The Eurasia Proceedings of
Educational & Social Sciences (EPESS)
ISSN: 2587-1730

The Eurasia Proceedings of Educational & Social Sciences (EPESS), 2022

Volume 27, Pages 17-35

IConMEB 2022: International Conference on Management Economics and Business

A Bibliometric Analysis of Artificial Intelligence-Based Stock Market Prediction

Farman ALI
Uttaranchal University

Pradeep SURI
Uttaranchal University

Abstract: The primary purpose of this study is to conduct a scientometrics analysis of stock market forecasts based on artificial intelligence. This research examined 1,301 publications that were published between January 2002 and June 2022. We investigated 183 journal articles among 1,329 papers. In addition to entering the keywords into Scopus, a comprehensive dataset of relevant research papers was compiled. These papers discussed the optimization of investment portfolios, artificial intelligence-based stock market forecasts, investor emotions, and market monitoring. We found the most prolific documents by affiliation, the most prolific author, the most cited papers, nations, institutions, co-authorship maps, inter-country co-authorship maps, and keywords occurrences in this study. Co-authorship analysis network maps and keyword occurrence linkages are generated using the VOS-viewer software. According to our findings, it is evident from the review that the body of literature is becoming more specific and extensive. Primarily, neural networks, support vector machines, and neuro-fuzzy systems are employed to predict the future price of a stock market index based on the composite index's historical prices. Artificial intelligence techniques are able to consider challenges facing financial systems when forecasting time series. Our findings provide actionable guidance on how artificial intelligence can be used to predict stock market movements for market participants, including traders, investors, and financial institutions.

Keywords: Neural network, Stock market prediction, Algorithm, Machine learning, Artificial intelligence, Sentiment analysis.

Introduction

The prediction of the stock market has become a contentious issue for academics in recent years. The rise in stock market investments helped to establish artificial intelligence as a critical and promising area of research. Incorporating machine learning into the prediction of the future value of stocks, bonds, and other financial assets on an exchange can be highly beneficial (Li et al., 2014). Forecasting the future performance of the stock market is difficult due to the additional economic and psychological components, rational and irrational behaviour, etc. that are incorporated into the projection. The combination of these factors produces dynamic and fluctuating stock prices. This makes it incredibly difficult to predict stock values effectively in a turbulent market.

Two traditional theories must be considered when predicting the stock price: the efficient market hypothesis (EMH) and the random walk theory (RW). EMH asserts that a stock's price incorporates all market knowledge at any given time. As a result of market players' optimal utilisation of all available information, price movements are unpredictable due to the random appearance of new information (Fama, 1970). In contrast, according to the random walk theory, stock prices conduct a "random walk," which indicates that future prices do not follow any trends or patterns and are a spontaneous deviation from prior values, making it impossible for an investor to predict the market (Ferson & Harvey, 1991; Jarrett, 2008). There has been controversy over the

- Selection and peer-review under responsibility of the Organizing Committee of the Conference

validity of the EMH and RW theories. With the advent of computational and smart finance, as well as behavioural finance, economists have attempted to establish the inefficient market hypothesis (IMH), which suggests that financial markets aren't necessarily efficient (Malkiel, 2003). The majority of studies (Goodell et al., 2021; Khadjeh Nassirtoussi et al., 2014; Pan et al., 2016; Zhang et al., 2018; Khaing et al., 2020;) have employed AI approaches to demonstrate these claims, and the fact that selected players may continuously outperform the market indicates that the EMH may not be applicable in practice.

Consequently, stock market analysis can be a difficult and multidimensional operation. AI and ML help simplify this effort. AI and ML can facilitate unbiased data collecting, data classification, stock analysis, and pattern recognition. Ding et al. (2015) has developed a model that improves S&P 500 index and individual stock forecasts by over 6% relative to current best practices. This research demonstrated that the model is able to consistently gain sustainable competitive advantage. According to Khaing et al. (2020) experiments, trend extraction with additional criteria on stock news extracts more trends. In addition to additional parameters, the stock trend extraction findings are more consistent with the actual stock price movement. Chen (2021) created the new neural network model to develop the prediction model's concepts. (Belciug et al., 2021) evaluated the efficacy of a statistical learning framework using an algorithm based on a competitive/collaborative method for generating a reliable real-time forecast of the next stock market transaction price for a share. Biswas et al.(2021) investigated numerous models and approaches used in stock market prediction and focused on their advantages and disadvantages. This study also examined over ten approaches used in the recent decade to estimate stock market values. Serrano (2022) demonstrated that the proposed methodology using RNN models accurately predicts the performance of various investment portfolios.

Using machine learning, Stock Price Prediction may determine the future price of a company's stock and other financial assets traded on an exchange (Nayak et al., 2016). The entire purpose of predicting stock prices is to generate substantial profits. Forecasting the future performance of the stock market is difficult. In addition to physical and psychological elements, reasonable and irrational conduct, etc., there are additional components involved in the forecast. All of these elements combine to create dynamic and volatile stock prices (Mamun et al., 2015). This makes it extremely difficult to accurately estimate stock prices. Researchers are constantly seeking ways to predict the future. Given the rapid rise of the economic-focused society, it is always necessary to research and discover relevant information to select a better stock in the stock market. Stock Market Predictions' bibliometric analysis was inspired by an increase in the number of articles that applied and measured this concept over the past two decades, demonstrating the richness of this concept in the research ground.

AI and Stock Market Prediction: Background Information

Research on artificial intelligence in the stock market has been well documented in previous studies. An accurate prediction of stock prices is impossible due to the complexity and uncertainty of the stock market. For the successful study of the future stock price of any company, a reliable forecasting system is required (Ishwarappa & Anuradha, 2021).

Previous research (Khadjeh Nassirtoussi et al., 2014) reviewed related articles on market prediction based on online text mining and drew a picture of its generic components. Reaz et al. (2002) showed the implementation of backpropagation on the Altera FLEX10K FPGA device for stock market prediction by exploiting the parallelism in the neural network design; this method increases the convergence speed of the network and the accuracy of the stock market forecast. Chen (2011) argued that artificial intelligence (AI) may be a more appropriate tool than classical statistics for predicting the possible short-term financial problems of a corporation. (Rodr\'\iguez-González et al., 2011) indicated that the CAST is capable of predicting both the market as a whole and particular IBEX 35 stocks. For example O et al. (2004) found in the Korean stock market, the trading system with the suggested asset allocator outperforms other systems with fixed asset allocation methods. Reinforcement learning can have synergistic impacts on the decision-making problem by utilising supervised-learned predictors. Yang and Chen (2014) implies that the neural network has the analytical capacity to deal with the current disordered and mixed information processing. In addition, it is already the most effective tool for intelligent processing. In numerous fields, including recognition processing, signal analysis, and control, the BP algorithm has been widely adopted and has represented a significant breakthrough. Ng et al. (2014) proposed the algorithm LG-Trader, which simultaneously identifies classifier architecture selection and feature selection using a genetic algorithm to minimize a new Weighted Localized Generalization Error (wL-GEM). In both stock and index trading, the LG-Trader generates higher profits and return rates, as demonstrated by experimental results. A two-stage fusion method utilizing Support Vector Regression (SVR) as the first stage

was used by (Patel et al., 2015) to establish predictions for 1–10, 15–30, and days in advance. The SVR-ANN, SVR-RF, and SVR-SVR fusion prediction models are produced in the second stage of the fusion approach using Artificial Neural Networks (ANN), Random Forests (RF), and Support Vector Regressions (SVR). Ding et al. (2015) introduced a deep learning strategy for event-driven stock market prediction, and discovered that the model can produce about 6% increases in S&P 500 index prediction and individual stock prediction, respectively, compared to baseline methods at the forefront of the field. Wang et al. (2015) investigated extensive information diffusion-related knowledge and modelled it scale-independently. Extensive testing on a Sina Weibo reposting dataset revealed the suggested method's higher performance in forecasting the burst time of posts. Shynkevich et al. (2016) predicted stock price movement using the multiple kernel learning technique, which integrates information from multiple news categories while separate kernels investigate each category. They also observed that increasing the number of related news categories used as data sources for market prediction positively affects the predictive framework relative to techniques based on fewer categories. Pan et al. (2016) evaluated the impact of data normalization on SVM and technical indicator stock index price prediction.

Experimental results suggested that a prediction system based on SVM and technical indicators should carefully choose a data normalization strategy to decrease forecast accuracy and training time. Due to the prevalence of the Internet, Google, Wikipedia, and other sources. Weng et al. (2018) predicted the price of the stock market. This data provides insight into the financial performance of companies and captures traders' interest through search trends, website visits, and financial news sentiments. The study uses a meticulous approach to gathering its data. The AI platform subsequently trains the following four ensemble machine learning techniques: (a) a neural network regression ensemble; (b) a support vector regression ensemble; (c) a boosted regression tree; and (d) a random forest regression. The AI platform selects the "best" ensemble for a certain stock during the cross-validation phase. Zhou et al. (2020) predicted the directions of stock price movements using a variety of heterogeneous data sources, including historical transaction data, technical indicators, stock posts, news, and the Baidu index. Researchers looked at the support vector machine's (SVM) ability to anticipate price movements for a single firm under various activity levels, and their results show that this method is more effective at doing so during periods of moderately and highly active trading.

Ghanavati et al. (2016) proposed a hierarchical beta process (HBP) approach for predicting stock market trends. Preliminary results indicate that the technique is promising and outperforms other prevalent techniques. Ghanavati, et al. (2016) discovered that metric learning-based methodologies can substantially increase performance. In addition, based on the results, it was determined that adding news to historical stock prices to feed the algorithms will not improve the outcomes for all stocks. A detailed examination of each stock revealed that considering an additional source such as news is more advantageous for larger and more popular stocks. Several attempts have been made using the Recurrent Neural Network (RNN) as a benchmark. Singh and Srivastava (2017) observed that the accuracy for Hit Rate has been enhanced by 15.6% when using a model of deep learning. DNN outperforms RBFNN and RNN by a factor of 43.4% in terms of the correlation coefficient between actual and expected returns. Nelson et al. (2017) employed LSTM networks to predict price movements based on market history and technical analysis. A prediction model was built and a series of experiments were done to assess if this algorithm improves on existing Machine Learning techniques and investing strategies. The results were good, with 55.9% accuracy when predicting a stock's price rise.

A number of researchers have been (Waqar et al., 2017) applied principal component analysis (PCA) and linear regression to predict stock market patterns. PCA improves machine learning predictions and reduces data redundancy. Experiments were performed on a high-dimensional spectrum of the NYSE, LSE, and KSE. According to Maini and Govinda (2017), the Random Forest model is an ensemble learning technique that has proven to be a highly effective classification and regression model. Support vector machine is a classification-based machine learning model. Sato et al. (2018) suggested a method for short-term foreign currency forecasting and demonstrated its utility. EA (Expert Advisor) was implemented on Meta Trader (MT4)6. EA runs MT4. Once accomplished, the purchase can be repeated automatically per regulation. In this investigation, the author used the free edition of EA, ran two functions concurrently at the modified function frequency and the usual time, and proved the usefulness of the proposed method by comparing real volume differences for price movement and time series prediction. Ebadati and Mortazavi (2018) developed a hybrid approach combining Genetic Algorithm (GA) and Artificial Neural Network (ANN) technologies. It is feasible to correct faults in the GA method by feeding its output values into an ANN-built algorithm. The results of the tests revealed that the GA and ANN can be deployed to enhance accuracy with fewer trials.

Recently investigators have (Shastri et al., 2019) determined that a mix of sentiment analysis and neural networks is utilized to generate a statistically significant association between the historical numerical data records of a specific stock and other sentimental variables that can affect the stock values. Rajab and Sharma

(2019) developed an effective and interpretable neuro-fuzzy system for predicting stock prices employing various technical indicators, with an emphasis on the interpretability–accuracy trade-off. Cheng et al. (2020) confirmed the ARIMA model for model testing, selected the model with the lowest AIC, BIC, and hqlc values, and visualised 10 percent of the total data. The prediction effect is poor, there are relatively large errors, and the closing price trend is inconsistent, according to the visual results. Almehmadi (2021) applied artificial intelligence to obtain a stock market forecast accuracy of 99.71 percent, which is far higher than the 89.93 percent accuracy recorded in the relevant literature; the addition of COVID-19 data increased accuracy by 9.78 percent. The application of the ARIMA model to the stock market is inadequate and must be improved. Nayak et al. (2016) constructed a model using algorithms for supervised machine learning. In the daily prediction model, previous prices and sentiments are linked. Using supervised machine learning techniques on the daily prediction model yields up to 70% accuracy. Qiu et al. (2016) predicted the return of the Japanese Nikkei 225 index using an artificial neural network (ANN) that can map any nonlinear function without a previous assumption and provided a new set of input variables for ANN models to improve the efficacy of prediction algorithms. Zhang et al. (2018) determined that four well-known machine learning models could accurately predict the growth and fall of a stock in the Shanghai Stock Exchange (SSE) 50 index after 30 trading days. Results show that ANN (Artificial Neural Network) is superior than the other three models in terms of accuracy. Finding valuable patterns in the stock market may be possible with the help of neural networks, according to our research. The AUC of the model is consistent between 0.72 and 2.74, and the value of F1 is constant between 0.66 and 0.70, as demonstrated by Wu et al. (2020), proving that discretized technical indicators can accurately forecast short-term changes in share price. Yang et al. (2021) designs experiments to validate the function of the model from the perspectives of stock data collecting and processing, and stock price prediction accuracy, and draws statistical graphs in accordance with the statistical research results. TupeWaghmare (2021) revealed various techniques for forecasting and analysing the movement of stock values. They can indeed be broadly categorized as statistical or artificial intelligence-based. Artificial intelligence is used to predict future stock prices, employing a variety of algorithms such as SVMs, CNNs, LSTMs, RNNs, etc. Hogenboom et al. (2021) investigated the reliability of generated buy and sell signals based on anticipated stock price movements, as well as the excess profits offered by a trading strategy that incorporates these signals, and found that Event-based stock price forecasts appear to be the most accurate two days in advance. Hájek (2018) applied a combination of financial indicators, readability, sentiment categories, and bag-of-words (BoW) to improve prediction accuracy, demonstrating that the prediction quality risen exponentially when applying the correlation-based feature selection of BoW. This prediction performance is independent of industry classification and event timeframe.

The sentiment analysis and market movements have been studied by many researchers using AI based neural network. Coyne et al. (2017) examined the conceptual model and reported that there was no association between general stock Twits postings and stock price. While the second and third models adopted an innovative approach and effectively filtered through the twits to discover relevant tweets, the first model struggled to do so. Based on sentiment analysis and intelligent user identification, these influential Twitter users could anticipate stock price changes with a greater degree of accuracy (about 65% on average). Li et al. (2018) applied to predict tweet sentiment and acquire insight into the relationship between twitter sentiment and stock prices. Tweet sentiment is determined via SVM-based sentiment analysis according to Batra and Daudpota (2018). Therefore, each tweet is either bullish or bearish. The sentiment score and market data are used to build an SVM model that predicts stock movement the next day. People's opinions and market data are correlated, and the proposed study predicts stock prices with 76.65% accuracy. This association is found by using Twitter's search API and analysing the results. The Twitter sentiment is determined employing Nave Bayes classification and Support vector machines. The support vector machine is the most accurate model to predict the sentiments based on cross-validation. Camara et al. (2018) proposed a computationally estimating technique for forecasting the impact of hurricanes on the stock market using fuzzy logic-based data analytics. PCA-WSVM is effective and can be used to forecast the stock trading signals in a real-world application, as shown by the experiment results Chen and Hao (2018). Kumar et al. (2018) tested stock market prediction models' efficiency. These models are based on SVM, Random Forest, KNN, Naïve Bayes, and SoftMax. The Random Forest approach performs better with big databases than the Naïve Bayesian Classifier. The HyS3 hybrid supervised semi-supervised model for movement prediction was put forth by Kia et al. (2018). The graph-based semi-supervised component of HyS3 simulates global market interactions using a ConKruG-generated network. The supervised half of the model injects historical market data into the network when the hybrid model allows it. Malagrino et al. (2018) identified the model that accounts for a single index per continent. This design had a mean accuracy of approximately 71%. (With almost 78 percent top accuracy). In addition to producing results equivalent to those of the relevant literature, this model is also simpler and more user-friendly. Nam and Seong (2019) indicated that establishing causal relationships is significant in prediction problems, and they recommend that it is also important to construct machine learning algorithms and find linkages with well-established theories such as the complex system theory. Artificial intelligence and signal processing-based techniques are more efficient than

traditional financial forecasting methodologies, according to Nair and Mohandas (2015) survey. According to a literature review, neural networks (NNs), support vector machines, and neuro-fuzzy systems are used to estimate a stock's future price.

The literature discussed above can be divided into five categories: return prediction, stock trend forecasting using artificial intelligence, market sentiment analysis, use of AI in the financial market, and combinations incorporating two or more approaches. The researcher outlines the study that led up to the current applications in each area. Existing reviews of AI in stock market prediction are narrowly focused and discuss different topics separately. None of these assessments classifies AI's financial applications to predict the movement of stock market comprehensively. This review adopts a holistic and inclusive approach to describe AI's adoption and deployment in the financial market.

Research Methodology and Data Collection

In academia, bibliometric analysis has been used frequently to examine the growth rate and the prominence of numerous academic topics. A Bibliometric analysis is a publication-based statistical technique that provides measurable insight into academic literature. To ensure the relevance and validity of research, it is essential to identify and choose high-quality international scientific articles that provide original and reliable information and knowledge sources. Regarding artificial intelligence in the stock market, the Scopus database is systematically searched (Ahmed et al., 2022).

We used the following protocol [TITLE-ABS-KEY (artificial AND intelligence+stock+market)]. This study analysed 1,301 papers published between January 2002 and June 2022. Among these 1,329 documents, 183 journal articles were determined as pertinent to the investigation's purpose. After putting "Artificial Intelligence application in the stock market" into the Scopus database, a significant set of research publications was reviewed (Ruiz-Real et al., 2021). With a focus on the most important scientific methodologies and tools employed, as well as the most significant results and conclusions made by the authors (Berradi et al., 2020).

Finally, it's essential to reveal which topics remain open in this domain and focus future research on these gaps. Data gathering and research technique selection are crucial to the process for analysing scientific articles and contributions. In this section, we have introduced the effective bibliometric tool VOS Viewer version 1.6.18 and database selection and data collecting, including establishing various parameters to assure research reliability. We follow (Goodell et al., 2021) four steps procedure for bibliometric reviews:(1) establishing the review's aims and scope; (2) selecting the analysis tools; (3) collecting the data for analysis; and (4) analysing and reporting the findings.

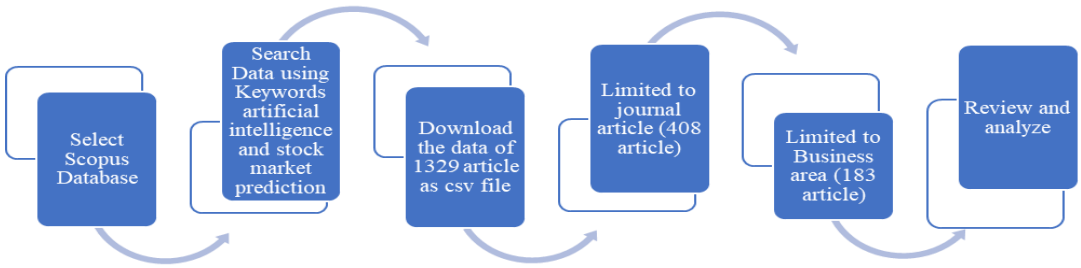

Figure 1. A flowchart depicting the process for literature review.

In order to analyse co-authorship, inter-country, and keyword co-occurrence, the software VOS viewer 1.6.18 is used; it is a tool for making network maps that are based on the network analysis database. Additionally, these maps can be visualized as well.

a. Top prolific Institutions which have published the highest number of papers.
b. Which year publishes maximum number of the papers.
c. Analysis of Publication based on source
d. Analysis of Publication based on the type
e. The highest number of cited documents in the study.
f. Top prolific authors.
g. Top prolific countries.
h. Analysis of co-authorship connection with the other authors.
i. Most occurring keywords.

Analysis and Discussion of Results

Analysis based on Affiliation

Figure 2 shows that various universities have published research papers on stock market prediction using artificial intelligence. Universities in China and India have made significant contributions. Research on Stock Market Prediction using artificial intelligence has been increasing day by day. Further, looking at the key institution that published the most papers on stock market prediction using AI, as shown in Figure 2.

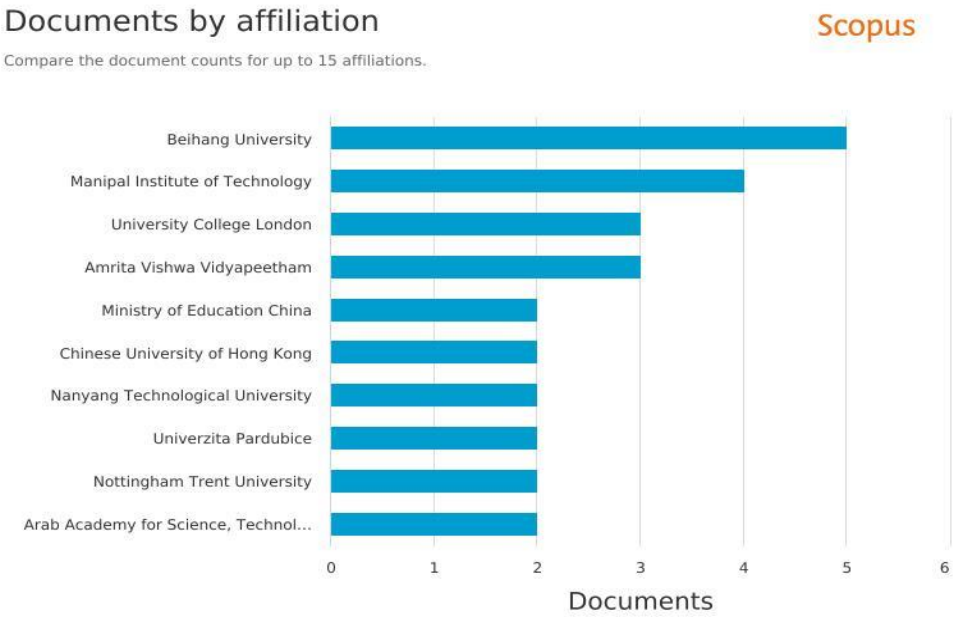

Figure 2. An analysis of publications based on affiliations

Analysis of Publication based on Year

Stock Market Prediction using Artificial Intelligence is investigated based on the keywords extracted from 183 different types of publications during 2002-2022. As shown in figure 3, the number of publications per year is analysed. A majority of the work was published in 2016 and 2018, with no paper being published in 2003.

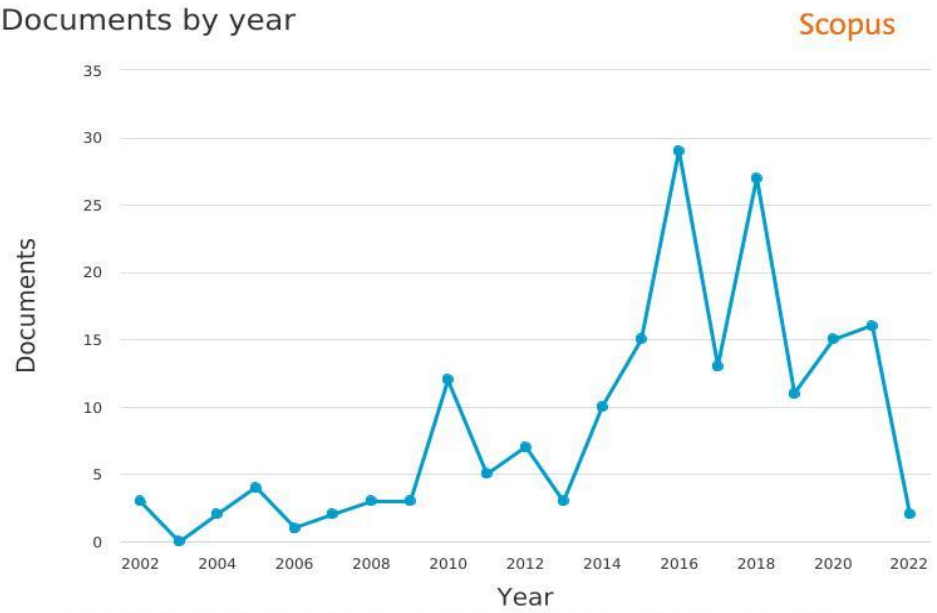

Figure 3. Analysis of publication based on year (source Scopus)

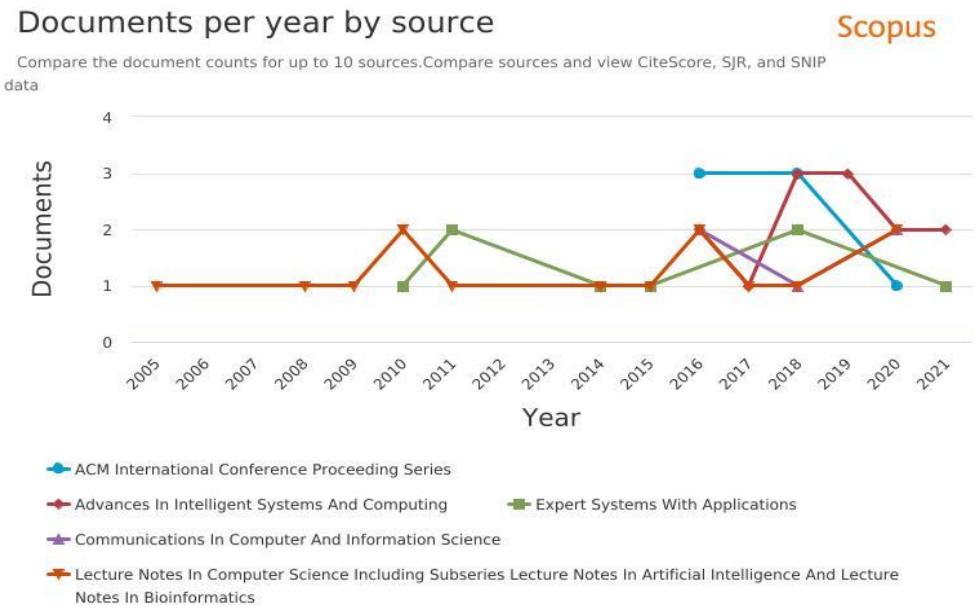

Figure 4. Analysis of publication based on source

Analysis of Publication based on Source and Publications

Figure 4 depicts a stratification of document sources. The significant substantial research was published in Lecture Notes in Advances in Intelligent Systems and Computing, Lecture Notes in Computer Science, including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, and expert system with applications. Communication in Computer and Information Science has minor papers in Stock Market Prediction and ACM International conference proceedings series.

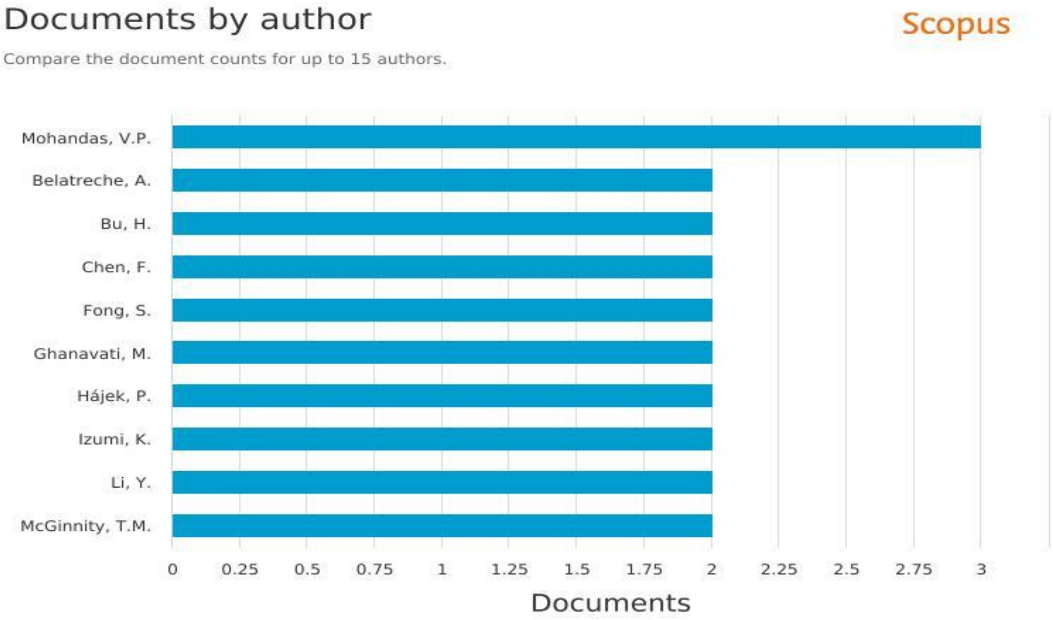

Figure 5. Analysis of publication based on author

Figure 5 depicts the biggest contributors to Stock Market Prediction by applying artificial intelligence. The first ten researchers were considered based on the Scopus website's available statistics.This survey has been the subject of a study published in journal articles, book chapters, conference proceedings, etc. The majority of the Researchers in the field of Stock Market Prediction applying artificial intelligence have published recent research at conferences. There were 73.8% of conference papers, 22.4% of journal articles, 2.2% of review articles, and 1.6% of book chapters as shown in figure 6.

Table 1. Top prolific authors based on citations

Sr. No.	Author Name	Citations	Sr. No.	Author Name	Citations
1	Zhang Y.	420	29	Pan R.	61
2	Ding X.	418	30	Zhang X.-D.	61
3	Duan J.	418	31	Colomo-Palacios R.	59
4	Liu T.	418	32	García-Crespo A.	59
5	Aghabozorgi S.	323	33	Guldrís Iglesias F.	59
6	Khadjeh Nassirtoussi A.	323	34	Gómez-Berbís J.M.	59
7	Ngo D.C.L.	323	35	Rodríguez-González A.	59
8	Ying Wah T.	323	36	Belatreche A.	57
9	De Oliveira R.A.	322	37	Mcginnity T.M.	57
10	Nelson D.M.Q.	322	38	Shynkevich Y.	57
11	Pereira A.C.M.	322	39	Malagrino L.S.	54
12	Ghanbari A.	267	40	Monteiro A.M.	54
13	Hadavandi E.	267	41	Roman N.T.	54
14	Shavandi H.	267	42	Li J.	52
15	Kotecha K.	258	43	Nam K.	49
16	Patel J.	258	44	Seong N.	49
17	Shah S.	258	45	Nayak A.	48
18	Thakkar P.	258	46	Pai R.M.	48
19	Srivastava S.	128	47	Chung H.	43
20	Singh R.	121	48	Li Z.	43
21	Chen M.-Y.	117	49	Shin K.-S.	43
22	Akagi F.	116	50	Coleman S.A.	42
23	Qiu M.	116	51	Romanowski A.	42
24	Song Y.	116	52	Skuza M.	42
25	De Lima B.S.L.P.	87	53	Adekoya A.F.	41
26	Evsukoff A.G.	87	54	Nti I.K.	41
27	Vargas M.R.	87	55	Weyori B.A.	41
28	Li A.	61	56	Pai M.M.M.	40

Table 2. Top prolific countries

Sr. No.	Id	Country	Documents	Citations
1	15	India	40	715
2	6	China	34	715
3	41	United Kingdom	15	175
4	42	United States	11	124
5	1	Australia	10	88
6	37	Taiwan	8	146
7	19	Japan	7	126
8	14	Hong Kong	6	57
9	16	Iran	6	324
10	33	South Korea	6	102

Analysis of Top Prolific Authors based on Citations

Table 2 lists the ten countries with the highest number of English-language publications on stock market forecasting using artificial intelligence. India ranks first with a total of 40 papers. China, the United Kingdom, the United States, Australia, Taiwan, Japan, Hong Kong, Iran, and South Korea are the following highest-documented countries. Out of a total of 183 papers, more than half, or 100 documents, are provided by authors from the top four nations.

Table 3. Top prolific titles based on citations

Sr. No.	Authors	Title	Citation
1	Ding X., Zhang Y., Liu T., Duan J.	Deep learning for event-driven stock prediction	418
2	Khadjeh Nassirtoussi A., Aghabozorgi S., Ying Wah T., Ngo D.C.L.	Text mining for market prediction: A systematic review	323
3	Nelson D.M.Q., Pereira A.C.M., De Oliveira R.A.	Stock market's price movement prediction with LSTM neural networks	322
4	Hadavandi E., Shavandi H., Ghanbari A.	Integration of genetic fuzzy systems and artificial neural networks for stock price forecasting	267
5	Patel J., Shah S., Thakkar P., Kotecha K.	Predicting stock market index using fusion of machine learning techniques	258
6	Singh R., Srivastava S.	Stock prediction using deep learning	121
7	Chen M.-Y.	Predicting corporate financial distress based on integration of decision tree classification and logistic regression	117
8	Qiu M., Song Y., Akagi F.	Application of artificial neural network for the prediction of stock market returns: The case of the Japanese stock market	116
9	Vargas M.R., De Lima B.S.L.P., Evsukoff A.G.	Deep learning for stock market prediction from financial news articles	87
10	Zhang X.-D., Li A., Pan R.	Stock trend prediction based on a new status box method and AdaBoost probabilistic support vector machine	61
11	Rodríguez-González A., García-Crespo A., Colomo-Palacios R., Guldrís Iglesias F., Gómez-Berbís J.M.	CAST: Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator	59
12	Malagrino L.S., Roman N.T., Monteiro A.M.	Forecasting stock market index daily direction: A Bayesian Network approach	54
13	Nam K., Seong N.	Financial news-based stock movement prediction using causality analysis of influence in the Korean stock market	49
14	Chung H., Shin K.-S.	Genetic algorithm-optimized multi-channel convolutional neural network for stock market prediction	43
15	Shynkevich Y., McGinnity T.M., Coleman S.A., Belatreche A.	Forecasting movements of health-care stock prices based on different categories of news articles using multiple kernel learning	42
16	Skuza M., Romanowski A.	Sentiment analysis of Twitter data within big data distributed environment for stock prediction	42
17	Nti I.K., Adekoya A.F., Weyori B.A.	A systematic review of fundamental and technical analysis of stock market predictions	41
18	Nayak A., Pai M.M.M., Pai R.M.	Prediction Models for Indian Stock Market	40
19	Batra R., Daudpota S.M.	Integrating Stock Twits with sentiment analysis for better prediction of stock price movement	39
20	Wang S., Yan Z., Hu X., Yu P.S., Li Z.	Burst time prediction in cascades	39

Table 3 contains the titles of the most cited papers and the number of citations they've got as of the date the data for this study have been extracted.

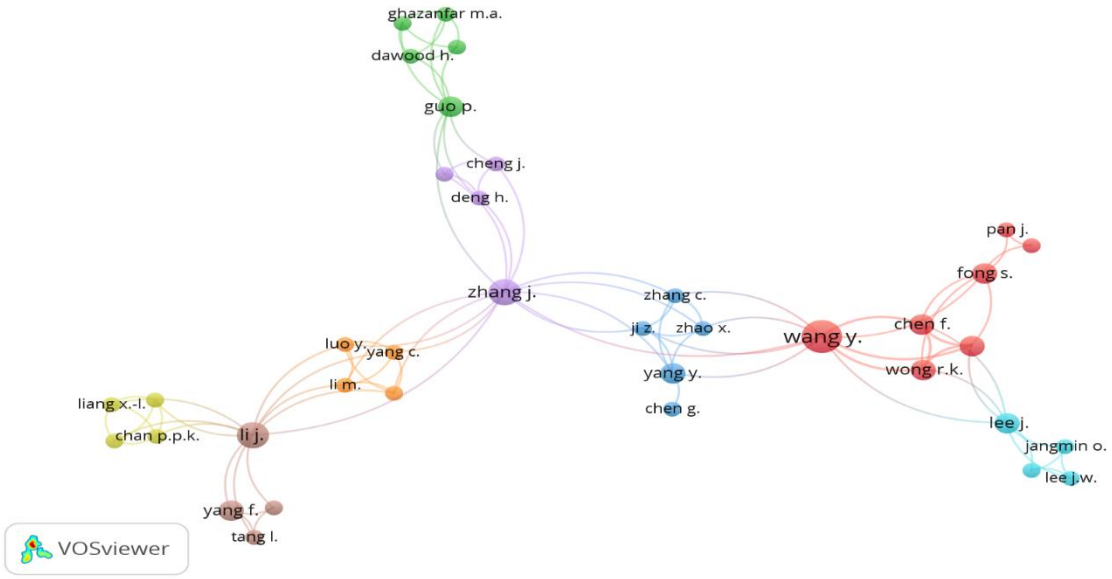

Figure 7. Analysis of co-authorship connection with the other authors

Analysis of Co-authorship Connection

The cluster to which an item belongs determines what colour it is. Lines between things signify links. In Figure 7, there are eight different groups of various colours. These colours show how the authors are connected. In this study, we searched at how eight groups of authors worked together. In the network visualization, each item is shown by its name and, by default, by a circle. A large circle shows how well an author has contributed to a related field.

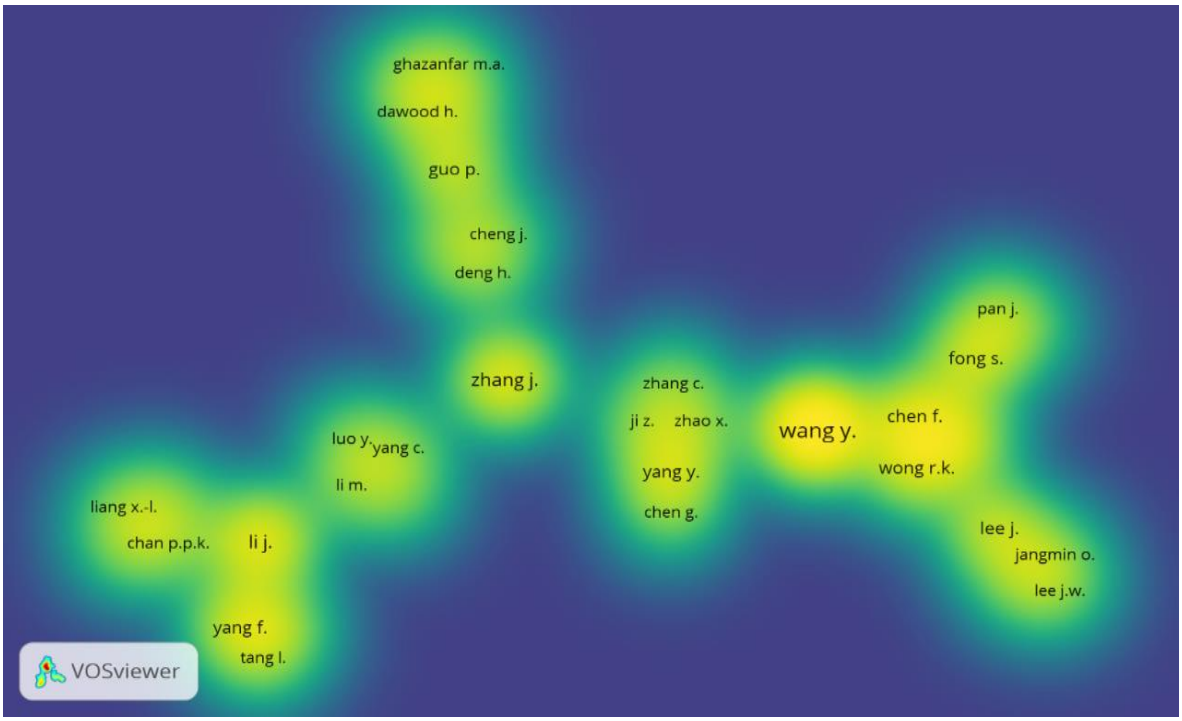

Figure 8. Authorship density visualization

Similar to the network visualisation and the overlay visualisation, authors are represented by their label in the author density view. Each point in the author density image is coloured according to the item density at that location. The default colour palette consists of blue, green, and yellow. The greater the number of things in a point's neighbourhood and the greater their weights, respectively

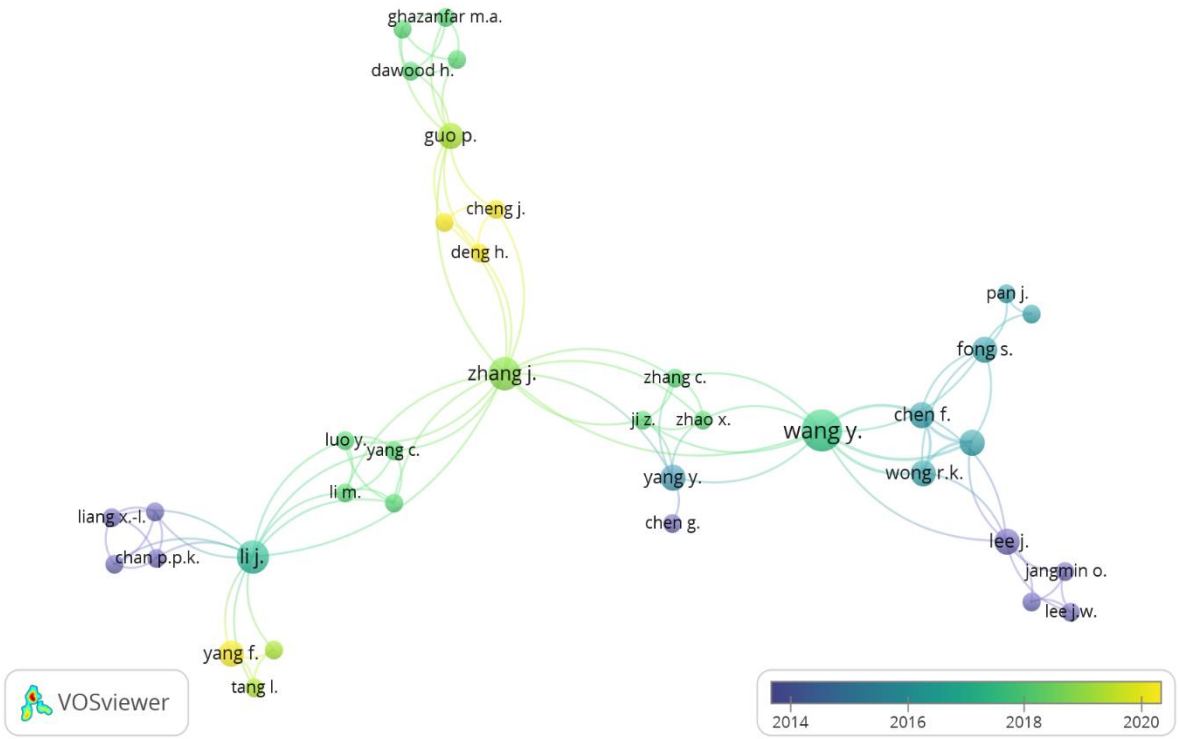

Figure 9. Authorship network overlay visualization

The Prediction of the Stock Market Using Artificial Intelligence is examined using authorship overlay visualization extracted from 183 distinct categories of articles published between 2002 and 2022. The number of publications based on the most prolific author per year is analysed, as shown in figure 9. The majority of articles have been published between 2016 and 2018.

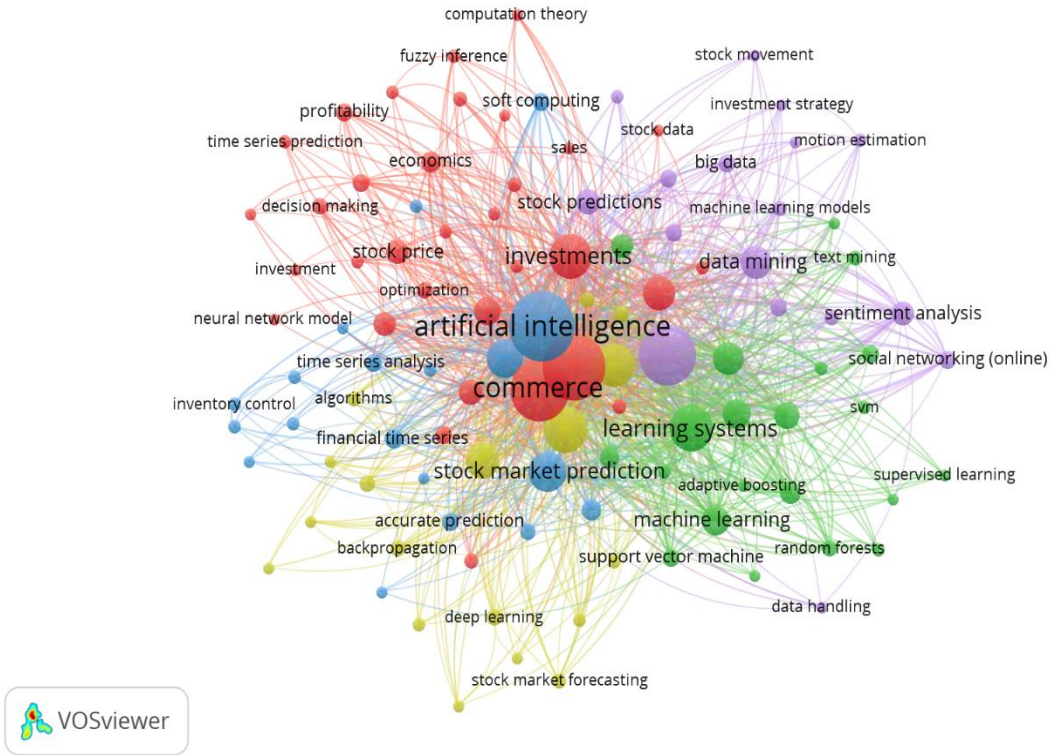

Figure 10. Keywords occurs the maximum number of times

Analysis of Co-occurrence of Keywords

Figure 10 illustrates the co-occurrence analysis of keywords. There are a total of 1,123 terms in the study's database. These 108 keywords that have appeared in the database more than five times are used to generate a keyword map.

Table 4. Keywords occurrences

Id	Keyword	Occurrences	Total Link	Id	Keyword	Occurrences	Total Link
13	Accurate Prediction	12	121	895	Mean Square Error	8	98
21	Adaptive Boosting	5	71	925	Motion Estimation	7	72
43	Algorithms	8	98	945	Multilayer Neural Networks	5	47
72	Artificial Intelligence	167	1708	972	Natural Language Processing Systems	6	84
76	Artificial Intelligence Techniques	7	53	976	Nearest Neighbour Search	5	75
80	Artificial Neural Network	11	128	998	Neural Network	9	131
114	Backpropagation	10	132	1004	Neural Network Model	5	42
115	Backpropagation Algorithms	5	64	1007	Neural Networks	44	519
138	Big Data	11	129	1072	Optimization	10	120
185	Classification (Of Information)	11	138	1121	Prediction	21	241
203	Clustering Algorithms	6	70	1122	Prediction Accuracy	16	176
210	Commerce	130	1423	1127	Prediction Model	8	98
217	Complex Networks	6	83	1132	Prediction Performance	8	96
220	Computation Theory	5	63	1137	Prediction Systems	6	70
224	Computational Intelligence	5	61	1159	Principal Component Analysis	6	72
249	Convolutional Neural Network	5	56	1174	Profitability	11	100
256	Costs	40	488	1189	Random Forest	6	88
277	Data Handling	5	54	1195	Random Forests	9	122
279	Data Mining	37	461	1216	Recurrent Neural Networks	5	55
297	Decision Making	9	98	1224	Regression Analysis	10	91
300	Decision Support System	5	53	1274	Sales	5	66
301	Decision Support Systems	11	118	1305	Sentiment Analysis	19	229
309	Decision Trees	24	303	1330	Signal Processing	7	79
311	Deep Learning	10	111	1351	Social Networking (Online)	12	140

374	Economics	15	166	1355	Soft Computing	12	141
386	Electronic Trading	71	840	1389	Stock Data	5	49
462	Feedforward Neural Networks	5	42	1391	Stock Exchange	6	54
465	Finance	65	788	1395	Stock Forecasting	6	65
472	Financial Data Processing	23	248	1398	Stock Market	50	496
480	Financial Forecasting	5	55	1399	Stock Market Analysis	5	53
489	Financial Markets	124	1397	1401	Stock Market Forecasting	8	95
503	Financial Time Series	13	151	1407	Stock Market Prediction	56	587
508	Fintech	8	73	1410	Stock Market Prices	12	152
515	Forecasting	151	1626	1412	Stock Markets	7	46
552	Fuzzy Inference	6	68	1413	Stock Movement	5	53
555	Fuzzy Logic	8	88	1416	Stock Prediction	12	122
556	Fuzzy Neural Networks	6	53	1418	Stock Predictions	23	233
561	Fuzzy Systems	6	65	1419	Stock Price	19	182
581	Genetic Algorithm	5	63	1421	Stock Price Forecasting	8	86
582	Genetic Algorithms	9	109	1423	Stock Price Movements	11	131
693	Information Science	5	45	1424	Stock Price Prediction	29	327
736	Inventory Control	7	50	1439	Stock Trend Prediction	7	80
737	Investment	5	50	1451	Supervised Learning	5	74
744	Investment Strategy	5	64	1452	Supervised Machine Learning	5	75
745	Investments	68	754	1454	Support Vector Machine	11	140
793	Learning Algorithms	36	480	1457	Support Vector Machines	32	414
799	Learning Systems	74	898	1465	SVM	6	93
843	Machine Learning	31	343	1477	Technical Analysis	7	82
845	Machine Learning Methods	5	52	1481	Technical Indicator	16	189
846	Machine Learning Models	8	100	1493	Text Mining	8	104
849	Machine Learning Techniques	18	251	1513	Time Series	20	212
877	Market Trends	6	53	1514	Time Series Analysis	12	136
879	Marketing	7	50	1519	Time Series Prediction	7	60
887	Mathematical Models	7	61	1553	Trend Prediction	5	55

The keyword map displays relevant keywords that are interconnected through several lines. These lines denote the co-occurrence network map for the Keywords that have co-occurred and are connected. As indicated in Table 4, the most frequently occurring keywords recommend the study fields relating to the keywords that need to be undertaken more in the future.

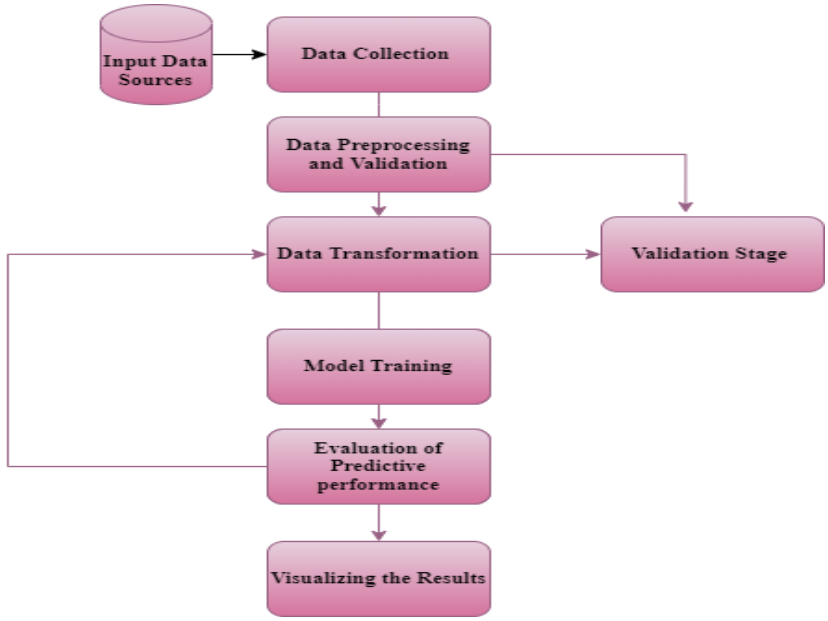

Figure 11. Flowchart for stock market forecasting with artificial intelligence

The scholarly literature on stock prediction has highlighted the rise of various opposing ideas. In contrast to the efficient market theory, numerous researchers (Hargreaves & Hao, 2012; Nti et al., 2020) believe that market prices follow a trend. Following this approach, there are two schools of market analysis: technical analysis defends tendencies in stock price movements and seeks to anticipate them using prior asset prices; and fundamental analysis argues that a firm's socioeconomic background impacts its future stock price and, thus, gives knowledge that may be used to forecast future asset prices. Figure 11 illustrates the overall structure for an Artificial Intelligence prediction model applied to financial forecasting. The initial stage is to collect all of the data needed to train and test the prediction model. These data can be processed, modified, or decreased in order to eliminate noise and emphasise crucial information. The predictor then utilises the treated data to train its model, after which it may tune its hyperparameters in a validation step. Finally, the trained model's performance with tuned hyperparameters must be assessed in a test phase.

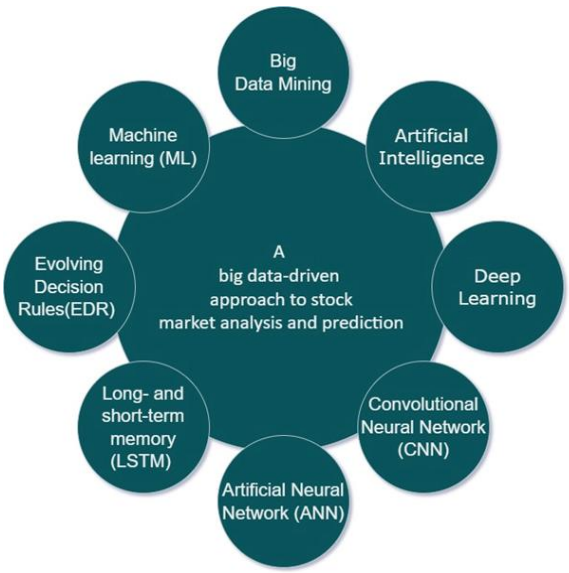

Figure 12. Shows the different techniques to predict the stock market movements

In this portion of the study, we intend to examine the research around the tools and platforms utilized in artificial intelligence for stock price movement prediction. However, for this part, we go beyond the papers originally selected because they frequently do not describe the research methods employed. The stock market is evaluated using the approaches shown in Figure 12: Deep learning; machine learning; neural networks; LSTM, ANN, CNN; and data mining, among others.

Conclusion

In the past two years, a vast number of experimental research has been conducted on stock market prediction using artificial intelligence, as demonstrated by this study. If we discuss the research questions in this study, we must begin with the journal Lecture Notes in Advances in Intelligent Systems and Computing, Lecture Notes in Computer Science, including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics which has the most records. According to the analysis, "Deep learning for event-driven stock prediction" is the title with the highest number of citations and the author with the highest number of citations. Zhang et al., 2018) developed a model of multiple sine functions extraction (MSFE), for example, to anticipate the future stock market, and predicted the Chinese stock market's peak. Artificial Intelligence, Commerce, and forecasting are the keywords that appeared most frequently in the study. Table 2 includes the 10 countries with the most English-language AI stock market forecasting publications. India has 40 papers, the most. China, the UK, the US, Australia, Taiwan, Japan, Hong Kong, Iran, and South Korea are well-documented. The literature of the study classified the five categories for further research: return prediction, stock trend forecasting using artificial intelligence, market sentiment analysis, use of AI in the financial market, and combinations incorporating two or more approaches. Furthermore, an exhaustive comparison analysis was conducted, and it was determined that SVM, DNN and LSTM are the most often utilised approach for stock market prediction(Nelson et al., 2017; Weng et al., 2018; Zhou et al., 2020). Techniques like as ANN and CNN, on the other hand, are widely employed because they generate more accurate and quicker predictions (Wu et al., 2020). In addition, using both market data and textual data from web sources enhances forecast accuracy.

It is evident from the review that much attention is being given to this field of research, and the literature is becoming more specialized and comprehensive. Our findings provide practical advice to market players, particularly traders, investors, and financial institutions, on how artificial intelligence could be utilized to predict stock market movements. The study uses only Scopus database publications, resulting in a blending of research keywords. It does not analyse many databases that contain research publications, such as PubMed, Web of Science, and Google Scholar. These databases have the potential to be considered for future research.

Challenges and Scope for Further Study

The most difficult aspect of reading articles is creating Scopus searches that eliminate irrelevant documents while including as many relevant documents as feasible. The second significant challenge is analysing the staggering number of published articles sorted by clustering. As a result, this work solely looks at the most important articles. Stock prices have recently been forecasted with machine learning techniques based on historical data. There has been a significant development in Deep Learning approaches, which have generated a promising result. Meanwhile, the elements used in various research, including technical and fundamentalist indications, differ significantly. Despite this, little research has been conducted to assess the contribution of each of these features to the performance of the approaches.

Declaration of conflict of interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication.

Funding

The authors of this paper received no financial assistance for their research, authorship, or publishing.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPESS journal belongs to the authors.

Acknowledgements or Notes

* This article was presented as an oral presentation at the International Conference on Management Economics and Business (www.iconmeb.net) held in Antalya/Turkey on November 15-18, 2022

References:

Ahmed, S., Alshater, M. M., Ammari, A. El, & Hammami, H. (2022). Artificial intelligence and machine learning in finance: A bibliometric review. *Research in International Business and Finance*, *61*.

Almehmadi, A. (2021). COVID-19 pandemic data predict the stock market. *Computer Systems Science and Engineering*, 451–460.

Batra, R., & Daudpota, S. M. (2018). Integrating StockTwits with sentiment analysis for better prediction of stock price movement. *2018 International Conference on Computing, Mathematics and Engineering Technologies (ICoMET)* (pp.1–5). Sukkur,Pakistan: The Institue of Electrical and Electronics Engineers (IEEE).

Belciug, S., Sandita, A., Costin, H., Bejinariu, S. I., & Matei, P. G. (2021). Competitive/collaborative statistical learning framework for forecasting intraday stock market prices: A case study. *Studies in Informatics and Control*, *30*(2), 43–54.

Berradi, Z., Lazaar, M., Mahboub, O., & Omara, H. (2020). A comprehensive review of artificial intelligence Techniques in Financial Market. *2020 6th IEEE Congress on Information Science and Technology (CiSt)* (pp.367–371).Agadir, Morocco: The Institue of Electrical and Electronics Engineers (IEEE).

Biswas, M., Nova, A. J., Mahbub, M. K., Chaki, S., Ahmed, S., & Islam, M. A. (2021). Stock Market Prediction: A Survey and Evaluation. *2021 International Conference on Science \& Contemporary Technologies (ICSCT)*(pp. 1–6). Dhaka, Bangladesh: The Institue of Electrical and Electronics Engineers (IEEE).

Camara, R. C., Cuzzocrea, A., Grasso, G. M., Leung, C. K., Powell, S. B., Souza, J., & Tang, B. (2018). Fuzzy logic-based data analytics on predicting the effect of hurricanes on the stock market. *2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*(pp.1–8).Janeiro, Brazil: The Institue of Electrical and Electronics Engineers (IEEE).

Chen, M.Y. (2011). Predicting corporate financial distress based on integration of decision tree classification and logistic regression. *Expert Systems with Applications*, *38*(9), 11261–11272.

Chen, S. (2021). Correlation analysis of financial indicators and stock price fluctuations based on artificial intelligence system. *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)* (pp.43–46). Coimbatore, İndia: The Institue of Electrical and Electronics Engineers (IEEE).

Chen, Y., & Hao, Y. (2018). Integrating principle component analysis and weighted support vector machine for stock trading signals prediction. *Neurocomputing*, *321*, 381–402.

Cheng, J., Deng, H., Sun, G., Guo, P., & Zhang, J. (2020). Application of ARIMA model in financial time series in stocks. In X. Sun, J. Wang., & E. Bertino (Eds.), *Artificial Intelligence and Security* (pp. 232–243). Hohhot,China:Springer.

Coyne, S., Madiraju, P., & Coelho, J. (2017). Forecasting stock prices using social media analysis. *2017 IEEE 15th Intl Conference on Dependable, Autonomic and Secure Computing, 15th Intl Conf on Pervasive Intelligence and Computing, 3rd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress* (pp.1031–1038). Orlondo,USA: The Institue of Electrical and Electronics Engineers (IEEE).

Ding, X., Zhang, Y., Liu, T., & Duan, J. (2015). Deep learning for event-driven stock prediction. *Twenty-Fourth International Joint Conference on Artificial Intelligence* (pp.2327-2333).Buenos Aires, Argentina: AAAI Publications.

Ebadati, O. M. E., & Mortazavi, M. T. (2018). An efficient hybrid machine learning method for time series stock market forecasting. *Neural Network World*, *28*(1), 41–55.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417.

Ferson, W. E., & Harvey, C. R. (1991). Sources of predictability in portfolio returns. *Financial Analysts*

Journal, *47*(3), 49–56.

Ghanavati, M., Wong, R. K., Chen, F., Wang, Y., & Fong, S. (2016). A generic service framework for stock market prediction. *2016 IEEE International Conference on Services Computing (SCC)*(pp. 283–290).San Francisco,CA: The Institue of Electrical and Electronics Engineers (IEEE).

Ghanavati, M., Wong, R. K., Chen, F., Wang, Y., & Lee, J. (2016). A hierarchical beta process approach for financial time series trend prediction. In H. Cao, J. Li, & R. Wang (Eds.), *Trends and Applications in Knowledge Discovery and Data Mining* (pp. 227–237). Springer .

Goodell, J. W., Kumar, S., Lim, W. M., & Pattnaik, D. (2021). Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. *Journal of Behavioral and Experimental Finance*, *32*.

Hájek, P. (2018). Combining bag-of-words and sentiment features of annual reports to predict abnormal stock returns. *Neural Computing and Applications*, *29*(7), 343–358.

Hargreaves, C., & Hao, Y. (2012). Does the use of technical & fundamental analysis improve stock choice? : A data mining approach applied to the Australian stock market. *2012 International Conference on Statistics in Science, Business and Engineering (ICSSBE)* (pp 1-6). Langkawi, Malaysia: The Institue of Electrical and Electronics Engineers (IEEE).

Hogenboom, A., Brojba Micu, A., & Frasincar, F. (2021). The impact of word sense disambiguation on stock price prediction. *Expert Systems with Applications*, *184*.

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*.

Jarrett, J. E. (2008). Random walk, capital market efficiency and predicting stock returns for Hong Kong exchanges and clearing limited. *Management Research News*, *31*(2), 142–148.

Khadjeh Nassirtoussi, A., Aghabozorgi, S., Ying Wah, T., & Ngo, D. C. L. (2014). Text mining for market prediction: A systematic review. *Expert Systems with Applications*, *41*(16), 7653–7670.

Khaing, E. T., Thein, M. M., & Lwin, M. M. (2020). Enhance trend extraction results by refining with additional criteria. *International Conference on Computational Collective Intelligence* (pp.777–788). Da Nang, Vietnam: Advances in Computational Collective Intelligence.

Kia, A. N., Haratizadeh, S., & Shouraki, S. B. (2018). A hybrid supervised semi-supervised graph-based model to predict one-day ahead movement of global stock markets and commodity prices. *Expert Systems with Applications*, *105*, 159–173.

Kumar, I., Dogra, K., Utreja, C., & Yadav, P. (2018). A comparative study of supervised machine learning algorithms for stock market trend prediction. *2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT)*(pp.1003–1007). Coimbatore,India: he Institue of Electrical and Electronics Engineers (IEEE).

Li, M., Yang, C., Zhang, J., Puthal, D., Luo, Y., & Li, J. (2018). Stock market analysis using social networks. *Proceedings of the Australasian Computer Science Week Multiconference* (pp. 1–10). Canberra, Australia: Association for Computing Machinery.

Li, X., Huang, X., Deng, X., & Zhu, S. (2014). Enhancing quantitative intra-day stock return prediction by integrating both market news and stock prices information. *Neurocomputing*, *142*, 228–238.

Maini, S. S., & Govinda, K. (2017). Stock market prediction using data mining techniques. *2017 International Conference on Intelligent Sustainable Systems (ICISS)*, 654–661.

Malagrino, L. S., Roman, N. T., & Monteiro, A. M. (2018). Forecasting stock market index daily direction: A Bayesian Network approach. *Expert Systems with Applications*, *105*, 11–22.

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of Economic Perspectives*, *17*(1), 59–82.

Mamun, A., Syeed, A., & Yasmeen, F. (2015). *Journal of Economic & Financial Studies Are investors rational , irrational or normal ? 03*(04), 1–15.

Nair, B. B., & Mohandas, V. P. (2015). Artificial intelligence applications in financial forecasting--a survey and some empirical results. *Intelligent Decision Technologies*, *9*(2), 99–140.

Nam, K., & Seong, N. (2019). Financial news-based stock movement prediction using causality analysis of influence in the Korean stock market. *Decision Support Systems*, *117*, 100–112.

Nayak, A., Pai, M. M. M., & Pai, R. M. (2016). Prediction Models for Indian Stock Market. *Procedia Computer Science*, *89*, 441–449.

Nelson, D. M. Q., Pereira, A. C. M., & De Oliveira, R. A. (2017). Stock market's price movement prediction with LSTM neural networks. *2017 International Joint Conference on Neural Networks (IJCNN)*, 1419–1426.

Ng, W. W. Y., Liang, X.-L., Li, J., Yeung, D. S., & Chan, P. P. K. (2014). LG-Trader: Stock trading decision support based on feature selection by weighted localized generalization error model. *Neurocomputing*, *146*, 104–112.

Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis

of stock market predictions. *Artificial Intelligence Review*, *53*(4), 3007–3057.

O, J., Lee, J. W., Lee, J., & Zhang, B.-T. (2004). Dynamic Asset Allocation Exploiting Predictors in Reinforcement Learning Framework. In J.-F. Boulicaut, F. Esposito, F. Giannotti, & D. Pedreschi (Eds.), *Machine Learning: ECML 2004* (pp. 298–309). Springer Berlin Heidelberg.

Pan, J., Zhuang, Y., & Fong, S. (2016). The Impact of Data Normalization on Stock Market Prediction: Using SVM and Technical Indicators. In M. W. Berry, A. Hj. Mohamed, & B. W. Yap (Eds.), *Soft Computing in Data Science* (pp. 72–88). Springer Singapore.

Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Predicting stock market index using fusion of machine learning techniques. *Expert Systems with Applications*, *42*(4), 2162–2172.

Qiu, M., Song, Y., & Akagi, F. (2016). Application of artificial neural network for the prediction of stock market returns: The case of the Japanese stock market. *Chaos, Solitons \& Fractals*, *85*, 1–7.

Rajab, S., & Sharma, V. (2019). An interpretable neuro-fuzzy approach to stock price forecasting. *Soft Computing*, *23*(3), 921–936.

Reaz, M. B. I., Islam, S. Z., Ali, M. A. M., & Sulaiman, M. S. (2002). FPGA realization of backpropagation for stock market prediction. *Proceedings of the 9th International Conference on Neural Information Processing, 2002. ICONIP'02.*, *2*, 960–964.

Rodriguez González, A., Garcia Crespo, Á., Colomo-Palacios, R., Iglesias, F. G., & Gómez Berbis, J. M. (2011). CAST: Using neural networks to improve trading systems based on technical analysis by means of the RSI financial indicator. *Expert Systems with Applications*, *38*(9), 11489–11500.

Ruiz Real, J. L., Uribe Toril, J., Torres, J. A., & De Pablo, J. (2021). Artificial intelligence in business and economics research: Trends and future. *Journal of Business Economics and Management*, *22*(1), 98–117.

Sato, H., Ogasawara, N., & Wang, Y. (2018). Predicting Short-Term Exchange Rates for Automatic Purchasing Using News Article Data. *2018 IEEE 7th Global Conference on Consumer Electronics (GCCE)* (pp.414–418).

Serrano, W. (2022). The random neural network in price predictions. *Neural Computing and Applications*, *34*(2), 855–873.

Shastri, M., Roy, S., & Mittal, M. (2019). Stock price prediction using artificial neural model: an application of big data. *EAI Endorsed Transactions on Scalable Information Systems*, *6*(20).

Shynkevich, Y., McGinnity, T. M., Coleman, S. A., & Belatreche, A. (2016). Forecasting movements of health-care stock prices based on different categories of news articles using multiple kernel learning. *Decision Support Systems*, *85*, 74–83.

Singh, R., & Srivastava, S. (2017). Stock prediction using deep learning. *Multimedia Tools and Applications*, *76*(18), 18569–18584.

Tupe Waghmare, P. (2021). *Prediction of Stocks and Stock Price using Artificial Intelligence: A Bibliometric Study using Scopus Database*.

Wang, S., Yan, Z., Hu, X., Philip, S. Y., & Li, Z. (2015). Burst time prediction in cascades. *Proceedings of the AAAI Conference on Artificial Intelligence*.Texas,USA:PKP Publishing.

Waqar, M., Dawood, H., Guo, P., Shahnawaz, M. B., & Ghazanfar, M. A. (2017). Prediction of stock market by principal component analysis.*13th International Conference on Computational Intelligence and Security (CIS)* (pp.599–602).Hong Kong:IEE.

Weng, B., Lu, L., Wang, X., Megahed, F. M., & Martinez, W. (2018). Predicting short-term stock prices using ensemble methods and online data sources. *Expert Systems with Applications*, *112*, 258–273.

Wu, W., Zhao, Y., Wang, Y., & Wang, X. (2020). Stock price forecasting and rule extraction based on L1-orthogonal regularized GRU decision tree interpretation model. In P. Qin, H. Wang, G. Sun, & Z. Lu (Eds.), *Data Science* (pp. 309–328). Singapore:Springer.

Yang, F., Chen, J., & Liu, Y. (2021). Improved and optimized recurrent neural network based on PSO and its application in stock price prediction. *Soft Computing*, 1–16.

Yang, Y., & Chen, G. (2014). Stock prices prediction research of BP algorithm. In S. Zhong (Ed.), *Proceedings of the 2012 International Conference on Cybernetics and Informatics* (pp. 2033–2040). New York, NY:Springer.

Zhang, C., Ji, Z., Zhang, J., Wang, Y., Zhao, X., & Yang, Y. (2018). Predicting Chinese stock market price trend using machine learning approach. *Proceedings of the 2nd International Conference on Computer Science and Application Engineering* (pp.1–5). New York, NY: Association for Computing Machinery.

Zhou, Z., Gao, M., Liu, Q., & Xiao, H. (2020). Forecasting stock price movements with multiple data sources: Evidence from stock market in China. *Physica A: Statistical Mechanics and Its Applications*, *542*.

Author Information

Farman Ali
Uttaranchal University
Dehradun, India
Contact e- mail:*farmanali@uttaranchaluniversity.ac.in*

Pradeep Suri
Uttaranchal University
Dehradun, India

To cite this article:

Ali, F., & Suri, P. (2022). A bibliometric analysis of artificial intelligence-based stock market prediction. *The Eurasia Proceedings of Educational & Social Sciences (EPESS), 27,* 17-35.