International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

A Systematic Review of Recent Advances on Stock Markets Predictions Using Deep Learning Approach

Visakh Chandran Melveetil[1]*, Saumendra Mohanty[2]

Submitted: 17/01/2024 **Revised**: 25/02/2024 **Accepted**: 03/03/2024

***Abstract*:** The landscape of stock market prediction is undergoing a profound transformation driven by technological advancements and data-driven methodologies. Within this shifting paradigm, artificial intelligence (AI), particularly deep learning (DL), is emerging as a transformative tool to enhance predictive accuracy. This systematic literature review explores recent trends in the integration of AI, specifically DL, in stock market prediction, with a focus on the use of DL models for time series data analysis, sentiment data, and news data. The review aimed to investigate the effectiveness of DL-based models for stock market prediction using time series data, sentiment analysis, and news data, while also exploring their role in mitigating the impact of fake news and news sentiment. This paper systematically assessed 3,621 articles from 2019 to 2023, with rigorous selection criteria. The final dataset synthesis included 48 articles. The findings revealed that DL models have proven to be effective in predicting stock price based on time series data when used along with sentiment and news. Further, it is also evident that the use of DL models in mitigating the influence of fake news and news sentiment on market behavior contributes to enhanced predictive accuracy. The review concludes by identifying research gaps and outlining future directions to advance the field of stock market prediction. Future research endeavors in the stock market prediction field should prioritize the use of Transformer-based models for time series data, BERT models, and lightweight language models for sentiment analysis and fake news detection integration. The use of optimization algorithms in hyperparameter tuning can further improve prediction accuracy and reduce computational complexities. This review offers valuable insights not only for advanced stock prediction but also for financial market researchers, investors, and analysts in the context of advanced stock prediction

Keywords: *Stock Market Prediction, Deep Learning (DL), Sentiment Analysis, Fake News Detection, Artificial Intelligence (AI)*

1. Introduction

India has emerged as one of the world's fastest-expanding markets, with two leading stock exchanges: the Bombay Stock Exchange (BSE) & the National Stock Exchange (NSE). The NSE is India's largest stock exchange, having a market capitalization of more than $3.7 Trillion USD as of March 2023. The stock market provided a forum for investors to purchase firm shares to increase their returns. As a result, understanding and forecasting stock prices remain critical factors for reducing the uncertainties and risks associated with stock investment. Stock markets have a crucial role in the global economy. Hence, Stock market prediction (SMP) has inspired the attention of researchers because of its potential advantages for both investors and the broader economies - impacting companies, individuals, and economies alike. According to Liu et al. (2022), stock price forecasting provides investors with various benefits, including making informed investment decisions, optimizing portfolios, efficiently managing risks, and improving financial planning.

[1]*Research Scholar, Doctor of Philosophy (PhD), Business Analytics, IIC University of Technology, Combodia. Email: visakhc@gmail.com* (Corresponding Author)*

[2]*Adjunct Research Supervisor, Directorate of Research, LIUTEBM University,Lusaka,Zambia.*

The Efficient Market Hypothesis (EMH), a primary concept in this field, posits that financial markets are efficient in disseminating information **(Monge, 2022).** According to EMH, publicly available information is quickly and precisely integrated into stock prices, making it extremely difficult to outperform. However, recent studies show that this is no longer the case.

The inherent volatility of the stock market is shaped by a multitude of internal and external factors, including (but not limited to) economic conditions, industry prospects, company performance, sectorial performance, etc. Regarding SMP, traditional analysis methods utilize fundamental and technical approaches to study this complex behavior. However, it's vitally important to note that these methods have limitations, mainly due to their inability to effectively capture the ever-evolving dynamics of modern financial markets.

In the domain of stock price prediction, recent years have witnessed the emergence of three key strategies.

- Technical Analysis: This approach uses historical information about the stock and correlates with inherent market trends to make the prediction. It relies heavily on using various indicators and charts. The approach lacked cohesiveness as it did not consider various qualitative factors (associated with the company, markets, etc.,) and other factors which could influence the movement of the stock price (e.g.: Sentiment of the investor etc.,) **(Swati et al., 2023)**.
- Fundamental Analysis: This focuses on identifying a company's intrinsic value by considering aspects like financial statements, economic conditions, etc. However, the approach is highly

inefficient in predicting short-term price movements. Also, it does not consider the impact of market sentiment or any external factors that could influence the momentum of the stock price **(Shende et al., 2022).**

- The influence of social media and news on stock prices extends beyond technical indicators, as sentiment and public perception can significantly affect market movements (**Zhang et al., 2021).** Additionally, interconnected stock price movements involving simultaneous rises and falls, or reversals triggered by shared news, remain a central focus. Stock market prediction holds immense significance in the financial landscape. Forecasted models, when judiciously employed, empower investors to outperform their peers. These models not only enhance portfolio performance but also bolster risk management capabilities, contributing to more informed investment decisions. Notably, **Wang et al. (2022)** underscored that investors utilizing stock price forecasting models exhibit a remarkable ability to stay steadfast in their investment strategies, especially in times of market turbulence, ultimately surpassing their competitors. This highlights the pivotal role of stock market prediction in providing investors with a competitive edge, improving financial planning, and navigating the ever-shifting dynamics of the stock market.
- Analyzing the vast, multifaceted stock market data requires highly efficient models capable of discerning intricate patterns and complex relationships within extensive datasets. The recent developments in deep learning-based stock prediction are of paramount significance **(Ronaghi, 2021)**. Several studies have demonstrated that DL models such as Gated Recurrent Units (GRU), Transformer-based models, and Long Short-Term Memory (LSTM) perform well in forecasting complex and time-dependent data such as stock prices **Ding et al., 2015**. Deep Learning enhances predictive accuracy, mitigates financial risks, and adapts to modern data sources, including sentiment data and fake news detection models. These outcomes help detect misinformation, enabling more informed decision-making for investors, businesses, and policymakers **(Wu & Gu, 2023)**. The goal of this review is to conduct a comprehensive analysis of recent developments in deep learning-based stock prediction. This review focuses explicitly on studies that utilize time series data, sentiment data-based models, company news or fake news detection models, and the models aiming to merge these factors with the aim of enhancing stock market predictions.

2. Related work:

Several review articles related to the "Recent Advances on Stock Markets Predictions using Deep Learning" have been written and published. Below is a list of some significant studies:

Shahi et al. (2020) compared LSTM & GRU models for stock market forecasting, noting their effectiveness with only stock features and improved performance when integrating financial news sentiments. The proposed cooperative architecture suggested LSTM-News and GRU-News models as equally effective. Limitations encompassed context-specific findings, lack of external validation, and reliance on sentiment analysis.

Li et al. (2020) emphasized the vital role of DL models in stock market forecasting, focusing on risk management, profitability metrics, predictor techniques, and trading strategies. LSTM stood out as the predominant method at 73.5%, while limited attention was given to profitability (35.3%) and risk management.

Hu et al. (2021) highlighted the profitable potential of DL in stock and Forex prediction. They categorized research using methods such as DNN, CNN, LSTM, and more from the DBLP database. Notably, recent trends favored LSTM-DNN combinations and reinforcement learning, yielding significant returns in financial modeling.

Chaudhari and Purswani (2022) reviewed stock price prediction studies using automated Python frameworks and open-source code. They categorized the studies into statistical, machine learning, deep learning, hybrid, and combinations. Yahoo! Finance data and sentiment data, especially from Twitter, improved predictions in many cases.

Despite numerous published review articles on the stock market, a conspicuous gap exists in the current literature regarding a comprehensive exploration of NSE BSE, sentimental analysis, and fake news prediction. In recent years, this field's research landscape has witnessed the ascendancy of deep learning models. Concurrently, data science, datasets, visual-based methods, and associated elements persist in their pivotal roles. Consequently, a systematic literature review (SLR) is imperative to advance scientific comprehension and knowledge within this domain.

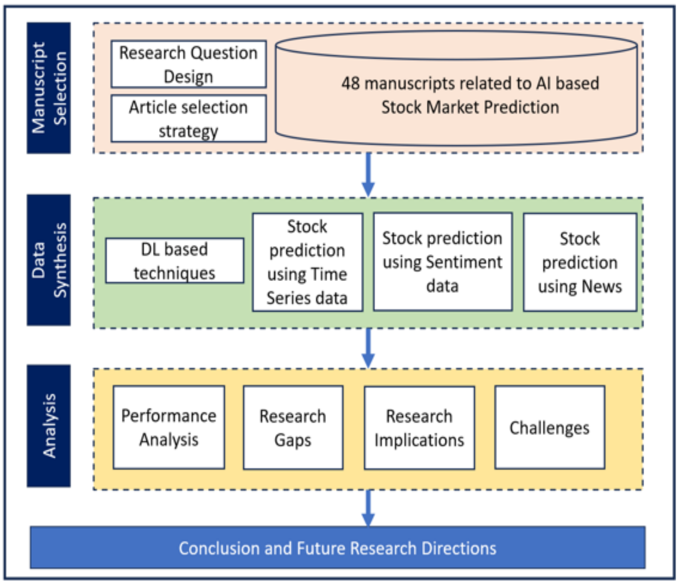

Fig 1: Manuscript workflow

3. Research questions:

In this section, we delineate a series of insightful research questions designed to probe the multifaceted realm of stock market prediction, deep learning, and their interconnections, offering a comprehensive exploration of this pivotal field.

RQ1: How does deep learning affect stock market prediction when using time series data?

RQ2: What role does deep learning play in stock market prediction when incorporating sentiment analysis data?

RQ3: How does the relationship between stock markets and news, encompassing the impact of fake news and news sentiment, contribute to enhancing stock market predictions through the integration of multiple factors?

RQ4: How DL improve accuracy when multiple sources of data used together for stock prediction?

RQ5: What are the research gaps that required further exploration, and what future directions hold potential for advancing the field of stock market prediction and deep learning?

Article segregation strategy (ass):

"The outlined strategy is essential for evaluating the suitability of articles aligning with our research questions. We rigorously employed a systematic search process to curate a selection of relevant articles that comprehensively address and respond to our stated queries. To ensure comprehensive coverage, we incorporated various keywords, including 'Stock prediction using 'deep learning', 'NSE data', 'BSE data', 'NIFT data', 'Time Series data', 'Sentiment analysis data', 'company news data', and 'fake news', along with their synonyms, in the article selection process. We leveraged Google Scholar and the Scopus database for both searching and downloading papers. This review specifically encompassed works published over the past decade (2019–2023), resulting in the identification of a total of **3,621** research articles. Subsequently, a meticulous evaluation of titles, abstracts, and complete content has led to the refined selection of **48** articles."

3.1 Data synthesis and analysis:

3.1.1 Publication trends in ai and its application in the stock market prediction analysis:

Publication trend Analysis shows **3621** articles focused on "Time series data" "Sentimental analysis" and "fake news prediction" in the context of "Stock market prediction using deep learning," from 2015 to 2023. This heightened research interest in 2022 may be indicative of a shift towards technology-driven solutions and data-driven decision-making processes in the stock market field. Researchers in the field appear to have been particularly active in exploring how AI can optimize various aspects of stock market predictions.

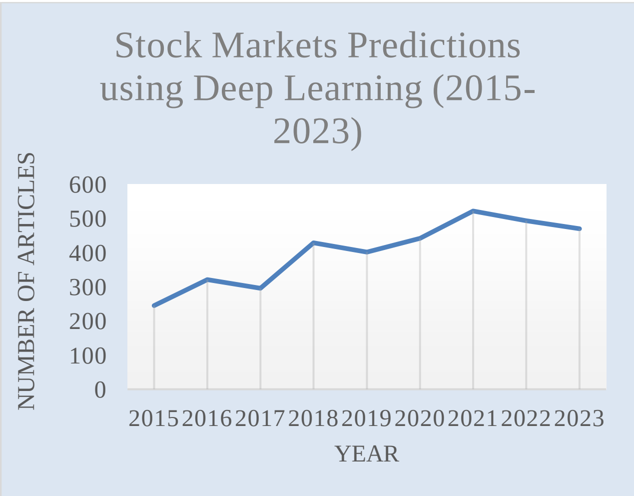

Fig 2: Publication Trend Analysis Stock Markets Predictions using DL

The concept map for this systematic literature review highlights several key themes in the domain of "Stock market predictions using deep learning" and related fields (See Figure 2) These major themes (Time series data, Deep learning, Sentimental analysis, fake news detection) collectively illustrate the multifaceted nature of research within the context of stock market predictions encompassing technological advancements, and broader societal implications.

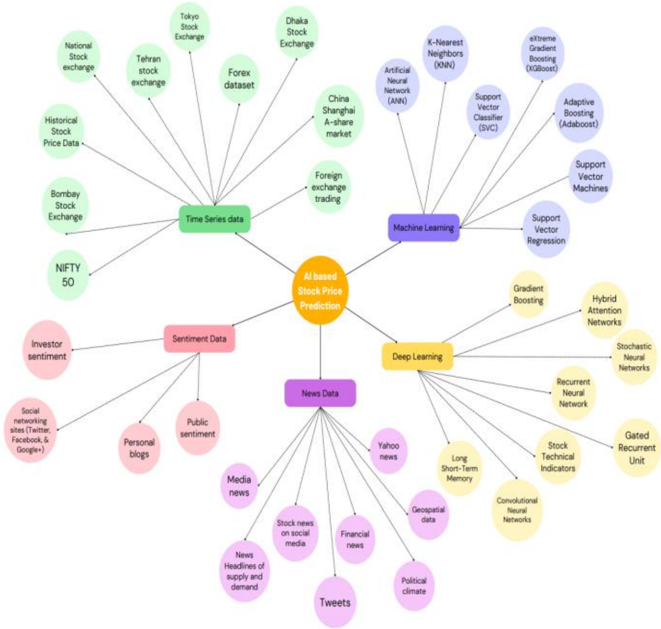

Fig 3: Concept Map Illustration

Deep learning's role in stock market predictions using time series data

This section conducts a comprehensive review of empirical research related to the application of deep learning on Stock Market Predictions using time series data.

Time series data

Stock prediction using time series data is fundamental in the realm of financial analysis, particularly within complex markets like the stock market. In this context, India's dynamic economic landscape provides a promising opportunity for both domestic and foreign investors to engage in the Indian stock market. This market is facilitated by major exchanges, including the NSE and BSE. To gauge the overall market performance, essential stock market indices like Nifty and Sensex play pivotal roles. While using Time Series data, there exists a fundamental dichotomy between traditional statistical models, exemplified by ARIMA model, and cutting-edge Deep Learning-based models **(Hiransha et al., 2018)**. ARIMA, a well-established statistical tool, follows an autoregressive approach, making predictions based on past values, a methodology rooted in the analysis of historical data patterns. Deep Learning-based models, on the other hand, represent the vanguard of predictive technology, leveraging complex neural networks to decipher intricate relationships within time series data. The key question pertains to their comparative efficacy when pitted against traditional ARIMA models. Traditional statistical models like ARIMA offer interpretability and a foundation in statistical theory, ensuring a certain level of transparency in their predictions. However, they often struggle when faced with the nonlinear, multifaceted nature of stock market data. In contrast, Deep Learning-based models, particularly RNNs and LSTMs, excel at capturing intricate patterns and dependencies within the data, offering the potential for more accurate predictions.

The crux of the argument lies in the trade-off between interpretability and predictive power. While ARIMA provides clear insights into the factors influencing predictions, it might miss out on subtle, nonlinear relationships in the data that DL models can uncover. DL models, with their formidable ability to learn and adapt from data, may offer superior predictive accuracy, but their inner workings often remain opaque, leaving investors and analysts in the dark about the rationale behind specific predictions. Ultimately, the choice between ARIMA and Deep Learning-based models for stock prediction using Time Series data hinges on the specific goals, preferences, and risk tolerance of investors and analysts. While traditional statistical models continue to serve as a reliable foundation, Deep Learning-based models represent the future's promise, offering the potential to navigate the intricate landscape of stock markets with greater accuracy and effectiveness.

Table 1: Predicting the stock market with DL and Time Series data

Author Year	Model used	Dataset used	Accuracy	Limitation
Bathla, Rani, & Agarwal, 2023	LSTM	Yahoo Finance API (from January 2010 to March 2020)	MAPE ranges from 0.86 to 3.89	Difficulty capturing long-term dependencies, overfitting
Mukherjee et al., 2023	ANN CNN	NSE stock market dataset	97.66% 98.92%	Overfitting, extensive training, and synthetic image generation
Ishwarappa & Anuradha (2021)	Deep CNN with reinforcement-LSTM	Real-time stock future prices including FTSE, BSE, NASDAQ, and TAIEX,	POCID (>85%), R^2 (>80%), ARV (<0.024 %), and MAPE (<0.04%).	High computational Complexity and uncertainty
Singh et al., 2022	B-LSTM	15-minute intervals of historical high-frequency data along with real-time NSE and NASDAQ stock feeds.	RMSE 1.780 MAE 1.268	Intraday prediction complexity due to market dynamics
Rajkar et al., 2021	RNN	Real-time stock data for selected companies	90%	Vanishing gradients, limited memory, overfitting susceptibility
Saravanan et al., 2023	LSTM	TWTR and FB datasets	81%	Poor accuracy due to volatility and noise
Bhuvaneshwari & Beena (2021).	TFCMA-DRL	Historical stock prices, stock-related news articles, and tweets over a 12-month period from October 2018 to September 2019	96.67%	Challenges in cohesive sentiment and event extraction
Sen et al., 2022	RF XG Boost Gaussian NB LR KNN	Real time data	81.96% 82.58% 78.5% 69% 57.45%	Volatile stock prices pose challenges in prediction
Hiransha et al., 2018	MLP RNN LSTM CNN	Day-wise closing price data from NSE of India and NYSE.	93.71% 92.14% 93.63% 94.64%	Struggles with non-linearities in data.
Yadav, Jha, K., & Sharan, 2020	LSTM	Indian stock market data from NIFTY 50	More Stable & better accuracy	Computation resources are a limitation for more extensive hyper-parameter tuning
Chen & Zhou, 2020	GA-LSTM	China Construction Bank dataset and CSI 300 stock dataset	MSE 0.0039	Limited interpretability and sensitivity to hyperparameter tuning
Zaheer et al., 2023	Single-layer RNN	Shanghai Composite Index (000001)	R^2 - 0.986	Limitations of historical data-driven predictions.
Barra et al., 2020	Ensemble CNNs with GAF	Standard & Poor's 500 index future	56.63%	Limited stock market predictive accuracy.
Lakshminarayanan, & McCrae, 2019	LSTM	Dow Jones Index stock price data	98.97%	Challenges in modeling stock market volatility.
Lee, & Kim 2020	NuNet	S&P500, KOSPI200, and FTSE100	99%	Higher computational complexity

		index data.		
Shahvaroughi Farahani, & Razavi Hajiagha, 2021	ANN	Stock price data from S&P500, DAX, FTSE100, Nasdaq, and DJI indices	R^2 - 0.9975	Uncertain algorithm superiority due to complexity and parameters.
Shen, & Shafiq. (2020).	FE + RFE + PCA + LSTM	Price data of 3558 stock ID from 2017 to 2018 collected from Chinese stock market	93%	Sensitivity of RFE algorithm to terms
Zhao et al., (2023)	TSRM and GCN	Shenzhen Stock and Shanghai Stock Datasets	-	Limited recent data for analyzing correlation, lacks external data for comprehensive analysis
Li et al., (2023)	LSTM, RNN, GRU	Daily US stock price data sets	99.82% 99.3% 99.75%	Performance variation with clustering and different models.

Table 1 presents an overview of studies focusing on the prediction of the stock market through the utilization of DL models and time series data. In the factors of stock market prediction using time series data, deep learning models, particularly LSTM and CNN, excel in capturing complex temporal dependencies and intricate patterns within the data. CNN's ability to detect local features and LSTM's capacity to model long-term dependencies make them well-suited for analyzing the sequential nature of stock market time series data. These models offer superior predictive accuracy, addressing the non-linear and multifaceted characteristics of financial data, which often challenge traditional statistical models like ARIMA. However, common challenges across these studies include issues related to overfitting, computational complexity, sensitivity to hyperparameter tuning, and limitations in historical data-driven predictions, highlighting the need for further advancements in this domain.

Analysis-based stock market prediction

Sentiment analysis is a pivotal aspect of stock market prediction, bridging the gap between investors and market behavior. By harnessing the power of Natural Language Processing (NLP) and machine learning algorithms, this analytical approach dissects financial news and social media data to classify sentiments as negative, neutral, or positive. As depicted in Fig. 4, this method considers both textual sources as valuable external data for prediction. Accuracy and spam detection are key requirements, especially in the age of spammers utilizing multiple social media accounts for promotional purposes. The removal of spam messages from the dataset is a vital step in ensuring the reliability of sentiment-based predictions in the dynamic world of stock markets.

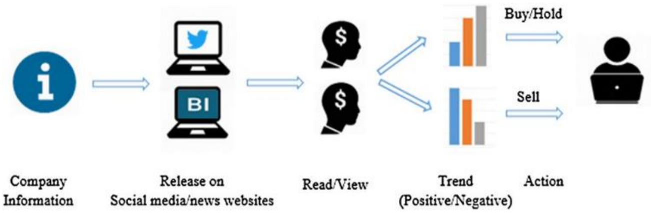

Fig 4: A general plot that illustrates how financial news and social media affect stock market trends (**Khan et al., 2020**)

Table 2.Prediction of the Stock market using DL from Sentiment analysis data

Author & Year	**Model used**	**Dataset used**	**Accuracy**	**Limitation**
Souma, Vodenska, & Aoyama, 2019	RNN with LSTM	Historical dataset (Utilized Wikipedia, Gigaword, word vectors, Reuters, and DJIA data from 2003 to 2013)	97.5%	Market volatility, noisy data, limited interpretability
Jing, Wu, & Wang, 2021	CNN-LSTM	SSE data	95.51%	Prediction accuracy relies on China's peculiar market conditions and trading restrictions.
Othan et al., 2019	CNN RNN LSTM BERT	BIST100	96.26% 96.56% 98.71% 98.63%	Stock direction considers limited external factors; social media introduces noise.
Nti et al., 2021	IKN-ConvLSTM	HSD from GSE, MD, GTI	98.31%	High computational cost, data integration challenges, limited prediction window
Swathi, Kasiviswanat	TLBO with LSTM	Twitter data	94.73%	Relies on Twitter, oversimplifi

h, & Rao, 2020				es complex stock dynamics.
Lin et al., 2022	LSTMGA	Multilingual sentiment data from social media, trading data (from Yahoo Finance)	MAPE < 5%	Limited to non-native English-speaking regions
Sohangir et al., 2018	CNN	StockTwits	90.93%	Computational Complexity
Jin, Yang & Yuhong Liu (2019)	S_EMDAM_LSTM LSTM	Comments on stock market from StockTwits & Yahoo Finance, HSD	70.56%	Sensitivity to quality and quantity of data
Li, Wu, & Wang (2020)	Two-layer LSTM neural network	Real Hong Kong stock market data spanning over five years	82.8%	Event-based sentiment analysis essential for accuracy.

From Table 2, we can observer that time series data alongside sentiment analysis data using DL models, has proven to be a potent strategy for significantly enhancing stock market prediction accuracy. As demonstrated in the research detailed in Table 2, the integration of sentiment analysis data into these models, including LSTM and CNN, has played a pivotal role in improving overall accuracy. For instance, Souma, Vodenska, & Aoyama (2019) achieved an impressive accuracy of 97.5% using LSTM on historical data, exemplifying the potential of DL models. This approach enables the nuanced dissection of financial news and social media data, allowing the classification of sentiments into positive, neutral, or negative categories. This multidimensional methodology not only harnesses the power of natural language processing but also adeptly addresses challenges posed by data noise and regional nuances. ML models, like logistic regression, further complement these DL models, offering transparency and interpretability in sentiment analysis. The findings underscore the pivotal role of these models in augmenting stock market prediction accuracy, providing invaluable insights into sentiment trends that influence market behavior. While some models achieve high accuracy, they may require significant computational resources. Additionally, reliance on specific sources, like Twitter, may oversimplify complex stock dynamics. Further Challenges include market volatility, noisy data, and limited interpretability. Predicting stock volatility remains challenging due to various factors, particularly in China's unique market conditions.

Stock Market And News (Fake News Or News Sentiment) Relationship

In the rapidly evolving landscape of financial markets, availability of timely and accurate financial news is of paramount importance for investors. However, the recent surge in the prevalence of fake news, defined as "news articles that are intentionally and verifiably false and could mislead readers," has raised significant concerns. It is crucial to address this issue, as fake financial news can have detrimental effects on both individual investors and the broader stability of financial markets. This has prompted a surge of interest in the field of fake news detection.

To conduct robust research in fake news detection, a foundational requirement is a reliable dataset with accurately annotated information. Ensuring the accuracy of these annotations is critical, as emphasized by **Allcott and Gentzkow (2017**). Scholars have been diligently exploring a variety of methods, particularly leveraging DL and machine learning (ML) techniques, to enhance the efficacy of fake news detection. This research is imperative to fortify the mechanisms that safeguard investor interests and maintain the integrity of financial markets.

Table 3. Stock market and News (fake news or news sentiment) relationship

Author Year	Model used	Dataset used	Accuracy	Limitation
Li, & Pan, (2022).	RNN (LSTM+GRU)	News data (from CNBC.com, Reuters.com, WSJ.com, and Fortune.com) & Stock data (from the S&P 500 Index)	57.55% reduction in mean-squared error	Predicting stock volatility is challenging due to diverse factors.
Almalis, Kouloumpris, & Vlahavas, 2022	Multiple RNNs	Financial news data	-	Limited consideration of linguistic nuances in financial news
Ji, Wang & Yan (2020)	ARIMA RNN LSTM Doc-W-LSTM	1. Investor comments and news from "Oriental Fortune" (15 companies). 2. Stock transaction data from Tushare financial database.	R^2 = -0.140 0.882 0.906 0.957	Limited representation from one social media platform
Chandola et al., (2023)	LSTM	News headlines dataset from Reuters website, Datasets of different companies (PepsiCo,	65.4%	Short temporal effect of news on investors

		Apple, APEI, NRG, AT&T)		
Li et al., 2020	Tensor-based event-driven LSTM model	45,021 news points from Eastmoney.com for 91 CSI 100 companies	62.4%	Modeling diverse, time-changing data interactions
Liu et al., 2018	CNN	Standard & Poor's 500 index (S&P 500) for predicting Apple's stock price movement.	97.66%	Complex model, may require significant computational resources
Li et al., 2019	DP-LSTM	S&P 500 stocks data.	99.58%	Privacy measures may introduce imprecision in predictions.
Ingle, & Deshmukh (2021)	Ensemble deep learning (DBN, RBM, CNN, and RNN)	Online finance news data	~ 85% accurate prediction	Dynamic stock market nature challenges 100% accuracy

Table 3 presents an overview of studies examining the relationship between stock market dynamics and news, encompassing either fake news or news sentiment analysis. Deep learning models, including LSTM, CNN, and DP-LSTM, along with traditional methods, for news sentiment analysis, demonstrate the capacity to offer insightful information on stock market activity. These models are effective in mitigating the impact of fake news and news sentiment, harnessing their ability to decipher complex patterns within news data. The rise of fake news has made their role even more crucial, as fake news can significantly mislead investors and disrupt market stability. Company news plays a crucial role in stock prediction, serving as a real-time source of information that influences market sentiment and investor decisions. However, challenges related to linguistic nuances, temporal effects, and the dynamic nature of financial markets necessitate continuous exploration and refinement in the pursuit of more accurate and reliable stock market predictions.

Stock market prediction using multiple factors (or combinations of above factors)

Over the last few years, the domain of stock market prediction has witnessed a paradigm shift, with a growing emphasis on harnessing a diverse range of factors to enhance forecasting accuracy. This transformative approach involves integrating a myriad of elements, including time-series analysis, sentiment analysis, and real-time news data. By synergistically leveraging the power of advanced techniques such as LSTM neural networks and BERT models, researchers and analysts aim to develop more precise forecasting models (Ko & Chang, 2020). These models are designed to consider historical transaction data, sentiment analysis derived from news articles and forum discussions, and other relevant variables. Through this multifaceted methodology, the goal is to unravel the intricate dynamics of stock markets and improve the predictive prowess, thereby empowering stakeholders to make informed decisions in an increasingly complex financial landscape.

Table 4. Stock market prediction using multiple factors or combinations of above factors

Author Year	Model used	Dataset used	Accuracy	Limitation
Ko & Chang, 2020	LSTM with BERT-based sentiment analysis	News articles, PTT forum discussions, stock historical transaction information	12.05% RMSE reduction	Limited emotion types, potential for more precision
Zhang, & Lou (2021).	BP algorithm NN	Stock price data for Gree Electric, Guizhou Moutai, and others	73.29%	External factors not considered in prediction results poor performance
Yu & Yan 2020	DNN based LSTM	S&P 500, Nikkei 225, ChiNext index, Hang Seng index, DJIA and China Securities index 300	62.87%	The model overlooks macro factors, affecting accuracy in volatile markets.
Rezaei, Faaljou, & Mansourfar, 2021	CEEMD-CNN-LSTM, EMD-CNN-LSTM	S&P 500, Dow Jones, DAX, and Nikkei 225	99.46%, 99.38%	Sensitivity to noise, tuning dependence, overfitting.
Baek, & Kim (2018).	ModAugNet	KOSPI200 and S&P500	99.14%	Focus on stock index limits generalization.
Hoseinzade, & Haratizadeh, (2019)	CNNpred	Historical data (from S&P 500, NASDAQ, DJI, NYSE, and RUSSELL)	F Score - 0.4837	Limited interpretability and data inefficiency
Wu et al., 2021	SACLSTM	Historical data	90.4%	Complexity, potential overfitting
Peng et al., 2021	DNN	Utilized daily data (2008-2019)	65.37%	Profitability challenges; no significant outperformance observed.
Chung et al., 2018	GA-LSTM	KOSPI data.	99.09%	Trading commissions not considered in the analysis

Liu et al., 2019	CNN	Tomson Reuters, Cable News Network (CNN)	69.23%	Limited labeled data hinders deep learning.
Li, Shang, & Wang, 2019	CNN	A financial market dataset, a historical oil price dataset, and a news headline dataset	61%	Market complexity, news bias, real-time influence
Chen, Zhang, & Lou, 2020	Hybrid DL with AM, MLP, and BiLSTM	Google index	R^2 - 0.8693	Parameters were manually set, and internal structure of AM not improved

Table 4 summarizes different models that use various combinations of factors for stock market prediction. In recent years, there has been a notable surge in adopting a multifaceted approach to stock market prediction, combining various methodologies such as time-series analysis, sentiment analysis, and real-time news data, and harnessing advanced techniques like LSTM neural networks and BERT models. Models such as LSTM with BERT-based sentiment analysis by Ko & Chang (2020), the BP algorithm neural network employed by Zhang & Lou (2021), DNN-based LSTM used by Yu & Yan (2020), and EMD-CNN-LSTM and CEEMD-CNN-LSTM models applied by Rezaei, Faaljou, & Mansourfar (2021) have demonstrated varying levels of accuracy. They work with diverse datasets, including stock price data, historical information, and news headlines. However, each model faces its set of challenges, from sensitivity to noise and overfitting to the limitations in interpretability and the complexities of market news and real-time influences. Despite these limitations, they underscore the need for continuous exploration and refinement in this dynamic and multifaceted field, as the stock market prediction landscape continues to evolve.

3. Performance analysis and dataset used

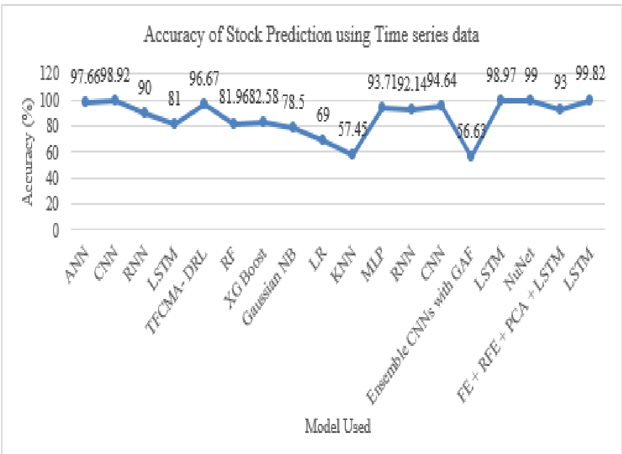

Fig 5. Accuracy of various DL models in Stock prediction in Time series data

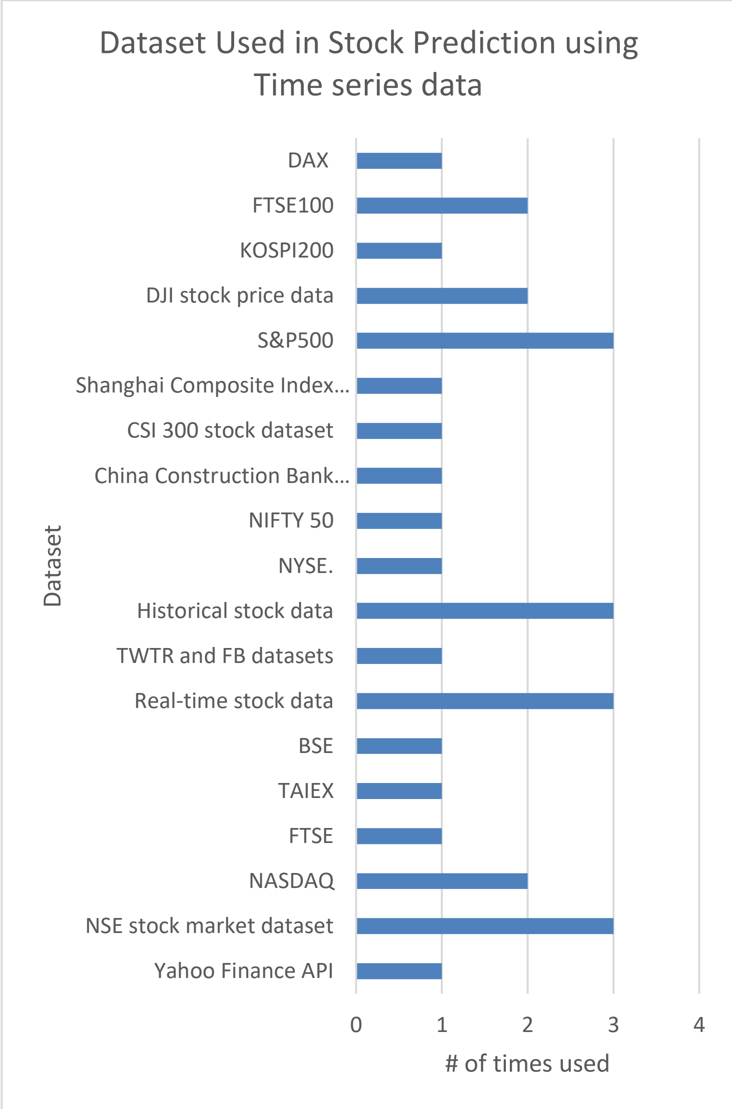

Fig 6: Dataset Used in DL models in Stock Prediction using Time series data

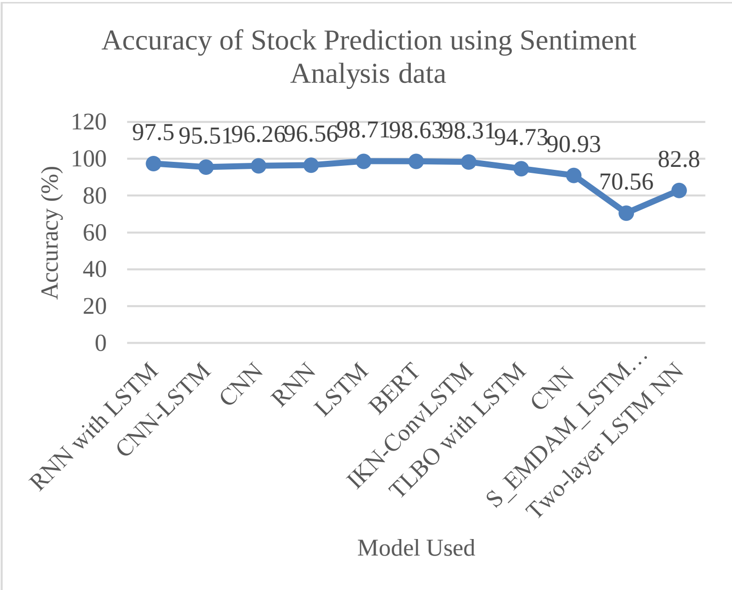

Fig 8. Dataset Used in DL models in Stock Market Prediction using Sentiment data

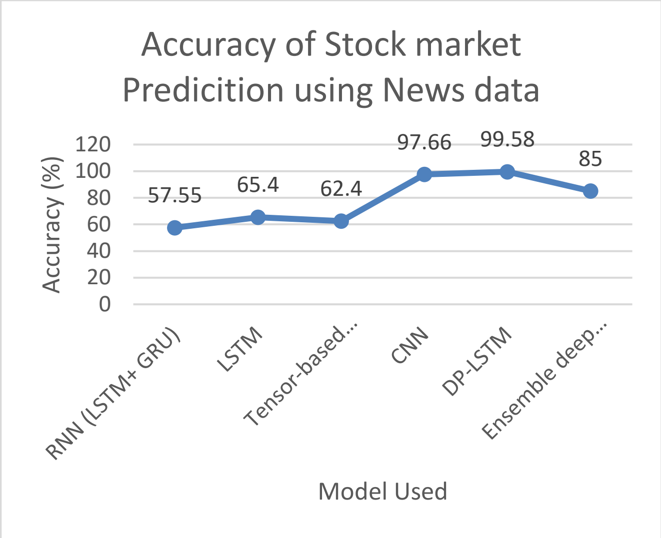

Fig 9: Accuracy of various DL models in Stock prediction in News data

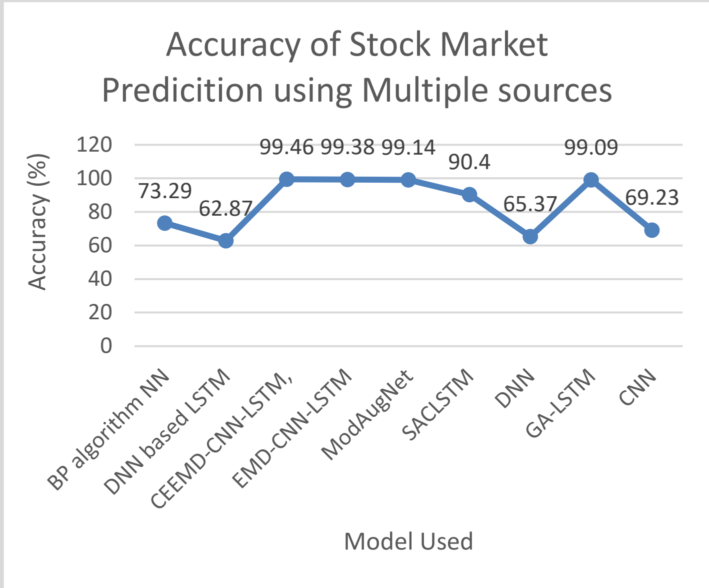

Fig 11: Accuracy of various DL models in Stock prediction in Multiple sources

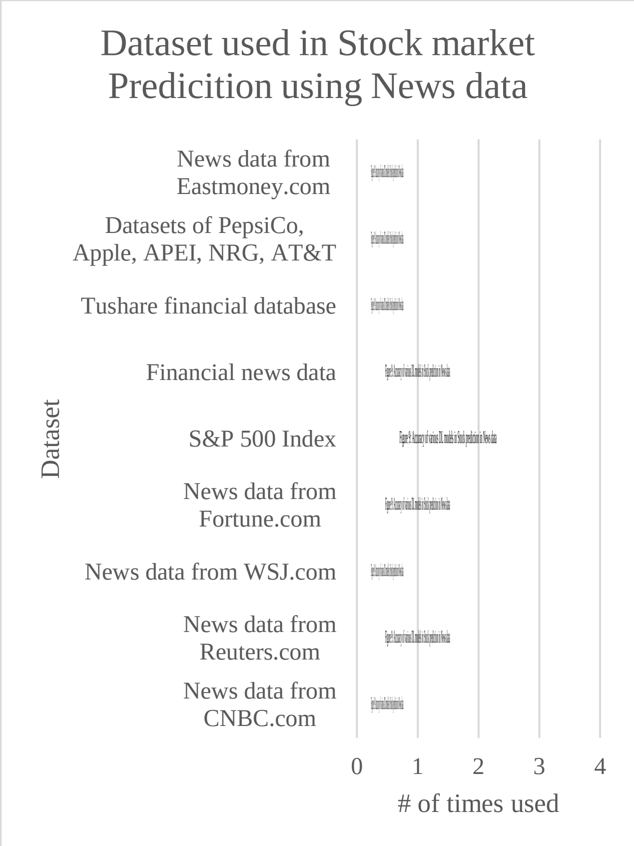

Fig 10: Dataset Used in DL models in Stock Market Prediction using News data

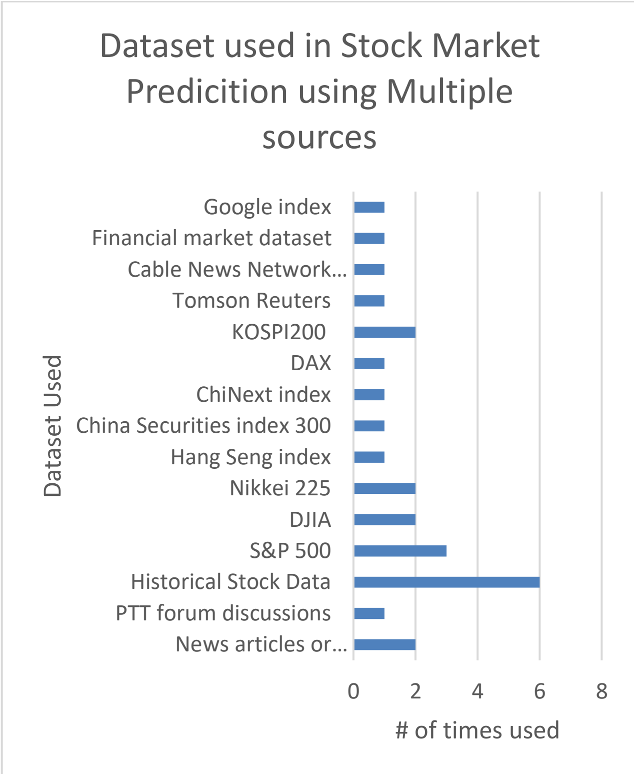

Fig 12: Dataset Used in DL models in Stock Market Prediction using Multiple sources

5.Discussion

The review reveals significant variations in the accuracy of DL models, with CNN and LSTM emerging as strong contenders in time series data analysis, while KNN and LR demonstrate limitations. Our systematic review also highlights the diversity in the datasets used, encompassing real-time stock data, historical stock data, and key market indices, emphasizing a holistic data acquisition approach. Shifting the focus to sentiment data, BERT, LSTM, and IKN-ConvLSTM models exhibit noteworthy performance, underscoring the potential of sentiment analysis in stock prediction. We delve into the dataset variety, including sources like Twitter data and Yahoo Finance, enriching the sentiment-based stock prediction landscape. Furthermore, our review demonstrates the instrumental role of DL models in news data-based stock prediction. DP-LSTM stands out with exceptional accuracy, and ensemble models showcase robust performance. Dataset sources span reputable outlets such as CNBC.com and Reuters.com, contributing to the credibility of the predictions. Finally, in the realm of stock prediction using multiple factors, CEEMD-CNN- EMD-CNN-LSTM and LSTM lead the way in terms of accuracy, with dataset sources ranging from news articles to historical stock data and market indices.

Gaps and opportunities for future research

- **Incorporating Economic Context:** Existing research often overlooks the broader economic context's influence on stock market behavior. Future studies should consider incorporating economic factors, such as fiscal policies and global events, to enhance prediction accuracy.**Sentiment Analysis and Market Dynamics:** While sentiment analysis is recognized as crucial for predicting stock prices, there's room for further research in capturing market dynamics accurately through sentiment analysis.
- **Hybrid Model Efficiency**: Hybrid models, combining deep learning with traditional machine learning, show promise in improving forecasting accuracy. Challenges, such as complexity and resource-intensive nature, require solutions for real-time prediction and large datasets.
- **Robust Validation and Hyperparameter Optimization**: Robust validation frameworks, advanced data preprocessing, and hyperparameter tuning are central to ensuring model accuracy and generalizability. Advancements in hyperparameter optimization methodologies are crucial for enhancing predictive capabilities.
- **Big Data Analytics and Event-Based Segmentation**: The application of big data analytics and event-based segmentation techniques holds promise for ensuring model robustness during market crashes and extreme fluctuations.
- **Data Generalizability**: Diversifying data sources and implementing robust data preprocessing can enhance the adaptability of predictive models to different financial ecosystems. Cross-market validation and robustness testing are integral for research.
- **Model Interpretability**: Enhancing model interpretability, especially in complex deep reinforcement learning models, is vital for regulatory compliance and investor trust.
- **Concept Drifts**: Addressing the challenges of concept drift in stock market prediction is essential to ensure continued accuracy as financial markets evolve.
- **Handling Time Series Data Challenges**: Tackling non-stationarity and autocorrelation in time series data used for stock market prediction is crucial for improving forecast reliability. Research should focus on data preprocessing and transformation techniques to mitigate these issues effectively.

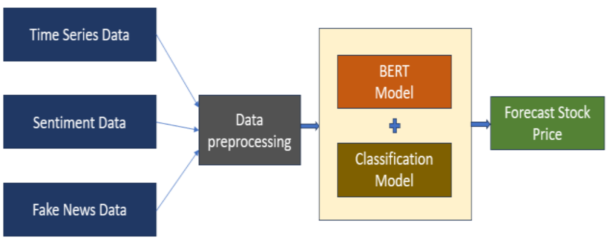

Fig 10: Proposed Future Research Directions

Implications

The systematic literature review on "Recent Advances on Stock Markets Predictions using Deep Learning" has profound implications. It contributes to advancing the understanding of DL's role in stock market predictions and identifies key research directions. In practical terms, this review provides valuable insights for financial decision-makers, potentially leading to improved investment strategies and risk assessment methods, ultimately enhancing the accuracy of stock forecasts and financial outcomes.

Challenges

Predicting stock market trends in the NSE and BSE using deep learning presents several formidable challenges. Acquiring consistent and dependable historical market data, crucial for training deep learning models, poses a daunting task. Stock market data exhibits dynamic, ever-evolving statistical properties, rendering it a challenging arena for deep learning models to capture emerging patterns effectively. The abundance of variables within stock market data adds complexity, as selecting pertinent features while guarding against overfitting remains a demanding task. External factors like news, events, and rumors wield significant influence over stock prices, introducing volatility and noise that deep learning models must adeptly navigate. Interpreting deep learning models is also a complex undertaking, owing to their perceived intricacy. Pervasive limitations in historical data availability persistently vex this field, given the substantial data demands of deep learning models. Ensuring model generalization to future data, integrating qualitative data such as market sentiment, embracing risk management strategies, and adapting to evolving regulations all compound the complexity. Addressing these challenges necessitates a comprehensive approach that encompasses data preprocessing, feature engineering, model selection, and adaptation to the dynamic financial landscape.

Limitations

The limitations of this systematic literature review revolve around specific exclusions and focused criteria. First, the review's emphasis solely on deep learning models restricts its coverage of potential insights from traditional machine learning and statistical models, potentially excluding valuable research avenues. Second, the exclusive focus on recent papers within a specific timeframe may overlook seminal works that laid the foundation for current research. Third, the review's concentration on three major themes—time series, sentiment data, and news data—omits the exploration of other potentially relevant dimensions within the stock market prediction landscape. These limitations underscore the need for future research to consider a broader spectrum of methodologies, historical perspectives, and thematic dimensions in this dynamic field.

6.Conclusion

This systematic literature review (SLR) delves into the deployment of deep learning methods for Recent Advances on Stock Markets Predictions. The review encompasses an exhaustive exploration of diverse studies, shedding light on the promising outcomes achieved by deep learning and machine learning models in effectively identifying and categorizing NSE and BSE data, sentimental analysis, and the relationship with fake news. Incorporating both quantitative (e.g., financial ratios) and qualitative indicators in stock prediction models can provide a more comprehensive understanding of the factors influencing stock prices. By addressing the discussed challenges, we can unlock the full potential of deep learning to revolutionize the field of stock markets, enhancing accuracy, efficiency, and accessibility in diagnosing Recent Advances on Stock Markets Predictions using Deep Learning. In summary, this SLR provides an extensive overview for researchers, clinicians, and developers, illuminating the potential of deep learning in facilitating timely and precise stock market predictions.

References

[1] Agarwal, A., Mittal, M., Pathak, A., & Goyal, L. M. (2020). Fake news detection using a blend of neural networks: An application of deep learning. SN Computer Science, 1, 1-9.

[2] Ahmad, T., Faisal, M. S., Rizwan, A., Alkanhel, R., Khan, P. W., & Muthanna, A. (2022). Efficient fake news detection mechanism using enhanced deep learning model. Applied Sciences, 12(3), 1743.

[3] Allcott H and Gentzkow M (2017). Social media and fake news in the 2016 election. Journal of Economic Perspectives 31(2): 211–236.

[4] Almalis, I., Kouloumpris, E., & Vlahavas, I. (2022). Sector-level sentiment analysis with deep learning. Knowledge-Based Systems, 258, 109954.

[5] Alzubaidi, L., Zhang, J., Humaidi, A. J., Al-Dujaili, A., Duan, Y., Al-Shamma, O., ... & Farhan, L. (2021). Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. Journal of big Data, 8, 1-74.

[6] Amer, E., Kwak, K. S., & El-Sappagh, S. (2022). Context-based fake news detection model relying on deep learning models. Electronics, 11(8), 1255.

[7] Baek, Y., & Kim, H. Y. (2018). ModAugNet: A new forecasting framework for stock market index value with an overfitting prevention LSTM module and a prediction LSTM module. Expert Systems with Applications, 113, 457-480.

[8] Bangyal, W. H., Qasim, R., Rehman, N. U., Ahmad, Z., Dar, H., Rukhsar, L., ... & Ahmad, J. (2021). Detection of fake news text classification on COVID-19 using deep learning approaches. Computational and mathematical methods in medicine, 2021, 1-14.

[9] Barra, S., Carta, S. M., Corriga, A., Podda, A. S., & Recupero, D. R. (2020). Deep learning and time series-to-image encoding for financial forecasting. IEEE/CAA Journal of Automatica Sinica, 7(3), 683-692.

[10] Bathla, G., Rani, R., & Aggarwal, H. (2023). Stocks of year 2020: prediction of high variations in stock prices using LSTM. Multimedia Tools and Applications, 82(7), 9727-9743.

[11] Bathla, G., Rani, R., & Aggarwal, H. (2023). Stocks of year 2020: prediction of high variations in stock prices using LSTM. Multimedia Tools and Applications, 82(7), 9727-9743.

[12] Bhuvaneshwari, C., & Beena, R. (2021). TFCMA-DRL: Tolerant Flexible Coordinated Multi-Agent Deep Reinforcement Learning for Prediction of Future Stock Price Trends from Multi-Source Data. International Journal of Intelligent Engineering & Systems, 14(2).

[13] BL, S., & BR, S. (2023). Combined deep learning classifiers for stock market prediction: integrating stock price and news sentiments. Kybernetes, 52(3), 748-773.

[14] Can, U., & Alatas, B. (2019). A new direction in social network analysis: Online social network analysis problems and applications. Physica A: Statistical Mechanics and its Applications, 535, 122372.

[15] Chaudhari, C., & Purswani, G. (2022, September). Stock Market Prediction Techniques Using Artificial Intelligence: A Systematic Review.In Congress on Intelligent Systems (pp. 219-233). Singapore: Springer Nature Singapore.

[16] Chauhan, T., & Palivela, H. (2021). Optimization and improvement of fake news detection using deep learning approaches for societal benefit. International Journal of Information Management Data Insights, 1(2), 100051.

[17] Chen, Q., Zhang, W., & Lou, Y. (2020). Forecasting stock prices using a hybrid deep learning model integrating attention mechanism, multi-layer perceptron, and bidirectional long-short term memory neural network. IEEE Access, 8, 117365-117376.

[18] Chen, S., & Zhou, C. (2020). Stock prediction based on genetic algorithm feature selection and long short-term memory neural network. IEEE Access, 9, 9066-9072.

[19] Chowdhury, E. K., Khan, I. I., & Dhar, B. K. (2022). Catastrophic impact of Covid-19 on the global stock markets and economic activities. Business and Society Review, 127(2), 437-460.

[20] Chung, H., & Shin, K. S. (2018). Genetic algorithm-optimized long short-term memory network for stock market prediction. Sustainability, 10(10), 3765.

[21] Goel, A., Tripathi, V., & Agarwal, M. (2021). Market microstructure: a comparative study of Bombay stock exchange and national stock exchange. Journal of Advances in Management Research, 18(3), 414-442.

[22] Hiransha, M., Gopalakrishnan, E. A., Menon, V. K., & Soman, K. P. (2018). NSE stock market prediction 0075sing deep-learning models. Procedia computer science, 132, 1351-1362.

[23] Hoseinzade, E., & Haratizadeh, S. (2019). CNNpred: CNN-based stock market prediction using a diverse set of variables. Expert Systems with Applications, 129, 273-285.

[24] Hu, Z., Zhao, Y., & Khushi, M. (2021). A survey of forex and stock price prediction using deep learning. Applied System Innovation, 4(1), 9.

[25] Huang, J. Y., & Liu, J. H. (2020). Using social media mining technology to improve stock price forecast accuracy. Journal of Forecasting, 39(1), 104-116.

[26] Ishwarappa, & Anuradha, J. (2021). Big data based stock trend prediction using deep cnn with reinforcement-lstm model. International Journal of System Assurance Engineering and Management, 1-11.

[27] Jibril, A. B., Kwarteng, M. A., Chovancova, M., & Pilik, M. (2019). The impact of social media on consumer-brand loyalty: A mediating role of online based-brand community. Cogent Business & Management, 6(1), 1673640.

[28] Jing, N., Wu, Z., & Wang, H. (2021). A hybrid model integrating deep learning with investor sentiment analysis for stock price prediction. Expert Systems with Applications, 178, 115019.

[29] Kaliyar, R. K., Goswami, A., & Narang, P. (2021). FakeBERT: Fake news detection in social media with a BERT-based deep learning approach. Multimedia tools and applications, 80(8), 11765-11788.

[30] Khan, M. H., & Anupam, A. (2023, May). Sentiment Analysis Towards Bankruptcy of Silicon Valley Bank: Twitter-Based Study. In 2023 IEEE IAS Global Conference on Emerging Technologies (GlobConET) (pp. 1-5). IEEE.

[31] Khan, W., Ghazanfar, M. A., Azam, M. A., Karami, A., Alyoubi, K. H., & Alfakeeh, A. S. (2020). Stock market prediction using machine learning classifiers and social media, news. Journal of Ambient Intelligence and Humanized Computing, 1-24.

[32] Kumar, R., Kumar, P., & Kumar, Y. (2022). Design of Hybrid Classifiers for Time Series Prediction using Stock Market Data (Doctoral dissertation, Jaypee University of Information Technology, Solan, HP).

[33] Kumar, S., Asthana, R., Upadhyay, S., Upreti, N., & Akbar, M. (2020). Fake news detection using deep learning models: A novel approach. Transactions on Emerging Telecommunications Technologies, 31(2), e3767.

[34] Lakshminarayanan, S. K., & McCrae, J. P. (2019, December). A Comparative Study of SVM and LSTM Deep Learning Algorithms for Stock Market Prediction. In AICS (pp. 446-457).

[35] Lee, S. W., & Kim, H. Y. (2020). Stock market forecasting with super-high dimensional time-series data using ConvLSTM, trend sampling, and specialized data augmentation. expert systems with applications, 161, 113704.

[36] Li, A. W., & Bastos, G. S. (2020). Stock market forecasting using deep learning and technical analysis: a systematic review. IEEE access, 8, 185232-185242.

[37] Li, D., Guo, H., Wang, Z., & Zheng, Z. (2021). Unsupervised fake news detection based on autoencoder. IEEE access, 9, 29356-29365.

[38] Li, M., Zhu, Y., Shen, Y., & Angelova, M. (2023). Clustering-enhanced stock price prediction using deep learning. World Wide Web, 26(1), 207-232.

[39] Li, X., Shang, W., & Wang, S. (2019). Text-based crude oil price forecasting: A deep learning approach. International Journal of Forecasting, 35(4), 1548-1560.

[40] Li, Y., & Pan, Y. (2022). A novel ensemble deep learning model for stock prediction based on stock prices and news. International Journal of Data Science and Analytics, 1-11.

[41] Lin, Y. L., Lai, C. J., & Pai, P. F. (2022). Using deep learning techniques in forecasting stock markets by hybrid data with multilingual sentiment analysis. Electronics, 11(21), 3513.

[42] Liu, T., Ma, X., Li, S., Li, X., & Zhang, C. (2022). A stock price prediction method based on meta-learning and variational mode decomposition. Knowledge-Based Systems, 252, 109324.

[43] Liu, Y., Zeng, Q., Ordieres Meré, J., & Yang, H. (2019). Anticipating stock market of the renowned companies: A knowledge graph approach. Complexity, 2019.

[44] Liu, Y., Zeng, Q., Yang, H., & Carrio, A. (2018). Stock price movement prediction from financial news with deep learning and knowledge graph embedding. In Knowledge Management and Acquisition for Intelligent Systems: 15th Pacific Rim Knowledge Acquisition Workshop, PKAW 2018, Nanjing, China, August 28-29, 2018, Proceedings 15 (pp. 102-113). Springer International Publishing.

[45] Mukherjee, S., Sadhukhan, B., Sarkar, N., Roy, D., & De, S. (2023). Stock market prediction using deep learning algorithms. CAAI Transactions on Intelligence Technology, 8(1), 82-94.

[46] Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2021). A novel multi-source information-fusion predictive framework based on deep neural networks for accuracy enhancement in stock market prediction. Journal of Big data, 8(1), 1-28.

[47] Othan, D., Kilimci, Z. H., & Uysal, M. (2019, December). Financial sentiment analysis for predicting direction of stocks using bidirectional encoder representations from transformers (BERT) and deep learning models. In Proc. Int. Conf. Innov. Intell. Technol (Vol. 2019, pp. 30-35).

[48] Palani, B., Elango, S., & Viswanathan K, V. (2022). CB-Fake: A multimodal deep learning framework for automatic fake news detection using capsule neural network and BERT. Multimedia Tools and Applications, 81(4), 5587-5620.

[49] Peng, Y., Albuquerque, P. H. M., Kimura, H., & Saavedra, C. A. P. B. (2021). Feature selection and deep neural networks for stock price direction forecasting using technical analysis indicators. Machine Learning with Applications, 5, 100060.

[50] Rajkar, A., Kumaria, A., Raut, A., & Kulkarni, N. (2021). Stock Market Price Prediction and Analysis. International Journal of Engineering Research & Technology (IJERT) Volume, 10.

[51] Rani, S., & Kumar, P. (2019). Deep learning based sentiment analysis using convolution neural network. Arabian Journal for Science and Engineering, 44, 3305-3314.

[52] Rezaei, H., Faaljou, H., & Mansourfar, G. (2021). Stock price prediction using deep learning and frequency decomposition. Expert Systems with Applications, 169, 114332.

[53] Ronaghi, F. (2021). Deep Learning-based Information Fusion Frameworks for Stock Price Movement Prediction (Doctoral dissertation, Concordia University).

[54] Roscoe, P., & Willman, P. (2021). Flaunt the imperfections: Information, entanglements and the regulation of London's Alternative Investment Market. Economy and Society, 50(4), 565-589.

[55] Saravanan, V., Paudel, L., Acharya, P., Paramasivam, P., & Pillai, A. S. (2023). An Efficient LSTM-Based Deep Learning Model for Stock Prediction Analytics and Real-time Visualization.

[56] Sen, J., Awad, A., Raj, A., Ray, G., Chakraborty, P., Das, S., & Mishra, S. (2022). Stock Performance Evaluation for Portfolio Design from Different Sectors of the Indian Stock Market. arXiv preprint arXiv:2208.07166.

[57] Serrano-Monge, E. (2022). Inferences from Portfolio Theory and Efficient Market Hypothesis to the Impact of Social Media on Sovereign Debt: Colombia, Ecuador, and Peru. Journal of Risk and Financial Management, 15(4), 160.

[58] Shahi, T. B., Shrestha, A., Neupane, A., & Guo, W. (2020). Stock price forecasting with deep learning: A comparative study. Mathematics, 8(9), 1441.

[59] Shahvaroughi Farahani, M., & Razavi Hajiagha, S. H. (2021). Forecasting stock price using integrated artificial neural network and metaheuristic algorithms compared to time series models. Soft computing, 25(13), 8483-8513.

[60] Shanthini, P. M., Parthasarathy, S., Venkatesan, P., & Nandhini, S. (2023). HRSR-SVM: Hybrid Reptile Search Remora-based Support Vector Machine for forecasting stock price movement. International Journal of Information Technology, 1-8.

[61] Shen, J., & Shafiq, M. O. (2020). Short-term stock market price trend prediction using a comprehensive deep learning system. Journal of big Data, 7(1), 1-33.

[62] Shende, S. D., Singh, A. S., Shah, S. S., Shinde, M. M., More, S. R., & Ainapure, B. (2022, December). Stocks Price Prediction by Fundamental Analysis Using Machine Learning Algorithms. In 2022 5th International Conference on Contemporary Computing and Informatics (IC3I) (pp. 1515-1522). IEEE.

[63] Singh, T., Kalra, R., Mishra, S., Satakshi, & Kumar, M. (2022). An efficient real-time stock prediction exploiting incremental learning and deep learning. Evolving Systems, 1-19.

[64] Sohangir, S., Wang, D., Pomeranets, A., & Khoshgoftaar, T. M. (2018). Big Data: Deep Learning for financial sentiment analysis. Journal of Big Data, 5(1), 1-25.

[65] Souma, W., Vodenska, I., & Aoyama, H. (2019). Enhanced news sentiment analysis using deep learning methods. Journal of Computational Social Science, 2(1), 33-46.

[66] Swathi, T., Kasiviswanath, N., & Rao, A. A. (2022). An optimal deep learning-based LSTM for stock price prediction using twitter sentiment analysis. Applied Intelligence, 52(12), 13675-13688.

[67] Swati, K., Ankita, K., Shivani, D., Namratha, H. (2023). Stock Price Prediction using Technical Analysis. International Journal of Advanced Research in Science, Communication and Technology, 308-315. doi: 10.48175/ijarsct-9510

[68] Umer, M., Imtiaz, Z., Ullah, S., Mehmood, A., Choi, G. S., & On, B. W. (2020). Fake news stance detection using deep learning architecture (CNN-LSTM). IEEE Access, 8, 156695-156706.

[69] Wang, Q., Leippold, M., & Zhou, W. (2022). Machine learning in the Chinese stock market. Journal of Financial Economics, 145(2), 64-82.

[70] Wu, J. M. T., Li, Z., Herencsar, N., Vo, B., & Lin, J. C. W. (2021). A graph-based CNN-LSTM stock price prediction algorithm with leading indicators. Multimedia Systems, 1-20.

[71] Wu, S., & Gu, F. (2023). Lightweight Scheme to Capture Stock Market Sentiment on Social Media Using Sparse Attention Mechanism: A Case Study on Twitter. Journal of Risk and Financial Management, 16(10), 440. https://doi.org/10.3390/jrfm16100440

[72] Xiao, D., & Su, J. (2022). Research on stock price time series prediction based on deep learning and autoregressive integrated moving average. Scientific Programming, 2022.

[73] Yadav, A., Jha, C. K., & Sharan, A. (2020). Optimizing LSTM for time series prediction in Indian stock market. Procedia Computer Science, 167, 2091-2100.

[74] Yu, P., & Yan, X. (2020). Stock price prediction based on deep neural networks. Neural Computing and Applications, 32, 1609-1628.

[75] Yue, L., Chen, W., Li, X., Zuo, W., & Yin, M. (2019). A survey of sentiment analysis in social media. Knowledge and Information Systems, 60, 617-663.

[76] Zaheer, S., Anjum, N., Hussain, S., Algarni, A. D., Iqbal, J., Bourouis, S., & Ullah, S. S. (2023). A Multi Parameter Forecasting for Stock Time Series Data Using LSTM and Deep Learning Model. Mathematics, 11(3), 590.

[77] Zeng, B., Fahad, S., Bai, D., Zhang, J., & Işık, C. (2023). Assessing the sustainability of natural resources using the five forces and value chain combined models: The influence of solar energy development. Resources Policy, 86, 104079.

[78] Zhang, C., Gupta, A., Kauten, C., Deokar, A. V., & Qin, X. (2019). Detecting fake news for reducing misinformation risks using analytics approaches. European Journal of Operational Research, 279(3), 1036-1052.

[79] Zhang, D., & Lou, S. (2021). The application research of neural network and BP algorithm in stock price pattern classification and prediction. Future Generation Computer Systems, 115, 872-879

[80] Zhang, S., Chen, Y., & Zhang, W. (2021). Spatiotemporal fuzzy-graph convolutional network model with dynamic feature encoding for traffic forecasting. Knowledge-Based Systems, 231, 107403.

[81] Zhang, Y., Wang, Y., & Ma, F. (2021). Forecasting US stock market volatility: How to use international volatility information. Journal of Forecasting, 40(5), 733-768.

[82] Zhao, C., Hu, P., Liu, X., Lan, X., & Zhang, H. (2023). Stock market analysis using time series relational models for stock price prediction. Mathematics, 11(5), 1130.