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AI in Stock Market Forecasting: A Bibliometric Analysis

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Abstract. In recent years, the swift progress of artificial intelligence (AI) has significantly influenced trading practices, providing traders with advanced algorithms that improve decision-making and enhance trading strategies, leading to increased profits and reduced risks. The onset of the era of big data has further enriched this field, offering access to extensive financial data, such as historical stock prices, company financial statements, financial news articles, social media sentiments, and macroeconomic indicators—all publicly available. By identifying complex patterns and correlations within this vast data set, deep learning (DL) algorithms have proven their ability to predict stock prices and market trends more accurately than traditional methods. This comprehensive survey aims to provide an insightful examination of various deep-learning models employed in stock market forecasting. The primary objective is to categorize these models into two distinct types: Uni-modal and multi-modal models. By exploring the nuances within each category, this literature survey provides a comprehensive understanding of these models' strengths, applications, and contributions to the constantly evolving research landscape of stock market forecasting. Our survey adopts a systematic approach to categorize and analyze deep-learning models in stock market forecasting. Leveraging established databases and repositories, we will compile a comprehensive dataset comprising academic articles, conference papers, and other scholarly publications related to DL in finance. This dataset will span a defined period, allowing us to capture the temporal evolution of research trends in stock market prediction. The first phase involves extracting and compiling relevant literature from established databases, including but not limited to Scopus, Web of Science, and Google Scholar. This dataset will serve as the foundation for exploring the evolving landscape of DL applications in stock market forecasting. Subsequently, advanced techniques and methodologies will be employed to analyze citation patterns, model co-occurrence, and the intellectual structure of research in this domain. Our research identifies influential authors, collaboration networks, and geographical distribution of research activities to uncover emerging clusters of research excellence. The findings of this survey contribute valuable insights to both academia and industry. By categorizing and examining

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the strengths of uni-modal and multi-modal deep-learning models, researchers can refine their methodologies, and practitioners can make informed decisions regarding adopting predictive models in financial markets. Furthermore, the survey aims to guide future research directions, enhancing the overall effectiveness of predictive models in the dynamic landscape of stock market forecasting. In conclusion, this survey aims to provide a comprehensive overview of deep-learning models in stock market forecasting. By systematically categorizing and analyzing these models, our study aspires to contribute to the ongoing dialogue on integrating AI in financial practices, fostering a deeper understanding of the field's evolution and future directions.

1 Introduction

The stock market plays a crucial role in shaping global economic development. It attracts the attention of investors, predicting stock market trends, which is a focus for researchers in finance and technology. Stock prices fluctuate due to company earning reports, national policies, influential shareholders, financial news articles, and expert opinions. In this era of big data, the application of machine learning(ML) and deep learning (DL) in predicting stock market prices and trends has gained unprecedented popularity. The primary purpose of AI models is to respond quickly and logically to all stock market information, ensuring that stock prices accurately, sufficiently, and promptly reflect all pertinent facts encompassing a company's present and future value. Consequently, a need arises to leverage ML and DL techniques for diverse stock market prediction tasks, spanning stock movement prediction, stock price prediction, portfolio management, and trading strategies. The stock market, marked by uncertainty and variability, poses challenges for accurate trend prediction. ML techniques have been integrated into stock price prediction to address these challenges, aiming to enhance prediction accuracy. Historically, conventional models such as decision tree-based models [1],[2],[3] SVM[4] have been prominent in stock market forecasting, utilizing stock prices as a numeric modality. With the evolution of DL models, the landscape of stock market prediction has transitioned from traditional techniques to advent models like Recurrent Neural Networks (RNNs)[5], Long Short-Term Memory (LSTM) [6], [7], Gated Recurrent Units (GRU)[8],[9], Graph Neural Networks (GNNs)[10],[11], and Convolutional Neural Networks (CNNs)[12],[13], where stock prices serve as inputs. Furthermore, some studies have explored the analysis of news articles for predicting stock market trends[14],[15],[16]. In recent times, research has expanded to incorporate Transformer-based models and Reinforcement Learning (RL) models in stock market forecasting, considering both numeric modality (stock market prices) and text modality (news articles) as inputs[17]. Despite the abundance of surveys on stock market forecasting, existing surveys have certain limitations. Some surveys focus solely on traditional techniques without examining recent advancements, such as transformer-based models. Additionally, some surveys concentrate on the algorithms used without analyzing the differences between the input data modality used. This comprehensive literature review aims to provide a new vision of trends in utilizing AI techniques, specifically ML and DL models, in stock market forecasting tasks. This survey examines various DL models utilized in stock market forecasting, aiming to categorize them into Uni-modal and multi-modal models. By delving into the modalities these models use, the survey aims to offer a profound understanding of their strengths, applications, and contributions to the evolving landscape of stock market forecasting. Through this exploration, the goal is to contribute valuable insights that can guide future research directions and enhance the effectiveness of predictive models in financial markets. The key contributions of this survey are as follows: This survey introduces new classification approaches for predicting stock market performance. We categorize the reviewed literature based on the modality of ML and DL models. Additionally, it provides a summary of datasets and evaluation metrics used in these studies, offering a clear overview of the methodologies adopted. This survey delves into various aspects of stock market prediction, covering tasks such as stock price prediction, stock market trend prediction, portfolio management, and trading strategies. The study encompasses a broad range of topics to provide a comprehensive understanding. To conduct this study, we compiled a collection of high-quality and highly cited papers from 2000 to 2022. This inclusive time frame allows us to capture the evolution and advancements in stock market prediction using ML and DL techniques. The survey concludes by offering insights for future research in ML and DL-based stock market prediction, serving as a guide for researchers and practitioners to enhance predictive models in financial markets.

2 Research Questions

The purpose of this paper is to systematically examine the evolving trends in artificial intelligence (AI) applications within the business sector, with a particular focus on stock market forecasting. Specifically, the following points are emphasized:

- The shift from traditional ML techniques to advanced DL methodologies.
- The shift from uni-modal to multi-modal models in processing and analyzing data.
- The shift from single-function to complex, multifaceted AI systems that offer enhanced decision support and risk management capabilities.

3 A Review of the Literature

Over the past two decades, predicting stock market trends has become increasingly pivotal for global economic development. Initially, conventional methods incorporating ML techniques like Support Vector Machines (SVM), regression, and k-Nearest Neighbors (KNN) were widely adopted to enhance prediction accuracy. However, with the progression of DL methodologies, there has been a notable shift towards leveraging neural networks in stock market prediction research. DL models, including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRUs), Graph Neural Networks (GNNs), and Convolutional Neural Networks (CNNs), have played a significant role in improving predictive capabilities.

More recently, researchers have explored the application of Transformer-based models and Reinforcement Learning (RL) models in the realm of stock market forecasting. This evolution in techniques underscores the dynamic landscape of predictive analytics within the financial markets. Many survey studies have been conducted on stock market forecasting over the past two decades. A notable survey study was conducted by George et al.[18]. This survey has 100 paper references focusing on neural networks and neuro-fuzzy techniques for stock market prediction. From 1990 to 2006, the study looked at various aspects, including individual stock markets, input variables, forecasting methods, and evaluation metrics. Through comprehensive analysis, the survey aims to offer comparisons and insights across a wide range of documents from this time frame. Another survey, undertaken by Li et al.[19] and published in 2010, concentrated on using ANN in financial market applications. The primary focus of this survey encompassed areas such as stock price prediction and option pricing within the financial domain. In 2015, Ballings et al.[20] undertook an exploration survey focused on classifier models for both ensemble methods and single classifier models in the context of stock price prediction. Ensemble methods investigated encompassed Random Forest, AdaBoost, and Kernel Factory, while single classifier models involved Neural Networks, Linear Regression, SVM, and KNNs. This study initially explored a comprehensive benchmark for stock market prediction models. The following year, Michal et al.[21] delivered a systematic review encompassing over 400 papers released from 1994 to 2015, exploring the commercial implementation of artificial neural networks (ANN) within the financial sector. The survey focused on applications such as financial distress, the bankruptcy problem, and decision support for stock price forecasting. In that same year, Cavalcante et al.[22] reviewed literature from 2009 to 2015, exploring the utilization of diverse ML algorithms in financial applications. This survey not only examined the applications but also the challenges and limitations encountered in this domain. The primary ML methods included ANN, SVMs, hybrid approaches, optimization methods, and ensemble methods. Applications ranged from preprocessing and clustering financial data to forecasting future market trends and mining information from financial text sources.

In 2017, Li et al.[23] surveyed 229 papers published between 2007 and 2016. Their focus was on exploring the correlation between web media and stock markets. In their study, they introduced a taxonomy categorizing ML techniques into statistical models, regression models, and ML-based models. The neural network models examined within this framework included Bayesian classifiers and SVMs In 2018, Xing et al.[24] conducted a survey investigating neural network models, including Bayesian classifiers and SVMs. The study explored papers that applied natural language processing (NLP) methods to financial forecasting tasks, focusing on three key aspects: various types of text sources, employed algorithms, and outcomes evaluated using diverse metrics. The analyzed text sources comprised news articles, social media content, financial reports, and messages from online boards. This survey represents the first exploration of models utilizing NLP techniques and text source data in the context of stock market prediction. One recent research conducted by Nti et al.[25] surveyed about 122 research works reported in academic journals over 11 years from 2007 to 2018. This survey focused on three categories of analysis: technical, fundamental, and combined analysis. Notably, the scope of models was restricted, particularly emphasized on three ML techniques: decision tree, SVM, and ANN. Ersan et al.[26] conducted a survey that concentrated on three ML methods employed in stock market forecasting over a span of 10 years: KNN, ANN, and SVM. The primary objective of this survey was to compare various ML approaches using DAX 30 and S&P 500 datasets at both daily and hourly intervals. However, all the mentioned surveys primarily focus on traditional and ML approaches in the field of stock market prediction.

Recent surveys on stock market prediction, focusing on DL techniques, are presented in several studies. One of the earliest surveys was conducted by Jiang et al.[27]. This survey prioritized the implementation and reproducibility of research. Specifically, the paper highlighted key frameworks employed for implementation, including Keras, TensorFlow, PyTorch, Theano, and Scikit-Learn. Additionally, the availability of data and code in some papers was investigated to demonstrate reproducibility. The survey emphasized the recent advancements in DL methods applied to stock market prediction. Thakkar et al.[28] explored diverse DL models for stock market prediction, focusing on the applicability of various Deep Neural Network (DNN) variations to temporal stock market data. The study extended its scope to include hybrid and metaheuristic approaches combined with DNNs. Potential limitations in stock market prediction using different DNNs were also observed. The study conducted experiments using nine DL-based models, analyzing their impact on forecasting stock market data. The performance of individual models was evaluated with varying numbers of features. The survey addresses challenges, outlines potential future research directions, and concludes with an experimental study. This survey is a valuable reference for recent perspectives on DNN-based stock market prediction, summarizing research from 2017 to 2020. Kumbure et al.[29] conducted a literature review included 138 journal articles published between 2000 and 2019, focusing on stock market forecasting. Their survey examines the datasets, emphasizing the markets, stock indices, and 2173 unique variables employed for predictions. The review also focused on in-depth analysis of the ML techniques and their variants utilized in these predictions. The survey categorizes DL methods into two groups: supervised and unsupervised learning methods. However, it observes a gap in some surveys, lacking coverage of the latest techniques such as Transformers and pre-trained BERT models, which are thoroughly reviewed in this survey. The recent surveys by Zou et al.[30] offer a comprehensive analysis of critical studies on employing DL for stock market prediction. They introduce a classification system to categorize and group similar works to enhance the understanding and organization of prior research in this domain. The surveys further provide insights into the current primary methods, evaluation metrics, and datasets utilized in stock market prediction. However, it's noteworthy that this survey lacks in classifying the types of input data used and identifying models suitable for specific input data.

Existing surveys have predominantly covered traditional methods and older neural network techniques, resulting in a gap in understanding contemporary research trends. Recent surveys, however, still need to be fully updated to encompass the latest techniques. Furthermore, specific existing surveys need proper classification of papers by targets or exclusively concentrate on stock market forecasting tasks. Recognizing the need for an updated survey incorporating the latest advancements in stock market prediction, this study introduces a novel deep-learning model classification method. The aim is to deliver a more comprehensive and up-to-date analysis. Moreover, there needs to be more surveys addressing the input data type and its corresponding models. This survey focuses on newer papers and the most current technologies in response to this gap. The approach involves a comprehensive survey organized according to a model flowchart, with classification based on input data and model type. The classification system will distinguish between uni-modal and multi-modal models, providing a nuanced perspective on the evolving landscape of stock market prediction.

4 Methods

Applying bibliometric research, the study systematically investigates the literature regarding AI forecasting financial market or stock market prediction. The study "Artificial Intelligence in Stock Market Forecasting" utilizes VOSviewer for network visualization, emphasizing its usefulness in identifying keyword co-occurrences, citations, author or publication trends, and thematic relationships. This study provides guidance for researchers and practitioners to enhance financial market forecasting models, which can shed light on future ML and DL based stock market forecasting research for strategic decision making. This study uses a detailed search string, focusing on architecture and stock forecasting keywords, to screen papers published between 2000-2023 and rank them by citation count. Relevant studies were filtered from more than 5349 papers. This study illuminates the theme of artificial intelligence in stock market forecasting by preparing Scopus data, creating maps based on bibliometric data, and employing various analytical methods such as co-occurrence and density visualization. This approach highlights the importance of organized, reliable data and strategic visualization to gain insights from complex information networks.

4.1 Research methodology

4.1.1 Identification of appropriate search terms

A bibliometric analysis was conducted to address the research questions. The 16 terms used in this study cover two interdisciplinary elements: artificial intelligence and stock market forecasting. It was necessary to include keywords related to each element to ensure that all aspects could be captured. Table 2 lists the keyword strings and keyword sets. These keywords were identified by the authors after an initial survey of key relevant articles.

Table 1: Search string and keywords

Keywords relating to architecture: (ml) OR (ML) (dl) OR (deep learning) OR (cnn) OR (cnns) OR (rnn) OR (rnns) OR (lstm) OR (lstms) OR (gnn) OR (gnns) OR (transformers) OR (transformer) OR (gru) OR (grus)
AND
Keywords relating to stock prediction: (stock prediction) OR (financial forecasting) OR (stock price prediction) OR (stock price forecasting) OR (stock forecasting) OR (stock forecast) OR (financial forecast) OR (stock price forecast)
Filters: Years(2000-2023) Sort by: Cited count(highest)

4.1.2 Search results

To systematically identify relevant articles, a three-step approach was used. First, Scopus databases were selected for the search. Its main advantage is its comprehensive coverage of relevant studies. The search was initially set free to include as many articles as possible up to 2023. This produced a total of 5349 articles. All results were saved in multiple formats (e.g., CVS, TXT) and included all basic information such as title, author name, affiliation, keywords, and abstract. The second step was to eliminate duplicate and irrelevant articles. Articles were screened by reviewing their titles and abstracts and applying a series of inclusion and exclusion criteria (see Table 2). This resulted in 2000 articles being screened in the third step.

Finally the authors created a table that includes a table of all 2000 articles that were used as a sample for the bibliometric analysis. Figure.1 shows a summary of the data sampling process.

4.2 How to create Network Visualization and Keyword Density Maps

In this section, we describe how to create Network Visualization and Keyword Density Maps. First, we saved the data as a CSV file from Scopus as instructed in the procedure shown in

Table 2: Search string and keywords

Inclusion criteria	Exclusion criteria
Focus on the use of AI in stock market prediction	AI not related to stock market prediction
High citation	Stock market prediction not related to AI
From 2000 to 2023	Non-English language

Figure 1: A summary of the data sampling process

Figure.2, and then we used VOSviewer to create those maps. In VOSviewer, it is possible to switch between displaying a Network Visualization map or a Density Map. The creation of density maps is explained in detail here. We created two keyword density maps, Models density map, and Economic keywords density map. This section describes how to create these Density maps.

After choosing the data file for VOSviewer, set up the following:

- Type of analysis: Co-occurrence
- Unit of analysis: Index keywords
- Counting method: full counting
- Minimum number of occurrences of a keyword: 5 (models), 20 (economic keywords)

We used a thesaurus file to combine keywords with the same meaning into one. For example, “convolution neural network” and “convolutional neural networks” both refer to the same thing, but if nothing is set, they are considered different keywords and are displayed separately on the map. Therefore, by setting the label “cnn” for each, they can be treated as one keyword. Also, we eliminated keywords, leaving the necessary items. For example, in models density map, “forecasting”, and “deep learning” are keywords that are not needed, so these were removed. We explain why the Minimum number of occurrences of a keyword set differs between the two maps below. First, setting this minimum number low increases the number of keywords displayed on the map, while setting it high decreases that number. The models density map needs to keep this number small, because if the number of keywords to be displayed is low, GNNs and other low-occurrence items will not be displayed. The “Transformer” actually disappears. Since removing keywords is all manual work, if the number is set so that the “Transformer” does not disappear, it will take a very long time to remove unwanted keywords. As for the economic keywords density map, if the number of keywords is large, it is very time-consuming to decide one by one whether to keep or remove keywords. Therefore, it is necessary to set a larger value to limit the number of keywords. For these reasons, we set the above values when creating the two maps.

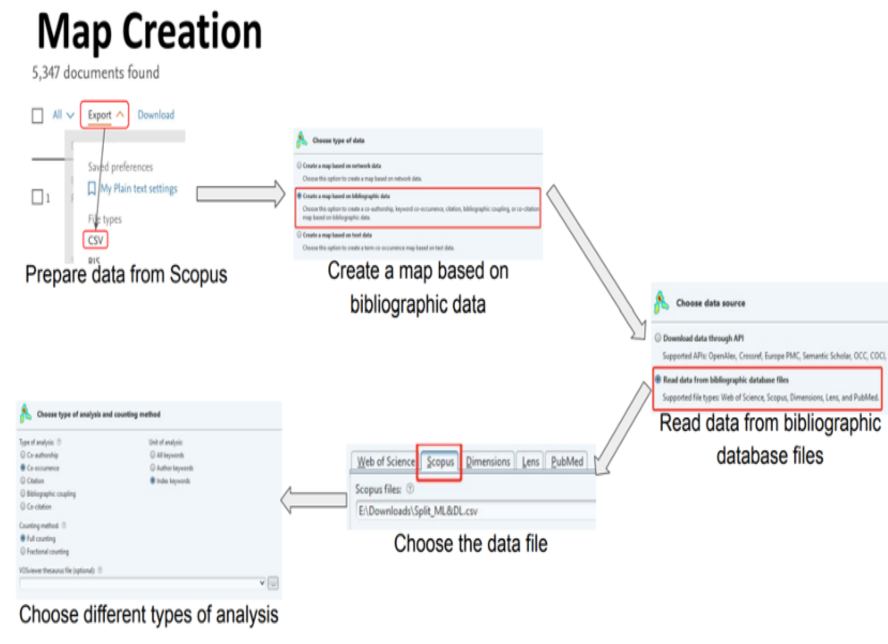

Figure 2: Map creation

5 Findings - Data Visualization and Tables with Explanations

5.1 Basic Network Visualization

This image (Fig.3) is a network visualization map created by VOSviewer, in which the nodes (large and small circles) represent various concepts related to the financial markets, and the lines (edges) connecting them represent the relationships or connections between these concepts.

The size of the nodes usually indicates the weight or frequency of the concept in the literature or dataset being analyzed - larger nodes are usually more important or prominent in the field. The thickness of the lines indicates the strength or number of connections between concepts. Different colors represent different clusters or groups of closely related concepts. For example, concepts closely related to "Financial Markets" are grouped in one color, while concepts related to "Investments" are grouped in another color, indicating that they form distinct but related subject areas. The terms shown are keywords or index terms that have been used in the literature (e.g. academic papers or reports) on financial markets. They cover a range of topics, including "stock price forecasting", "investment decision-making", "risk assessment" and "bankruptcy forecasting", indicating that the research focuses on forecasting, risk management and decision-making in the financial sector.

Figure.4 is another example of a network visualization map generated by VOSviewer, but it represents a different type of network than the first example. In this visualization, the nodes may represent researchers, indicated by their last names and initials. The lines connecting the nodes represent collaborations or connections between these researchers, such as co-authorship of an academic paper. The size of the nodes indicates the number of published

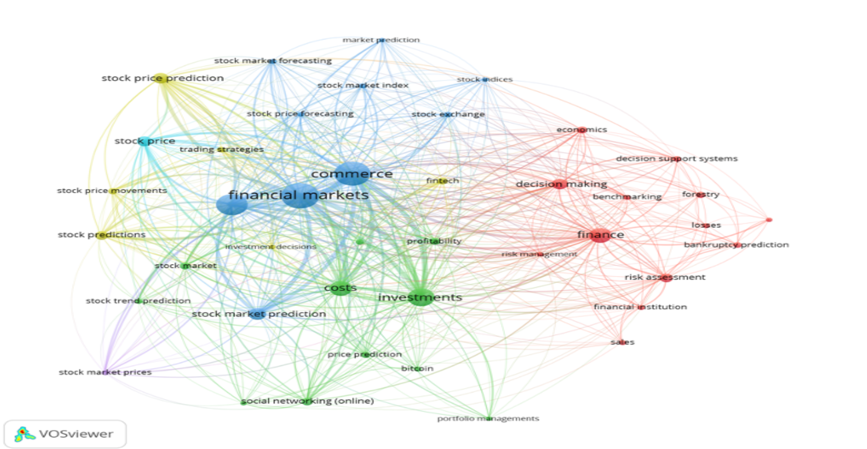

Figure 3: The concept network visualization map created by VOSviewer

papers or the degree of collaboration: larger nodes indicate that the authors have more connections in the network, which usually means that these individuals have co-authored more works with others in the network. The colors of the nodes represent different groups or communities in the network, indicating groups of researchers who often collaborate with each other. The timeline at the bottom ranges from 2016 to 2022, and this network visualization also shows how collaborations have evolved over time. Authors who are at the center of the network and have many lines connected to them are the key researchers in the field with extensive collaborations. In contrast, authors who are at the edge and have fewer connections are newer researchers or those with fewer collaborations.

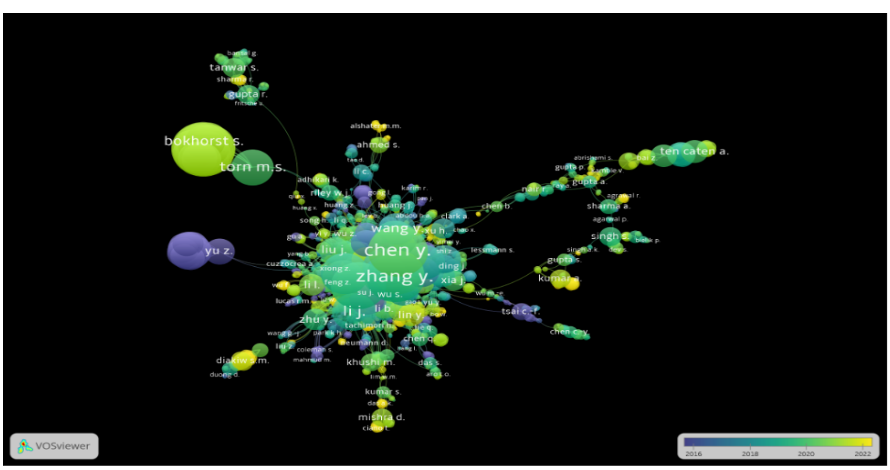

Figure 4: Researchers network visualization map created by VOSviewer

5.2 Deep learning and ML map

5.2.1 Deep Learning Map

: This map (Figure5) focuses on the node labeled "deep learning" and highlights the connections between DL and other concepts such as neural networks, convolutional neural networks, recurrent neural networks, data processing, and image recognition. It also emphasizes the specific techniques and applications within the field of DL, like image and speech recognition, natural language processing, and other areas where DL models, particularly those with many layers of neural networks, are applied.

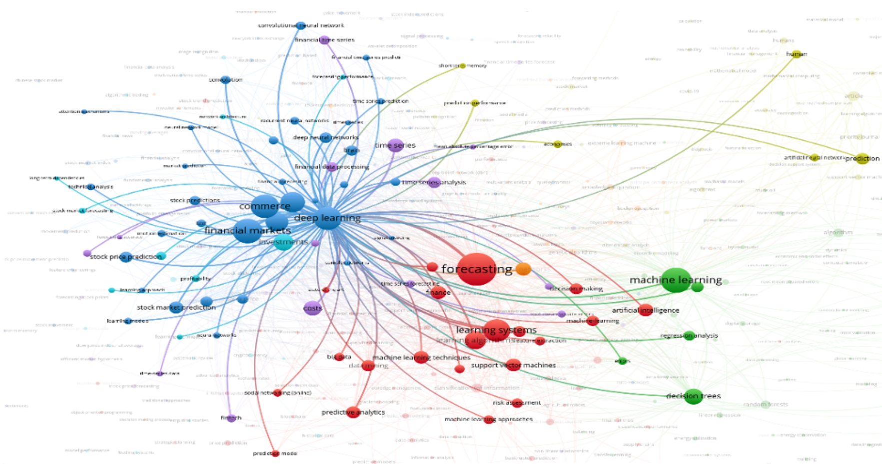

Figure 5: Deep learning network visualization map created by VOSviewer

5.2.2 ML Map

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The Figure.6 map centers on the "machine learning" node and illustrates its connections with broader concepts and methodologies in ML such as classification, regression, SVM, decision trees, and random forests. It also shows the application of ML in various domains like finance, healthcare, and more, as well as connections to fundamental topics like algorithms, data analytics, and predictive modeling.

5.3 Density Visualization

Density visualization makes it easy to see visually what the important items are. When creating the following maps, the settings are made in VOSviewer to separate the colors for each cluster.

5.3.1 Models density map

: The models density map (Figure7) shows only the names of the models, as mentioned above. As you can see, LSTM is the most used and important model. We can also see that CNN and RNN are the next most important.

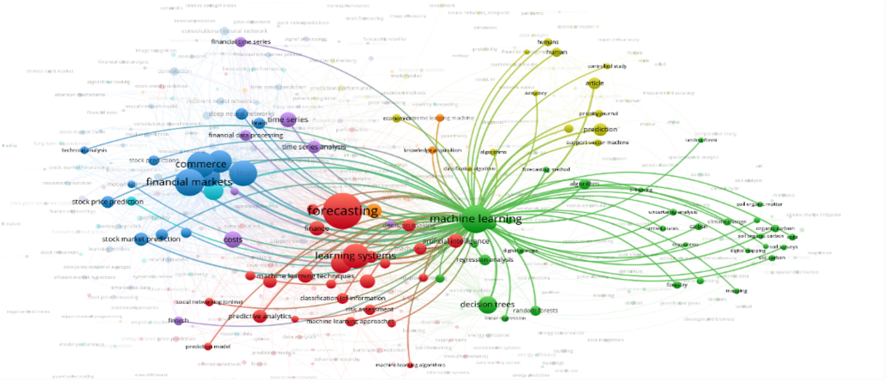

Figure 6: Machine learning network visualization map created by VOSviewer

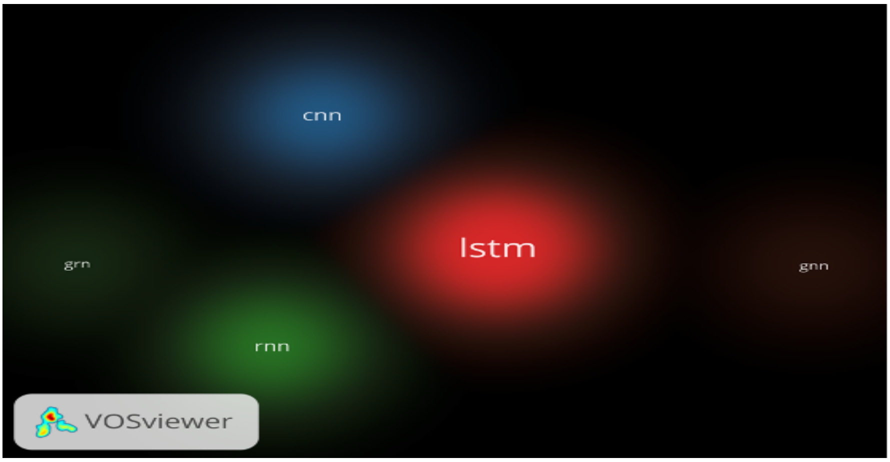

Figure 7: Density visualization map created by VOSviewer

5.3.2 *Economic keywords density map*

The map (figure.8) showcases the evolving landscape of publication purpose across the broader spectrum of financial-related fields over 20 years. The blue and green clusters have similar meanings, so it is not necessary to pay that much attention to them. In contrast, the red clusters show keywords such as "decision making" and "risk assessment". These are economic keywords that are strongly related to stock price prediction.

6 Analytical Description of the Chart

Our presentation shows a comprehensive comparative analysis of various DL models, including GNN, Transformer, CNN, LSTM, RNN, and GRU, based on a review of 13 articles from Scopus. This analysis, aided by tools like VOSviewer, focuses on unimodal and multimodal methodologies primarily applied in the stock forecasting domain. We have delineated the timeline of each method's popularity and its specific contributions to the industry. From a business perspective, our study highlights the potential of these models in shaping new

Figure 8: Economic keywords map created by VOSviewer

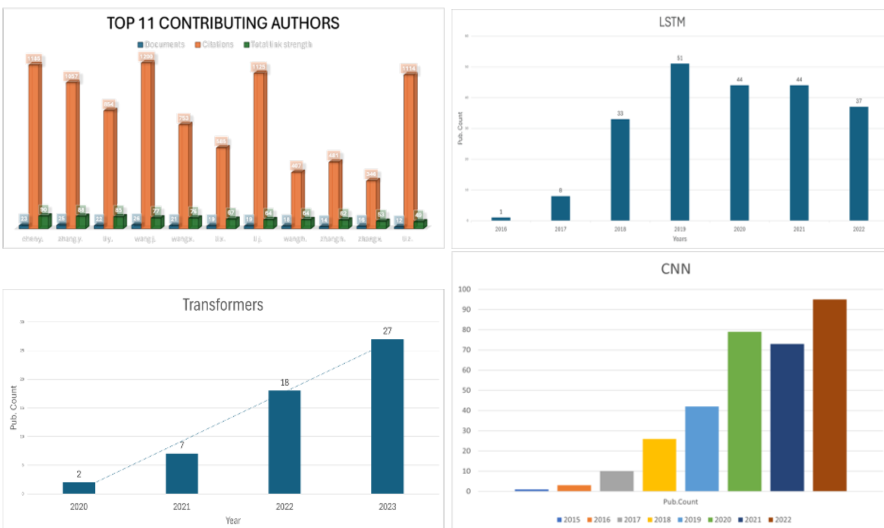

Figure 9: Bar chart representing bibliometric data

investment strategies, managing risk, complementing traditional market analysis tools, and enhancing the investment decision-making process. However, feedback from reviewers underlines the need for a more detailed and nuanced presentation. Specifically, the following six key aspects need to be improved: First, we need to clarify the specific applications, i.e., we need to be more explicit about the strengths and specific applications of each DL model in stock market prediction. Second, we will incorporate specific examples and insights from the existing literature to enrich context and understanding. Third, we elucidate how our findings can be beneficial, particularly in addressing current challenges and offering practical solutions in stock market prediction. In addition, potential challenges need to be discussed, such as overfitting, data bias, and model interpretability, to present a balanced view of the limitations and considerations associated with these models. Next, the quality of this paper needs to be improved by detailing the methods and experiments to ensure reproducibility, and by assessing the relevance and quality of the data used. Finally, we will reflect on the potential impact of our findings on future research, methodologies, and practical applications in stock market forecasting. In summary, our goal is to refine our paper to not only contribute to the advancement of knowledge in this field but also to fill existing gaps in research. We acknowledge the constructive feedback and recognize the importance of a more comprehensive and clear presentation, especially regarding the limitations and challenges of the methodologies used. This will not only ensure a more rigorous academic contribution but also provide a reliable resource for industry practitioners seeking to apply DL in stock market forecasting.

7 Findings

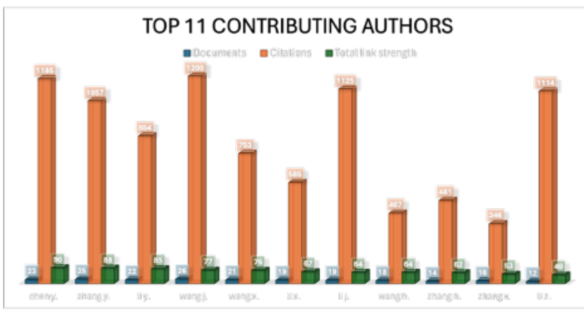

Figure 10: Barchat of publication over the years

The image (Figure.9) is a bar chart representing bibliometric data on the scholarly contributions of the different authors, expressed as author names and acronyms. There are three categories of data for each author: Literature: Refers to the number of publications or literature published by the author. This is indicated by the dark blue bar. Citation: This indicates the number of times other authors have cited the author's work, indicated by the orange bar. Total Link Strength: This is a measure unique to VOSviewer that indicates the total strength of an author's connections in the citation or co-authorship network, and is represented by the green bars. The number above each bar indicates the count for each category. Authors are sorted by citation count, in descending order from left to right. This chart visualizes the influence and productivity of these authors in their respective fields, with more documents and citations indicating greater influence or contribution. The total link strength adds another dimension, showing the centrality of the authors' work in the network of documents analyzed.

The bar chart (Figure.10) displays the trend in publications over the years. Each bar represents the number of publications in a given year, allowing us to observe how the volume of publications has changed over time.

7.1 Analysis of using Unimodal model and Multimodal model in Stock market prediction

Before delving into the specifics of DL models for stock market prediction, it's essential to understand the overarching categories of prediction tasks within this domain. These tasks can be broadly categorized into Stock Price Prediction, Stock Movement Prediction, and Trading Strategies, each serving distinct purposes in financial forecasting.

7.1.1 ***Stock Price Prediction***

This task revolves around forecasting the future values of stocks and financial assets traded on exchanges. Researchers aim to achieve substantial profits by anticipating price movements accurately. Time-series data, such as pricing or index data, serves as the primary input for this task.

7.1.2 ***Stock Movement Prediction***

Stock movement prediction involves categorizing stock trends into uptrends, downtrends, or sideways movements. Analysts typically analyze the variance in adjusted closing prices over a specific period to make these categorizations. While numeric data like index and pricing information is crucial, some models integrate textual data from news articles to enhance prediction accuracy. This often necessitates the use of multimodal models.[31]

7.1.3 ***Trading Strategies***

Trading strategies are predefined sets of guidelines used to make buying and selling decisions systematically. These strategies can be simple or complex, considering factors such as investment style, market indicators, risk tolerance, and leverage. In DL-based stock market prediction, common trading strategies include event-driven, data-driven, and policy optimization approaches. These tasks form the foundation of stock market prediction, and understanding them is crucial for grasping DL-based approaches. The process typically involves selecting and collecting relevant stock features, followed by inputting these features into a DL model for training. The resultant experimental results are then analyzed for insights. Given the multifaceted nature of stock market data, multimodal models, which integrate various data types such as stock data, graphs, and textual information, are often employed to enhance prediction accuracy and robustness.

7.2 Unimodal model and Multimodal model

We categorized the papers based on the models and presented the different models as shown in Figure.11

7.2.1 ***Unimodal model***

The input for these models encompasses various data types, including stock price-related data, textual information, and inter-company relationships. These models generate outputs based on the objectives specified in the research papers. It's important to note that while Unimodal models are capable of handling different types of input data modalities, they typically process only one modality at a time. To provide a comprehensive understanding, the following classification of input data variables can offer an overall perspective on this categorization:

Stock Price-Related Data:

Stock Price-Related Data includes historical stock prices, trading volumes, market capitalization, and other relevant financial metrics. Such data provide insights into past market behavior and are crucial for price prediction tasks. In the first decades of this research, a substantial body of research focused on utilizing numeric data for stock market prediction, primarily due to the significance of stock prices as indicators of success or failure in the

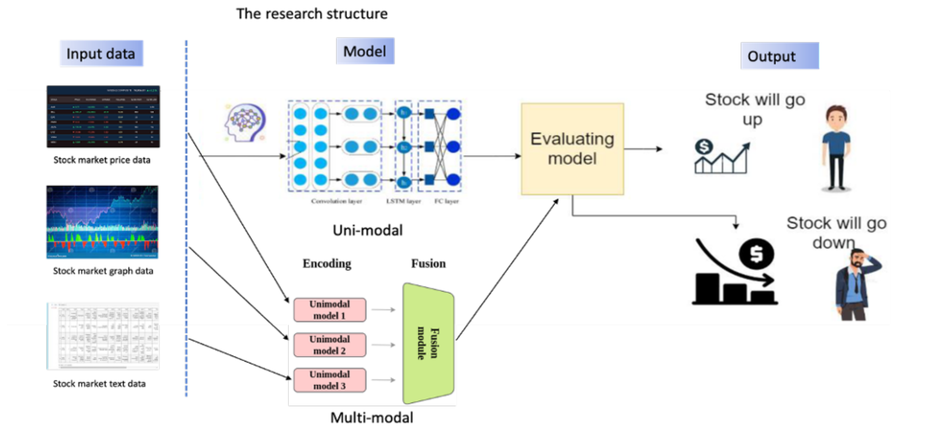

Figure 11: The workflow of Unimodal/Multimodal deep learning models used in stock market prediction

market. Time-series data plays a critical role in forecasting future prices. Researchers predominantly employed ML algorithms from the early 1990s to 2017 for stock price prediction [32–35]. Several methods were commonly utilized during this period, including Ensemble methods (e.g., Random Forest, AdaBoost, Kernel Factor), Single classifier models (e.g. SVM, KNNs), and various ML Algorithms (e.g., ANN, ensemble methods).

With the advancement of DL techniques since around 2010, researchers have increasingly turned to DL methods for stock market price prediction. One of the pioneering approaches was the adoption of Recurrent Neural Network (RNN) Based Models. RNNs are DL models designed to process sequential data efficiently. Since stock market data is commonly represented as time series, RNNs became an ideal choice for predicting by modeling historical data. However, RNNs face the challenge of gradient vanishing when processing data over extended periods [5, 36, 37].

To mitigate this issue, several variants of RNN have emerged, including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (Bi-LSTM). LSTM, in particular, has shown dominance in handling long-term data due to its ability to control short-term and long-term memory through the update, forget, and output gates. GRU is an enhancement over LSTM, combining the input and forget gates into an update gate while introducing a reset gate to manage information retention [38, 39]

Researchers have explored hybrid applications of RNN with other machine-learning techniques to enhance performance. For instance, Rather et al.[40] proposed a robust hybrid prediction model combining RNN with Exponential Smoothing and Autoregressive Moving Average models. They employed genetic algorithms to optimize the model weights, improving prediction accuracy. Another approach, by Zhang et al.[41], introduced the State Frequency Memory based on RNN, capable of capturing multi-frequency trading patterns underlying stock price fluctuations.

The evolution from traditional ML algorithms to DL techniques, particularly RNN variants, has significantly advanced stock market prediction capabilities. There is also a stock market movement prediction based on the stock price. This task is well explained in the research of Nelson et al .[42], which used LSTM for stock movement prediction. Still, the model inputs were numerical information, including stock prices and volume.

In 2019, Feng et al.[43] proposed a method that combines attentive LSTM and adversarial training to predict stock market movements. Another approach to predicting multiple stock prices is the associated network model proposed by Ding and Qin[44], which consists of three branches that predict the opening price, the lowest price, and the highest price, respectively.

An effective model that utilizes pricing data as input is the CNN-based model. CNNs, renowned for their efficacy in computer vision and natural language processing, consist of convolutional and pooling layers designed for feature extraction. In stock prediction, CNNs process time series data, typically represented as one-dimensional features. For instance, Hoseinzade et al.[45] introduced a CNN-based framework capable of extracting features from a collection of stock index data sourced from diverse markets. This framework was applied to predict the next day's direction of movement for indices such as S&P 500, NASDAQ, DJI, NYSE, and RUSSELL, outperforming state-of-the-art methods.

Furthermore, integrating CNN with LSTM can enhance time series prediction even further. Lu et al.[46] proposed a forecasting method for stock prices based on CNN-LSTM. This research chose eight features, including opening price, highest price, lowest price, closing price, volume, turnover, ups and downs, and change. They employed CNN to efficiently extract features from the data, which comprised the items of the previous 10 days. Subsequently, LSTM was utilized to predict stock prices using the extracted feature data. According to the experimental results, the CNN-LSTM-based model demonstrated reliable stock price forecasting with the highest prediction accuracy.

Graph data:

GNN is an artificial neural network that processes data through graphs[47]. GNNs are essential in stock market prediction, as they can operate on irregularly structured data. The structure of a GNN is made up of nodes and edges, which allows it to model the relationship between entities. In stock market prediction, nodes typically represent companies or stocks, and edges represent their relationship. For this input data, four main graph-based models have been proposed in the stock market prediction task: GNN, Graph Convolutional Networks (GCN), and Graph Attention Network (GAT). For the GNN model, Matsunaga et al.[48] employed a knowledge graph to integrate information on companies and GNN models to predict individual stock performance. Xu et al.[49] proposed the Hierarchical Graph neural Network to investigate the market state in a hierarchical view for stock type prediction. For GCN, this is a type of DL model specifically designed to deal with graph data, which uses graph convolutional layers to extract features from the graph and make predictions based on the relationship between nodes in the graph. GCN is often combined with other DL models. One example is the research of Wu et al. [50], who proposed a graph-based CNN model that combines the Convolution Neural Network (CNN) and Long–Short-Term Memory Neural Network (LSTM). Chen et al.[51] proposed a pipeline prediction model that integrates the relationship between corporations by using a GCN model. A note in the graph represents each corporation, with edges representing the relationship between the corporation and the weights of those edges representing the shareholding ratios.

Predicting the price movement of individual stocks can be challenging due to various factors. However, stock market indices provide a more reliable means of understanding the overall trend of a specific industry. Wang et al.[52] proposed a model that utilized GCN to analyze the correlation of indicators in stock trend prediction. They introduced a model based on a multi-graph convolutional neural network and utilized static graphs between indices constructed using constituent stock data.

For GAT, this model combines the strengths of GNN and attention layers to improve performance in large-scale graphs. For example, Kim et al.[53] proposed a hierarchical attention network for stock prediction (HATS) using relational data for stock market prediction. The HATS method aggregates information on different relation types and adds the information to the representations of each company. HATS is used as a relational modeling module with initialized node representations. Then, node representations with the added information are fed into a task-specific layer for predicting individual stock prices and market index movements, which is similar to the graph classification task.

Text Data:

Text data in the stock market is textual information from various sources such as news articles, company reports, social media, and financial blogs that can significantly impact stock market movements. Natural language processing techniques are often employed to extract relevant insights from textual data for prediction purposes.

Long Short-Term Memory (LSTM) model can effectively handle text and time-series data, making it ideal for stock market forecasting. LSTM addresses the problem of preserving information over longer intervals through the gradient method, improving RNN models. For example, Akita et al.[54] proposed a Paragraph Vector method to represent textual information and utilized LSTM for the prediction model. Another example is Ma et al.[55], proposed the News2vec model that used LSTM with the self-attention mechanism as the predictive model. Chen et al.[56] used Bi-LSTM to encode stock data and financial news representations in their models, namely the Structured Stock Prediction Model (SSPM) and the multi-task Structured Stock Prediction Model (MSSPM).

While RNNs have shown effectiveness in tasks involving temporal or sequential data, such as financial news, tweets, and stock price time-series, they may face limitations when processing long sequences, leading to forgetting distant content or mixing up nearby positions. The Transformer model addresses this limitation by employing a self-attention mechanism and positional embedding to process sentences. As a result, the Transformer model has demonstrated promising results in various stock market prediction tasks. For instance, Eduardo et al. [57] introduced a neural network-based architecture called Multi-Transformer, a variation of the existing Transformer model. It utilizes a strategy of randomly selecting various training data subsets and incorporates a multi-attention method to increase the stability and accuracy of the attention process. Similarly, in the work of Ding et al.[58], the hierarchical multi-scale Gaussian Transformer was proposed for predicting stock movements. They improved upon the traditional Transformer by incorporating multi-scale Gaussian priors and optimizing locality. Many studies have utilized Transformer-based models to analyze textual information in stock news media, aiming to understand sentiment and predict market reactions to news.

BERT, a language model based on the Transformer architecture, has became as a popular choice for pre-training in Natural Language Processing (NLP) tasks. The model employs two training methods: masked-language modeling and next sentence prediction, enabling it to capture word relationships and long-term dependencies between sentences. Moreover, the pre-trained BERT model can be fine-tuned for specific use cases. For instance, Dong et al. [59] proposed a model named BERT-LSTM (BELT), which leverages BERT to extract informative features on stock price direction from Twitter news. These features are then used as input to LSTM model, which also incorporates historical stock prices to predict future price direction. Similarly, Sonkiay et al.[60] employed the BERT model for sentiment analysis on news and headlines related to Apple Incorporation. The sentiment scores obtained from this analysis were used as input vectors for a Generative Adversarial Network (GAN), consisting of a GRU and a CNN as the generator and discriminator.

7.2.2 ***Multimodal model***

Multimodal models in stock market prediction research not only rely on single-modality input data but also explore the integration of multiple modalities to enhance accuracy in prediction and classification tasks. Li and Pan[66] proposed an ensemble DL model that combines LSTM and GRU to account for various factors influencing stock prices. They determined the optimal window size for textual information based on psychological and economic theories, considering the lasting or fleeting impact of news. Incorporating expert opinions, Wang et al.[63] proposed a framework called the multi-view fusion network stance detection model (MFN), which uses text features and financial knowledge to predict stock trends. For graph input data, Sawhney et al. [61] designed an architecture that fuses information from financial data, social media, and inter-stock relationships using a graph neural network with hierarchical attention. Additionally, Cheng et al. [62] introduced an attribute-driven graph attention network (AD-GAT) to model momentum spillovers, utilizing an unmasked attention mechanism and a tensor-based feature extractor.

To fully leverage industrial relations, Deng et al. [67]] integrated knowledge graphs with CNNs, employing causal convolution to address data leakage issues. This approach has been effective in explaining abrupt price changes by extracting significant features from price time series. In the research on utilizing multiple input data for stock market prediction, Li, Qing, et al.[64] introduced a novel multimodal event-driven Long Short-Term Memory (LSTM) model with several key contributions. They first represent the intricate market information space using tensors to preserve interconnections among different information modalities. Additionally, they address the heterogeneity of sampling times in different modes by proposing an event-driven LSTM model, which effectively fuses continuous data sampled at equal intervals (fundamental data) with discrete values sampled at unequal intervals (news). To account for the indirect influence of related companies on media-aware stock movements, they construct a media-based enterprise network to reshape the market information space represented by tensors. This approach allows for the preservation of the multifaceted and interrelated nature of the data. Subsequently, the proposed multimodal event-driven LSTM model captures nonlinear relationships between market information and stock movements. He et al.[65] introduced a multi-modality attention network aimed at reducing conflicts and integrating semantic and numeric features to comprehensively predict future stock movements. Initially, they extracted semantic information from social media and assessed its credibility based on posters' identity and public reputation. Subsequently, they integrated this semantic information from online posts with numeric features from historical records to formulate trading strategies. Experimental results demonstrated that their multimodal model significantly outperformed previous methods, achieving a prediction accuracy of 61.20% and trading profits of 9.13%. This highlights the effectiveness of the multimodal approach in improving stock movement prediction and underscores the importance of further research on multi-modality fusion in this domain

8 Discussion

The comprehensive survey and analysis of DL models in stock market forecasting, as presented through the abstract, introduction, literature review, and extensive bibliometric analysis, underscore a significant evolution in the application of artificial intelligence (AI) within financial markets. This evolution reflects not just the advancements in technology but also a deeper integration of complex data analysis techniques in predicting stock market trends. The transition from traditional ML methods to sophisticated DL approaches, including Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), and Transformers, has marked a pivotal shift in the accuracy and reliability of stock market predictions. Each model has shown strengths in handling different types of data and capturing various aspects of market dynamics. Uni-modal models have excelled in analyzing single data types, while multi-modal models have leveraged the integration of diverse data sources, such as financial news, social media sentiments, and historical stock prices, to provide a more comprehensive analysis. The bibliometric analysis further illuminates the growing interest and collaboration in this field, highlighting the global distribution of research activities and the emergence of influential authors and clusters of research excellence. The analysis of literature from 2000 to 2023 reveals a clear trend towards the adoption of DL techniques, with a particular emphasis on models that can handle the temporal and spatial complexities inherent in financial data.

9 Challenges and Limitations

Despite the advancements, challenges persist in model interpretability, data quality, and the handling of unpredictable market events. The complexity of DL models often leads to difficulties in understanding the decision-making process, raising concerns about transparency and trustworthiness. Additionally, the quality and accessibility of financial data can significantly impact model performance, necessitating ongoing efforts to enhance data preprocessing and feature engineering techniques. Furthermore, the integration of this field with research from other disciplines has not been adequately considered at this stage. Recently, ANN with outstanding performance, such as Large Language Models (LLMs), have been developed and utilized in various studies. Due to the novelty of LLMs and the challenge of identifying a deep correlation with the field of stock price prediction, they were not taken into consideration in this paper.

10 Potential Future Studies and Conclusion

This paper conducted offers a detailed examination of the use of DL models in stock market forecasting, providing valuable insights into the evolution of these models and their contributions to financial market analysis. By categorizing models into uni-modal and multi-modal types, the survey not only highlights the advancements in AI-driven forecasting but also sheds light on the future direction of research in this domain. The findings underscore the potential of DL in enhancing stock market prediction accuracy and offer a roadmap for future research to explore new models, improve data processing techniques, and address the challenges of model interpretability and data quality. As the field continues to evolve, it is imperative for both academia and industry to foster collaboration and innovation, leveraging the strengths of various DL models to navigate the complexities of financial markets effectively. In future work, exploring the potential of Large Language Models in stock price prediction presents a promising avenue. The integration of LLMs could enhance the accuracy of predictive models by leveraging their superior natural language processing capabilities to analyze financial news, reports, and social media commentary in real-time. This approach could provide deeper insights into market trends and investor sentiment, factors that are crucial in stock market dynamics but often challenging to quantify with traditional models. Consequently, incorporating LLMs into our methodology not only aligns with the cutting-edge developments in artificial intelligence but also opens up new possibilities for more sophisticated and nuanced stock market analysis. In summary, this survey contributes to the ongoing dialogue on integrating AI in financial practices, encouraging further exploration and adoption of DL models in stock market forecasting. The advancements in AI offer promising opportunities to enhance decision-making processes, reduce risks, and uncover new insights in the ever-changing landscape of the financial markets.

References

[1] Kamble, Rupesh A. "Short and long term stock trend prediction using decision tree." 2017 International Conference on Intelligent Computing and Control Systems (ICICCS). IEEE, 2017.

[2] Nugroho, FX Satriyo D., Teguh Bharata Adji, and Silmi Fauziati. "Decision support system for stock trading using multiple indicators decision tree." 2014 The 1st International Conference on Information Technology, Computer, and Electrical Engineering. IEEE, 2014.

[3] Vu, Tien Thanh, et al. "An experiment in integrating sentiment features for tech stock prediction in twitter." Proceedings of the workshop on information extraction and entity analytics on social media data. 2012.

[4] Xie, Boyi, et al. "Semantic frames to predict stock price movement." Proceedings of the 51st annual meeting of the association for computational linguistics. 2013.

[5] Raj, Nimesh. "Prediction of Stock Market Using LSTM-RNN Model." 2023 International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS). IEEE, 2023..

[6] Bao, Wei, Jun Yue, and Yulei Rao. "A deep learning framework for financial time series using stacked autoencoders and long-short term memory." PloS one 12.7 (2017): e0180944.

[7] Selvin, Sreelekshmy, et al. "Stock price prediction using LSTM, RNN and CNN-sliding window model." 2017 international conference on advances in computing, communications and informatics (icacci). IEEE, 2017.

[8] Gao, Ya, Rong Wang, and Enmin Zhou. "Stock prediction based on optimized LSTM and GRU models." Scientific Programming 2021 (2021): 1-8.

[9] Althelaya, Khaled A., El-Sayed M. El-Alfy, and Salahadin Mohammed. "Stock market forecast using multivariate analysis with bidirectional and stacked (LSTM, GRU)." 2018 21st Saudi Computer Society National Computer Conference (NCC). IEEE, 2018.

[10] Matsunaga, Daiki, Toyotaro Suzumura, and Toshihiro Takahashi. "Exploring graph neural networks for stock market predictions with rolling window analysis." arXiv preprint arXiv:1909.10660 (2019).

[11] Wang, Jianian, et al. "A review on graph neural network methods in financial applications." arXiv preprint arXiv:2111.15367 (2021).

[12] Hoseinzade, Ehsan, and Saman Haratizadeh. "CNNpred: CNN-based stock market prediction using a diverse set of variables." Expert Systems with Applications 129 (2019): 273-285.

[13] Pandey, Sakshi. "Forecasting of the Stock Market Price Using LSTM-CNN Model with Various Representations of Collected Dataset." 2023 4th International Conference on Smart Electronics and Communication (ICOSEC). IEEE, 2023.

[14] Chan, Wesley S. "Stock price reaction to news and no-news: drift and reversal after headlines." Journal of financial economics 70.2 (2003): 223-260.

[15] Schumaker, Robert P., and Hsinchun Chen. "Textual analysis of stock market prediction using breaking financial news: The AZFin text system." ACM Transactions on Information Systems (TOIS) 27.2 (2009): 1-19.

[16] Ashtiani, Matin N., and Bijan Raahemi. "News-based intelligent prediction of financial markets using text mining and machine learning: A systematic literature review." Expert Systems with Applications 217 (2023): 119509.

[17] Avramelou, Loukia, et al. "Deep reinforcement learning for financial trading using multi-modal features." Expert Systems with Applications 238 (2024): 121849.

[18] George S Atsalakis and Kimon P Valavanis. 2009. Surveying stock market forecasting techniques–Part II: Soft computing methods. Expert systems with applications 36, 3 (2009), 5932–5941.

[19] Yuhong Li and Weihua Ma. 2010. Applications of ANN in financial economics: a survey. In 2010 International symposium on computational intelligence and design, Vol. 1. IEEE, 211–214

[20] Michel Ballings, Dirk Van den Poel, Nathalie Hespeels, and Ruben Gryp. 2015. Evaluating multiple classifiers for stock price direction prediction. Expert systems with Applications 42, 20 (2015), 7046–7056

[21] Michal Tkáč and Robert Verner. 2016. ANN in business: Two decades of research. Applied Soft Computing 38 (2016), 788–804

[22] Rodolfo C Cavalcante, Rodrigo C Brasileiro, Victor LF Souza, Jarley P Nobrega, and Adriano LI Oliveira. 2016. Computational intelligence and financial markets: A survey and future directions. Expert Systems with Applications 55 (2016), 194–211.

[23] Qing Li, Yan Chen, Jun Wang, Yuanzhu Chen, and Hsinchun Chen. 2017. Web media and stock markets: A survey and future directions from a big data perspective. IEEE Transactions on Knowledge and Data Engineering 30, 2 (2017), 381–399

[24] Frank Z Xing, Erik Cambria, and Roy E Welsch. 2018. Natural language based financial forecasting: a survey. Artificial Intelligence Review 50, 1 (2018), 49–73.

[25] Isaac Kofi Nti, Adebayo Felix Adekoya, and Benjamin Asubam Weyori. 2020. A systematic review of fundamental and technical analysis of stock market predictions. Artificial Intelligence Review 53, 4 (2020), 3007–3057

[26] Deniz Ersan, Chifumi Nishioka, and Ansgar Scherp. 2020. Comparison of machine learning methods for financial time series forecasting at the examples of over 10 years of daily and hourly data of DAX 30 and S&P 500. Journal of Computational Social Science 3, 1 (2020), 103–133.

[27] Weiwei Jiang. 2021. Applications of deep learning in stock market prediction: recent progress. Expert Systems with Applications 184 (2021), 115537.

[28] Ankit Thakkar and Kinjal Chaudhari. 2021. A comprehensive survey on deep neural networks for the stock market: the need, challenges, and future directions. Expert Systems with Applications 177 (2021), 114800.

[29] Mahinda Mailagaha Kumbure, Christoph Lohrmann, Pasi Luukka, and Jari Porras. 2022. Machine learning techniques and data for stock market forecasting: a literature review. Expert Systems with Applications (2022), 116659.

[30] Zou, Jinan, et al. "Stock Market Prediction via Deep Learning Techniques: A Survey." arXiv preprint arXiv:2212.12717 (2022).

[31] Abraham A., Philip N.S., Nath B. and Saratchandran P, Performance Analysis of Connectionist Paradigms for Modeling Chaotic Behavior of Stock Indices, Second International Workshop on Intelligent Systems Design and Applications, Computational Intelligence and Applications, Dynamic Publishers Inc., USA, pp. 181-186, 2002.

[32] Chen, Yingjun, and Yongtao Hao. "A feature weighted support vector machine and K-nearest neighbor algorithm for stock market indices prediction." Expert Systems with Applications 80 (2017): 340-355.

[33] Chen, Yingjun, and Yongtao Hao. "A feature weighted support vector machine and K-nearest neighbor algorithm for stock market indices prediction." Expert Systems with Applications 80 (2017): 340-355.

[34] Shen, Shunrong, Haomiao Jiang, and Tongda Zhang. "Stock market forecasting using machine learning algorithms." Department of Electrical Engineering, Stanford University,

Stanford, CA (2012): 1-5.

[35] Qian, Bo, and Khaled Rasheed. "Stock market prediction with multiple classifiers." Applied Intelligence 26 (2007): 25-33.

[36] Yoshihara, Akira, et al. "Predicting stock market trends by recurrent deep neural networks." PRICAI 2014: Trends in Artificial Intelligence: 13th Pacific Rim International Conference on Artificial Intelligence, Gold Coast, QLD, Australia, December 1-5, 2014. Proceedings 13. Springer International Publishing, 2014.

[37] Gandhmal, Dattatray P., and K. Kumar. "Systematic analysis and review of stock market prediction techniques." Computer Science Review 34 (2019): 100190.

[38] Althelaya, Khaled A., El-Sayed M. El-Alfy, and Salahadin Mohammed. "Stock market forecast using multivariate analysis with bidirectional and stacked (LSTM, GRU)." 2018 21st Saudi Computer Society National Computer Conference (NCC). IEEE, 2018.

[39] Sethia, Akhil, and Purva Raut. "Application of LSTM, GRU and ICA for stock price prediction." Information and Communication Technology for Intelligent Systems: Proceedings of ICTIS 2018, Volume 2. Springer Singapore, 2019.

[40] Rather, Akhter Mohiuddin, V. N. Sastry, and Arun Agarwal. "Stock market prediction and Portfolio selection models: a survey." Opsearch 54 (2017): 558-579.

[41] Zhang, Liheng, Charu Aggarwal, and Guo-Jun Qi. "Stock price prediction via discovering multi-frequency trading patterns." Proceedings of the 23rd ACM SIGKDD international conference on knowledge discovery and data mining. 2017.

[42] Nelson, David MQ, Adriano CM Pereira, and Renato A. De Oliveira. "Stock market's price movement prediction with LSTM neural networks." 2017 International joint conference on neural networks (IJCNN). Ieee, 2017.

[43] Fuli Feng, Huimin Chen, Xiangnan He, Ji Ding, Maosong Sun, and Tat-Seng Chua. 2018. Enhancing stock movement prediction with adversarial training. arXiv preprint arXiv:1810.09936 (2018).

[44] Guangyu Ding and Liangxi Qin. 2020. Study on the prediction of stock price based on the associated network model of LSTM. International Journal of Machine Learning and Cybernetics 11, 6 (2020), 1307–1317.

[45] Ehsan Hoseinzade, Saman Haratizadeh, and Arash Khoeini. 2019. U-cnnpred: A universal cnn-based predictor for stock markets. arXiv preprint arXiv:1911.12540 (2019).

[46] Wenjie Lu, Jiazheng Li, Yifan Li, Aijun Sun, and Jingyang Wang. 2020. A CNN-LSTM-based model to forecast stock prices. Complexity 2020 (2020)

[47] Scarselli, Franco, et al. "The graph neural network model." IEEE transactions on neural networks 20.1 (2008): 61-80.

[48] Daiki Matsunaga, Toyotaro Suzumura, and Toshihiro Takahashi. 2019. Exploring graph neural networks for stock market predictions with rolling window analysis. arXiv preprint arXiv:1909.10660 (2019)

[49] Cong Xu, Huiling Huang, Xiaoting Ying, Jianliang Gao, Zhao Li, Peng Zhang, Jie Xiao, Jiarun Zhang, and Jiangjian Luo. 2022. HGNN: Hierarchical Graph Neural Network for Predicting the Classification of Price-Limit-Hitting Stocks. Information Sciences (2022).

[50] DJimmy Ming-Tai Wu, Zhongcui Li, Norbert Herencsar, Bay Vo, and Jerry Chun-Wei Lin. 2021. A graph-based CNN-LSTM stock price prediction algorithm with leading indicators. Multimedia Systems (2021), 1–20.

[51] Yingmei Chen, Zhongyu Wei, and Xuanjing Huang. 2018. Incorporating corporation relationship via graph convolutional neural networks for stock price prediction. In Proceedings of the 27th ACM International Conference on Information and Knowledge Man-

agement. 1655–1658

[52] Changhai Wang, Hui Liang, Bo Wang, Xiaoxu Cui, and Yuwei Xu. 2022. MG-Conv: A spatiotemporal multi-graph convolutional neural network for stock market index trend prediction. Computers and Electrical Engineering 103 (2022), 108285. https://doi.org/10.1016/j.compeleceng.2022.108285

[53] Raehyun Kim, Chan Ho So, Minbyul Jeong, Sanghoon Lee, Jinkyu Kim, and Jaewoo Kang. 2019. Hats: A hierarchical graph attention network for stock movement prediction. arXiv preprint arXiv:1908.07999 (2019)

[54] Ryo Akita, Akira Yoshihara, Takashi Matsubara, and Kuniaki Uehara. 2016. Deep learning for stock prediction using numerical and textual information. In 2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS). IEEE, 1–6.

[55] Ye Ma, Lu Zong, Yikang Yang, and Jionglong Su. 2019. News2vec: News network embedding with subnode information. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). 4843–4852.

[56] Deli Chen, Yanyan Zou, Keiko Harimoto, Ruihan Bao, Xuancheng Ren, and Xu Sun. 2019. Incorporating fine-grained events in stock movement prediction. arXiv preprint arXiv:1910.05078 (2019).

[57] Ramos-Pérez, Eduardo, Pablo J. Alonso-González, and José Javier Núñez-Velázquez. "Multi-transformer: A new neural network-based architecture for forecasting S&P volatility." Mathematics 9.15 (2021): 1794.

[58] Ding, Qianggang, et al. "Hierarchical Multi-Scale Gaussian Transformer for Stock Movement Prediction." IJCAI. 2020.

[59] Dong, Yingzhe, et al. "Belt: A pipeline for stock price prediction using news." 2020 IEEE International Conference on Big Data (Big Data). IEEE, 2020.

[60] Sonkiya, Priyank, Vikas Bajpai, and Anukriti Bansal. "Stock price prediction using BERT and GAN." arXiv preprint arXiv:2107.09055 (2021)

[61] Sawhney, Ramit, et al. "Deep attentive learning for stock movement prediction from social media text and company correlations." Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP). 2020.

[62] Cheng, Rui, and Qing Li. "Modeling the momentum spillover effect for stock prediction via attribute-driven graph attention networks." Proceedings of the AAAI conference on artificial intelligence. Vol. 35. No. 1. 2021.

[63] Wang, Heyuan, Tengjiao Wang, and Yi Li. "Incorporating expert-based investment opinion signals in stock prediction: A deep learning framework." Proceedings of the AAAI Conference on Artificial Intelligence. Vol. 34. No. 01. 2020.

[64] Li, Qing, et al. "A multimodal event-driven lstm model for stock prediction using online news." IEEE Transactions on Knowledge and Data Engineering 33.10 (2020): 3323-3337.

[65] He, Shwai, and Shi Gu. "Multi-modal Attention Network for Stock Movements Prediction." arXiv preprint arXiv:2112.13593 (2021).

[66] Yang Li and Yi Pan. 2022. A novel ensemble deep learning model for stock prediction based on stock prices and news. International Journal of Data Science and Analytics 13, 2 (2022), 139–149

[67] Shumin, et al. "Knowledge-driven stock trend prediction and explanation via temporal convolutional network." Companion Proceedings of The 2019 World Wide Web Conference. 2019.