indian	2017 - 2018	Daily	OHLCV + 12TIs	Deep-ConvLSTM	DL, ARMA, NARX	MSE, RMSE	—	—
10	[43]	American	2016	M1	Close price + 8 TIs	LSTM	MLP	RMSE	—	—
11	[44]	Moroccan	2016 - 2017	M10, M30, M60	21 TIs	LSTM	MLP	Accuracy, Precision, Recall, F1 Score	—	—
12	[45]	Taiwanese	2009 - 2018	Daily	OHLCV + 4 TIs	Arima + LSTM	—	MAE, RMSE	—	—
13	[46]	Taiwanese	2007 - 2017	Daily	OHLCV + News	RCN: CNN + LSTM	RCN-C, LSTM	RMSE	Yes	Yes
14	[47]	Chinese	2008 - 2015	Daily	OHLC + 19 TIs	SVM, Naive Bayes, Decision Tree, MLP, RNN e LSTM	SVM, Naive Bayes, Decision Tree, MLP, RNN e LSTM	Accuracy, F1 Score	—	Yes
15	[48]	Chinese	2003 - 2008	Daily	OHLCV + TIs + News	LSTM	SVM, Multiple Kernel Learning	Accuracy, Precision, Recall, F1 Score	—	—
16	[49]	American and Japanese	2001 - 2013	Daily	Close price + News	Deep Autoencoder	SVM, MLP	Accuracy, Statistical validations	Yes	Yes
17	[8]	Brasilian	2008 - 2015	M15	OHLCV + 175 TIs	LSTM	MLP, Random Forest, Pseudo-random	Accuracy, Precision, Recall, F1 Score	Yes	Yes
18	[50]	American	2006 - 2017	Daily	OHLCV + 7 TIs + News	CNN + LSTM	CNN, LSTM	Accuracy	Yes	Yes
19	[51]	American	2006 - 2016	Daily	OHLCV + 4 TIs + News	CNN + LSTM	MA, BB, RSI, Stochastic	F1 Score	Yes	Yes
20	[52]	Mixed	2017 - 2019	M1, Daily	OHLCV + 22 TIs + News	GCN: Graph CNN	LR, ARIMA	RMSE, MAPE, MAE	—	—
21	[53]	Chinese	2016 - 2019	Daily	9 TIs	LSTM + GRU	12 state-of-the-art models	Accuracy, MSE, RMSE, Recall, F1 Score, AUC	—	—
22	[54]	Forex	1993 - 2018	Daily	OHLCV + 13 TIs	LSTM	RNN	MAE, RMSE	—	—
23	[55]	American	2002 - 2017	Daily	15 TIs with 15 periods	CNN-TA	B&H, RSI, MA, LSTM, MLP	Accuracy, Precision, Recall, F1 Score	Yes	Yes
24	[56]	American	4/2017 - 5/2017	M1	Close price + 9 TIs	CNN	ANN, SVM	Hit ratio, Statistical validations	—	Yes
25	[57]	Korean	1990 - 2016	Daily	OHLCV + 715 TIs + patterns	DNN	DNN with OHLCV	Accuracy	Yes	Yes
26	[58]	Korean	2000 - 2019	Daily	250 binary event	DNN	DNN with TIs	Accuracy	Yes	Yes

TABLE 5. ***(Continued.)*** **Analysed articles.**

ID	Author(s)	Market	Period	Time-frame	Attributes	Predictor	Comparisons	Performance Metrics	Profitability Metrics	Trading Strategy
27	[59]	Chinese	2016	M30	OHLCV + 21 TIs	Sharpe-Optimised SDNN: LSTM	LR, XGBoost, Random Forest, LSTM	—	Yes	Yes
28	[60]	American	2006 - 2013	Daily	7 TIs + News	SI-RCNN: CNN + LSTM	ANN	Accuracy	—	—
29	[61]	American	2006 - 2013	Daily	6 TIs + News	SI-RCNN: CNN + LSTM	SI-RCNN, I-RNN	Accuracy	Yes	Yes
30	[62]	Chinese	2012 - 2015	Daily	14 TIs + News	DBN-DRSE: Deep Belief Network (DBN)	ANN, SVM, RF, DBN, RNN, LSTM	Accuracy, Precision, Recall, F1 Score, AUC, ROC	—	—
31	[10]	American	2010 - 2017	M5	OHLCV + 11 TIs	1D CNN	SVM, MLP	Weighted-F-Score	Yes	Yes
32	[63]	Chinese	2016 - 2018	Daily	OHLCV + Turnover	PCA-LSTM	CNN, MLP, MA	RMSE, MAPE	—	—
33	[64]	American	2016 - 2018	Daily	OHLCV + 9 TIs + News	LSTM with Attention	LSTM	Accuracy, Statistical validations	—	—
34	[65]	Chinese	2016	M1	OHLCV + 9 TIs	GAN-FC: LSTM + GAN + CNN	Arima-Garch, ANN, SVM, GAN-F, GAN-D, LSTM-FD	RMSRE, Direction Prediction Accuracy (DPA)	—	—

output was used for the model based on LSTM. In contrast, Wen *et al.* [63] proposed the PCA-LSTM, whose the PCA (Principal Component Analysis) technique was responsible for extracting TI characteristics and reducing dimensionality, resulting in better predictions concerning the compared models.

In turn, Tan *et al.* [59] reduced dimensionality through an elastic net model and used LSTM as a predictor, but integrated with the Sharpe-Optimized method to achieve a balanced investment strategy with the risk-return. They obtained a financial accumulation of 75% higher than the traditional linear model and performance above the ML models.

Despite Nelson *et al.* [8] used the same predictor of other studies, the authors generated a large number of indicators and normalized them using the log-return transform. The results showed an accuracy slightly above 50%, but it reduced the maximum drawdown in most studied assets.

Works that made use of textual data, such as news, also obtained good results as shown in [48], [49], [62], [64], which used predictors based on LSTM, autoencoders, deep belief network (DBN), and AM, respectively. In all models, textual data is pre-processed using sentiment analysis techniques and later concatenated with the price and TI data.

Several authors have developed research using hybrid models for forecasting, and all models had LSTM or RNN layers linked to CNN layers. In the works of [46], [50], [51], [60], [61], the authors used CNN to extract textual data patterns, such as news channels and social networks, thus generating more information than just the asset price. All of them showed better results than a network with only LSTM implemented.

It is worth highlighting the work of Oncharoen and Vateekul [51] since it was proposed to change the loss function by adding Sharpe ratio information to the cross-entropy equation. Thus, the risk-return was calculated and weighted during the training. A metric based on the Sharpe ratio and F1 score, called Sharpe-F1 score, was proposed to select the best models based on risks presented.

Finally, Alonso-Monsalve *et al.* [36] used CNN layers to extract patterns in an 18 TIs set and OHLCV formed by six cryptocurrency, and an LSTM layer to generate a trend. Kelotra and Pandey [42] proposed an optimization algorithm, Rider-based monarch butterfly optimization, used to train the predictor based on a Convolutional LSTM Network (ConvLSTM), an algorithm used for sequential images. Furthermore, Zhou *et al.* [65] used a network with LSTM layers linked to CNN layers to market direction forecasting and implemented the GAN (Generative Adversarial Network) technique for the training process.

2) ANALYSIS BASED ON TRADING STRATEGIES

A trading strategy is understood as the logic used by the authors to buy or sell an asset. Most works used a simple rule of the type: if the forecaster indicates a buy signal, the algorithm makes the purchase and waits for a sell indication to effectuate the profit or loss. As can be seen in the publications of [34], [40], [41], [55].

Other authors also addressed the neutral, or hold, class in addition to the buy and sell classes. This is used not to perform any action; that is, if the system is not positioned, it waits for the buy class to make a transaction. If the system has a long transaction open and the forecasting indicates a neutral class, the algorithm maintains the transaction until the sell signal. This is the case with works like [47], [51], [59].

According to the model forecasting, other works implemented long or short strategies and finished the operation after a certain period. Matsubara *et al.* [49] and Oncharoen and Vateekul [50] chose to buy or sell the asset at the trading session opening and closed the operation at the end of the same day. While Lee and Soo [46] made the purchase and closed it after five days, once that they trained the model with a 5-day forecast horizon. Nelson *et al.* [8] proposed

a model classified as upward or not an upward trend and only bought the stock. Although the transactions are intraday, the authors did not work on sold transactions. After 15 minutes, the algorithm ended the operation. Finally, the trading system developed by [61] bought or sold an asset at the close of the current day and discontinued the transaction at the close of the next day.

Regarding Day Trading (DT), Borovkova and Tsiamas [37] and Sim *et al.* [56] carried out buying and selling operations with 5 and 1-minute timeframes, respectively. With inputs and outputs based on the high and low classifications provided by the predictors. In turn, Wang *et al.* [10] and Alonso-Monsalve *et al.* [36] traded similarly, but with a hold class forecast, in addition to the buy and sell.

Finally, unlike previous works, Song *et al.* [57] and Song and Lee [58] made purchases and stipulated the asset appreciation and devaluation; thus, once the price reached the model predicted valuation, profit was made and vice versa.

3) ANALYSIS BASED ON PROFITABILITY METRICS

As it is a study focused on the stock market, it is crucial to analyse the metrics used to calculate profitability. A model with high precision and accuracy is not necessarily a profitable model.

The works usually show gross profit, regardless of operating costs and fees, as well as [8], [49], [57], [58], as it is the most trivial way to analyse and compare profitability between models. Song *et al.* [57] presented an exciting result, where one of the tested models obtained 81.6% accuracy, but its profitability was close to zero. If costs were taken into account, the model would report losses, despite the high accuracy. While Matsubara *et al.* [49] showed a test with accuracy above 60% but obtaining a loss of -22%.

Considering the costs, Fazeli and Houghten [40] presented the results using ROI, percentage of profit as a function of costs. While the publications by [46], [50], [51], [61] provided the net profitability, that is, the gross profit discounted the costs. Oncharoen and Vateekul [50] and Vargas *et al.* [61] obtained losses in some of their tests, despite the models reaching accuracy above 50% (69% and 51%, respectively).

Some works were not limited to presenting only accumulated profit, Sezer and Ozbayoglu [55] analysed the total annual transactions, percentage of success, average profit per operation, number of days positioned, average profit and loss per operation, and Sharpe ratio, in addition to considering costs. While Tan *et al.* [59] showed the average annual volatility, the maximum drawdown, annual Sharpe ratio, Sortino ratio, and Calmar ratio, but did not cost account.

Finally, Wang *et al.* [10] proposed a profitability metric called Weighted-F-Score, since the authors stated, and proved with experimental results, that the commonly used ML metrics, such as accuracy and F1 score, do not apply to financial market forecasting. Since different forecasting types, errors impact financial performance in different ways; therefore, different weights are applied for each type of error. It was also the only work analysed that took into account slippage, the difference between the desired price and the price executed in the trading.

4) ANALYSIS BASED ON RISK MANAGEMENT

Risk management is understood as techniques used to avoid a significant loss of capital (stop loss (ST) by operation or period) or techniques to maximize profit (take profit (TP) by operation or period). Only two publications presented these procedures in their studies.

Reference [49] adopted in their tests two different thresholds for TP and SL: 1% and 2%. Thus, according to the forecasting, the trading strategy executed the asset long or short at the trading session opening and concluded the transaction at the end of the same day. However, if the asset price were to increase or decrease by more than 1%, the TP or SL would be triggered. For the threshold of 2%, the logic is analogous.

In turn, Song and Lee [58] used an SL of -12%, TP of 24%, and maximum days positioned. For example, set up a maximum of days positioned equal to ten and if the asset has not reached the SL or TP within this period, the operation was closed.

III. DISCUSSIONS

From the analyses made in previous subsections and the information obtained through Table 5, it is possible to visualize the most used tools for this review, the research trend over the years, besides mentioning several possible gaps to be explored in future works.

Although this systematic research does not limit publication year, after carrying out the inclusion and exclusion criteria, the remaining articles date from 2017 to 2020, showing that studies involving DL with technical analysis for the stock market are relatively recent. There was an increase in the number of publications over the years, as shown in Figure 2.

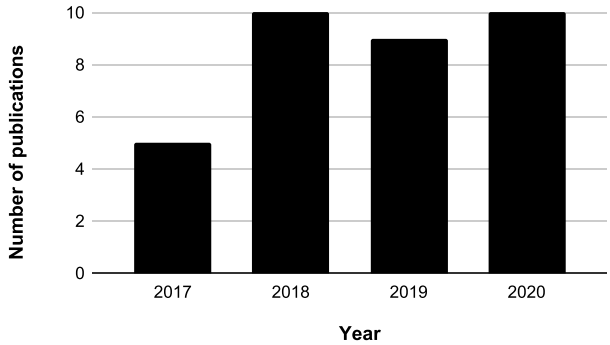

FIGURE 2. Number of publications per year.

Another interesting point to analyse is the DL technique used in each proposed model, thus answering the first question (**RQ1 - Which DL techniques are mostly used to forecast prices in the stock market?**). Most studies used the LSTM network, since it is an ideal algorithm for time series forecasting, as it can store memory and solve the gradient vanishing problem. The works that implemented only this technique were 17. However, if hybrid models are considered,

which all have this recurrent network, eight articles should be added, totaling 25 works and representing 73.5% of the analysed publications. Figure 3 illustrates the DL techniques used.

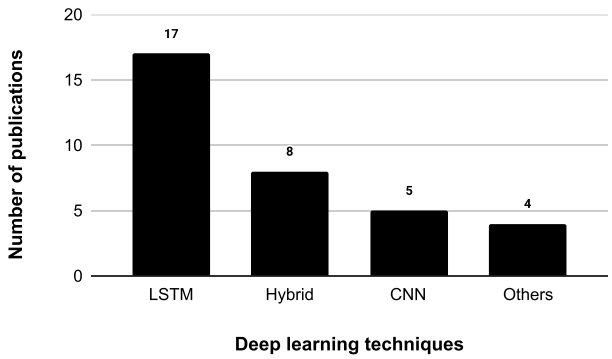

FIGURE 3. Deep Learning techniques used in each proposed model.

Regarding the works that mention which tools were used to develop the predictor based on historical price data, they all did programming in Python[3] and Tensorflow.[4] Other tools also widely used were NumPy,[5] Pandas,[6] Scikit-Learn,[7] Keras,[8] TA-Lib,[9] and TA4J[10]; the last two being libraries to generate TIs.

Answering the second question (**RQ2 - Which markets and timeframes are most used for price prediction?**), there is a wide variety of assets from the North American, Indian, Chinese, Brazilian, Korean, European, Taiwanese, German, Belgian, Moroccan, and cryptocurrency markets. This probably occurs due to prior knowledge of each author local market; also, for implementation in a real environment and trading assets from another country, it is usually necessary to open an account in that country, making the process bureaucratic and costly.

Table 6 shows a variety of datasets used to collect historical stock prices. However, most authors choose Yahoo Finance due to the ease of acquiring data using a library developed in Python, yahoo-finance.[11]

In addition, publications that used news data for hybrid algorithms with sentiment analysis collected information from Reuters, Bloomberg, FiNet,[12] Google News, Sina Weibo,[13] Twitter, Tiingo,[14] Kaggle,[15] Epoch Times,[16] and Nihon Keizai Shimbun newspaper.[17]

TABLE 6. Database used by the articles.

Database	Total	Articles
Yahoo Finance[18]	11	[34], [40], [41], [46], [50]–[52], [55], [60], [61], [64]
Wind[19]	2	[59], [65]
Taiwan Stock Exchange Corporation (TWSE)[20]	2	[45], [46]
UC Irvine Machine Learning Repository[21]	1	[53]
Epex Spot[22]	1	[39]
KesciLab[23]	1	[56]
RESSET[24]	1	[63]
Collected from online brokers	1	[10]
Money Control[25]	1	[42]

Regarding the timeframe, those who used daily data add up to 23 works, while the other 11 chose DT with varying graphic times, as can be seen in Figure 4. Most works in the literature use daily data, as this information is easily and freely obtained from finance sites, such as Yahoo Finance. However, this page does not offer the option to import intraday data.

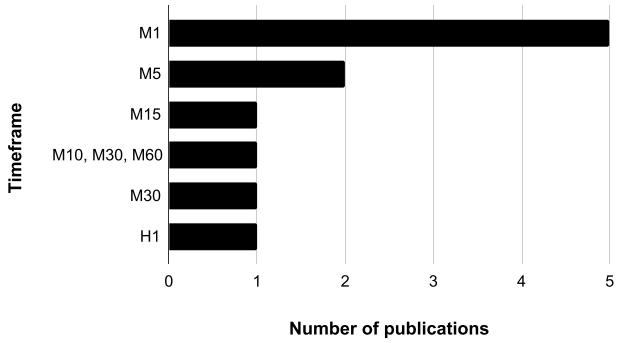

FIGURE 4. Timeframes used in each work.

The advantage of adopting DT is the large volume of data available for training the network, as previously mentioned. Furthermore, it is also possible to make a performance analysis and measuring the model accuracy degradation since a large amount of data make it possible to apply a larger number of sliding windows for testing and validation. Also, for high volatility assets, it is possible to develop an algotrading to

[3] https://www.python.org
[4] https://www.tensorflow.org
[5] https://numpy.org
[6] https://pandas.pydata.org
[7] https://scikit-learn.org
[8] https://keras.io
[9] https://ta-lib.org
[10] https://github.com/ta4j/ta4j
[11] https://pypi.org/project/yahoo-finance
[12] https://www.finet.net/news
[13] http://weibo.com
[14] https://api.tiingo.com
[15] https://www.kaggle.com/aaron7sun/stocknews
[16] https://www.epochtimes.com/b5/nsc420.htm
[17] https://www.japantimes.co.jp/tag/nihon-keizai-shimbun
[18] https://finance.yahoo.com
[19] https://www.wind.com.cn/en/wft.html
[20] http://www.twse.com.tw/zh
[21] https://archive.ics.uci.edu/ml/index.php
[22] https://www.epexspot.com/en
[23] https://www.kesci.com/home/dataset/5bbdc2513631bc00109c29a4/files
[24] http://www.resset.cn/endatabases
[25] https://www.moneycontrol.com

generate profitability by exploiting this market characteristic. Moreover, as operations are started and closed in a shorter period, capital will be less exposed, since assets are sensitive to micro and macroeconomic behaviors, news, and other factors capable of strongly moving the asset price and resulting in losses.

Figure 5 illustrates the number of studies using performance metrics, profitability, trading strategy, risk management, and application in the real environment. It is possible to see that metrics like accuracy, precision, recall, and F1-score are the most used to compare models, thus answering the third question (**RQ3 - What are the metrics used to validate the performance of the proposed model?**).

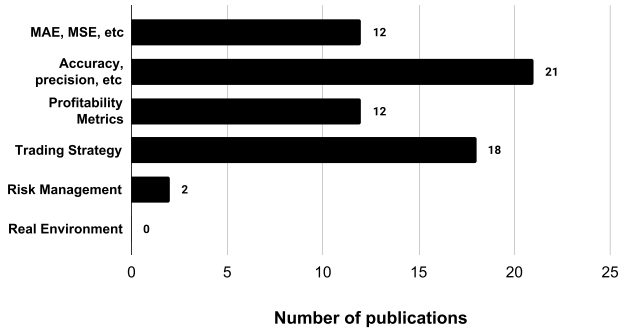

FIGURE 5. Number of studies using performance metrics, profitability, trading strategy, risk management and application in the real environment.

However, these results cannot be analysed in isolation, since the model is used for financial time series, it is essential also to analyse the profitability obtained. Works such as [49], [50], [57], [61] corroborate this statement, showing that it is possible to create a model with high accuracy, but reporting losses.

Answering the fourth question (**RQ4 - The works using automated trading systems, which the methods employed?**), the strategies used for trading are mostly quite simple and can be:

- The trading system does long operation based on the forecasting and holds until forecasting change to short;
- System buys and maintains the operation for a specific time;
- In addition to the long strategy, the system can operate short and make a purchase later to effectuate the profit or loss.

Regarding the 18 works that implemented a trading system, none used artificial intelligence-based approaches, making a decision based on the predictive model estimation, nor do they use techniques commonly used by market analysts, such as break-even, trailing stop, and dynamic leverage.

For a unitary forecast horizon, simple strategies can be used, but increasing the horizon requires more sophisticated techniques due to some assets high volatility. Another disadvantage of a naive strategy is many operations, resulting in higher costs and reduced profitability.

Finally, answering the fifth question (**RQ5 - What are the metrics used for profitability evaluation?**), the most used profitability metric is accumulated profit, which can be presented as gross or net value, after deducting costs. Only 12 articles (35.3%) presented this result showing that the concern of [5], [6], [19] is still valid since the articles analysed comprise from 2017 to 2020 and most do not address this vital metric.

Among these 12 publications, only two works used risk management, which used a threshold for both asset valuation or devaluation. It is crucial to use this type of technique since the data in a financial series show noisy and chaotic behaviors, which can go beyond the limit of loss and cause severe property damage.

Although the 34 studies analysed the accuracy, error, or profitability, none implemented the proposed model in a real environment. It was a significant phase to validate if the model would be applicable in the stock market. The application using a real trading platform is essential because the market is formed by intraday candles, so dynamic and sensitive to macroeconomic data and news, generating high volatility throughout the day. Without a system to protect capital and without carrying out exhaustive tests, doubts may arise regarding the model efficiency and, mainly, the profitability.

Regarding the gaps and future work proposed by the articles explored, the most cited are related to implementing an algotrading with trading strategy [8], [36], [38], [43], [53], [58], [60]–[62]. It shows that the authors realize the importance of model validation through a simulated or real environment. Alonso-Monsalve *et al.* [36] and Vargas *et al.* [60] also consider the cost calculation to be an essential factor for the final result of the system profitability. As previously mentioned, works that use qualitative data, such as news, have gained prominence for financial market forecasting and are proposed as future works in [38], [40], [48], [62]. Another proposal presented was implementing other markets to test the model generalization [34], [43], [55], [58]. Finally, it is possible to note that there is no consensus on which and how many TIs should be used since some propose to reduce the dimensionality [53], [58] and others propose to vary and increase the TIs quantity [34], [36], [39].

IV. CONCLUSION

This article aimed to review the academic literature on financial time series forecasting using DL and technical analysis. Using a research methodology was possible to select 34 articles for this study. Thus, analysis and discussions were made based on four main points of view: predictor techniques, trading strategies, profitability metrics, and risk management.

It was noted the extensive use of the recurrent neural network LSTM due to memory storage capacity and the ability to solve the vanishing gradient problem. Some hybrid models used LSTM to treat technical indicators and other techniques to deal with news, presenting more robust results, and potential future research.

Regarding the trading strategy, a little more than half of the articles used it; meanwhile, using simple logic. It is essential to use more sophisticated strategies for more extended horizon forecasts due to some assets volatility.

This study significant contribution was to show that a small portion of articles (35.3%) assessed the profitability and only two addressed risk management. Despite that, several authors cited the importance of these steps for model validation. Also, some analysed publications have obtained losses even with the model performance above 50%.

Therefore, some literature gaps allow research in future works, such as hybrid models with qualitative and quantitative input data, an intelligent and adaptive trading strategy, metrics with a positive correlation between performance and profitability, implementation of risk management, and others.

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AUDELIANO WOLIAN LI was born in São Paulo, Brazil, in December 1987. He received the B.S. degree in control and automation engineering and the M.S. degree in computer science and technology from the Federal University of Itajubá, Brazil, in 2014 and 2016, respectively, where he is currently pursuing the Ph.D. degree in electrical engineering. His research interests include machine learning, deep learning, financial market, financial time series forecasting, data science, and autonomous robotics.

GUILHERME SOUSA BASTOS (Member, IEEE) was born in Volta Redonda, Brazil, in December 1977. He received the M.Sc. degree in electrical engineering from the Federal University of Itajubá (UNIFEI), Itajubá, Brazil, in 2004, and the D.Sc. degree in electronic and computer engineering from the Aeronautics Institute of Technology (ITA), São José dos Campos, Brazil. He is currently an Associate Professor with UNIFEI. He has authored over 70 journal articles, book chapters, and conference papers. His research interests include machine learning, autonomous robotics, power systems, and technology for autism spectrum disorder.