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Review Article

Stock market prediction using artificial intelligence: A systematic review of systematic reviews

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ABSTRACT

There are many systematic reviews on predicting stock. However, each reveals a different portion of the hybrid AI analysis and stock prediction puzzle. The principal objective of this research was to systematically review the existing systematic reviews on Artificial Intelligence (AI) models applied to stock market prediction to provide valuable inputs for the development of strategies in stock market investments. Keywords that would fall under the broad headings of AI and stock prediction were looked up in Scopus and Web of Science databases. We screened 69 titles and read 43 systematic reviews, including more than 379 studies, before retaining 10 for the final dataset. This work revealed that support vector machines (SVM), long short-term memory (LSTM), and artificial neural networks (ANN) are the most popular AI methods for stock market prediction. In addition, the time series of historical closing stock prices are the most commonly used data source, and accuracy is the most employed performance metric of the predictive models. We also identified several research gaps and directions for future studies. Specifically, we indicate that future research could benefit from exploring different data sources and combinations, while we also suggest comparing different AI methods and techniques, as each may have specific advantages and applicable scenarios. Lastly, we recommend better evaluating different prediction indicators and standards to reflect prediction models' actual value and impact.

1. Introduction

Predicting the stock market is challenging yet crucial for investors, traders, and researchers. Various methods, including mathematical, statistical, and Artificial Intelligence (AI) techniques, have been proposed to forecast stock prices and outperform the market. AI techniques, particularly Machine Learning (ML) and Deep Learning (DL), have garnered increasing attention. (Alshater, Kampouris, Marashdeh, Atayah, & Banna, 2022; Chhajer, Shah, & Kshirsagar, 2022; Liang, Tang, Li, & Wei, 2020; Macchiarulo, 2018; Mokhtari, Yen, & Liu, 2021; Samitas, Kampouris, & Kenourgios, 2020; Song & Jain, 2022; Sun, Lachanski, & Fabozzi, 2016). Different angles have been taken when discussing the prediction of AI technology and the stock market (Petropoulos et al., 2022; Shmueli & Tafti, 2022). More hybrid technology and information can be associated with better prediction accuracy in stock markets (Bustos & Pomares-Quimbaya, 2020, p. 156; Kumar et al., 2022a,b; Smyl, 2020). In contrast, many factors, such as data quality, feature selection, model architecture, parameter tuning, and evaluation metrics, affect the performance of AI techniques (Bustos & Pomares-Quimbaya, 2020, p. 156; Hewamalage, Bergmeir, & Bandara, 2021).

While a variety of definitions of the terms AI, ML, and DL have been suggested, this paper will use the definition suggested by Jakhar and Kaur (2020). For the aspect of AI, incorporating human intelligence into machines is one way to define AI broadly, and any computer program with elements of human intelligence is referred to as AI. For the aspect of ML, a subset of AI called ML consists of all techniques that let computers learn from data without being explicitly programmed. The goal of ML is to train computers using the available data and methods. Machines learn how to make decisions using the data and information processed. In essence, ML is just a method for making AI. For the aspect of DL, A subset of ML, DL includes the artificial neural network (ANN) that mimics the structure of biological neural networks seen in the brain. Every time the brain learns new information, it attempts to make sense of it by comparing it to previously learned knowledge. DL uses a strategy similar to the brain, which organizes information by categorizing and labeling objects. Generally speaking, DL is more accurate than ML and performs exceptionally well on unstructured data, but it also needs a massive

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amount of training data and expensive hardware and software (Jakhar & Kaur, 2020).

Many systematic reviews have synthesized statistical results concerning AI and stock price; however, consensus is lacking on which AI techniques are most effective and suitable for stock market prediction and how they compare with other methods. (Makridakis, Hyndman, & Petropoulos, 2020). A recent literature review identified several gaps and emphasized the need to reconsider how we approach AI and stock using analysis from previous systematic reviews (Pinto, Figueiredo, & Garcia, 2021).

Stock prices are driven by new information that cannot be obtained utilizing an analysis through the stock market, according to two significant financial theories: the Random Walk Model (Fama, 1995; Fama, Fisher, Jensen, & Roll, 1969) and the Efficient Market Hypothesis (Fama, 1965). Nevertheless, numerous researchers have disproved the underlying assumptions of these two hypotheses and demonstrated that the market could be partially forecast in accordance with socioeconomic theory and behavioral economics/finance (Chong, Han, & Park, 2017; Oliveira, Cortez, & Areal, 2017; Patel, Shah, Thakkar, & Kotecha, 2015; Weng, Ahmed, & Megahed, 2017).

Recent research suggests that the methods of stock market analysis are split into mathematical and AI techniques. Mathematical-related technology refers to statistical tools, and AI technology refers to ML algorithms (Januschowski et al., 2020). Furthermore, it has been observed that most of the selected studies utilize ML algorithms to analyze the performance of stock market prediction (Kumar, Sarangi, & Verma, 2022a). Previous research has established that ML, a subset of AI, includes DL (Jakhar & Kaur, 2020). From this perspective, the various techniques utilized to predict stock prices can be preliminarily split into 1. Traditional ML algorithms, and 2. DL and Neural Network (NN) (Soni, K, & Tewari, 2022). However, numerous traditional ML, DL, and NN methods exist for predicting stock prices. One of the most significant current discussions in predicting the stock market is which methods are most frequently employed to forecast stock market prices (Li & Bastos, 2020).

This paper introduces a meta-review, a systematic review of systematic reviews aimed at understanding the most recent advancements in AI and stock market prediction. It spans various disciplines, including economics, statistics, finance, and computer science. We will utilize tailored methodologies to comprehend the diverse approaches to AI and stock research. This process will encompass a meticulous review, comparison, and summarization of the strength of evidence from prior systematic reviews. Each review will be critically evaluated to guide the design, strategy, and execution of future AI and stock research.

The primary objective of this work is to offer valuable insights for future stock market investment strategies. It will be achieved by identifying the most prevalent AI methods employed for stock market investment prediction, the most pertinent data sources used in existing literature for this task, and the most commonly used metrics for performance evaluation.

Furthermore, we aim to pinpoint gaps and limitations in the existing systematic reviews and propose ways to augment the quality and rigor of future reviews. Through this process, we will identify areas of consensus and divergence among the existing systematic reviews and attempt to elucidate the potential reasons for any conflicting results and conclusions. This study will also illuminate emerging trends and challenges in AI and stock market prediction and suggest potential avenues and opportunities for future research.

Our meta-review encompasses reviews that focus on stock market prediction from the stock price or return perspective, employing various AI techniques such as ML, DL, NN, Support Vector Machines (SVM), and Sentiment Analysis. However, we exclude reviews that concentrate on other facets of the stock market, such as volatility, risk, portfolio optimization, and trading strategies, as well as reviews that employ non-AI techniques, such as mathematical or statistical methods, for stock market prediction.

2. Methods

In order to ascertain the methodologies employed and reporting practices followed by researchers in the field of systematic literature reviews, we undertook a systematic review of such reviews available in the public domain. This review was conducted in accordance with the PRISMA 2020Statement (Page, McKenzie, et al., 2021), which comprises a checklist and a flow diagram. The PRISMA Elaboration and Explanation (Page, Moher, et al., 2021) enhances the understanding, usage, and dissemination of the PRISMA 2020 Statement by providing examples and explanations for each checklist item.

This review encompassed all published articles of systematic reviews that pertained to stocks and the application of AI technology. AI is defined by Kaplan and Haenlein (2019) as “a system’s ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation.” We included reviews that examined stocks from the stock market perspective or stock prices.

To carry out the meta-review, we adhered to the PRISMA 2020guidelines (Page, McKenzie, et al., 2021) and searched for pertinent systematic reviews on the prediction of stock markets using AI technologies, including ML and DL methods, in two significant databases: Scopus and Web of Science. We employed inclusion and exclusion criteria to screen the retrieved records and selected ten papers for the final dataset. Subsequently, we extracted and coded the data from the included reviews and analyzed them from four essential perspectives: predictor methodologies, informational sources, performance metrics of the predictive model, limitations, and future recommendations.

In addition to following a well-defined research methodology, specific criteria must be met for selecting primary publications for this work. Kitchenham and Charters (2007) proposed a three-step process for conducting a systematic review: planning, execution, and analysis of results.

2.1. Planning the systematic review

Consequently, the initial stage should encompass several queries that need to be addressed subsequent to the systematic review and the criteria for inclusion, exclusion, and quality. The research questions that this systematic review aims to answer are presented in Table 1.

The inclusion (IC) and exclusion (EC) criteria are presented in Table 2.

2.2. Conducting the systematic review

The second stage of our research process involved retrieving pertinent publications for the systematic review and selecting works based on predefined criteria. The significance of this stage was further underscored through a strategic selection of databases, judicious choice of search terms, effective utilization of screening tools, and a rigorous review process.

The databases were selected strategically, considering their extensive coverage of literature relevant to our research topic. Consequently, the Web of Science database was incorporated to supplement the existing platform, given its status as one of the oldest and most

Table 1
Research questions.

ID	Research Questions (RQ)
RQ1	Which AI methods and technologies are most commonly utilized to forecast stock market prices?
RQ2	Which informational sources are most frequently utilized to predict stock market prices?
RQ3	Which metrics are most commonly employed to verify the performance of the predictive models?

Table 2
Inclusion and exclusion criteria.

Inclusion Criteria (IC)	Exclusion Criteria (EC)
Searched in Title.	Not Searched in Title.
Published in English Language.	Not Published in English Language.
Studies from US, UK, and Europe.	Studies not from the US, UK, and Europe.
Published between 2009 and April 2022.	Published before 2009.
Works using AI as the primary technique.	Works not using AI or using AI as the Secondary technique.

comprehensive repositories of research articles across various disciplines (Paras et al., 2018). Additionally, the Scopus platform was utilized for paper extraction, owing to its reputation as a respected academic reference known for its wide array of high-quality academic articles (Wang et al., 2016).

The search descriptors, namely "*Systematic Review*," "*Systematic Literature Review*," and "*Stock*" were chosen to ensure the retrieval of the most relevant articles. Recognizing the importance of a broad search scope, we also included possible variations of these terms in our search query to include the most significant number of articles relevant to the themes. Thus, the following search terms were utilized:

(("*Systematic Review*") **OR** ("*Systematic Literature Review*")) **AND** ("*Stock ?*")

Each search was configured to select these terms exclusively in the title documents of Web of Science and Scopus. The term "articles" was also employed as a limitation for data collection. The final search was conducted on April 11, 2022, publishing 69 articles using the keywords on each platform. Table 3 presents the number of studies extracted from each database.

To expedite the initial screening process of abstracts and titles, we utilized Rayyan,[1] a free web and mobile app that helps accelerate the initial abstract and title screening with the application of a semi-automated approach that incorporates excellent usability (Ouzzani, Hammady, Fedorowicz, & Elmagarmid, 2016), duplicate publications could be eliminated, resulting in 43 articles.

Articles not systematic reviews, such as empirical, descriptive, and conceptual papers, were excluded. This decision was made after two independent reviewers separately evaluated the titles and abstracts of the records. Subsequently, these reviewers independently and meticulously read the full texts of the remaining papers to conduct an eligibility evaluation. This rigorous process ensured the reliability and validity of our review. Any reviewer disagreements were resolved through discussion and consensus at this stage.

Upon reviewing the abstracts, the inclusion and exclusion criteria were applied, which resulted in 17 articles. Works that were duplicates or belonged to the same authors were considered in their entirety, excluding one publication. Among the 16 remaining articles, there were no studies for which we could not retrieve the full text. The final step involved thoroughly reading these 16 articles, with any that did not meet the inclusion and exclusion criteria being excluded. Consequently, the next step will involve the analysis of the final ten articles. As per the PRISMA Elaboration and Explanation (Page, Moher, et al., 2021), the number of articles excluded during the specified method is illustrated in Fig. 1.

Table 3
A table that discriminates the number of studies mined through each database.

Database	Number of Studies
Scopus	40
Web of Science	29

[1] http://rayyan.qcri.org.

Data extraction from the included studies was performed by one author and verified by a second author. Any disagreements were resolved through discussion between the two reviewers. The data was subsequently extracted and coded meticulously from the selected studies. Following a comprehensive review of the chosen articles, all relevant data for each reference was compiled in Table 4. It included the review's aim, the date range of the included studies, the type of review, the search sources, the included studies, and the adopted Journal/Conference. Table 5 was populated with the retrieved attributes and the AI analysis/method/technology used for training or testing the forecast model, including algorithms, tools, metrics, and databases.

2.3. Analysis of results

The final process involves analyzing the selected articles and categorizing them based on predictor methodologies, information sources, metrics used to validate the predictive model's effectiveness, and the research's limitations and future recommendations.

2.3.1. Analysis based on predictor methodologies

This section attempts to examine the methods for predicting the trends or prices of the stock market. The analysis will cover the following methods as per the general significance. Firstly, DL, particularly LSTM. Secondly, ML, like SVM, NN, ANN, and feature selection methods. Thirdly, sentiment analysis and text mining. Fourthly, time Series Analysis and statistical techniques, including Principal Component Analysis (PCA). In addition, fundamental and technical analysis. Lastly, fuzzy logic.

DL and ML produce better results than conventional time-series models because they use the modern computer's rising processing capability (Siami-Namini, Tavakoli, & Namin, 2018). DL is one of the most popular methods in ML, and it is suitable for event-driven stock price movement prediction based on a combination of long-term and short-term events. DL methods, especially LSTM in 58% of the 12 selected studies, have been widely applied and have shown promising results in stock prediction (Li & Bastos, 2020; Ketsetsis et al., 2020; Soni et al., 2022). LSTM networks have the advantage of capturing the context of the data as they are being trained and can address the gradient vanishing problem, making them the ideal approach for time series forecasting (Li & Bastos, 2020; Soni et al., 2022). RNN has the advantage of capturing the context of the data as they are being trained (Soni et al., 2022). RNN is the most extensively studied by researchers, according to Sezer et al. (2020), who surveyed DL approaches for forecasting financial time series. In addition, Di Persio and Honchar (2016) presented a combination of CNN and wavelets for forecasting the S&P500 index by using closing prices as the testbed. They concluded that CNN outperforms traditional neural networks in predicting market indexes. Moreover, social network analysis has proven effective for stock predictions using sentiment indexes and other derived series as inputs (Bustos & Pomares-Quimbaya, 2020, p. 156).

ML is a subset of AI that consists of all techniques that let computers learn from data without being explicitly programmed. ML algorithms are widely used for stock market prediction, and the most commonly employed ML algorithms are Decision Tree (DT), SVM, and ANN (Nti et al., 2020; Pinto, da Silva Figueiredo, & Garcia, 2021). Furthermore, the most cited algorithm was SVM in 25% of the 57 selected studies (Pinto, da Silva Figueiredo, & Garcia, 2021). Four ML methodologies, including genetic algorithms mixed with other techniques, ANN, SVM, and hybrid methods, were identified after (Strader, Rozycki, Root, & Huang, 2020) studied journal publications from the previous twenty years. The various techniques to predict stock prices can be broadly classified into four groups. The article employed various computational intelligence techniques, primarily ANN, Fuzzy, evolutionary computing

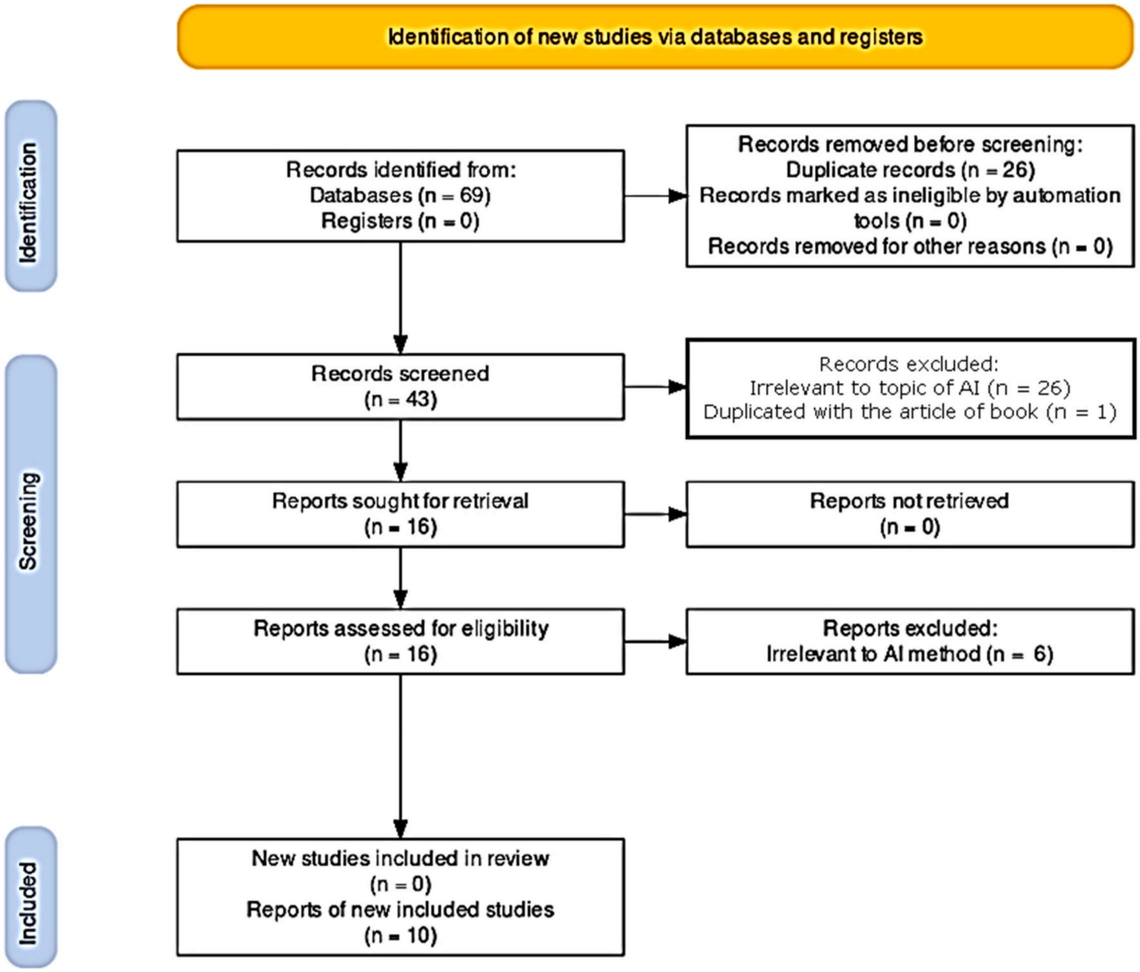

Fig. 1. The number of articles separated during PRISMA.

algorithms, and Support Vector Regression (SVR), to forecast stock market shares (Zavadzki et al., 2020). To achieve exact stock market predictions, the most extensively utilized techniques in 30 studies are ANN (24%) and NN (33%) (Kumar, Sarangi, & Verma, 2022b).

Traditional ML methods perform worse than DL approaches, while DL can still not investigate streaming data, distributed computing, and computing scalability (Islam et al., 2018). In addition, the application of complex ML methods, such as ensemble models and DL, has grown in popularity. Ensemble models have demonstrated significant predictive power, outperforming other techniques such as SVM and ANN in some comparison studies. In general, DL models have not outperformed standard models. Likely, the data sets employed to train these algorithms are insufficient to give accurate predictions (Bustos & Pomares-Quimbaya, 2020, p. 156). Nevertheless, the application of DL, NN, and SVM has distinguished itself and demonstrated a potential trend of producing accurate predictions among various ML methods (Pinto, da Silva Figueiredo, & Garcia, 2021).

Sentiment analysis and text mining analyze textual data, such as news articles, social media posts, and financial reports, to extract useful information and sentiment that can affect the stock market. These techniques are gaining significance as they allow the incorporation investor sentiment data, which can provide valuable predictive insights (Bustos & Pomares-Quimbaya, 2020, p. 156; Pinto, Figueiredo, & Garcia, 2021). One of the most common feature-representation techniques for textual data was the Term Frequency-Inverse Document Frequency (TF-IDF). However, feature selection techniques based on correlation analysis are utilized in 99% of the works assessed (Nti et al., 2020).

Time series analysis and statistical techniques are traditional methods that treat financial time series as linear systems (Li & Bastos, 2020). Some researchers claimed that works based on statistical methods did not perform well and produced inferior results than models based on AI (Atsalakis & Valavanis 2009; Boyacioglu & Avci, 2010; D. A. Kumar & Murugan 2013; Bisoi & Dash 2014). PCA is a well-known method for condensing high-dimensional datasets and extracting the essential features from training inputs. PCA reduced the data needed to train the models while improving the predictions' accuracy (Bustos & Pomares-Quimbaya, 2020, p. 156). Thus, Islam et al. (2018) focused on alternative approaches and strategies for usability textual and numerical data on the stock price trend based on the PCA methodologies. (Misra, Yadav, & Kaur, 2018) also discovered that the accuracy of predictions made using the linear regression model increases when PCA is applied to choose the most pertinent components from the data.

Fundamental and Technical Analysis are traditional methods used in finance that involve analyzing a company's financials and stock trends. Fundamental analysis is less frequently discussed in the literature because it is more difficult to construct models that explain why a stock is moving **(Bustos & Pomares-Quimbaya, 2020, p. 156)**. The technical analysis accounted for 66% of the studies examined, while fundamental and combination analyses accounted for 23% and 11%, respectively **(Nti et al., 2020)**.

Fuzzy logic is a methodology that manages uncertainty and imprecision. While it is employed in stock market prediction, it is not as prevalent as other methods. The objective of fuzzy logic is to emulate human reasoning. It facilitates the formulation of flexible if-then rules where categories rather than exact values represent the premises. Fuzzy logic serves as a powerful approach for learning rules from human

Table 4
Review characteristics of analyzed articles (All Pertinent Data for Each Reference).

Reference	Aim of Review	Date range of included studies	Type of review	Search sources	Included studies	Journal or Conference
Jabbar Alkubaisi G.A.A. (2017)	Define the relationship between stock market forecast accuracy and feature selection by addressing specific studies that utilize sentiment analysis on financial news and reports and research that utilizes sentiment analysis on Twitter using machine learning classifiers.	2011 to 2017	SR	No mentioned.	27	Journal of Theoretical and Applied Information Technology
Islam, V, Al-Shaikhli, and Nor (2018)	Systematically review text mining techniques, methodologies, and principal component analysis that are utilized to help minimize dimensionality in the characteristics and outstanding features. Systematically review the most complex soft-computing approaches and techniques that are evaluated for their performance using electronic textual data in terms of analysis, comparison, and evaluation.	No mentioned.	SR	No mentioned.	No mentioned.	Indonesian Journal of Electrical Engineering and Computer Science
Bustos and Pomares-Quimbaya (2020)	Update systematic review of forecasting machine learning (ML) techniques utilized in the stock market, such as Deep Learning (DL), Text Mining Techniques, and Ensemble Techniques, including classification, characterization, and comparison.	2014 to 2018	SR	Scopus, Web of Science	53	Expert Systems with Applications
Ketsetsis et al. (2020)	Systematically review primary studies that utilize DL techniques to predict European Union (EU) stock markets.	2011 to 2019	SR	Google Scholar	12	2020 International Conference on Computational Science and Computational Intelligence (CSCI)
Li and Bastos (2020)	Collect, analyze, and review existing academic articles on financial time series forecasting using DL and technical analysis.	2017 to 2020	SR	Scopus, Web of Science, IEEE Xplore	34	IEEE Access
Nti, Adekoya, and Weyori (2020)	Systematically and critically review the research works reported in academic journals using ML for stock market forecast. Systematically review studies on stock market predictions based on fundamental and technical analyst perspectives, resulting in a better understanding of the current state of the art and possible future directions.	2007 to 2018	SR	No mentioned.	122	Artificial Intelligence Review
Zavadzki, Kleina, Drozda, and Marques (2020)	Systematically review the literature on research involving stock market forecasting techniques and seek to identify research in which advanced computational models have been applied to the stock market, as well as to describe the main computational intelligence techniques utilized by such research.	2014 to 2018	SR	IEEE Xplore Digital Library, Science Direct, Scopus, Web of Science.	24	IEEE LATIN AMERICA TRANSACTIONS
Pinto, Figueiredo, and Garcia (2021)	Systematically review the selected papers using time series, text mining, and sentiment analysis applied to predict financial stock market behavior.	2015 to 2019	SR	ACM Digital Library, Google Scholar, IEEE Digital Library, Science @ Direct e Springer Link	57	2021 IEEE 24th International Conference on Computer-Supported Cooperative Work in Design (CSCWD)
Kumar et al. (2022a,b)	Systematically review stock market forecast methodologies and academic papers that suggest techniques, including calculating techniques, ML algorithms, performance factors, and top journals.	2002 to 2019	SR	IEEE, Springer, ScienceDirect, Scopus, MDPI	30	Materials Today: Proceedings
Soni et al. (2022)	Investigate the various techniques utilized in stock price prediction, ranging from traditional ML and DL methods to neural networks and graph-based approaches.	2016 to 2021	SR	No mentioned.	20	Journal of Physics: Conference Series (JPCS)

experts. The Adaptive Neuro-Fuzzy Inference System (ANFIS) is the algorithm most frequently used in this context (**Bustos & Pomares-Quimbaya, 2020, p. 156**).

According to the papers that disclose what tools were applied, most authors employed Python and Tensorflow to program the predictor based on past price data. Pandas, NumPy, Keras, Scikit-Learn, TA-Lib, and TA4J were additional extensively applied tools (**Li & Bastos, 2020**). However, another review indicated that MATLAB is the most popular modeling software for stock market forecasting (**Nti et al., 2020**).

2.3.2. Analysis based on informational sources

For predicting share prices, only historical data was applied in the past. Analysts now understand that numerous additional aspects are crucial in determining the stock price, making it inaccurate to rely solely

Table 5
Most utilized review characteristics of analyzed articles (stock analyses and predictive techniques for each reference).

Reference	Method of Stock Market Prediction	Informational Sources	Metrics
Jabbar Alkubaisi G.A.A. (2017)	1. ML. 2. Sentiment Analysis. 3. Statistical Measurements.	1. Twitter 2. Timestamps (temporal feature) 3. Geographic location (Spatial feature)	No mentioned.
Islam et al. (2018)	1. Principle Component Analysis (PCA). 2. Technical Approach in Text Mining, including Genetic Algorithms, DL, ML, Apriori-Like Algorithm, and Fuzzy Algorithm.	1. Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) 2. (1) Correlation among different stocks (2) Historical stock prices (3) Newspapers content	No mentioned.
Bustos and Pomares-Quimbaya (2020)	1. PCA. 2. Fundamental and Technical Analysis. 3. ML, including DL, Text Mining, and Ensemble Techniques. 4. Artificial Neural Network (ANN). 5. Support Vector Machine (SVM). 6. Bio-Inspired Computing. 7. Sentiment Analysis. 8. Social Network Analysis.	1. Structured data: (1) Market Information (2) Technical Indicators (3) Economic Indicators 2. Unstructured data: (1) News (2) Social Network (3) Blogs	1. Accuracy 2. Precision 3. Recall 4. F1-score
Ketsetsis et al. (2020)	1. ML. 2. DL. 3. Time Series Analysis. 4. Text Mining. 5. GRU, GRU-SVM (Gated Recurrent Unit-SVM), SVM. 6. NN, CNN (Convolutional Neural Network), DNN (Deep neural network). 7. Long short-term memory (LSTM). 8. MLP (Multilayer Perceptron), Mixed ARMA-MLP (Auto Regression Moving Average-MLP). 9. Hybrid Fuzzy-Neural Network. 10. GA-SVR (Genetic Algorithm-Support Vector Regression).	1. Financial indicators 2. EUR/USD Exchange Rates 3. Gold Prices.	1. Mean Squared Error (MSE) 2. Accuracy 3. Mean Absolute Error (MAE).
Li and Bastos (2020)	1. Technical Analysis. 2. DL. 3. LSTM. 4. CNN. 5. Tools: Python, Tensorflow, NumPy, Pandas, Scikit-Learn, Keras, TA-Lib, and TA4J10.	Historical stock prices (most authors utilize daily data), e.g. 1. Yahoo Finance. 2. Wind. 3. Taiwan Stock Exchange.	1. Accuracy 2. Precision 3. Recall 4. F1-score
Nti et al. (2020)	1. Fundamental and Technical Analysis. 2. ML. 3. SVM. 4. ANN. 5. Term Frequency-Inverse Document Frequency (TF-IDF). 6. Feature Selection Techniques. 7. Correlation Analysis. 8. Tool: MATLAB.	1. Historical stock prices and technical indicators in technical analysis 2. Financial ratios of the firm and unstructured nature of fundamental factors in fundamental analysis	1. Mean Absolute Percentage Error (MAPE) 2. MSE 3. MAE 4. Root Mean Squared Error (RMSE) 5. Correlation coefficient (R) 6. Volatility 7. Momentum 8. Accuracy 9. Precision 10. Recall 11. F-score 12. Normalized Mean Squared Error (NMSE) 13. Prediction of Change in Direction (POCID)
Zavadzki et al. (2020)	1. ANN. 2. Fuzzy. 3. Evolutionary Computation (Comp. Evol.). 4. Support Vector Regression (SVR). 5. K-Nearest Neighbor (KNN). 6. Principal Component Analysis (PCA). 7. Random Forest (RF). 8. Empirical Mode Decomposition (EMD). 9. SVM. 10. Adaptive Network-based Fuzzy Inference System (ANFIS)	1. Dow Jones indices 2. NASDAQ (National Association of Securities Dealers Automated Quotations) 3. TAIEX index (Taiwan Capitalization Weighted Stock Index)	1. RMSE 2. MAPE
Pinto, Figueiredo, and Garcia (2021)	1. Time Series Analysis (applicable method). 2. Text Mining (applicable method). 3. Sentiment Analysis (applicable method). 4. ML and SVM (the most cited algorithm). 5. DL (the most commonly utilized technique). 6. NNs (the most commonly utilized techniques).	1. Microblogs, news, lexical dictionaries, and Twitter for text mining. 2. News and Twitter for sentiment analysis. 3. Time series	No mentioned.
Kumar et al. (2022a,b)	1. ML algorithms, e.g., NN, ANN, SVM 2. Statistical Techniques, e.g., ARIMA (An Autoregressive Integrated Moving Average) and Clustering.	NASDAQ (most of the selected studies utilized dataset)	1. Accuracy 2. MSE 3. RMSE

(*continued on next page*)

Table 5 (*continued*)

Reference	Method of Stock Market Prediction	Informational Sources	Metrics
Soni et al. (2022)	1. Traditional ML Method 2. DL and NNs, e.g., Recurrent neural network (RNN) and LSTM. 3. Time-Series Analysis. 5. Graph-Based Analysis.	1. Historical stock prices 2. News 3. Technical indicators 4. Data from various online platforms such as Yahoo Finance and Twitter.	1. Accuracy 2. RMSE 3. MAPE 4. MAE

on past data (**Soni et al., 2022**). Technical indicators are the most widely employed source of information for stock market forecasting. Technical indicators have been indicated to be the most accurate data. The input from social networks, on the other hand, helps the models perform better (**Bustos & Pomares-Quimbaya, 2020, p. 156**). In 66% of the 12 selected studies, time series is by far the most frequently used feature set for stock price prediction models, with financial indicators coming in second (**Ketsetsis et al., 2020**).

Studies reveal that human sentiments and emotions can aid in predicting stock market returns in addition to historical financial information about companies or stock markets. Twitter is one of the primary information sources from social networks that are now accessible to everyone, and tweets from important people emotionally impact people, ultimately impacting their investing decisions (**Jabbar Alkubaisi G.A. A., 2017**). In other words, the application of data from social media and websites is a combined source of information that allows for more accurate forecasting (**Pinto, Figueiredo, & Garcia, 2021**).

Furthermore, future research is likely to focus on identifying new sources of information that may be utilized in conjunction with technical analysis to forecast stock markets. Technical indicators, demonstrated to be the most accurate data, are the most widely applied source of information for stock market forecasting. In other respects, the input from social networks helps the models perform better (**Bustos & Pomares-Quimbaya, 2020, p. 156**).

In contrast to technical indicators, fundamental ones are less frequently discussed in the literature because it is more difficult to construct models explaining why a stock is moving. The most frequently utilized data relates to macroeconomic time series, including, but not limited to, Gross Domestic Product (GDP), Customer Pricing Index (CPI), currency exchange rates, and interest rates (**Boyacioglu & Avci, 2010**). Other information sources are just as familiar as financial news but are more challenging due to their unstructured character and erratic behavior. Techniques for text mining have been employed to deal with this complexity. In addition, the news analysis is usually taken from three different sources: specialized media in finance, news in general, and news generated by the same company (**Bustos & Pomares-Quimbaya, 2020, p. 156**).

In another respect, the stock market returns can also be influenced by regional and temporal characteristics. The spatial characteristic may be other stock markets that have the potential to impact the local stock market, or it may be the various emotions of individuals from other geographic locations. Similar to this, a temporal effect depicts how something changes over time. People may have various perspectives at different times, and depending on their feelings at that particular moment, they may behave in different ways. Finally, all of these variables aid in our ability to forecast stock market returns (**Jabbar Alkubaisi G.A.A., 2017**).

Although closing prices are the most frequently employed data, volume and ranges have also proven helpful in making predictions. Most research utilizes periods of 1000 days, which can be easily handled by most machine-learning algorithms (**Bustos & Pomares-Quimbaya, 2020, p. 156**).

Most authors choose Yahoo Finance as the informational source because of the simplicity with which they may obtain data using Yahoo Finance, a Python module. Most literary works employ daily data because it is simple and cost-free to collect this information from financial websites like Yahoo Finance (**Li & Bastos, 2020**). Also, the NASDAQ dataset was employed in most of the selected research for stock market prediction and forecasting (**Kumar et al., 2022a**).

Simple-Moving Average (SMA), Exponential Moving Average (EMA), Moving Average Convergence/Divergence rules (MACD), Relative-Strength Index (RSI), and Rate of Change (ROC) were indicated to be the most commonly utilized technical indicators for stock market prediction (**Nti et al., 2020**). The most popular oscillators are the RSI, Commodity Channel Index (CCI), Williams R, and Stochastic Oscillators (**Bustos & Pomares-Quimbaya, 2020, p. 156**).

The most popular trend indicators are Momentum (MOM) and Moving Averages. The Simple Day Moving Average (SMA) summarizes the previous day's performance. When the crossover of trends occurs, it is employed with various long-term averages for uptrend forecasting. Another well-known indicator that gives more weight to recent prices than historical prices is the Weighted Day Moving Average (WMA). Whether MOM is valued above or below zero, it recognizes trend lines. The MOM is determined by subtracting the two SMA (**Bustos & Pomares-Quimbaya, 2020, p. 156**).

2.3.3. Analysis based on the metrics employed to verify the performance of the predictive model

Given the focus of this review on the stock market, it is crucial to examine the metrics used to verify the accuracy of the predictive model (**Kumar et al., 2022a**). Research indicates that Mean Squared Error (MSE) was the most frequently employed, appearing in 42% of the 12 studies, closely followed by Accuracy and Mean Absolute Error (MAE), both of which were used in 33% of the 12 studies (**Ketsetsis et al., 2020**). Moreover, in a broader perspective, 32% of the selected 30 studies used the accuracy performance parameter to evaluate their model and dataset (**Kumar et al., 2022a**). However, only 11% of the selected studies used the Mean Absolute Percentage Error (MAPE) parameter for prediction, indicating a preference for specific metrics (**Kumar et al., 2022a**).

Regarding model comparison, accuracy, precision, recall, and F1-score are the most commonly employed measures, as evidenced in 62% of the 34 studies (**Li & Bastos, 2020**). The problem of stock market prediction can be classified by two significant problems: classification and regression. On the classification problem, the performance metrics are usually accuracy metrics used in 80% of the 45 studies. (**Bustos & Pomares-Quimbaya, 2020, p. 156**). Furthermore, in another systematic literature review, it was found that error metrics such as Root Mean Squared Error (RMSE), used in 30% of the 122 studies, MAPE, used in 23% of the 122 studies, and MSE, used in 15% of the 122 studies, were the metrics that were most frequently employed (**Nti et al., 2020**).

In conclusion, Accuracy, RMSE, MAPE, MSE, and MAE are the metrics most frequently used for evaluating the performance of predictive models in the stock market. However, it is essential for future research to carefully consider the choice of metrics and provide a clear rationale for their selection.

2.3.4. Analysis based on the limitations and future recommendations of research

This section analyzes the limitations and future recommendations of the existing systematic reviews on AI and stock market prediction. Notably, it focuses on the challenges of meaningfully selecting and combining data sources, which may affect the accuracy and validity of their results, as highlighted in the studies reviewed (**Pinto, Figueiredo,**

& Garcia, 2021). Therefore, the study highlighted the limitations of the works and made several suggestions for future research.

Future research could concentrate on identifying new sources of data or information that can be utilized to supplement technical analysis to predict the movements of the stock market. More articles are expected to automatically find the best technical indicators (Bustos & Pomares-Quimbaya, 2020, p. 156). Researchers can also merge sentiment analysis of stock-related data with the numeric value linked with previous stock value to forecast stock values (Soni et al., 2022). On the other hand, the possibility that the accuracy of ensemble algorithms may vary over different datasets from different continents presents another option for future research (Ballings, Van den Poel, Hespeels, & Gryp, 2015).

None of the one hundred and twenty-twos reviewed studies included social media sentiment, financial news, historical stock data, or macroeconomic data as input variables (Nti et al., 2020). According to Geva and Zahavi (2014), if all of these data sources are utilized as input for a predictive model, a better and higher level of prediction accuracy may be attained.

In recent years, the application of time series, text mining, and sentiment analysis has increased. DL, SVM, and NN have all shone out. Despite advancements in research publications, utilizing these three methodologies has some limits. Using numerical data, textual information, and social media limits the ability of the proposed models. Future research will look into combining time series, text mining, and sentiment analysis to automate better stock market prediction (Pinto, Figueiredo, & Garcia, 2021).

The main difficulty in stock market prediction is that most modern methods cannot be detected with the help of historical stock data. As a result, other factors, such as governmental policy choices and consumer attitudes, have an impact on stock markets (Kumar et al., 2022a).

3. Discussion

The systematic review of systematic reviews aims to identify, evaluate, and synthesize the findings of all extant reviews on a given topic. The value and contribution of such a study lie in its capacity to provide a comprehensive overview of the current state of knowledge. By aggregating and synthesizing the findings from all pertinent reviews, we can gain a holistic understanding of the field. This approach aids in clarifying the existing body of knowledge and pinpointing areas that necessitate further research. In addition to identifying gaps in the research, such a review can underscore areas of consensus and disagreement among extant studies. It assists in reconciling conflicting results and accentuates areas where additional research is required to resolve discrepancies.

Furthermore, this review can effectively steer future research by pinpointing areas that warrant further exploration and suggesting potential avenues for subsequent study. It ensures that ensuing studies are well-grounded and tackle critical questions that have not been sufficiently explored. Lastly, by offering a comprehensive overview of the current state of knowledge and identifying gaps in the research, this review can enhance the quality of future research. It guarantees that future studies are well-grounded and address significant questions that have not been sufficiently addressed. Such an approach, in turn, contributes to advancing knowledge in stock market prediction using artificial intelligence.

Previous systematic reviews have encapsulated the statistical results pertaining to AI and stock prices. However, these literature reviews provide us with fragments of AI and the puzzle of stock prediction. One of the objectives of this study was to meticulously analyze and summarize the systematic reviews on AI and stocks to generate forecasts that would be particularly beneficial when devising future stock market strategies. The research questions in this study aimed to ascertain the most prevalent AI methods, informational sources, and performance metrics for stock market prediction.

Based on the analyses conducted in previous subsections and the data presented in Tables 5 and it is feasible to conclude the most frequently utilized methods for this review, the trend of the study over time, and several potential gaps that could be investigated in future works.

Although this systematic review restricted publication years between 2009 and April 2022, the remaining articles, which date from 2017 to 2022 after applying the inclusion and exclusion criteria, indicate that research conducted by AI with prediction analysis for the stock market is relatively recent. An unexpected finding was that most articles about stocks are relevant studies of AI methods, even though the description of AI technology is not included in the search term. As depicted in Fig. 2, the number of publications has increased.

In ML, DL, and AI models, hyperparameters are paramount, especially in the context of stock market prediction. As elucidated by Tkáč and Verner (2016), this discussion highlights the significance of various hyperparameters such as learning rate, number of epochs, hidden layers, neurons, activation function, dropout rate, batch size, and optimizer. These elements are instrumental in shaping the architecture and training of models like ANNs, DNNs, RNNs, LSTM networks, CNNs, and hybrid models.

Various hyperparameter optimization techniques, including grid search, random search, Bayesian optimization, and evolutionary algorithms, each have merits and demerits. The selection of a method hinges on factors such as model complexity, data size, computing resources, evaluation metrics, and prior knowledge. It is crucial to underscore that no universal set of hyperparameters applies to all stock markets and periods. Consequently, hyperparameters should be regularly adjusted, verified, updated, and fine-tuned to ensure the robustness and accuracy of the model (Bustos & Pomares-Quimbaya, 2020, p. 156).

The intricate nature of ML and DL in stock market forecasting presents a paradox. While these techniques enhance the performance and accuracy of prediction models, they also amplify data and computational needs, thereby diminishing interpretability and robustness. Each method embodies distinct trade-offs. For instance, basic ML methods like linear regression and SVMs may struggle with complex patterns, whereas DL methods can decipher these patterns but at a higher complexity. The method selection should be contingent upon the problem, the available data, and the anticipated result. It is essential to balance complexity and precision, considering parameters, computational cost, data prerequisites, interpretability, and robustness (Bustos & Pomares-Quimbaya, 2020, p. 156; Li & Bastos, 2020).

Another significant yet unexpected point to consider is the AI technique examined in each proposed systematic review, which addresses the first research question **(RQ1 - Which AI methods and technologies are most commonly utilized to forecast stock market prices?)**. In conclusion of the analysis of results, SVM, LSTM, and NN, including ANN, CNN, and RNN, are the most popular AI predictor approaches among different reviews. This study supports evidence from previous

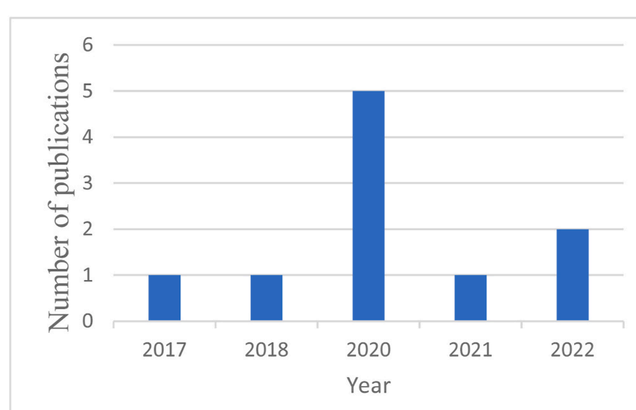

Fig. 2. The number of publications per year.

observations. SVM is the most frequently cited algorithm in 25% of the 57 selected studies (**Pinto, da Silva Figueiredo, & Garcia, 2021**), and the scientific community preferred LSTM in 58% of the 12 selected studies (**Ketsetsis et al., 2020**). The most often used technique is NN in 33% of the 30 selected studies (**Kumar et al., 2022b**). RNN is the most extensively explored by researchers, according to Sezer et al. (2020). In predicting market indexes, CNN outperforms traditional neural networks (**Di Persio & Honchar, 2016**). This inconsistency may be due to the differences in data sets (**Bustos & Pomares-Quimbaya, 2020, p. 156**) and the performance of learning methods (**Islam et al., 2018**). In this respect, one point that must be clarified is that DL is a subset of ML, which is a subset of AI (**Jakhar & Kaur, 2020**). In general, SVM belongs to traditional Machine Learning (**Cortes & Vapnik, 1995**); on the other hand, NN and LSTM, a kind of RNN (**Hochreiter & Schmidhuber, 1997**), belong to DL. Another interesting point about which tools were utilized to create the forecaster based on stock price is that MATLAB is the most popular software besides Python and Tensorflow. These findings can help us to understand the relationship between data sets and prediction methods. In future investigations, it may be able to use diverse informational sources with different prediction approaches to maximize performance.

Responding to the second question (**RQ2 - Which informational sources are most frequently utilized to predict stock market prices?**), the most common feature set for stock price prediction models is time series in 66% of the 12 selected studies, followed by financial and technical indicators (**Ketsetsis et al., 2020**). Furthermore, closing prices are the most frequently employed data of historical stock prices, and SMA, EMA, MACD, RSI, and ROC are the most commonly utilized technical indicators. In addition, it is worth mentioning that social media sentiment, financial news, and macroeconomic data are also worthy informational sources for predicting stock prices. The present results are significant in at least two major respects. The stock market returns can also be influenced by regional and temporal characteristics (**Jabbar Alkubaisi G.A.A., 2017**); on the other hand, the use of data sources is influenced by their complexity and difficulty. Therefore, a further study with more comprehensive thinking on the above variables is suggested.

Finally, answering the last question (**RQ3 - Which metrics are most commonly employed to verify the performance of the predictive models?**), accuracy is generally the most popular and common metric employed to compare models. On the other hand, MSE is also a standard metric to verify the performance of the models. These findings suggest that accuracy and MSE are widely and easily applied. Therefore, accuracy and MSE can be the preliminary prediction performance metrics. Further studies, which take more metrics such as MAE, RMSE, and MAPE into account, will need to be undertaken.

The most often mentioned articles regarding the gaps and suggested future work is related to identifying new sources of data or information (**Bustos & Pomares-Quimbaya, 2020, p. 156**) and combining time series, text mining, and sentiment analysis to predict better the stock market (**Kumar et al., 2022a**). In other words, the more information and hybrid technologies, the better performance of the predictive models.

4. Conclusion

Systematic reviews of systematic reviews represent a type of literature review that seeks to synthesize the findings of multiple systematic reviews on a specific topic. These reviews are increasingly leveraged to provide a comprehensive and current overview of the evidence on a particular topic and identify research gaps.

This study has discovered that SVM, LSTM, and NN, including ANN, CNN, and RNN, are the most utilized predictive methodologies. SVM is the most frequently cited algorithm in 25% of the 57 selected studies (**Pinto, da Silva Figueiredo, & Garcia, 2021**), while the scientific community prefers LSTM in 58% of the 12 selected studies (**Ketsetsis et al., 2020**). NN is the most often used technique in 33% of the 30 selected studies (**Kumar et al., 2022b**). This study also found that time series is the most commonly employed informational source, used in 66% of the 12 selected studies (**Ketsetsis et al., 2020**).

In the domain of stock market prediction, the selection of metrics for evaluating the performance of predictive models is of utmost importance. A review of the literature reveals a preference for specific metrics over others. MSE emerges as the most frequently employed metric, appearing in 42% of a subset of 12 studies and 15% of a more extensive set of 122 studies. Accuracy and MAE follow closely, each used in 33% of the subset of 12 studies. When expanded to 30 studies, accuracy was used in 32%. In the context of model comparison, measures such as accuracy, precision, recall, and F1-score are commonly employed, as evidenced in 62% of a set of 34 studies. Particularly in classification problems, which are a significant aspect of stock market prediction, accuracy metrics are used in 80% of the 45 studies. However, only 11% of the selected studies used the MAPE parameter for prediction, and in a more extensive set of 122 studies, MAPE was used in 23%. RMSE was used in 30% of these 122 studies. These findings indicate a clear preference for specific metrics in the field. In conclusion, accuracy, RMSE, MAPE, MSE, and MAE are the most frequently used metrics for evaluating the performance of predictive models in the stock market. However, the choice of metrics should be carefully considered in future research, with a clear rationale provided for their selection (**Bustos & Pomares-Quimbaya, 2020**, p. 156; **Ketsetsis et al., 2020**; **Kumar et al., 2022a**; **Li & Bastos, 2020**; **Nti et al., 2020**).

The future recommendations for predicting stock prices advocate for the utilization and amalgamation of as much information and technology as feasible. This novel comprehension should enhance the precision of stock market forecasts. The major limitation of this study is that the systematic review includes the articles searched in the title for a briefer review. Another major constraint is that the reviewed systematic reviews seldom discuss the direct analysis or research outcomes of the hyperparameters and complexity of ML or DL models in stock market prediction. Despite the relatively limited number of articles, this work provides succinct yet valuable insights into stock price predictions using Artificial Intelligence technologies.

Future research could explore more articles searched in more extensive fields, including the terms of keywords in the title, abstract, and plus. Another crucial and practical implication is that most stock prediction research focuses on the index of study. Therefore, additional research should be conducted to forecast the stock of individual companies.

Availability of data and materials

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Chin Yang Lin: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation. **João Alexandre Lobo Marques:** Writing – review & editing, Supervision, Project administration, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Abbreviations

Abbreviations/Acronym	*Full name*
AI	Artificial Intelligence
ANFIS	Adaptive Network-based Fuzzy Inference System
ANN	Artificial Neural Network
ARIMA	Autoregressive Integrated Moving Average
ARMA	Auto Regression Moving Average
CCI	Commodity Channel Index
CNN	Convolutional Neural Network
Comp. Evol	Evolutionary Computation
CPI	Customer Pricing Index
DL	Deep Learning
DNN	Deep Neural Network
DT	Decision Tree
EC	Exclusion Criteria
EMA	Exponential Moving Average
EMD	Empirical Mode Decomposition
GA-SVR	Genetic Algorithm-Support Vector Regression
GDP	Gross Domestic Product
GRU	Gated Recurrent Unit
IC	Inclusion Criteria
KNN	K-Nearest Neighbor
LSTM	Long short-term memory
MACD	Moving Average Convergence/Divergence rules
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Machine Learning
MLP	Multilayer Perceptron
MOM	Momentum
MSE	Mean Squared Error
NASDAQ	National Association of Securities Dealers Automated Quotations
NMSE	Normalized Mean Squared Error
NN	Neural Network
PCA	Principle Component Analysis
POCID	Prediction of Change in Direction
RF	Random Forest
RMSE	Root Mean Squared Error
ROC	Rate of Change
RQ	Research Question
RSI	Relative-Strength Index
SMA	Simple-Moving Average
SVM	Support Vector Machines
SVR	Support Vector Regression
TAIEX index	Taiwan Stock Exchange Capitalization Weighted Stock Index
TF-IDF	Term Frequency-Inverse Document Frequency
WMA	Weighted Day Moving Average

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