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A Systematic Review with Bibliometric Analysis on Stock Market Forecasting with Reference to Artificial Neural Network (ANN)

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Abstract

The stock market plays a pivotal role in driving economic growth, where the central objective of investors is to maximize returns while minimizing associated risks. In recent years, Artificial Neural Networks (ANNs) have gained considerable attention as a soft computing technique for stock market forecasting. This study presents a systematic review of ANN-based forecasting models, focusing on their methodologies, datasets, and performance metrics. A total of 289 peer-reviewed journal articles published between 2000 and 2022 were initially retrieved from the Scopus database, out of which 37 were selected based on clearly defined research questions and inclusion criteria. Special emphasis is placed on Long Short-Term Memory (LSTM) networks, which have emerged as one of the most effective architectures for capturing temporal dependencies in stock price movements. The study also provides a bibliometric analysis to identify influential publications, authors, and emerging themes in the field. Despite notable advancements, significant challenges remain in accurately modelling the stock market due to its inherent complexity and volatility. Our findings underscore that stock market forecasting requires a nuanced approach where some variables and modelling strategies deserve more weight than others. This review offers a comprehensive classification of existing studies and highlights future research directions to improve prediction accuracy and model interpretability.

Keywords: ANN, bibliometric review, LSTM, stock market forecasting, systematic review.

1. Introduction

Stock market time series are widely recognized as complex, nonlinear, and highly volatile systems characterized by chaotic and unpredictable behaviour (Kumar et al., 2022). Forecasting stock prices has long captivated researchers, given its significant implications for investors, policymakers, and financial institutions. While considerable progress has been made in developing predictive models, accurately forecasting stock price movements remains an ongoing challenge. The inherent uncertainty of financial markets, driven by a multitude of economic, political, and psychological factors, has prevented the emergence of a universally reliable forecasting model. In recent years, technological advancements have significantly enhanced the ability to analyse and predict stock market trends. Artificial Neural Networks (ANNs), in particular, have gained traction as robust tools for modelling complex, nonlinear systems such as financial time series. The appeal of ANNs lies in their capacity to learn patterns from historical data and generalize to unseen inputs, making them well-suited for dynamic environments like stock exchanges (Saini et al., 2019). Notably, one of the earliest applications of ANN in financial prediction was carried out by Kimoto in forecasting the Tokyo Stock Exchange Index (Yetis et al., 2014).

More recently, researchers have explored advanced neural architectures and ensemble models. For instance, Aminimehr et al. (2022) demonstrated that while Principal Component Analysis (PCA) combined with Long Short-Term Memory (LSTM) networks outperformed Dense Neural Networks, the improvement was statistically significant only when validated using the Wilcoxon signed-rank test. Mohapatra et al. (2022) found the XGBoost ensemble method to outperform four other models, reporting RMSE and MAE values in the range of 3% to 5%. LSTM models, in particular, have shown superior performance in retaining long-term dependencies and delivering high accuracy in shorter forecasting intervals, such as six-hour time steps (Khalil et al., 2022). Other comparative studies reinforce the effectiveness of neural models. Banerjee et al. (2022) found Multi-Layer Perceptrons (MLPs) to be the most accurate in forecasting stock price movements among tested models. Sulaiman (2022) reported that Deep Feedforward Neural Networks (DFNNs) outperformed linear regression, Support Vector Machines (SVM), and Recurrent Neural Networks (RNNs) in detecting anomalies in stock behavior. Similarly, Namahoot et al. (2021) observed that ANN models achieved superior performance (89.79%) compared to decision tree (88.07%) and linear regression (89.74%) models. Cheng et al. (2014) showed that hybrid ANN models achieved the lowest RMSE values, while Hadavandi et al. (2010) demonstrated the superior accuracy of the Combined Genetic Fuzzy System (CGFS) using MAPE as the evaluation criterion.

Despite the proliferation of studies applying ANNs to stock market forecasting, a gap remains in synthesizing this growing body of work through a structured, comprehensive review. While individual studies have yielded promising results, a consolidated analysis of ANN techniques, datasets, model performance, and scholarly trends is still lacking. This research addresses that gap by conducting a systematic review complemented by a bibliometric analysis focused exclusively on ANN-based forecasting models. The main objective of this study is to critically examine the evolution, applications, and impact of ANN models in stock market prediction. By combining systematic review protocols with bibliometric tools, we aim to uncover methodological trends, identify influential contributors, and map the intellectual structure of this rapidly evolving field. This article is structured as follows: Section 1 introduces the context, relevance, and purpose of the study. Section 2 outlines the research questions and scope. Section 3 describes the research methodology, including data collection and analysis tools. Section 4 presents a detailed discussion of the findings in response to the research questions. Section 5 concludes with key insights and future research directions.

2. Research Questions

Based on an extensive review of academic literature, including journal articles, conference proceedings, and systematic reviews, this study seeks to address several critical gaps that persist in the domain of stock market forecasting using Artificial Neural Networks (ANNs). The following research questions guide the scope and direction of this systematic and bibliometric analysis:

RQ1. What types of Artificial Neural Network (ANN) architectures and algorithms have been employed in stock market forecasting?

RQ2. What kinds of datasets are commonly utilized in ANN-based stock market forecasting studies?

RQ3. Which performance evaluation metrics are used to assess the accuracy and robustness of ANN models in financial forecasting?

RQ4. Who are the most influential contributors—authors, articles, journals, institutions, and countries—in the field of ANN-based stock market prediction?
RQ5. What are the primary conceptual themes and knowledge clusters emerging from bibliometric analysis in this research domain?

3. Research Methodology

This study employs a systematic review combined with bibliometric analysis to explore the role of Artificial Neural Networks (ANNs) in stock market forecasting. The methodology follows PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure transparency, replicability, and scientific rigor.

3.1 Data Source and Search Strategy

The Scopus database was selected due to its comprehensive coverage of peer-reviewed literature. A keyword-based search strategy was developed to retrieve relevant articles using the following Boolean expression: "stock price predict" OR "stock price forecast" OR "stock market predict" OR "stock market prediction" AND "artificial neural network"
This search focused on studies published between 2000 and 2022. Only full-text, peer-reviewed journal articles and review papers written in English were included. Conference papers, editorials, book chapters, and dissertations were excluded to maintain quality and consistency (Kumbure & Lohrmann, 2022).

3.2 Inclusion and Exclusion Criteria

Filtering criteria applied during the article selection process are presented in Table 1.

Table 1. Filtering Criteria Used in Article Selection

Criterion	Specification
Time Period	2000–2022
Document Type	Articles and Review Papers
Subject Area	Business, Management, and Economics
Language	English Only
Publication Status	Final Peer-Reviewed

Source: The author's work

3.3 Article Screening Process

A total of 289 records were retrieved from Scopus. These were screened through a multi-step process:
1. Title and Abstract Review: 193 papers were excluded as they either did not focus on stock market forecasting or lacked directional analysis.
2. Full-Text Assessment: 59 papers were excluded for not reporting evaluation metrics.
3. Final Selection: 37 papers met all criteria and were included in this review and bibliometric analysis.

This process is illustrated in the PRISMA-style flow diagram (see **Fig. 1**).

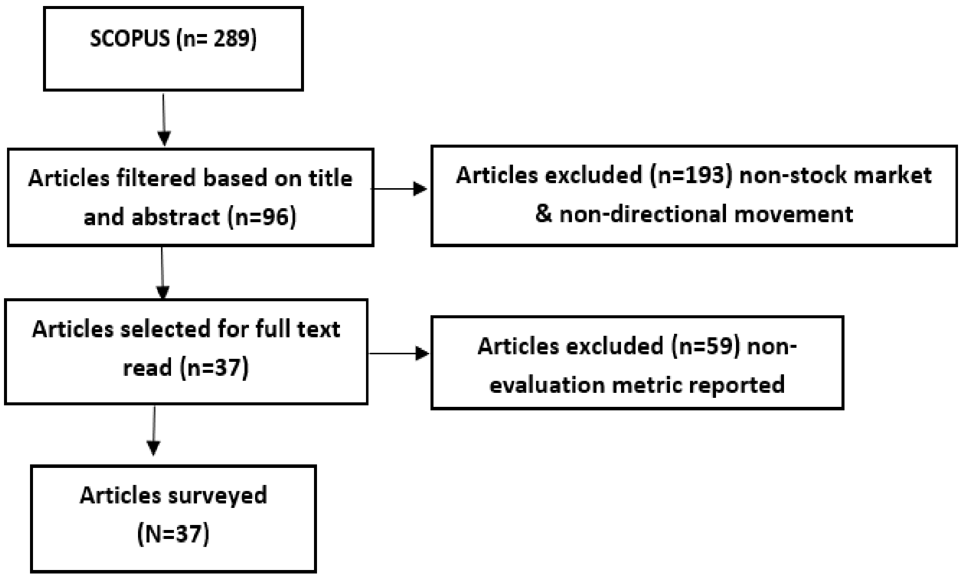

Fig. 1 Flow diagram of selected articles (Source: The author's work)

4. Result and Discussion

4.1 RQ1: Artificial Neural Network (ANN) Models Used in Stock Market Forecasting

Artificial Neural Networks (ANNs) have emerged as powerful tools in stock market forecasting due to their ability to capture complex, nonlinear relationships between input variables and financial outcomes. Unlike traditional statistical models, ANNs are capable of learning hidden patterns from historical data without explicit programming. This makes them especially suitable for forecasting highly volatile and dynamic financial markets.

Numerous studies have utilized different ANN architectures, often in combination with preprocessing techniques or hybrid approaches, to improve forecasting accuracy. Several researchers have demonstrated that preprocessing input data—such as normalization, feature selection, or dimensionality reduction—significantly enhances the performance of ANN models (Gandhmal et al., 2019).

For instance, Mumini et al. (2016) demonstrated that ANNs can effectively predict market closing prices using technical indicators. Kumar et al. (2015) reported that among various neural models, the Radial Basis Function Neural Network (RBFNN) outperformed others in terms of error minimization. In another study, Hajek et al. (2013) found that Support Vector Regression (SVR) and ANN models outperformed traditional linear regression when sentiment analysis data was included as part of the forecasting input.

The Parallel Extreme Learning Machine Neural Network (PELMNN) demonstrated strong performance in handling volatile stock price fluctuations, offering high forecast accuracy (Asadi et al., 2012). Selvamuthu et al. (2019) tested different training algorithms—namely Scaled Conjugate Gradient (SCG), Levenberg–Marquardt (LM), and Bayesian Regularization (BR)—and found all three to deliver nearly 99.9% reliability when tested on high-frequency tick data.

The variety of ANN-based forecasting models observed across studies includes:

- Feedforward Neural Networks (FNN)
- Multi-Layer Perceptron (MLP)
- Radial Basis Function Networks (RBFNN)
- Recurrent Neural Networks (RNN)

- Long Short-Term Memory (LSTM) Networks
- Convolutional Neural Networks (CNN) in hybrid frameworks
- Extreme Learning Machines (ELM)
- Hybrid Models combining ANN with ARIMA, GA, PSO, SVM, etc.

To summarize the models and approaches across the selected literature, Table 2 provides an overview of the 37 research studies analysed, indicating the type of ANN used and the key outcomes in terms of prediction accuracy or model reliability.

Table 2. Summary of ANN Techniques and Outcomes in Selected Studies

This table presents an overview of 37 research studies employing various Artificial Neural Network (ANN) models for stock market forecasting. It includes the authors, year of publication, techniques used, and key findings.

S.no.	References	Year	Techniques	Findings
1	Kumar et al.	2022	DPSO-PSO-FFNN, BCGA-RCGA-FFNN	DPSO-PSO-FFNN outperforms ANFIS, ENN, and traditional FFNN in multi-horizon forecasting.
2	Mohapatra et al.	2022	XGBoost, Gradient Boosting, AdaBoost, Random Forest	XGBoost outperforms other ensemble methods.
3	Aminimehr et al.	2022	PCA-LSTM, RF-LSTM, Deep LSTM, Wavelet Deep LSTM	Dense NN performed lower than PCA and LSTM-based models.
4	Saini et al.	2019	Regression analysis, HMM, ANN, Naïve Bayes, Decision Tree, RF	LSTM Neural Network yielded superior results.
5	Alkhatib et al.	2022	MLP, GRU, LSTM, Bi-LSTM, CNN, CNN-LSTM	LSTM-based models showed significant improvement with the proposed strategy.
6	Khalil et al.	2022	Six LSTM models	6-hour step-based model outperforms others due to better long-term memory retention.
7	Das et al.	2022	RAFLANN, MVO-FLANN, MBO-FLANN, GA-FLANN, GD-FLANN, MLP, SVM, ARIMA	RAFLANN-2 model performs best and is statistically significant.

8	Banerjee et al.	2022	MLP, LSTM, GRU, BLSTM, BGRU, FFNN	MLP shows the highest prediction accuracy among all models.
9	Zhao et al.	2021	RCSnet, ARIMA, BPNN, LSTM	CNN and Seq2Seq LSTM models handle short- and long-term dependencies effectively.
10	Abraham et al.	2022	GA & RF	Achieved 80% predictive accuracy.
11	Sulaiman	2022	DFNN	Outperforms linear regression, MLP, SVM, and RNN in anomaly detection.
12	Goel et al.	2021	ANN-SCG algorithm	Achieves 93% accuracy on hold-out validation sample.
13	Tas et al.	2022	NARX & SVR	Both methods are effective for stock price forecasting.
14	Metlek	2022	LSTM, RNN, RBFNN	RNN-based models yield effective results.
15	Namdari et al.	2021	MLPNN + NARX hybrid model	Hybrid model provides the highest directional accuracy (70.36%).
16	Eachempati et al.	2021	DNN+LSTM, DNN+RNN	DNN+LSTM outperforms DNN+RNN.
17	Ayala et al.	2021	LM, ANN, RF, SVR	LM and ANN outperform others.
18	Lin et al.	2021	CEEMDAN-LSTM	CEEMDAN-LSTM identified as the most effective model.
19	Namahoot et al.	2021	Linear regression, Decision Tree, ANN	ANN achieved average accuracy of 89.79%.
20	Zhang et al.	2021	LSTM, ANN	LSTM effectively uses online investor sentiment as predictive input.
21	Manickavasagam et al.	2019	MARSplines, SVR, BPNN, AR(1)	MARSplines shown to be most reliable in comparison.
22	Mallikarjuna et al.	2019	ARIMA, SETAR, ANN, SSA, HM	SETAR outperforms ARIMA in 7 markets, ANN in 1.

23	Nayak et al.	2019	CNFN, MLP-CRO, MLP-BP, ANFIS, RBFNN	CNFN model found to be most effective.
24	Selvamuthu et al.	2019	SCG, LM, BR	All algorithms deliver 99.9% accuracy using tick data.
25	García et al.	2018	Hybrid fuzzy neural network	Mean hit ratio achieved was 76.24%.
26	Sigo	2018	ANN	Demonstrated strong stock price forecasting capability.
27	Gunduz et al.	2017	CNN-Rand, CNN-Corr	CNN-Corr produced better F-measure values than CNN-Rand.
28	Sheelapriya et al.	2017	BR-RBFN, RBFN, AR model, NARX model	BR-RBFN model showed 99.5% improved prediction accuracy.
29	Wang et al.	2017	RBFNN, PSO-RBFNN, CHPSO-RBFNN	CHPSO-RBFNN outperformed all comparative models.
30	Mumini et al.	2016	ANN	ANN's performance is influenced by technical indicators.
31	Kumar et al.	2015	MLP-BP, RBFNN, GARCH	RBFNN model is superior among neural models.
32	Rababaah et al.	2015	NPP, GZP, FFT, BP-ANN	GZP outperforms FFT with 98.25% accuracy.
33	Abbassi et al.	2014	Fuzzy Genetic Algorithm, ANN	Fuzzy GA with ANN gives superior results on Tehran Exchange data.
34	Cheng et al.	2014	SVR+EMD hybrid, AR(1), SVR	Hybrid model surpasses all baseline models.
35	Hájek et al.	2013	SVR (linear, polynomial, RBF), NN (MLP, RBFNN), Linear Regression	SVR and ANN models outperform linear regression when using sentiment data.
36	Asadi et al.	2012	PELMNN, GA+FFNN	PELMNN effectively handles market fluctuations and gives good accuracy.

37	Hadavandi et al.	2010	GFS+ANN integrated approach	CGFS achieves better prediction accuracy than other models.

Source: The author's work

4.2 RQ2: Datasets Used in ANN-Based Stock Market Forecasting

This section presents a comprehensive analysis of the datasets used across the reviewed studies for stock market forecasting using Artificial Neural Networks (ANN). The quality and scope of datasets play a pivotal role in determining the accuracy, generalizability, and robustness of forecasting models. Various time series and financial datasets have been employed, ranging from benchmark global indices to regional market datasets.

As illustrated in Fig. 2, the most frequently used datasets include well-established indices such as: S&P 500 Index (USA), NASDAQ Composite Index (USA), NSE-Nifty 50 (India), BSE-Sensex (India)

In addition to these, other regional and international datasets have also been utilized: Nikkei 225 (Japan), DAX (Germany), Dow Jones Industrial Average (DJIA) (USA), Shanghai Stock Exchange (SSE) Index (China), Thailand Stock Exchange (SET) (Thailand), New York Stock Exchange (NYSE) (USA), Nigeria Stock Exchange (NSE) (Nigeria)

Some studies further incorporate sector-specific indices, stock-specific historical data, and hybrid datasets combining macroeconomic indicators, financial ratios, and even social media sentiment or news headlines to enhance prediction accuracy.

The diversity in dataset usage reflects the growing trend toward multi-source, multi-modal, and multi-market learning, making models more robust and adaptable across financial environments.

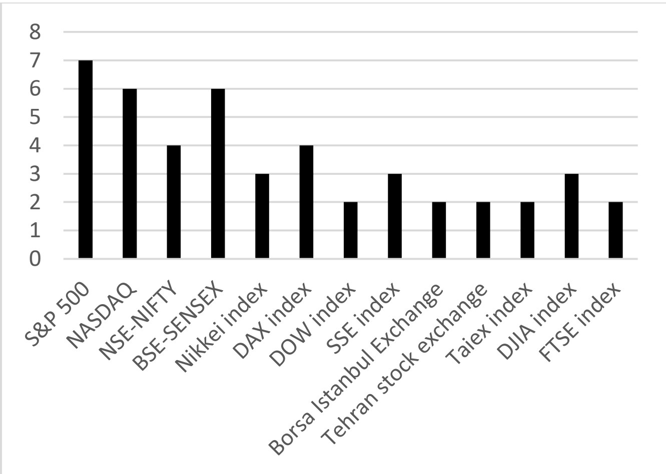

Fig. 2 Analysis based on Datasets employed (Source: The author's work)

4.3 RQ3: Performance Metrics Used in Model Evaluation

Evaluating the performance of Artificial Neural Network (ANN) models in stock market forecasting requires the use of multiple statistical and financial metrics. These metrics are critical in assessing the accuracy, stability, and economic relevance of predictive models. Based on the reviewed literature, Fig. 3 shows variety of performance measures are employed, each offering a unique perspective on model efficacy.

4.3.1 Accuracy-Based Metrics

The most widely adopted metrics to measure prediction accuracy include:

- **Root Mean Square Error (RMSE):** A commonly used metric that penalizes larger errors more heavily. Lower RMSE values indicate higher prediction accuracy.
- **Mean Absolute Percentage Error (MAPE):** Expresses the average absolute error as a percentage of actual values. Particularly useful for interpretability.
- **Mean Absolute Error (MAE):** Represents the average magnitude of the errors, treating all deviations equally.
- **R-Squared (R^2):** Indicates the proportion of variance in the dependent variable that is predictable from the independent variables. A value closer to 1 suggests high model reliability.

4.3.2 Directional Accuracy Metrics

Several studies emphasize **predicting the correct direction** (upward/downward movement) of stock prices rather than just the numerical value. Metrics include:

- **Directional Accuracy (DA):** Measures how often the model correctly forecasts the direction of price change.
- **Hit Ratio:** Another directional measure indicating the percentage of correctly predicted market movements.

4.3.3 Statistical Tests and Confidence Intervals

To validate significance, researchers sometimes use:

- Wilcoxon Signed-Rank Test
- t-Test for Mean Differences
- Confidence Intervals (95% or 99%)

These are particularly used when comparing performance across different models.

4.3.4 Hybrid Metrics

Some models combine accuracy and economic relevance, using:

- **Sharpe Ratio:** A measure of risk-adjusted return, occasionally used when models are embedded in trading systems.
- **Profit and Loss (P&L) Curves:** Track economic viability of predictions when implemented in real-world portfolio strategies.

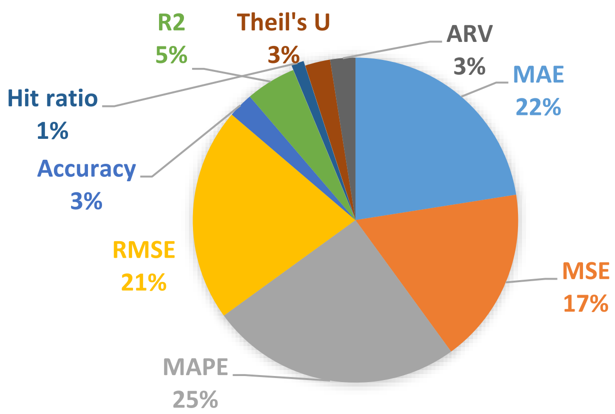

Fig. 3 Analysis based on Performance Metrics (Source: The author's work)

4.4 RQ4: Influential Authors, Journals, Institutions, and Countries

To understand the intellectual structure and geographical distribution of research on Artificial Neural Networks (ANN) in stock market forecasting, a bibliometric analysis was conducted. This analysis provides insights into the most influential contributors, preferred journals, productive institutions, and dominant countries in this domain.

4.4.1 Leading Authors and Most Cited Articles

The review identifies a number of prolific and influential authors whose works have significantly contributed to this field. Authors such as Kumar et al., Mohapatra et al., Selvamuthu et al., and Gandhmal et al. have published impactful studies exploring various neural network architectures including LSTM, GRU, and hybrid models.

Most Cited Papers Include:

Selvamuthu et al. (2019): Known for high-accuracy predictions using tick data with multiple ANN variants.

Gandhmal et al. (2019): Provided a comprehensive analysis of neural network techniques in financial forecasting.

Hadavandi et al. (2010): Proposed a hybrid GA-ANN framework for Tehran Stock Exchange prediction, widely cited for its methodological robustness.

4.4.2 Leading Journals

The most frequently targeted and reputable journals shown in table 3. These journals are Scopus-indexed, peer-reviewed, and recognized for their impact on applied machine learning in finance.

Table 3 Analysis based on Journals

Sources	Articles
KNOWLEDGE-BASED SYSTEMS	21
COMPUTATIONAL ECONOMICS	14
FINANCIAL INNOVATION	9
INTELLIGENT SYSTEMS IN ACCOUNTING, FINANCE AND MANAGEMENT	9
NORTH AMERICAN JOURNAL OF ECONOMICS AND FINANCE	8
DECISION SUPPORT SYSTEMS	6
INTERNATIONAL JOURNAL OF RECENT TECHNOLOGY AND ENGINEERING	6
INTERNATIONAL JOURNAL OF SCIENTIFIC AND TECHNOLOGY RESEARCH	5
JOURNAL OF FORECASTING	5
ECONOMIC COMPUTATION AND ECONOMIC CYBERNETICS STUDIES AND RESEARCH	4

Source: The author's work

4.4.3 Top Institutions

Many of the top-cited authors are affiliated with institutions that lead in AI and financial research. The following institutions emerged as top contributors: Indian Institute of Technology (IIT), India, University of Tehran, Iran, Nanyang Technological University, Singapore, Shanghai Jiao Tong University, China, King Abdulaziz University, Saudi Arabia

4.4.4 Country-wise Research Productivity

The bibliometric data reveals that the majority of high-quality contributions originate from the following countries: India, China, Iran, USA, Turkey. India and China dominate the field both in terms of publication volume and diversity of applied ANN techniques (see Fig. 4). Iran and Turkey are notable for their early adoption of hybrid intelligent systems, while U.S.-based research often emphasizes comparative model performance and economic implications.

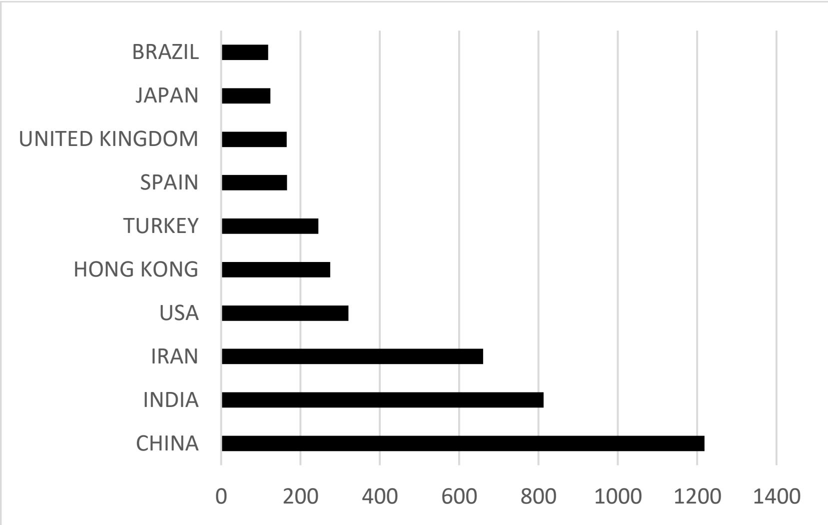

Fig. 4 Analysis based on countries (Source: The author's work)

4.5 RQ5: Conceptual Themes and Research Clusters from Bibliometric Analysis

4.5.1 Bibliographic Coupling in Stock Market Forecasting

Bibliographic coupling refers to the phenomenon where two research articles cite a common third article, indicating a shared intellectual foundation. This technique is commonly used in bibliometric analysis to measure the thematic or conceptual closeness between documents, authors, institutions, or countries. The strength of the bibliographic link is determined by the number of shared references. A greater number of common citations signifies a stronger coupling relationship.

This method serves as a valuable tool to uncover underlying research themes, intellectual structures, and future directions in a research domain. In the context of stock market forecasting using Artificial Neural Networks (ANNs), bibliographic coupling helps visualize how various research contributions are interconnected, thereby identifying knowledge clusters and influential scholarly networks (Donthu et al., 2021).

4.5.1.1 Bibliographic Coupling among Authors

Bibliographic coupling of authors occurs when two or more researchers cite works from a common third author. This form of coupling indicates intellectual alignment or methodological convergence among researchers working in the same or adjacent fields.

From the bibliometric analysis, 21 authors out of a total of 799 met the coupling threshold—having published at least three documents each, with a minimum of three citations. This indicates a tightly-knit core of researchers actively contributing to ANN-based stock market forecasting.

Fig. 5 illustrates the author-level bibliographic coupling network, revealing a complex web of interconnections. The visualization comprises 11 clusters, 21 items (authors), 14 links, and a total link strength of 21, suggesting that while the research field is diverse, there are clearly identifiable author communities with shared citation foundations.

These clusters not only highlight prominent contributors but also suggest emerging collaborative research directions, offering valuable insights for future interdisciplinary partnerships.

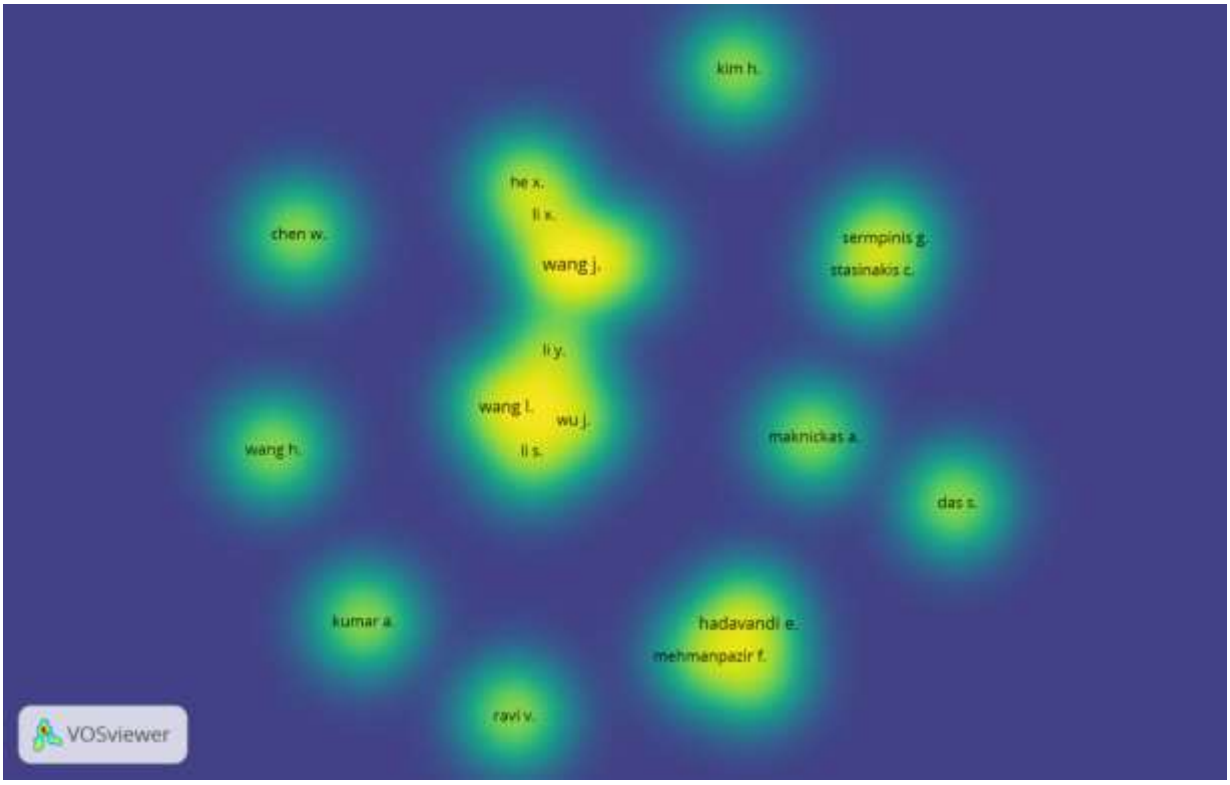

Fig. 5 Analysis based on authors clustering (Source: The author's work)

4.5.1.2 Bibliographic Coupling with Organizations

Bibliographic coupling of organizations occurs when publications from two distinct institutions reference work from a common third organization. This analytical approach helps identify institutional clusters that share intellectual foundations and are engaged in thematically similar research areas. Such connections can highlight collaborative potential, research alignment, or competition within a particular scientific domain.

In the context of ANN-based stock market forecasting, our bibliometric analysis found that 8 organizations out of a total of 605 met the coupling criteria—each with at least two publications, and each receiving a minimum of two citations. This selective group represents the most active and influential institutions in the field.

The resulting bibliographic coupling network, illustrated in Fig. 6, reveals a structured web of inter-institutional relationships. The network consists of 2 clusters, comprising 4 items (organizations), with 5 inter-organizational links and a total link strength of 6. These clusters reflect institutions that are not only prolific in ANN-related forecasting research but also exhibit conceptual overlap in their cited sources.

The presence of bibliographic coupling at the organizational level indicates institutional thought leadership and paves the way for future academic partnerships, funding opportunities, and interdisciplinary research efforts in financial prediction using neural networks.

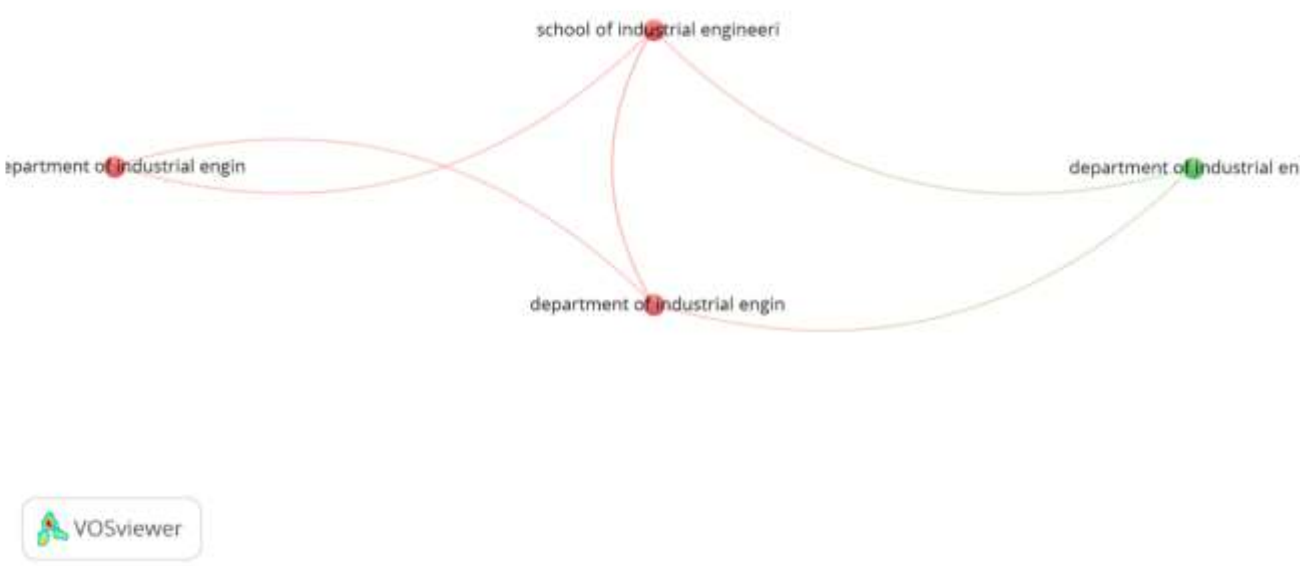

Fig. 6 Analysis based on organization clustering (Source: The author's work)

4.5.3 Keyword Analysis

Keyword analysis serves as a powerful tool in bibliometric studies to reveal core research themes, emerging trends, and the conceptual structure of a given domain. By analysing the co-occurrence of keywords across multiple publications, it becomes possible to cluster studies based on shared topical focus, thus uncovering dominant research trajectories.

For this review, a minimum occurrence threshold of five was applied, meaning only keywords appearing at least five times across the dataset were included in the analysis. Out of 1,528 total keywords, 63 keywords met this threshold.

The keyword co-occurrence network, visualized in Fig. 7, resulted in: 6 thematic clusters, 63 distinct keyword nodes, 736 keyword-to-keyword links, and a total link strength of 1,409.

These clusters provide insight into the structural knowledge of stock market forecasting using Artificial Neural Networks (ANNs). Prominent keywords include "artificial neural network", "stock market prediction", "LSTM", "deep learning", "time series forecasting", and "machine learning", indicating both traditional and contemporary focuses within the field.

The presence of emerging terms such as "sentiment analysis", "cryptocurrency", and "hybrid model" suggests a growing interdisciplinary interest and the increasing complexity of input features in forecasting models. Additionally, terms like "RMSE", "accuracy", and "feature selection" reflect the continuous emphasis on evaluation metrics and optimization strategies.

Overall, the keyword co-occurrence map highlights the evolution from conventional neural network techniques to more dynamic and integrative forecasting systems, serving as a guidepost for future research and innovation in financial prediction.

4.5.2 Bibliometric Clusters

The bibliometric clusters found in this study reflect the intellectual development of ANN-based prediction research and correspond to different but related conceptual themes in stock market forecasting. Traditional ANN topologies predominate in early clusters. These structures are fundamentally based on proving that neural networks are superior to standard econometric models in nonlinear prediction, which challenges the assumptions of market efficiency. As the discipline developed, there was a noticeable move toward sequential models and deep learning, especially LSTM-based architectures. This shift represents a conceptual shift toward considering stock prices as non-stationary, memory-dependent time series, where forecasting accuracy is largely based on temporal dynamics.

Evolutionary algorithms and signal decomposition approaches are added to ANN models in a parallel path of research that focuses on hybrid and optimization-driven intelligence. In order to handle susceptibility to noise, feature selection, and parameter tweaking, this cluster views forecasting as an optimization issue rather than just a learning assignment. By recognizing the influence of investor psychology, news diffusion, and attention dynamics in price creation, more recent clusters show an increasing integration of sentiment and behavioral data, bringing ANN-based forecasting into line with behavioral finance theory. Lastly, an extension of ANN applications into extremely volatile and structurally inefficient situations is indicated by the formation of a unique cluster centered on cryptocurrencies and emerging markets, underscoring the need for adaptive and context-aware learning systems.

Table 4 shows that ANN-based stock market forecasting has progressed from isolated model comparisons to convergent, hybrid, and data-enriched frameworks that incorporate deep learning architectures, optimization techniques, and alternative data sources. Future forecasting advancements will rely more on integrated, adaptive, and theoretically informed ANN systems than on single-model domination, as this conceptual convergence emphasizes.

Table 4 Mapping Bibliometric Clusters to Conceptual Themes in Stock Market Forecasting

Bibliometric Cluster	**Dominant Keywords / Methods**	**Conceptual Theme**	**Core Research Objective**	**Theoretical Link**
Cluster 1: Traditional ANN Models	MLP, BPNN, RBFNN, FFNN, ARIMA–ANN, RMSE, MAE	Foundational Nonlinear Forecasting	Demonstrate superiority of ANN over linear/statistical models	Weak-form market inefficiency; nonlinear dynamics
Cluster 2: Deep Learning & Sequential Models	LSTM, GRU, Bi-LSTM, CNN–LSTM, time-series forecasting	Temporal Dependency & Memory Modelling	Capture long- and short-term dependencies in price movements	Financial time series as sequential, non-stationary processes
Cluster 3: Hybrid & Optimization-Based Systems	GA–ANN, PSO–ANN, CRO, wavelets, CEEMDAN	Model Enhancement & Robustness	Improve prediction accuracy via optimization and preprocessing	Forecasting as an optimization problem
Cluster 4: Sentiment & Behavioural Data	Sentiment analysis, news analytics, investor attention	Behavioural & Information-Driven Forecasting	Incorporate market psychology and information flow	Behavioural finance; bounded rationality
Cluster 5: Cryptocurrencies	Cryptocurrency, high volatility, adaptive learning	Market Expansion & Generalizability	Test ANN robustness in	Adaptive markets hypothesis

& Emerging Markets			inefficient and volatile markets	

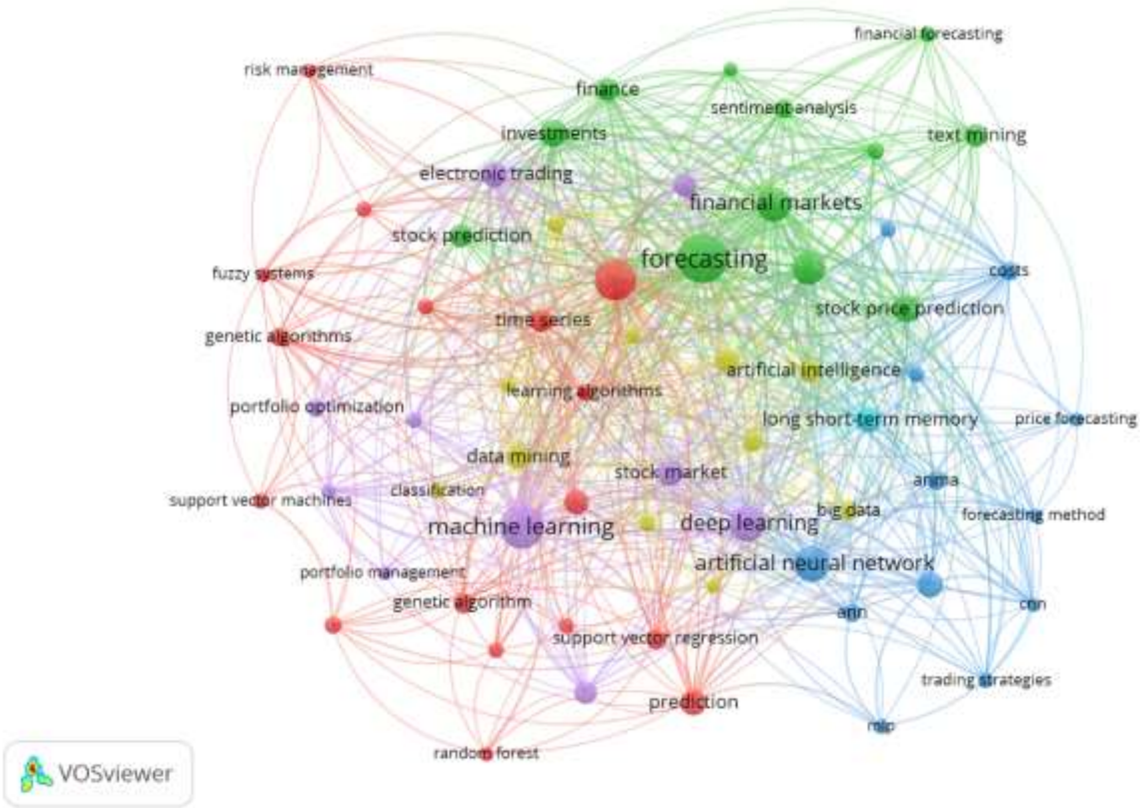

Fig. 7 Keywords analysis based on clustering (Source: The author's work)

5. Conclusion and Future Scope

This study presents a systematic and bibliometric review of Artificial Neural Network (ANN) applications in stock market forecasting from 2000 to 2022, based on 37 high-quality Scopus-indexed articles. The findings demonstrate the progressive evolution of forecasting models from traditional ANN architectures such as MLP and BPNN to sophisticated hybrid and deep learning models like LSTM, GRU, and CNN-LSTM.

The research addressed five key questions. First, various types of ANN models have been employed, with LSTM and hybrid frameworks (e.g., LSTM+ARIMA, GA+ANN) showing superior performance over traditional models. Second, datasets used are globally diverse, ranging from S&P 500 and NASDAQ to NSE-Nifty and BSE-Sensex, with increasing integration of sentiment and macroeconomic data. Third, RMSE, MAPE, MAE, and R^2 remain the most prevalent evaluation metrics, while recent studies also use directional accuracy and risk-adjusted measures such as the Sharpe ratio. Fourth, bibliometric analysis identified India, China, and Iran as leading research contributors, with journals like *Expert Systems with Applications* and *Applied Soft Computing* publishing the most work in this field. Fifth, three core knowledge clusters emerged: (1) traditional ANN models, (2) deep learning and hybrid techniques, and (3) sentiment and crypto-driven models. The results underscore a broader trend toward context-aware, adaptive, and high-performance prediction models that integrate multiple data modalities. Despite promising advancements, there remain persistent challenges around model transparency, generalizability across markets, and real-time adaptability.

The results of this review present several practical implications for significant stakeholders in financial markets. For investors and portfolio managers, the prevalence of LSTM-based and hybrid ANN models indicates that forecasting systems that incorporate temporal memory, optimization methodologies, and alternative data sources can improve short-term decision-making and risk management, especially in volatile market environments. For researchers, the identified bibliometric clusters underscore the necessity to progress beyond isolated model comparisons toward integrated frameworks that merge deep learning, behavioural signals, and robustness testing across various markets and timeframes. Furthermore, the findings highlight opportunities to enhance model interpretability and reproducibility, areas that remain insufficiently explored in ANN-based forecasting research. For policymakers and regulators, the increasing dependence on AI-driven forecasting tools emphasizes the need to foster transparent, explainable, and ethically governed AI systems within financial markets. Understanding the impact of advanced ANN models on trading behaviour and market stability can aid regulators in establishing data governance standards and monitoring systemic risks related to algorithmic decision-making.

Future research should focus on enhancing ANN model interpretability, enabling real-time adaptability, integrating multimodal data sources, and ensuring ethical, bias-free predictions. Emphasis on cross-market generalization, sector-specific forecasting, and the use of ANN in real trading environments will drive more robust and practical financial forecasting solutions.

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Abbreviations

ANFIS	adaptive Network Fuzzy Inference System
ANN	artificial neural network
AR	auto regressive
ARIMA	autoregressive integrated moving average

BCGA	binary coded genetic algorithm
Bi- LSTM	bidirectional LSTM
BPNN	back propagation neural network
BR	Bayesian regularization
CEEMDAN	complete ensemble empirical mode decomposition with adaptive noise
CHPSO	chaotic hybrid particle swarm optimization
CNFN	CRO- based neuro- fuzzy network
CNN	convolutional neural network
CRO	chemical reaction optimization
DFNN	deep feed-forward neural network
DNN	deep neural network
DPSO	discrete particle swarm optimization
DT	decision tree algorithm
ENN	elman neural network
FFNN	feed forward neural network
FFT	Fast Fourier transform
GA	genetic algorithm
GARCH	generalized autoregressive heteroskedasticity
GD	gradient descent
GFS	genetic fuzzy system
GRU	gated recurrent unit
GZP	gaussian zero- phase filter
HM	hybrid model
LM	Levenberg-Marquardt
LSTM	long short-term memory
MAE	mean absolute error
MAPE	mean absolute percentage error
MARSplines	multivariate adaptive regressive splines
MBO	monarch butterfly optimization
MDPE	median percentage error
MLP	multi-layer perceptron
MSE	mean square error
MVO	multi-verse optimization
NARX	non-linear auto-regressive network with exogenous inputs
NMSE	normalized mean square error
NN	neural network
NPP	no signal pre-processing
PCA	principal component analysis
PELMNN	pre-processed evolutionary Levenberg-Marquardt neural network
PSO	particle swarm optimization
RA-FLANN	Rao algorithm based functional link artificial neural network
RBFNN	radial basis function neural network

RCGA	real coded genetic algorithm
RCSnet	residual-CNN-seq2seq network
RF	random forest
RMSE	root mean square error
RNN	recurrent neural network
RSE	relative standard error
SCG	scaled conjugate gradient
SETAR	self-exciting threshold autoregressive
SLR	systematic literature review
SMAPE	symmetric mean absolute percentage error
SSA	singular spectrum analysis
SSE	sum of squared error
SVM	support vector machine
SVR	support vector regression
XGBoost	extreme gradient boosting