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Stock Market Prediction Using Deep Learning

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ABSTRACT :*"Addressing Stock Market Forecasting Challenges through Deep Learning: A Systematic Review" In the financial market, predicting stock market movements poses a formidable challenge due to the complex, noisy, and dynamic nature of its time series data. However, with advancements in computing power, intelligent models offer a promising avenue for investors and analysts to mitigate investment risks. Deep Learning models have garnered significant attention in recent years, with numerous studies exploring their efficacy in forecasting stock prices using historical data and technical indicators. Yet, to ensure reliability, it's crucial to validate these models using profitability metrics and performance evaluations tailored to financial markets. This systematic review delves into Deep Learning applications for stock market forecasting, emphasizing technical analysis methodologies. The discussion encompasses predictor techniques, trading strategies, profitability metrics, and risk management approaches. Notably, the review highlights the prevalence of LSTM techniques in this domain (73.5%). However, it also underscores gaps in current literature, such as limited analysis of profitability (35.3% of studies) and sparse implementation of risk management strategies (only two articles). Despite the extensive exploration of this topic, the review underscores the need for further research and development to address these shortcomings and foster advancements in stock market forecasting.*

INDEXTERMS :*Neural networks, financial performance measures, risk mitigation, predicting market trends, comprehensive evaluation, market analysis methods, market indicators.*

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I. INTRODUCTION

Forecasting stock market asset prices is an intricate challenge due to the multifaceted influences shaping price dynamics, encompassing micro and macroeconomic factors like political events, news cycles, and corporate financial performance. These variables contribute to the market's nonlinear and non-stationary nature, complicating prediction endeavours.

Market analysis endeavours to decipher these influences to anticipate future market trends, aiding decision-making processes. Fundamental Analysis (FA) and Technical Analysis (TA) represent two primary methodologies employed for this purpose. While FA delves into companyspecific data to assess long-term growth potential, TA focuses on market price data, assuming that all pertinent information is already reflected in asset prices. Technical analysts rely on a plethora of tools, including Technical Indicators (TI) and candlestick pattern analysis, to forecast price movements. However, the modeling approaches diverge, with TI-centric studies often adopting regression techniques, while candlestick pattern analyses may employ image processing techniques.

Despite advancements in computational intelligence, challenges persist in identifying the most effective TI sets for accurate forecasting. While statistical methods have traditionally been utilized, they often fall short compared to Artificial Intelligence (AI)-based approaches due to their linear assumptions, inadequately capturing the complexities of financial time series data.

Among AI techniques, Artificial Neural Networks (ANNs), particularly Deep Learning (DL) models, have demonstrated remarkable potential, outperforming traditional statistical methods in many instances. DL's ability to handle large datasets makes it particularly suitable for intraday trading scenarios, where data volumes are substantial.

The dominance of ANNs in financial forecasting underscores their superior generalization capabilities compared to other machine learning approaches. Moreover, recent advancements in sentiment analysis, driven by Natural Language Processing (NLP) technologies, have further enhanced forecasting accuracy by incorporating news sentiment alongside historical price data.

However, despite these advancements, many studies overlook crucial aspects such as trading strategies and profitability evaluation, leading to inconsistent models. Addressing these gaps is crucial for advancing financial forecasting methodologies and ensuring their long-term viability.

This systematic review aims to synthesize existing literature on DL techniques for stock market price forecasting, emphasizing the importance of accuracy and profitability metrics alongside the adoption of robust trading strategies.. 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 andexploredpublicationsfrom2016to2019,thatis,acontinuatio n 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 behaviour, and TIs. The work focus was to present and analyse the techniques used, including the performance criteria and platforms adopted.

II. RESEARCH METHODOLOGY

Kitchenham and Charters [29] provided a comprehensive framework for conducting systematic reviews, highlighting the importance of identifying, evaluating, and discussing relevant literature to address research inquiries effectively. They emphasized the necessity for a thorough and unbiased review process, underscoring the scientific rigor required for meaningful outcomes.Systematic reviews offer several advantages, including the ability to produce less biased findings through meticulous methodology. In quantitative studies, meta-analytic techniques allow for the synthesis of data from multiple sources, enhancing the likelihood of uncovering novel insights .Given the importance of these advantages, the criteria employed in this review are justified, ensuring a robust methodology. The systematic review process involves three key stages, as outlined by Kitchenham and Charters [29]: planning, conducting, and analysing results. To ensure the integrity of the review process, strict criteria are established, guided by a predefined research protocol. These criteria serve as the foundation for selecting the primary publications to be included in the review, facilitating a systematic and objective approach to literature evaluation.Following the guidelines provided by Kitchenham and Charters [29], meticulous planning is essential to define the scope of the review, establish inclusion and exclusion criteria, and develop a structured search strategy. The execution phase involves systematically identifying relevant studies, extracting pertinent data, and synthesizing findings. Finally, the analysis phase entails evaluating the collected data, identifying patterns or trends, and drawing meaningful conclusions. By adhering to this systematic approach, this review aims to provide a comprehensive and unbiased analysis of the literature, contributing to the advancement of knowledge in the field.

A. *PLANNING THE REVIEW*

Hence, the initial phase necessitates formulating key inquiries to be addressed upon completion of the systematic review, along with establishing criteria for inclusion, exclusion, and quality assessment. These predefined inquiries are delineated in Table 1 for reference.

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 predict-ion?
RQ3	What are the metrics used to validate the performance of the pro-posed 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 next phase involves retrieving pertinent literature for the systematic review and applying the established criteria to select appropriate works.

To accomplish this, the Scopus platform was employed for its esteemed reputation in academia [30], while the Web of Science (WoS) database was incorporated to complement Scopus, given its longstanding presence [31]. Additionally, the IEEE Xplore database was consulted, particularly valued within the engineering domain. Search terms such as "Stock Market," "Deep Learning," "Forecasting," and "Technical Analysis" were utilized as keywords to ensure comprehensive coverage of relevant articles. Variations of these terms were also considered to maximize article retrieval. Thus, the search query employed 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”)).*

Regarding Scopus, each search query was configured to target the specified terms exclusively within document keywords, abstracts, and titles. Furthermore, to refine data collection, filters such as "articles," "conferences," and "reviews" were applied. Conversely, limitations were not imposed on other databases due to the comparatively lower volume of publications available. The search for publications on each platform was conducted on May 3, 2020, yielding a total of 111 articles. Remarkably, Scopus yielded a substantial number of documents compared to WoS and IEEE Xplore, with 82, 18, and 11 articles, respectively .Utilizing the Start software, a dedicated tool designed for systematic reviews inspired by the methodology proposed by [32], duplicate publications were meticulously identified and removed, resulting in 84 unique articles. Following a thorough review of abstracts and relevant sections, inclusion and exclusion criteria were applied, leading to the identification of 46 eligible documents .From the pool of 46 studies, only those published in English and accessible via the Capes Portal for periodicals were retained, amounting to 37 publications. Subsequently, each remaining article underwent a comprehensive review, with particular attention to adherence to quality criteria. Additionally, works authored by the same individuals and deemed continuations of previous studies were treated as singular entities. Consequently, three publications were excluded, leaving 34 articles for further analysis. Upon a comprehensive examination of the selected publications, Table 5 was populated with essential details for each work, including market context, study period, utilized timeframe, attributes employed for model training/testing, predictor names, and the specific deep learning techniques utilized, as per the methodology depicted in Figure 1 [33].

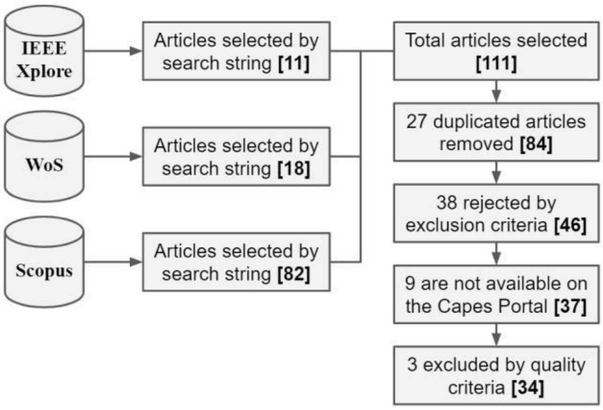


FIGURE 1. Number of articles separated during the conducting stage.

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 process initiated with Scopus, where each search query was meticulously configured to exclusively target the predefined terms within document keywords, abstracts, and titles. Additionally, filters were applied to refine data collection, specifically focusing on "articles," "conferences," and "reviews" to ensure the retrieval of relevant scholarly works. Conversely, other databases were not subjected to such limitations due to the relatively lower volume of publications available.

On May 3, 2020, the search for publications across each platform commenced, resulting in a total of 111 articles. Notably, Scopus emerged as the primary source, yielding a substantial number of documents compared to WoS and IEEE Xplore, with 82, 18, and 11 articles, respectively.

Leveraging the Start software, a specialized tool tailored for systematic reviews, inspired by the methodology outlined by [32], the process of identifying and eliminating duplicate publications was conducted with precision. This meticulous approach resulted in the identification and removal of redundant articles, ultimately yielding 84 unique documents for further analysis.

Subsequently, each retrieved article underwent a thorough review, with a focus on abstracts and other pertinent sections, as necessary, to assess their relevance against the predefined inclusion and exclusion criteria. This critical appraisal process facilitated the identification of 46 eligible documents that met the established criteria.

From the pool of 46 studies, only those published in English and accessible via the Capes Portal for periodicals were retained, aligning with the requirements for language and accessibility. This selective process resulted in a subset of 37 publications deemed suitable for further scrutiny.

Upon completing the initial screening phase, each remaining article underwent a comprehensive review, with particular attention given to adherence to quality criteria. Additionally, works authored by the same individuals and identified as continuations of previous studies were treated as singular entities to maintain consistency and avoid duplication of findings. Consequently, three publications were excluded from the analysis, leaving 34 articles for further examination.

With the selected publications identified, the subsequent phase involved conducting a detailed examination of each article to extract essential information relevant to the systematic review. This comprehensive data collection process aimed to capture key details such as market context, study period, utilized timeframe, attributes employed for model training/testing, predictor names, and the specific deep learning techniques utilized.

The extracted information was meticulously compiled and organized into Table 5, facilitating a structured overview of the relevant characteristics of each included publication. This comprehensive dataset served as a valuable resource for subsequent analysis and synthesis of findings.

Overall, the systematic approach adopted in this review ensured a rigorous and transparent process for selecting and analyzing relevant literature. By adhering to predefined criteria and employing specialized tools for data management and analysis, this review aimed to provide a comprehensive and insightful analysis of the current state of research in the field of stock market forecasting using deep learning techniques.

In conclusion, the systematic review process outlined above exemplifies a rigorous and methodical approach to identifying, selecting, and analyzing relevant literature in the field of stock market forecasting. By leveraging established methodologies and specialized tools, this review aimed to **TABLE 5.** Analysed articles.
provide valuable insights into the application of deep learning techniques in predicting stock market trends. Through meticulous data collection, analysis, and synthesis, this review sought to contribute to the advancement of knowledge in this important area of research.Reference [45] used OHLCV information to generate 4 TIs and feed the input of an ARIMA model, then the

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

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)	—	—

In contrast, Wen et al. [63] introduced the PCA-LSTM model, integrating Principal Component Analysis (PCA) to extract technical indicator (TI) characteristics and reduce dimensionality. This approach resulted in enhanced predictive performance compared to conventional models.

On a similar note, Tan et al. [59] employed an elastic net model for dimensionality reduction coupled with LSTM as a predictor. They further integrated the Sharpe-Optimized method to balance investment strategy risk-return, yielding significantly improved financial accumulation compared to linear models and outperforming traditional machine learning (ML) models.

Nelson et al. [8], while utilizing similar predictors as other studies, notably generated a multitude of indicators and normalized them using the log-return transform. Despite achieving an accuracy slightly above 50%, this approach effectively mitigated maximum drawdown across various assets.

Studies incorporating textual data, such as news, demonstrated promising results. For instance, [48], [49], [62], [64] utilized predictors based on LSTM, autoencoders, deep belief network (DBN), and AM, respectively, preprocessing textual data through sentiment analysis techniques before concatenating it with price and TI data.

Numerous researchers have explored hybrid forecasting models, integrating LSTM or recurrent neural network (RNN) layers with convolutional neural network (CNN) layers. In [46], [50], [51], [60], [61], CNNs were employed to capture textual data patterns from sources like news channels and social networks, yielding superior results compared to LSTM-only networks.

Of particular note is the work of Oncharoen and Vateekul [51], which proposed altering the loss function by incorporating Sharpe ratio information during training. They introduced a metric, the Sharpe-F1 score, based on Sharpe ratio and F1 score, to select optimal models based on risk considerations.

Alonso-Monsalve et al. [36] employed CNN layers to extract patterns from a set of 18 TIs and OHLCV data from six cryptocurrencies, subsequently utilizing LSTM layers for trend generation. Similarly, Kelotra and Pandey [42] introduced an optimization algorithm, Rider-based Monarch Butterfly Optimization, to train a predictor based on Convolutional LSTM Network (ConvLSTM), tailored for sequential image data. Additionally, Zhou et al. [65] utilized a network architecture comprising LSTM layers coupled with CNN layers for market direction forecasting, implementing the Generative Adversarial Network (GAN) technique in the training process.

2) ANALYSIS BASED ON TRADING STRATEGIES

A trading strategy encompasses the logic guiding asset buying or selling decisions, often based on forecasting signals. Many studies employ a straightforward rule: upon a buy signal, the algorithm executes a purchase and awaits a sell signal to realize profit or loss. This approach is evident in works by [34], [40], [41], and [55].

Some authors extend their strategies to include a neutral or hold class, in addition to buy and sell classes. This entails refraining from action when the system is not positioned and maintaining a long transaction upon a neutral signal until a sell signal emerges. Notable examples include works by [47], [51], and [59].

In line with model forecasting, certain studies implement long or short strategies, concluding operations after a specified period. For instance, Matsubara et al. [49] and Oncharoen and Vateekul [50] opt to buy or sell assets at the trading session opening and close operations by day end. Lee and Soo [46] adopt a five-day holding period, while Nelson et al. [8] classify models as upward or not and exclusively buy stocks, ending transactions after 15 minutes. Additionally, the trading system developed by [61] executes transactions at the close of the current day and discontinues them by the next day's close.

In the realm of Day Trading (DT), Borovkova and Tsiamas [37], Sim et al. [56], Wang et al. [10], and Alonso-Monsalve et al. [36] engage in buying and selling operations, with varying timeframes. Borovkova and Tsiamas [37] and Sim et al. [56] operate with 5-minute and 1-minute intervals, respectively, based on high and low classifications. Wang et al. [10] and Alonso-Monsalve et al. [36] follow a similar approach but incorporate a hold class forecast alongside buy and sell signals.

In contrast to conventional approaches, Song et al. [57] and Song and Lee [58] base purchases on predicted asset appreciation or devaluation, exiting positions upon reaching the predicted valuation.

Analyzing profitability metrics is crucial in stock market studies. While accuracy is essential, a model's profitability is paramount. Several works present gross profit without considering operating costs and fees, as seen in [8], [49], [57], and [58]. However, this simplistic approach may not accurately reflect profitability, as demonstrated by Song et al. [57], whose highly accurate model yielded minimal profits or even losses when accounting for costs.

Some studies incorporate costs into profitability metrics, such as ROI (Return on Investment) in Fazeli and Houghten [40], and net profitability in works by [46], [50], [51], and [61]. Despite achieving accuracy above 50%, Oncharoen and Vateekul [50] and Vargas et al. [61] reported losses in certain tests.

Additionally, Sezer and Ozbayoglu [55] and Tan et al. [59] delve deeper into profitability analysis, considering factors like success percentage, average profit per operation, and Sharpe ratio. Notably, Wang et al. [10] introduce the Weighted-F-Score metric, accounting for different error types' impact on financial performance.

Risk management techniques are crucial for capital preservation and profit maximization. Only a few studies, such as [49] and [58], incorporate stop loss (SL) and take profit (TP) thresholds into their strategies. Matsubara et al. [49] utilize different SL and TP thresholds to safeguard against significant losses or capitalize on gains, while Song and Lee [58] employ SL and TP alongside a maximum days positioned parameter to manage risk.

3) ANALYSIS BASED ON PROFITABILITY METRICS

In a stock market-focused study, assessing profitability metrics is pivotal. High precision and accuracy in a model do not guarantee profitability. Typically, studies display gross profit without factoring in operational costs and fees, as seen in [8], [49], [57], [58], representing the most straightforward method of analyzing and comparing profitability across models. Notably, Song et al. [57] demonstrated a model with 81.6% accuracy but negligible profitability, implying potential losses when costs are considered. Similarly, Matsubara et al. [49] achieved accuracy above 60% but incurred a loss of -22%.

Accounting for costs, Fazeli and Houghten [40] utilized ROI to depict profits relative to expenses. On the other hand, works by [46], [50], [51], [61] focused on net profitability, deducting costs from gross profit. Despite achieving accuracy above 50%, Oncharoen and Vateekul [50] and Vargas et al. [61] experienced losses in some tests.

Some studies extended beyond presenting accumulated profit alone. Sezer and Ozbayoglu [55] analyzed various metrics including total annual transactions, success percentage, average profit and loss per operation, and Sharpe ratio, while also considering costs. Conversely, Tan et al. [59] delved into metrics like average annual volatility, maximum drawdown, annual Sharpe ratio, Sortino ratio, and Calmar ratio, without factoring in costs.

Furthermore, Wang et al. [10] introduced the Weighted-FScore metric, acknowledging that conventional ML metrics like accuracy and F1 score may not be applicable to financial forecasting. Different forecasting errors impact financial performance differently, thus requiring distinct weights for each error type. Notably, Wang et al. [10] also accounted for slippage, the disparity between the desired and executed trading prices, distinguishing it as the sole work to address this factor.

4) ANALYSIS BASED ON RISK MANAGEMENT

Risk management encompasses strategies employed to mitigate significant capital loss (via stop loss (ST) per operation or period) and optimize profit (via take profit (TP) per operation or period). However, only a few studies have integrated these methods into their analyses.

For instance, in their research, Reference [49] applied two distinct thresholds for TP and SL: 1% and 2%. Accordingly, based on the forecast, their trading strategy initiated long or short positions at the start of the trading session, closing them by day's end. However, if the asset's price deviated by more than 1%, triggering TP or SL, the position was terminated. A similar logic applied to the 2% threshold.

On the other hand, Song and Lee [58] implemented an SL of -12% and a TP of 24%, alongside a maximum number of days in position. For example, if an asset did not reach the SL or TP within the specified timeframe (e.g., ten days), the position was automatically closed.

III. DISCUSSIONS

Based on the assessments conducted in earlier sections and the data gathered from Table 5, we can discern the prevalent methodologies employed in this review, track the research trajectory over time, and pinpoint potential areas for future investigation.

While this systematic inquiry does not impose constraints on the publication year, the articles retained after applying the inclusion and exclusion criteria span from 2017 to 2020. This timeframe underscores the relatively recent emergence of studies integrating deep learning with technical analysis for stock market analysis. Notably, there has been a discernible uptick in the volume of publications over the years, as illustrated in Figure 2.

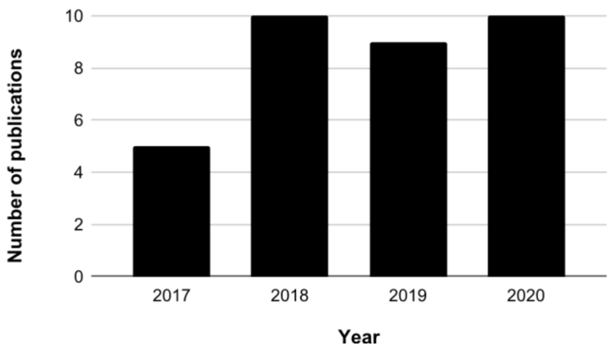


FIGURE 2. Number of publications per year.

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.

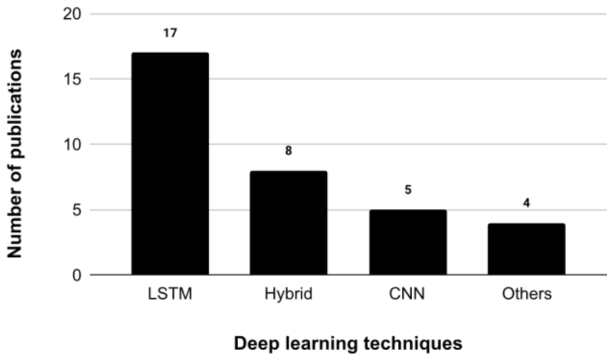


FIGURE 3. Deep Learning techniques used in each proposed model.

In addressing the inquiry about the tools employed in developing predictors based on historical price data, it was evident that Python and TensorFlow were universally favoured across the examined works. Complementing these, commonly utilized tools included NumPy, Pandas, ScikitLearn, Keres, TA-Lib, and TA4J, with the latter two serving as libraries specifically tailored for generating technical indicators.

In response to the second question regarding the prevalent markets and timeframes for price prediction (RQ2), a diverse array of assets spanning North American, Indian, Chinese, Brazilian, Korean, European, Taiwanese, German, Belgian, Moroccan, and cryptocurrency markets were identified. This diverse selection likely reflects authors' familiarity with their respective local markets and the practicalities involved in trading assets from different regions, which often necessitates opening accounts in foreign countries, a process typically beset by bureaucratic hurdles and associated costs.

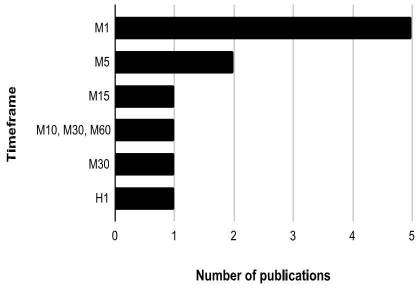
Table 6 provides insights into the datasets utilized for collecting historical stock prices, revealing Yahoo Finance as a popular choice due to the convenience offered by the yahoo-finance library in Python for data acquisition. Moreover, publications leveraging news data for hybrid algorithms with sentiment analysis predominantly sourced information from reputable sources such as Reuters, Bloomberg, FiNet, Google News, and Sina.

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]

Across the analysed studies, data from platforms like Weibo, Twitter, Tiingo, Kaggle, Epoch Times, and the Nihon Keizai Shimbun newspaper were utilized for various purposes, including sentiment analysis and news aggregation.

Regarding the timeframe, a majority of works, totalling 23, opted for daily data, while the remaining 11 selected intraday intervals for their analyses. The preference for daily data stems from its widespread availability and accessibility via financial websites like Yahoo Finance. However, the absence of intraday data import options on such platforms poses a challenge for researchers seeking finer granularity in their analyses.



FIGURETimeframes used in each

The utilization of DT offers several advantages, as highlighted previously. Firstly, it provides access to a vast dataset for training the network, facilitating comprehensive model development. Additionally, DT enables thorough performance analysis, allowing for the assessment of model accuracy degradation through the application of numerous sliding windows for testing and validation. Furthermore, for assets exhibiting high volatility, DT allows for the implementation of algo-trading strategies to capitalize on market fluctuations, thus enhancing profitability. Moreover, the shorter duration of operations inherent to DT reduces capital exposure, mitigating risks associated with sudden market shifts influenced by micro and macroeconomic factors, news events, and other variables impacting asset prices.Figure 5 provides a visual representation of the distribution of studies across various performance metrics, including accuracy, precision, recall, and F1-score. These metrics are commonly utilized for comparing models, addressing the third question posed in the analysis. **(RQ3 - What are the metrics used to validate the performance of the proposed model?)**.

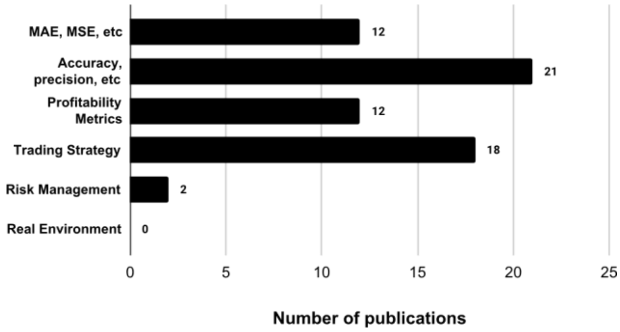


FIGURE 5. Number of studies using performance metrics, profitability, trading strategy, risk management and application in the real environment.

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.

None of the 18 studies that incorporated a trading system relied on artificial intelligence for decision-making based on predictive model estimates. Instead, they refrained from employing common market analyst techniques like breakeven, trailing stop, and dynamic leverage. While simple strategies suffice for a singular forecast horizon, extending it necessitates more sophisticated methods due to the heightened volatility of certain assets. Furthermore, employing a naive strategy leads to numerous operations, which escalates costs and diminishes profitability.

In response to the fifth question (RQ5 - What are the metrics used for profitability evaluation?), it is evident that the most prevalent metric for assessing profitability is accumulated profit, either presented as gross or net value after accounting for costs. Surprisingly, only 12 out of the 34 articles (35.3%) provided this crucial metric, indicating a persisting gap highlighted by prior studies [5],[6],[19]. This observation holds significance given that the analyzed articles span from 2017 to 2020, yet the majority overlook this vital aspect.

Among the subset of publications that did address profitability, merely two incorporated risk management techniques, employing thresholds for asset valuation or devaluation. Such techniques are imperative due to the inherent noise and chaotic nature of financial data, which can potentially lead to substantial losses beyond predefined limits.

Despite the focus on accuracy, error, or profitability metrics across the analyzed studies, none ventured to implement their proposed models in a real-world trading environment. This crucial step is essential for validating the model's applicability in the stock market, particularly given the market's intraday candle formation, sensitivity to macroeconomic factors and news, and resulting high volatility throughout the day. Without subjecting the model to real-world conditions and rigorous testing, doubts persist regarding its efficacy and, more importantly, its potential profitability.

Exploring the gaps and future directions proposed by the reviewed articles reveals recurring themes. Several studies emphasize the importance of implementing algorithmic trading with defined trading strategies, underscoring the need for model validation through simulated or real environments. Additionally, considerations for cost calculations are highlighted as critical for assessing the final profitability of the system, as evidenced by works such as Alonso-Monsalve et al. [36] and Vargas et al. [60].

IV. CONCLUSION

This study aimed to conduct a comprehensive review of academic literature focusing on financial time series forecasting, specifically utilizing Deep Learning (DL) in conjunction with technical analysis. Employing a rigorous research methodology, 34 articles were selected for analysis, enabling a thorough examination and discussion across four key perspectives: predictor techniques, trading strategies, profitability metrics, and risk management.

The prevalence of the Long Short-Term Memory (LSTM) recurrent neural network emerged prominently, attributed to its superior memory storage capabilities and effectiveness in mitigating the vanishing gradient problem. Notably, hybrid models integrating LSTM for processing technical indicators alongside other methodologies for handling news data showcased enhanced robustness and potential avenues for future research.

In terms of trading strategies, it was observed that slightly over half of the articles addressed this aspect, albeit predominantly employing simplistic approaches. However, the necessity for adopting more sophisticated strategies, particularly for longer-term forecasts, was underscored due to the heightened volatility exhibited by certain assets.

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