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Integrating sentiment analysis with graph neural networks for enhanced stock prediction: A comprehensive survey

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ABSTRACT

There has been significant interest in integrating sentiment analysis with graph neural networks (GNNs) for stock prediction tasks. This article thoroughly reviews the application of GNNs in conjunction with sentiment analysis for stock prediction. This study introduces the fundamental concepts of GNNs and sentiment analysis, emphasizing their respective contributions to the stock prediction domain and underlining the limitations of conventional methods. The potential advantages of combining GNNs and sentiment analysis in this context are highlighted. A comprehensive review of the literature on this subject is subsequently undertaken, covering diverse approaches and techniques utilized for sentiment analysis and stock prediction through the application of GNNs. Various graph structures, such as stock and investor networks, are used to represent financial data, and methodologies employed to incorporate sentiment analysis within these networks are explored. Challenges related to data collection, preprocessing, and annotation are discussed, along with the sources of sentiment data, including news articles, social media feeds, and financial reports. Evaluation metrics and performance benchmarks utilized to assess the precision and efficacy of GNN-based stock prediction models are also examined. This article highlights the limitations and unanswered research questions in this field, paving the way for future investigations. This article provides a comprehensive roadmap for utilizing GNNs with sentiment analysis to enhance stock prediction accuracy. It is a valuable resource for researchers and practitioners interested in exploring and advancing this emerging interdisciplinary domain.

1. Introduction

Stock prediction is a challenging task that has attracted significant attention from researchers and investors due to its potential for financial gain. Traditional approaches to stock prediction have relied on fundamental analysis, technical indicators, and historical price data. However, these methods often overlook the impact of market sentiment and investor behavior, which can significantly influence stock prices and market trends [1]. Sentiment analysis, a subfield of natural language processing, focuses on extracting and interpreting sentiment or emotions expressed in textual data. It has gained prominence in recent years as a valuable tool for understanding market sentiment and its impact on stock prices. By analyzing news articles, social media posts, and financial reports, sentiment analysis can provide insights into the collective mood of market participants and their sentiment toward specific stocks or the overall market [2–4].

The utilization of deep learning techniques has become increasingly prevalent in the domain of stock market prediction [5]. Particularly, Graph Neural Networks (GNNs), a subset of deep learning methods that surfaced as potent instruments for analyzing and learning from graph-structured data, have gained significant popularity in the realm of stock price prediction. By utilizing the relational structure of graphs, GNNs are capable of capturing intricate patterns and dependencies. They have been successfully applied in various fields, including physics, molecular biology, computer science and social network analysis [6]. Integrating sentiment analysis with GNNs for stock prediction holds great potential for enhancing the accuracy and effectiveness of stock prediction models. By combining the capabilities of sentiment analysis in capturing market sentiment and the relational reasoning of GNNs in modeling complex relationships between stocks, researchers can develop more robust and comprehensive stock prediction models [7]. The integration of sentiment analysis with GNNs enables the incorporation of sentiment information as node features in the graph, allowing the model to capture the importance of sentiment in stock prediction. This integration can enhance the ability of stock prediction models to capture the impact of market sentiment on stock prices, identify sentiment-driven market trends, and make more accurate predictions [7].

This comprehensive study explores the application of GNNs in the field of finance, with a particular emphasis on their use in stock price prediction. The investigation involves an exhaustive review and

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Abbreviation

GNN	Graph Neural Networks
DJIA	Dow Jones Industrial Average
SVM	Support vector machines
CNN	Convolutional neural networks
LSTM	Long Short-Term Memory
GAT	Graph Attention Networks
RNN	Recurrent neural networks
RecGNN	Recursive GNN
ConvGNN	Convolutional GNN
GAE	Graph Autoencoders
STGNN	Spatiotemporal Graph Neural Networks
MLP	Multilayer Perceptron
GCN	Graph Convolutional Networks
PLM	Pretrained Language Models
PRG	Personalized review generation
VAE	Variational autoencoder
FCNN	Fully Convolutional neural networks
MAPE	Mean absolute value percentage error
MdAPE	Median absolute value percentage error
DT	Decision Tree
RF	Random Forest
MKKM	Multiple Kernel K-Means Clustering
MHDA	Memory Based Hybrid Dragonfly Algorithm
BiLSTM	Bidirectional Long Short-Term Memory
WGAN	Wasserstein generative adversarial network
GAN	Generative adversarial network
MSE	Mean Squared Error
MAE	Mean Absolute Error
ARIMA	Autoregressive integrated moving average
TCN	Temporal Convolutional Networks
RMSPE	Root mean square percentage error
KNN	K-Nearest Neighbor
FCL	Fully Connected Layers
GCLSTM	Graph convolution embedded LSTM
LINE	Large-scale Information Network Embedding

evaluation of previous research, encompassing studies that employ sentiment analysis using GNNs for stock prediction and those that utilize GNNs in financial data analysis. The examination will concentrate on comprehending the approaches, techniques, and obstacles linked to the integration of sentiment analysis and GNNs for the specific objective of stock prediction. Researchers have been devising GNN models that can efficiently capture intricate patterns and dependencies in stock market data. GNNs, through their ability to model complex relationships among financial indicators, news sentiment, and market trends, have shown promise in making more accurate stock price predictions than traditional methods. The article also recognizes that GNNs have applications extending beyond stock price prediction, including risk management and portfolio optimization. GNNs can assist in assessing and mitigating financial risks by modeling intricate dependencies in financial networks. In portfolio optimization, GNNs can be employed to design diversified and well-informed investment strategies by considering the interconnectedness of various assets and their historical performance.

This research aims to address several key questions pertaining to the application of GNNs in the context of stock market analysis and sentiment evaluation. First, the investigation seeks to identify the specific design characteristics and functionalities of GNNs that contribute to their effectiveness in analyzing stock market trends and sentiment while also exploring their capacity to overcome challenges and leverage opportunities in these domains. Additionally, the study delves into how GNNs are utilized for stock price prediction, sentiment analysis, financial risk management, and portfolio optimization, providing evidence of their ability to capture complex market patterns and correlations. Furthermore, the research investigates ongoing efforts to address issues related to data quality, model interpretability, and overfitting GNNs in financial sectors. The study also explores the impact of incorporating sentiment analysis using GNNs on financial stock price forecasting accuracy and examines current trends in the use of GNNs in the finance sector, offering insights that can potentially inform policymakers, practitioners, and researchers in enhancing GNN-based financial prediction and analysis.

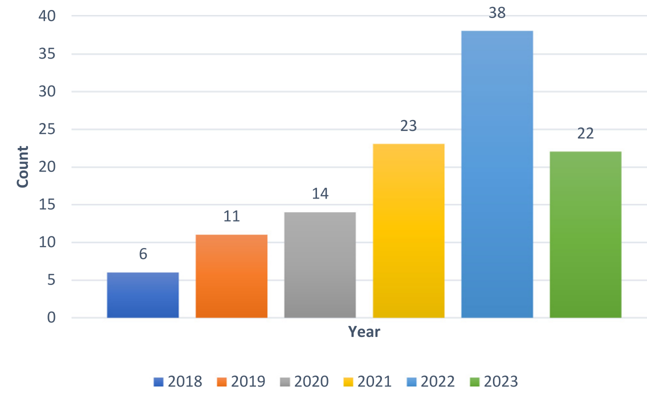

Fig. 1. Yearwise paper count.

Table 1
Leading publishers covered in this investigation.

Publisher(s) name	Count
Elsevier	27
IEEE	22
Springer Nature	11
Wiley	7
MDPI	6
Hindawi	3

The research aims to comprehensively review 129 scientific articles on various aspects of GNNs, exploring their architecture, capabilities, applications, and challenges. Fig. 1 illustrates the yearly distribution of published papers. Table 1 enumerates prominent source publishers and the number of articles included in this investigation. This study introduces various innovative methodologies for predicting financial outcomes, with a specific focus on emphasizing the crucial role of GNNs in risk management and portfolio optimization. The integration of sentiment analysis with GNNs for enhanced predictive modeling positions the research as an outstanding resource in this domain. Acknowledging the promise of GNNs in finance, the research also recognizes existing challenges that need to be addressed. These challenges include issues related to data quality, model interpretability, and overfitting in complex financial datasets. Ongoing research endeavors to address these challenges and further refine GNN models to ensure robustness in financial analysis.

This article makes the following contributions:

1. This research analyzes a substantial number of articles on GNNs and their design, capabilities, applications, and challenges, providing a comprehensive overview of their contributions to stock market analysis and sentiment analysis.
2. The article introduces various techniques for predicting stock prices and conducting sentiment analysis using the GNN. This highlights the efficacy of these methods in capturing intricate patterns and correlations in stock market data.

3. This paper emphasizes the crucial role of GNNs in risk management and portfolio optimization. GNNs are used to evaluate financial risk and develop diverse investment strategies by considering the interconnections between assets and their historical performance.
4. This paper highlights the challenges of GNNs in finance, such as data quality, model interpretability, and overfitting, and emphasizes ongoing research for refining these models.
5. A comprehensive survey of current GNN research within the finance domain is offered, addressing key aspects, including architecture, expressive capability, applications, and challenges. This resource holds significant value for policymakers, practitioners, and researchers seeking to leverage GNNs for enhanced financial prediction and analysis.

To the best of the authors' knowledge, there is no prior research publication that provides a thorough and lucid evaluation of stock market analysis and predictions, integrating sentiment analysis with GNNs in such a comprehensive manner.

The structure of this research is as follows: Section 2 conducts a comprehensive literature review on the integration of sentiment analysis with GNNs for stock market prediction. In Section 3, an in-depth theoretical background covering stock market prediction, sentiment analysis, and GNNs is provided. Section 4 analyzes all the reviewed articles, shedding light on key findings and limitations. Section 5 explores possibilities and challenges and highlights the superiority of GNNs. Finally, Section 6 concludes our investigation.

2. Literature review

In recent years, GNNs have emerged as powerful tools for natural language processing and other domains involving graph structured data. The emergence of GNNs has led to a new era in the field of stock market prediction and sentiment analysis, providing novel approaches to address the inherent difficulties in understanding the intricacies of financial markets. GNNs, known for their capacity to represent intricate connections inside graph structures, have been utilized in diverse applications, ranging from forecasting stock prices and volatility to integrating sentiment research and financial risk management. Various studies have harnessed the power of GNNs to enhance predictive models, incorporating diverse methodologies. One such study integrates GNNs for merging subgraphs to predict stock market trends, enhancing embedded representation methods for indices and incorporating trading data, news, and graphical indicators [8]. Through the integration of a gate recurrent unit (GRU), long short-term memory (LSTM), and metapath attention mechanisms within a GNN, the proposed method achieves a 16.64% greater accuracy in stock market volatility prediction than does dimensional reduction and a 14.48% improvement over other fusion methods using the same model. Chen et al. [9] introduced a novel framework utilizing ChatGPT's graph inference capabilities to enhance GNNs for inferring dynamic network structures from temporal financial news. The experimental results show superior stock movement forecasting performance, with higher annualized cumulative returns and reduced volatility, emphasizing ChatGPT's potential for text-based network inferences in the financial sector.

A novel framework was introduced in [10] for transforming stock price data into a graph structure using the visibility method and employing a GNN for classification. The future predictability of stock trends is demonstrated by using long-term dependency characteristics, with the combined application of the visibility graph and GNN enhancing the comprehension of stock movements. Matsunaga et al. [11] explored the integration of GNNs with financial market predictions using company knowledge graphs to mimic professional investors' decision-making processes. Preliminary results on predicting Japanese Nikkei 225 stock prices over a 20-year period demonstrate significant improvements, with a 29.5% increase in the return ratio and a 2.2-fold increase in the Sharpe ratio compared to the market benchmark, as well as a 6.32% increase and 1.3-fold improvement, respectively, compared to the baseline LSTM model. Three state-of-the-art spatial–temporal graph neural network (ST-GNN) architectures, namely, Graph WaveNet, multitopology graph neural network (MTGNN), and spectral temporal graph neural network (StemGNN), were applied to predict closing prices of shares on the Johannesburg Stock Exchange (JSE) [12]. The findings indicate that, compared with LSTM architectures, ST-GNN architectures, particularly Graph WaveNet, exhibit improved performance and have the capacity to capture intricate temporal correlations within and between shares in the JSE.

The effectiveness of GNNs in short-term stock price movement forecasting was investigated in [13] by using a finance-specific graph pooling operation called StockPool. StockPool, which utilizes domain knowledge to cluster stocks, outperforms existing graph pooling strategies in experiments conducted on the S&P 500 stock index, demonstrating enhanced prediction accuracy. Additionally, different graph pooling methods are employed to create uncorrelated GNN models, contributing to the construction of a graph ensemble model with enhanced performance. Chen et al. [14] proposed incorporating corporation relationships via graph convolutional neural networks for stock price prediction. The experimental results using Mainland China stock market data demonstrate that the learned representations effectively capture corporate relationships, leading to more accurate stock market predictions when incorporating information from related corporations. Feng et al. [15] introduced the Relation-Aware Dynamic Attributed Graph Attention Network (RA-AGAT), which uses a financial market graph structure and correlation attributes for improved stock return ratio prediction [15]. Demonstrating practicality and applicability in finance, the model captures local correlation topology information and employs a stacked GNN to recommend top-n return ratio stocks, surpassing previously used methods in predicting and recommending stock return ratios in the real-time China A-share market. A deep learning framework is introduced for stock price movement prediction utilizing a combination of a GCN and a GRU to capture cross effects among stocks [16]. Through the encoding of various relationships into graphs based on financial domain knowledge and the utilization of GCNs for extracting cross-effects, the model exhibits superior performance compared to other baseline methods in forecasting stock movements. This underscores the viability of integrating both expert knowledge and data-driven relationships. A novel deep learning approach for stock price forecasting is introduced, utilizing a stock correlation graph to capture information from similar stocks [17]. The model combines a GCN for extracting features and a GRU for capturing temporal dependence, demonstrating consistent outperformance over a baseline GRU model that neglects information from similar stocks in real stock price data experiments. Li et al. [18] attempted to predict overnight stock movement between previous closing and opening prices using a newly collected dataset of Reuters Financial News. The proposed LSTM Relational Graph Convolutional Network (LSTM-RGCN) model outperforms baseline models and can predict stock movements influenced by news and interconnections within the market.

Therefore, the reviewed literature emphasizes the adaptability and effectiveness of GNNs in advancing the domain of stock market prediction and sentiment analysis. The combination of several methods, including the use of attention mechanisms, the utilization of graph structures, and the integration of deep learning frameworks, has continuously demonstrated potential in enhancing forecast accuracy and capturing complex market dynamics. This research highlights the expanding range of applications of GNNs in the financial sector, including improved volatility prediction, dynamic network structure inference, and the integration of financial domain knowledge. These developments have both theoretical and practical significance for investors, policymakers, and financial practitioners. They provide more precise and dependable tools for decision-making in dynamic and intricate financial contexts.

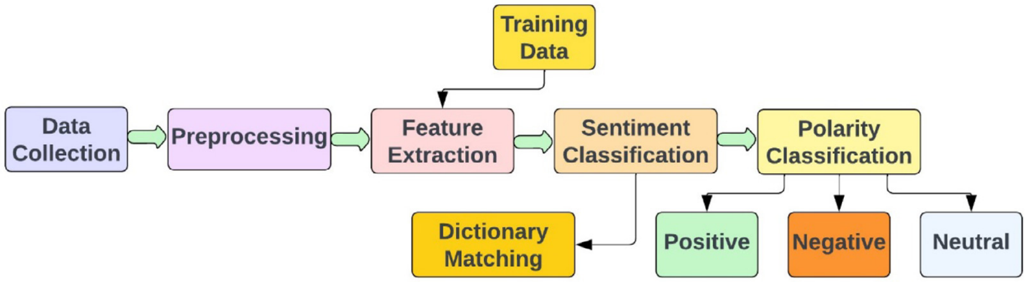

Fig. 2. Working principle of sentiment analysis.

Although the reviewed literature showcases the versatility and efficacy of GNNs in advancing stock market prediction and sentiment analysis, a notable research gap remains in the following aspects. First, the current research primarily concentrates on specific methodologies, such as attention processes, graph topologies, and deep learning frameworks. However, there is a research deficit in investigating comprehensive hybrid approaches that effectively combine various methods. Exploring the synergistic effects and interactions among several strategies has the potential to produce more resilient models. Second, the majority of related research has focused on prominent stock indices and markets, possibly disregarding the distinctive features and dynamics of smaller or specialized markets. Research must consider various market situations to ensure that GNN-based models can be applied and generalized to a wide range of financial landscapes. Finally, although the literature extensively explores the use of GNNs in finance, studies on promoting interdisciplinary collaboration are lacking. Collaboration between finance specialists, data scientists, and machine learning researchers could result in novel insights and approaches to improve stock prediction and sentiment analysis. Addressing these research gaps would contribute to a more comprehensive understanding of the capabilities and limitations of GNNs in the context of financial forecasting, fostering advancements in both theoretical knowledge and practical applications.

3. Theoretical background

This section delves into the intricate dynamics of stock market price prediction, sentiment analysis, and the transformative role played by GNNs in this landscape.

3.1. Significance of sentiment analysis in stock prediction

Stock prediction is a complex task that involves forecasting future stock prices and market trends. It is influenced by various factors, including fundamental analysis, technical indicators, market sentiment, and investor behavior. The empirical data demonstrate that the fluctuations in stock prices are nonstationary, signifying that they do not adhere to a consistent trend [19,20]. Sentiment analysis is crucial for stock prediction because it analyzes and evaluates the sentiment or emotions expressed in written material, such as news stories, social media posts, and financial reports. The goal is to assess the general sentiment of market participants, which can provide valuable insights into market trends and investment behavior [1]. Sentiment analysis is a categorization procedure that operates at three primary levels: the document level, sentence level, and aspect level. Document-level sentiment analysis categorizes opinion documents as either positive or negative, treating the complete text as the fundamental unit of information. Sentence-level sentiment analysis categorizes the sentiment conveyed in each sentence, discerning whether it is subjective or objective. Nevertheless, sentiment expressions can be objective, and there is no inherent distinction between classifying sentiments at the document level and classifying sentiments at the phrase level. Aspect-level sentiment analysis categorizes sentiment based on specific attributes of entities, enabling more nuanced opinions to be captured. Fig. 2 depicts the general working principle of sentiment analysis.

One of the key reasons for the importance of sentiment analysis in stock prediction is the influence of emotions on individual and collective decision-making processes. Behavioral economics suggests that emotions can significantly impact market dynamics and investor behavior. By analyzing sentiment, researchers and investors can gain a deeper understanding of market sentiment and its potential impact on stock prices. Sentiment analysis can also provide insights into investor sentiment, which is an important factor in stock market dynamics. Investor sentiment refers to the overall attitude and sentiment of investors toward the market or specific stocks. It can influence trading decisions, market volatility, and stock returns [21].

Deep learning methods are utilized for sentiment analysis in the context of stock prediction. An extensive examination of deep learning applications in sentiment analysis was presented in [22]. The integration of sentiment analysis with deep learning techniques, such as CNNs and RNNs, has further enhanced the accuracy of stock prediction models [23]. CNNs have shown strong performance in sentence classification tasks, including sentiment analysis [24]. By leveraging the power of deep learning, sentiment analysis models can effectively capture the sentiment expressed in textual data and incorporate it into stock prediction models.

The importance of sentiment analysis in stock prediction has been supported by several studies. Bollen et al. [1] found that public sentiment states obtained from Twitter feeds were predictive of variations in Dow Jones Industrial Average (DJIA) closing values. The authors achieved an accuracy of 87.6% in predicting daily up- and down changes in the DJIA. The study suggested that sentiment analysis of social media data can provide valuable insights into market trends and investor sentiment. An alternative method entails utilizing natural language processing tools to assess emotions in news stories and financial reports. The study investigated the application of sentiment analysis to blogs and news articles to predict or mirror stock trading volumes and financial returns [2]. They created a trading technique that was based on sentiment and aimed to achieve market neutrality. This method consistently generated positive returns with little fluctuation over an extended period of time. This approach showcases the efficacy of sentiment analysis in deriving significant insights from textual data for the purpose of stock prediction. Tetlock [25] investigated the influence of the media on the stock market and discovered that a reversion to fundamentals followed by downward pressure on market prices was foretold by high media pessimism. This indicates that sentiment analysis of media content can provide signals about market trends and volatility. The incorporation of sentiment analysis into stock prediction models has shown promising results. The importance of sentiment analysis in financial decision-making has been emphasized in recent research [26]. The researchers introduced a method for aspect-based sentiment analysis that offers a comprehensive knowledge of the correlation between sentiment analysis and stock prices. The methodology provides clarity and comprehensibility, assisting investors and financial analysts in making well-informed judgments. Additionally, sentiment analysis is combined with other machine learning techniques, such as ensemble learning and network-based approaches, to enhance stock prediction. For instance, ensemble learning methods, including random forests and gradient boosting machines, along with sentiment analysis, have been utilized to predict stock market trends [27]. Therefore, sentiment analysis is important in stock prediction because it provides intuition into market sentiment, investor behavior, and the potential impact of emotions on stock prices. By integrating sentiment analysis into stock prediction models, researchers and investors can gain a competitive edge in understanding market trends and making informed investment decisions.

3.2. Utilization of GNNs for stock prediction

The stock market evaluates the worth of publicly traded firms by incorporating investors' anticipations of forthcoming profits, expansion, and fiscal robustness. This assessment is molded by a combination of factors, including corporate performance, economic conditions, and the prevailing sentiment among investors. The stock market is an integral part of the financial system because it enables companies to raise capital, individuals to invest, and the valuation of publicly traded companies to be determined [28,29]. GNNs can analyze and predict stock market data by utilizing a graph structure, which captures company relationships as edges [11]. This information can be used to predict stock prices and market trends, such as the future performance of a company and market sentiment. Additionally, GNNs can be trained on news articles and sentiment analysis to enhance the precision of stock market forecasts [30].

GNNs depict financial data as a graph using graph theory, where nodes represent stocks and edges reflect associations. GNNs capture graph spatial correlations using convolutional methods. GNNs use message passing techniques to transmit information across the graph, iteratively updating node representations using local graph structures. Theoretical advances in graph convolutional layers have improved convolutional filters for nonuniform graph topologies, allowing GNNs to capture hierarchical financial graph patterns. The graph pooling method StockPool uses domain-specific knowledge and industry links to boost computational performance and maintain critical data.

Sentiment analysis uses word embeddings, semantic analysis, and feature extraction to turn text into numbers for financial sentiment research. Financial sentiment analysis uses sentiment lexicons and dictionaries to link words to sentiment ratings. This allows machines to accurately assess the emotional tone of financial content. Stock prediction models often use sentiment analysis to blend textual and numerical data for better accuracy. Due to the dynamic nature of financial markets, sentiment analysis for stock forecasting employs attention mechanisms or recurrent neural networks to monitor changing attitudes. GNN models with recurrent structures explicitly designed for time considerations facilitate the modeling of evolving relationships among stocks across various time intervals. This enhancement strengthens the models' ability to capture dynamic trends in the market. The incorporation of attention mechanisms into GNNs allows for a selective focus on influential stocks during information propagation. This strategy improves the models' capacity to prioritize pertinent information, ultimately contributing to enhanced prediction accuracy. Additionally, integrating external data sources, such as sentiments from news and social media trends, enriches the feature set, offering a more comprehensive market context for models based on GNNs.

In the context of financial market analysis, the interaction between stock price prediction and sentiment analysis can involve the utilization of GNNs. The interconnection of these three concepts can be articulated in the following manner:

(1) *GNN and Sentiment Analysis:* In sentiment analysis, GNNs are effective models for analyzing structured data, including graphs. They capture the relationships between entities such as businesses, news articles, and social media posts, propagating sentiment information through the graph structure and thereby enhancing sentiment analysis and network dynamics comprehension.

(2) *GNNs and Stock Price Prediction:* GNNs aid in the prognosis of stock prices by analyzing a variety of variables, such as financial indicators, news articles, market trends, and investor sentiment. GNNs can model relationships, including correlations, dependencies, and information flow, by representing these factors as nodes in a graph. This allows them to recognize patterns and make stock price predictions based on the interactions between these factors.

(3) *Sentiment Analysis and Stock Price Prediction:* Sentiment analysis aids in forecasting stock values by examining the emotional tone present in textual data, including news stories, social media messages, and financial reports. This information has an effect on investor behavior and stock prices. Techniques such as sentiment scores, classifiers, and indices provide valuable input for models that predict stock prices.

By combining these ideas, one approach would be to use sentiment analysis techniques to extract sentiment-related information from textual data and include it as a component in stock price prediction models. GNNs can be used to model the relationships between various sentiment sources, financial indicators, and other pertinent factors, thereby improving the accuracy of predictions.

3.3. Introduction to GNNs and their capabilities

Graph data consist of complex relationships between data items. Graphs are a data structure that represents a group of items (nodes) and the connections between them (edges) [31]. Graphs can be employed to represent several real-world issues, such as social networks, maps, and molecules. They can also be used to analyze images and text. GNNs are a new method for analyzing graphs via machine learning [32]. Depending on the directional dependencies between nodes, edges may have directions. GNNs gather information through the forwarding of messages among neighbors, in contrast to traditional neural networks [33]. They store state information for capturing the properties of neighboring nodes, which can be used for label classification or random function values. The network learns encoding through iterative message transmission and data exchange. The graph structure provides valuable information that can be leveraged to make predictions or decisions [34]. Real-world domains, such as social networks, citation networks, and biological networks, frequently contain graph-structured data [35]. Due to the complex dependencies and relationships between entities, analyzing and extracting meaningful information from such data poses unique challenges. GNNs were created as a result of the inadequacy of traditional graph-based algorithms and statistical techniques in capturing the inherent characteristics of these graphs [36]. A GNN is a deep learning technique specifically tailored for processing structured data as graphs [37]. Conventional machine learning techniques, including decision trees and support vector machines (SVMs), are not very effective at handling graph-structured data because they struggle to capture the intricate interactions between nodes in a graph [32,38]. To overcome this constraint, GNNs were proposed to analyze structured data in the form of graphs by utilizing deep learning techniques. This enables the network to effectively capture the connections between nodes, leading to a more thorough depiction of the graph. Hence, GNNs have the capability to generate more precise forecasts and choices, rendering them an invaluable asset in diverse domains, including drug exploration, recommendation systems, and social network analysis [39].

Data can be classified into two main categories: structured data, which encompass graph structures such as social networks and molecular structures; and unstructured data, which include text and images [40]. Before the GNN is employed, unstructured data are converted to graph structures. Convolutional neural networks (CNNs) are another reason for employing GNNs because they can operate in multilayered environments and spatial feature data, paving the way for deep learning. Local connections, weights, and a stratified environment are

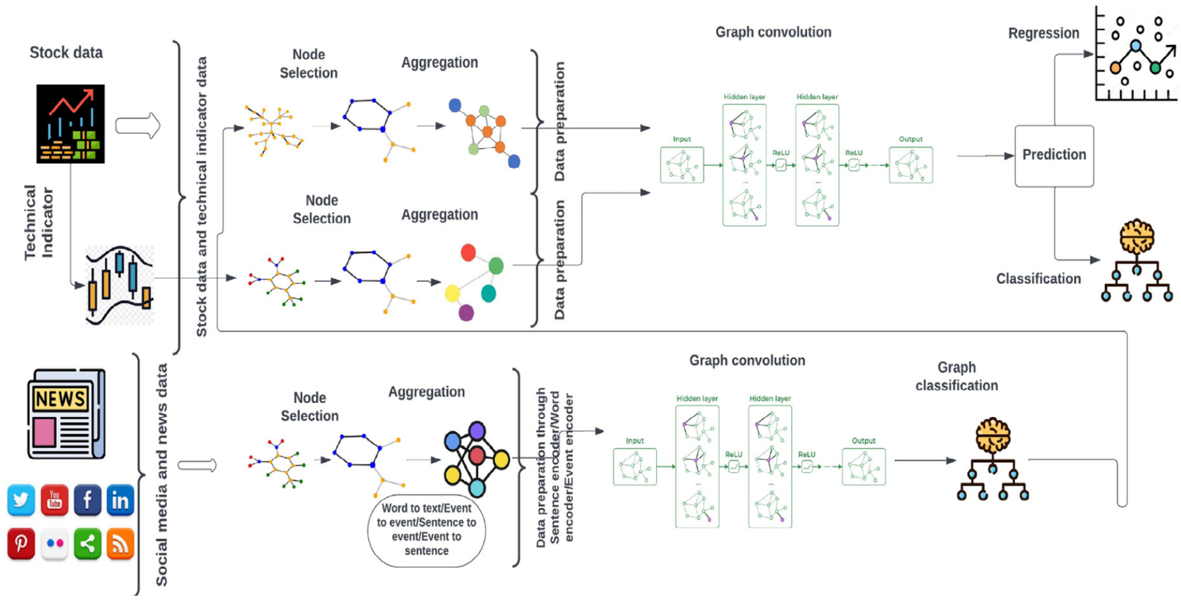

Fig. 3. Graph neural network architecture.

some of the most distinctive characteristics of CNNs. Learning nodes, edges, and subgraphs as low-dimensional vectors are needed for graph embedding [41]. GNNs are direct analogs of deep neural networks such as convolutional networks, graph encoders, attention networks, and LSTMs [42]. By utilizing a message passing algorithm, these networks discover messages and their effects on the edge and node states. GNNs utilize neural network designs to acquire comprehensive node and graph representations, enabling efficient dissemination of information and extraction of features throughout the graph structure [43]. GNNs have been utilized in several domains, such as link prediction, node classification, and graph categorization [44].

GNNs have emerged as powerful tools for learning from and analyzing graph-structured data. GNNs leverage the inherent relational structure of graphs to capture complex dependencies and patterns. They have been applied to various domains, including social network analysis [45], fake news detection [46], disease classification [47], and financial analysis [48,49]. Graph networks provide a strong relational inductive bias and enable the manipulation of structured knowledge and behaviors. They facilitate relational reasoning and combinatorial generalization, establishing the basis for more advanced and comprehensible patterns of reasoning. GraphSAGE, introduced by [50], is a versatile inductive framework that effectively produces node embeddings for data that have not been previously described. It utilizes node feature data and combines features from nearby nodes in a node's immediate vicinity. GraphSAGE has shown superior performance in inductive node classification tasks and generalizes to completely unseen graphs. As discussed by [51], heterogeneous graph-based GNNs focus on the heterogeneity of nodes and links in a graph. They preserve semantic knowledge when representing data interactions in real-world graph structures. Efficient graph representation learning was addressed by [52], who proposed a geodesic GNN. This model learns from the local neighborhood information of nodes and achieves efficient and effective graph representation learning. This approach overcomes the challenges related to the growing and versatile nature of graph data. GNNs have also been applied to graph classification tasks. Zhu et al. [53] proposed an "SLIM" network that generates informative, fixed-dimensional features for graphs of varying sizes and topologies. They achieved this through graph pooling, which summarizes a graph by compressing all its nodes into a single vector. An alternative method is EigenGCN, which integrates conventional graph convolutional layers with pooling layers utilizing the EigenPooling operator [54]. EigenPooling incorporates the characteristics of individual nodes and their local connections when performing the pooling operation, hence maintaining the underlying graph structure in the process of learning graph representations. The EigenGCN has proven to be effective in graph classification tasks on widely utilized benchmarks. Notably, GNNs have been expanded to different graph structures and utilized in a wide range of applications [55].

Nevertheless, it is crucial to acknowledge that GNNs possess certain constraints. Several studies have demonstrated that GNNs predominantly apply low-pass filtering to feature vectors and lack nonlinear manifold learning characteristics. Moreover, the primary function of the graph structure in GNNs is to remove noise from the data, whereas the feature vectors contain the majority of the information for classification tasks. Thus, GNNs have become a potent instrument for examining data that are structured as graphs in several fields. GraphSAGE and EigenGCN have proven useful in tasks such as node classification and graph classification.

The popularity of GNNs has experienced a substantial surge in recent years, owing to the significant contributions made by academics across several disciplines. This has led to the development of various GNN architectures, each with their own strengths and weaknesses. Despite their success, GNNs still face several challenges and limitations, including scalability to large graphs and interpretability. However, considering the limitations of GNNs and their reliance on feature vectors for classification tasks is important. However, further research is needed to explore and enhance the capabilities of GNNs in different applications and to address their limitations.

3.4. GNN architecture

GNNs are a subtype of deep learning algorithm designed to perform inference on graph-based data [56]. GNNs are utilized in the context of graphs and can perform predictive tasks at several levels, including the node, edge, and graph levels. Fig. 3 illustrates the general working principles of GNNs.

GNNs are a category of deep learning models designed to handle structured data represented as graphs. These models encompass various applications, spanning social networks, recommendation systems, citation networks, and biological networks. GNNs utilize graphs where nodes symbolize entities and edges signify interactions, providing a structured framework for organizing data [57]. GNNs are neural networks that consist of interconnected nodes with feature vectors. The

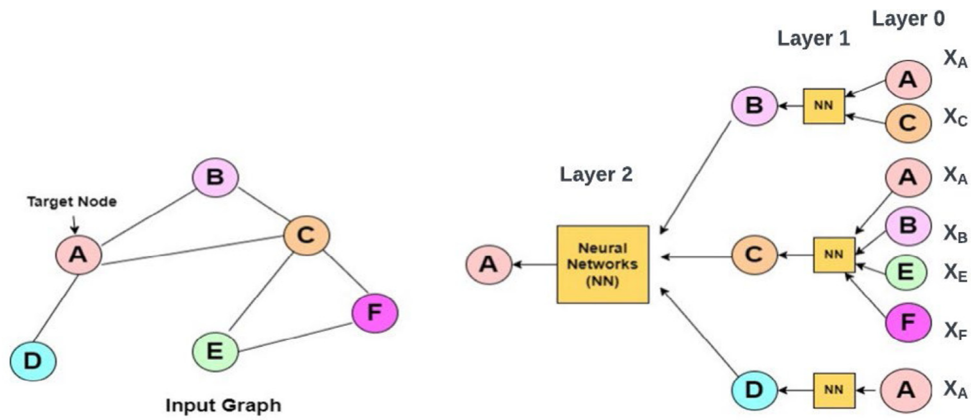

Fig. 4. GNN forward propagation operation.

fundamental operation of GNNs is message passing, where nodes communicate and share information with nearby nodes [58]. Graphs use aggregation functions such as the mean, sum, or attention-based methods for message forwarding. The selection of an aggregation function is contingent upon both the specific problem at hand and the design of the GNN [59]. GNN versions are impacted by graph convolution, where each layer imitates convolutional layers in conventional CNNs [60]. GNNs use techniques such as graph pooling and coarsening to reduce graph dimensions and gather hierarchical information. These methods produce outputs such as class probabilities and node categorization via backpropagation and gradient descent to optimize a task-specific loss function [61]. GNNs are efficient tools for data processing that leverage the connectivity and local structure of graphs to make predictions or classify data. The design of GNNs is flexible and may be tailored to specific problem domains and desired architectural specifications.

Node embedding is a graph theory concept that assigns nodes to a d-dimensional embedding space, aiming to position related nodes adjacent to each other and ensuring that similarity in the embedding space matches network similarity. Let us establish u and v as two vertices in a graph. x_u and x_v are two distinct feature vectors. Next, the encoder functions $Enc(u)$ and $Enc(v)$, which transform the feature vectors into z_u and z_v, respectively. The encoder should be able to execute locality information, aggregate information, and stack many layers. A computational graph incorporates locality information by examining the connections between nodes and their neighbors to capture the structure and simultaneously utilize feature information. After the location information has been retained in the computational graph, we proceed with the process of aggregation. Neural networks are mostly employed for this purpose. The forward propagation mechanism in GNNs governs the transmission of input information to the output layer of the neural network, as shown in Fig. 4. Each node possesses a feature vector. Node A's feature vector (X_A) is sent into a neural network that combines it with another vector (X_C) and transmits them to the subsequent layer. Forward propagation in a computational graph necessitates three sequential phases, represented through equations (1) to (3):

1. Initialize the activation units:

$$h_v^0 = X_v\,(feature\ vector) \tag{1}$$

2. The activation unit in each network layer is:

$$h_v^k = \sigma\left(W_k \sum \frac{h_u^{k-1}}{N(v)} + B_k h_v^{k-1}\right)\ where\ k = 1\ to\ k-1 \tag{2}$$

where the initial step ($W_k \sum \frac{h_u^{k-1}}{N(v)}$) involves calculating the average of all the adjacent nodes of node v and the second component ($B_k h_v^{k-1}$) involves multiplying the embedding of node v from the previous layer by a trainable weight matrix called B_k. This weight matrix acts as a bias and serves as a self-loop activation for node v. σ refers to the nonlinear activation that is applied to both components.

3. The ultimate equation (at the concluding layer):

$$Z_v = h_v^k \tag{3}$$

The training process involves applying a loss function to the embeddings obtained after K layers of neighborhood aggregation; these embeddings are subsequently used as input for stochastic gradient descent. Training can be categorized into two types: unsupervised and supervised. Unsupervised training primarily emphasizes graph structure and loss function.

3.5. Taxonomy of GNNs

GNNs are categorized into four types based on their architectural designs, learning paradigms, and capabilities. Here, is a simplified breakdown:

3.5.1. RecGNNs

RecGNNs represent an evolution of the GNN architecture tailored to handle graph-structured data, as shown in Fig. 5. They introduce a recursive mechanism that enhances the ability to capture hierarchical relationships and long-range interactions within the graph. This extension builds upon the foundation laid by GNNs and allows for more sophisticated modeling of complex graph structures [62]. GNNs, as mentioned before, excel in capturing local dependencies and propagating information through neighboring nodes. However, they might face limitations in capturing hierarchical patterns or long-range interactions that extend beyond immediate neighbors. This is where RecGNNs come into play by adding a recursive component that enables them to traverse the graph in a hierarchical manner and capture more intricate relationships.

The recursive mechanism in RecGNNs can be seen to navigate through the graph's hierarchy, capturing information from nodes that are distant from each other in the graph. This approach allows RecGNNs to recognize patterns and dependencies that may span multiple levels of the graph, providing a more comprehensive understanding of the data.

RecGNN utilizes the Banach Fixed-Point Theorem [62], which asserts that in a full metric space (X, d), a contraction mapping $(T : X -> X)$ exists. Furthermore, T possesses a single fixed point (x), and the sequence $T\ n(x)$ for n approaching infinity converges to $(x*)$ for any x belonging to X. This suggests that x^k should be near x^{k-1} if T is mapped x^k times, as illustrated in Eq. (4).

$$x^k = T\left(x^{k-1}\right), k \in (1, n) \tag{4}$$

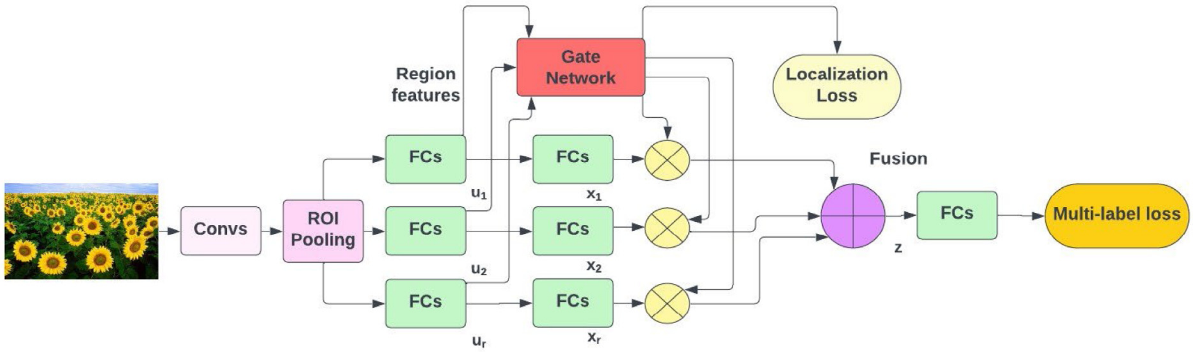

Fig. 5. Recursive graph neural network.

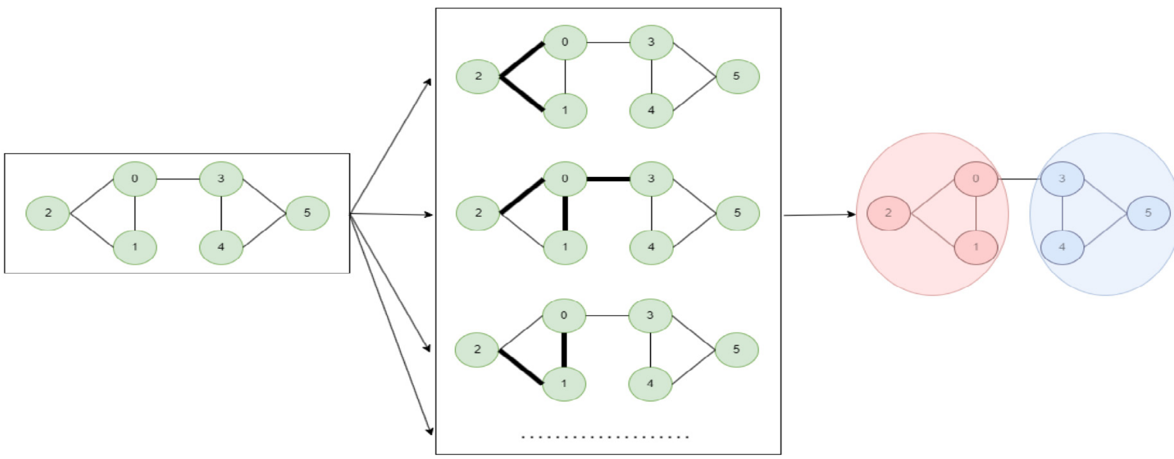

Fig. 6. Convolutional graph neural network (ConvGNN) architecture.

3.5.2. Convolutional GNNs (ConvGNNs)

ConvGNNs represent an advancement in the field of GNNs by extending the grid-to-graph convolution technique. This innovation involves stacking multiple graph convolutional layers to extract intricate, high-level node representations. The technique is visually depicted in Fig. 6, showcasing the process of creating sophisticated GNN models [63]. ConvGNNs are built upon the use of convolutional operations, similar to those found in grid-based CNNs but tailored to accommodate graph-structured data. The stacking of multiple graph convolutional layers allows ConvGNNs to iteratively refine and abstract node features, progressively capturing more complex patterns and relationships within the graph.

A convolutional spatial network uses convolutional layers to process spatial data, enabling it to derive local features and learn hierarchical patterns. Its adaptability to different tasks aligns with its application in computer vision and spatial data analysis.

Convolution Operation: The convolutional layer of a neural network involves element-by-element multiplication and addition via a small filter or kernel, particularly for 2D inputs and filters. For a 2D input and a 2D filter, the convolution process is represented in Eq. (5) below:

$$(I * K)(x, y) = \sum_{i=-\frac{k}{2}}^{\frac{k}{2}} \sum_{j=-\frac{k}{2}}^{\frac{k}{2}} I(x-i, y-j) . K(i, j) \tag{5}$$

where I represents the input data, K is the filter, x and y are spatial indices, and k is the odd-numbered size of the filter.

Convolution with stride and padding: In practical applications, the convolution operation uses stride and padding to control the filter step size and output size by adding zeros to the input. It is represented as follows:

$$(I * K)(x, y) = \sum_{i=-\frac{k}{2}}^{\frac{k}{2}} \sum_{j=-\frac{k}{2}}^{\frac{k}{2}} I(x \times stride - i, y \times stride - j) . K(i, j) \tag{6}$$

Convolution with Multiple Channels: In numerous instances, the input data and filters contain multiple channels (e.g., RGB images). It is represented as follows:

$$(I * K)(x, y) = \sum_{i=-\frac{k}{2}}^{\frac{k}{2}} \sum_{j=-\frac{k}{2}}^{\frac{k}{2}} \sum_{c=1}^{C} I_c(x \times stride - i, y \times stride - j) . K_c(i, j) \tag{7}$$

where C represents the number of channels.

3.5.3. Graph Autoencoders (GAEs)

GAEs are unsupervised learning frameworks designed to transform nodes or entire graphs into latent vector representations and subsequently reconstruct the original graph data using these encoded vectors. This process of encoding and decoding allows GAEs to capture meaningful patterns and relationships within graph-structured data in a lower-dimensional latent space [64]. The core idea behind GAEs draws inspiration from traditional autoencoders, which are neural network architectures designed to compress input data into a lower-dimensional representation (encoder) and then reconstruct the original data from this representation (decoder). However, GAEs are tailored to handle graph data and exploit the inherent structure and connectivity present in the graphs. They are employed in the computation of network embeddings and graph-generating distributions. GAEs can produce nodes and edges of a network in stages or output the entire graph at once. Fig. 7 represents the basic transformer architecture of the GAE models.

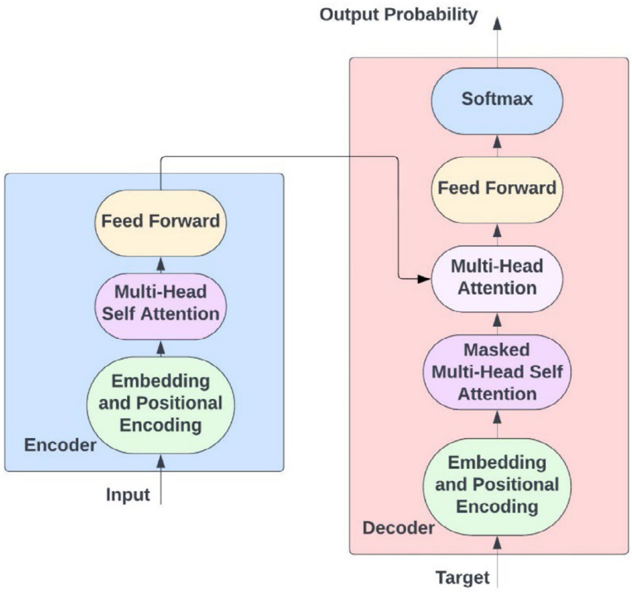

Fig. 7. Basic transformer architecture of GAEs.

The GAE employs a basic transformer architecture that shares similarities with the neural sequence transduction model, specifically the transformer model. Similar to other advanced models, the GAE model follows an encoder–decoder structure. The encoder comprises three key steps: first, input words undergo projection into an embedding vector space, with the addition of position embedding to capture token location within the sequence. The subsequent stage involves a multihead self-attention mechanism, where multiple attention blocks are calculated across the source, combined, and linearly projected back to the initial dimensionality. Scaled dot-product attention is computed over attention blocks individually with different linear projections. Finally, a positionwise fully connected feed-forward network is applied, consisting of two linear transformations with ReLU activation.

Similarly, the decoder in GAE operates by generating one word at a time from left to right through five steps. The initial step involves embedding and position encoding, resembling the encoder. The second phase implements masked multihead attention, ensuring that attention is focused only on past words by masking future words. The third phase includes a multihead attention mechanism that focuses not only on previous words but also on the final representations from the encoder. The fourth phase is another feed-forward network. Ultimately, a softmax layer converts the scores of target words into probabilities. For more in-depth details, the interested reader is referred to the original study by Vaswani et al. [65].

3.5.4. Spatiotemporal Graph Neural Networks (STGNNs)

STGNNs are specialized models designed to uncover hidden patterns within spatial–temporal graphs. These types of graphs represent data where both spatial and temporal dimensions are crucial, such as in scenarios involving geographical locations evolving over time. STGNNs play a pivotal role in extracting meaningful insights from such data, a significance that has surged in domains such as traffic speed prediction, driver maneuver anticipation, and human activity detection [66]. The defining characteristic of STGNNs is their capacity to capture intricate relationships across both space and time. By accommodating these dual dimensions, STGNNs can effectively model the interplay between geographical locations and their changes over various time intervals. This allows them to identify hidden patterns, correlations, and trends that might not be apparent when analyzing spatial and temporal dimensions separately.

3.6. Applications of GNNs in various domains

GNNs have found applications in various domains, including physics, computer science, mathematics, artificial neural networks and data mining [67]. They have been used to address a wide range of tasks, such as node classification, graph classification, link prediction, graph generation, and graph analysis. In the field of physics, GNNs have been employed to model and analyze physical systems represented as graphs. They have been used to predict protein functions, analyze protein – protein interactions, and study complex physical phenomena [50]. GNNs have also been applied in computer science to solve graph-related problems, such as finding connected components, performing graph classification, and offering recommendation systems [68]. Knowledge graphs, which represent structured knowledge and relationships between entities, have been a popular area of application for GNNs. GNNs have been used to embed knowledge graphs, perform link prediction, and enhance knowledge graph completion [69]. These methods have shown promise in organizing structured data and making sense of unstructured data in knowledge graphs. In the domain of artificial neural networks, GNNs have been explored as an alternative to traditional multilayer perceptrons (MLPs) for graph-related tasks. GNNs have demonstrated their ability to handle graph-related tasks, such as node classification and graph classification [70]. However, practical deployments of GNNs in industrial applications are still less common than those of MLPs. Data mining and graph analysis have also benefited from the application of GNNs. GNNs have been used to analyze social networks, identify communities, and predict links between nodes [68]. They have been employed in graph-based machine learning tasks, such as node classification and graph generation. Additionally, GNNs have been utilized in large-scale graph processing frameworks, such as MapReduce, to efficiently process and analyze massive graphs [71].

Fig. 8 depicts the application areas of the GNN. Early research on recurrent GNNs (RecGNNs) began with Sperduti et al.'s [72] application to directed acyclic graphs, which focused on finding target node representations by propagating neighbor information until a stable fixed point was reached. Recent efforts to overcome these obstacles have increased.

Convolutional GNNs (ConvGNNs) revolutionize the concept of convolution for graph data. Bruna et al. [73] pioneered spectral-based ConvGNNs, followed by spatial-based ConvGNNs. Alternative GNNs, such as graph autoencoders and spatial–temporal GNNs (STGNNs), have emerged, allowing for learning frameworks using RecGNNs, ConvGNNs, or other neural architectures.

GNNs are closely related to graph embedding and represent network nodes as low-dimensional vectors [74]. GNNs are deep learning models used for various applications, while network embedding refers to a range of approaches with the same objective. GNNs can address the issue of network embedding by utilizing a graph autoencoder architecture. In contrast, network embedding relies on nondeep learning methods such as matrix factorization and random walks. [75]. Graph kernel methods dominate graph classification methods by measuring the similarity between graphs with kernel functions [76]. GNNs classify graphs directly using extracted representations and are more effective than graph kernel methods. Fig. 9 illustrates domain-based applications of GNNs.

GNNs are widely used in different fields because they can effectively capture intricate linkages and dependencies in graph-structured data. The following are examples of how GNNs can be applied in different domains. GNNs are highly effective tools utilized in diverse domains, such as social networks, biology, chemistry, stock markets, cybersecurity, recommendation systems, transportation networks, knowledge representation, fraud detection, patient – doctor relationships, and NLP tasks. They possess the ability to forecast relationships, discern influential entities, and scrutinize community formations, hence offering valuable insights for recommendation systems and targeted marketing. In addition, they can simulate molecular structures, forecast the discovery of drugs, and determine viable drug candidates. GNNs are useful for

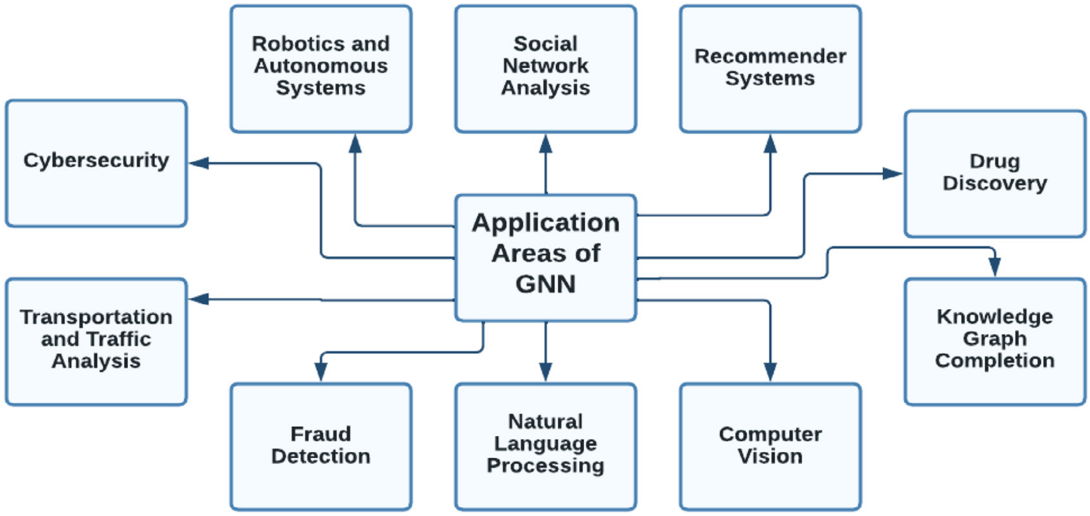

Fig. 8. Application areas of the GNN.

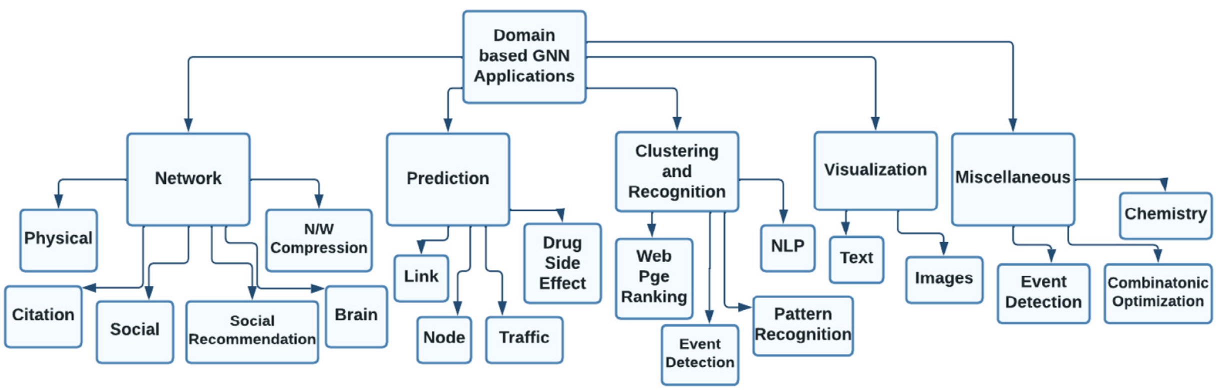

Fig. 9. Domain-based applications of GNNs.

identifying and stopping cyber attacks, offering customized suggestions, improving transportation networks, and strengthening knowledge representation and reasoning. Additionally, they contribute to the field of personalized medicine and the examination of medical data.

GNNs are a specific kind of neural network that is specifically built to process structured data in the form of graphs. They are based on the idea of propagating information from node to node in a graph, allowing the network to capture the relationships among nodes [77]. The ability of GNNs to manage graph-structured data has made them a popular tool for various tasks, including graph classification, graph generation, and link prediction [78]. These devices consist of two main components: a message passing mechanism and a readout function. The message passing mechanism updates the representation of each node by aggregating information from its neighboring nodes, while the readout function aggregates the node representations to produce the final prediction [79]. Data-based construction, knowledge-based construction, and similarity-based building are graph construction approaches. GNNs have shown promising results in various domains, such as drug discovery, recommendation systems, and social network analysis [80]. Despite their success, GNNs still face several challenges and limitations, including scalability to large graphs and difficulty in interpretability [39].

3.7. Integrating sentiment analysis with GNNs

Integrating sentiment analysis with GNNs is a promising approach for analyzing sentiment in graph-structured data. GNNs are neural network architectures that operate on graph-structured data, allowing for the modeling of relationships among entities [40]. GNNs leverage the graph structure to encode structural information and capture the relationships among entities. By representing data as graphs, GNNs can provide more insights into the underlying data. One approach to integrating sentiment analysis with GNNs is through the use of graph convolutional networks (GCNs). GCNs have been widely used in sentiment analysis tasks, including aspect-based sentiment analysis [6]. GCNs have the ability to extract and utilize syntactic dependency information from both contexts and aspects in syntactic dependency trees. This allows for the deduction of sentiment polarity associated with aspects. Additionally, GCNs can model the relationship between aspects and infer the sentiment polarities of aspects. Another approach is to combine GNNs with pretrained language models (PLMs) to enrich and strengthen the representations of aspects in sentiment analysis. By integrating contextual semantic information from PLMs with syntactic information from GCNs, the performance of sentiment analysis can be improved. This approach allows for the utilization of external knowledge, such as high-quality sentiment lexicons, to complement sentiment analysis methods. In addition, attention techniques can be utilized in GNNs to dynamically acquire syntactic information features and multiaspect sentiment dependency features [81]. This enables the better capture of aspect and opinion word representations in sentiment analysis. The integration of sentiment analysis with GNNs has shown promising results in various domains. For example, in transportation networks, GNNs combined with graph structures have led to significant improvements in traffic prediction [40]. In addition, GNNs have been applied to aspect-level sentiment analysis, where the goal is to identify the sentiment polarity of aspect terms in a sentence [81].

By incorporating syntactic structure information and multiaspect sentiment dependencies, GNNs have successfully attained state-of-the-art performance in aspect-level sentiment analysis.

3.8. Financial data analysis ethics and sentiment analysis biases

The development and deployment of data-driven models require careful evaluation of ethical concerns related to financial data analysis and potential biases in sentiment analysis algorithms. According to our financial data analysis, the utilization of sensitive financial data has given rise to issues related to privacy and security. To mitigate these concerns, it is imperative to implement measures to protect the data, obtain informed consent, maintain transparent communication, and conduct ethical analysis of the data to prevent unauthorized access, misuse, and unintended repercussions.

In sentiment analysis algorithms, sentiment analysis models can exhibit biases, which may result in the unfair treatment of specific demographic groups. It is essential to confront biases to avoid perpetuating stereotypes and engaging in discriminatory behavior. Comprehending cultural subtleties and context is crucial for preventing misunderstandings and prejudiced deductions. The progress of financial technology raises ethical challenges that necessitate strict data control, transparency, continuous bias monitoring, and the deployment of fair data analysis and sentiment analysis algorithms.

4. Analysis

In this section, an analysis is conducted on current publications that integrate sentiment analysis and GNNs for enhanced stock prediction. The analysis demonstrates the successful combination of sentiment scores and GNN models, confirming their combined influence on precise predictions of stock prices. The findings can lead to the development of prediction approaches in financial markets, providing significant insights for both scholars and practitioners.

4.1. Integrating sentiment analysis with GNNs

The integration of sentiment analysis with GNNs in various domains has been motivated by several factors. First, sentiment analysis provides valuable insights into the emotional and subjective aspects of textual data. By incorporating sentiment analysis with GNNs, researchers can capture the sentiment expressed in graph-structured data, such as social networks, online reviews, and financial reports. This integration allows for a more comprehensive understanding of the relationships and dynamics within the graph. Second, GNNs excel at capturing complex dependencies and patterns in graph-structured data. By combining sentiment analysis with GNNs, researchers can leverage the power of GNNs to model the relationships between sentiment and other graph elements, such as nodes, edges, or subgraphs. This integration enables the exploration of how sentiment influences the overall structure and dynamics of the graph. Third, sentiment analysis can enhance the interpretability of GNNs. By incorporating sentimental information, GNNs can provide insights into the sentiment-driven decision-making processes within the graph. This approach can be particularly useful in domains such as social networks, where understanding the sentiment of individuals or communities is crucial for various applications, including recommendation systems, opinion mining, and targeted advertising. Furthermore, the integration of sentiment analysis with GNNs can improve the performance of various tasks. For example, in text classification, GNNs can leverage sentiment information to enhance the representation learning of textual data and improve the accuracy of sentiment classification. In stock prediction, sentiment analysis can provide valuable signals for predicting stock market trends, and incorporating sentiment information into GNNs can enhance the accuracy of stock prediction models. Therefore, the integration of sentiment analysis with GNNs is motivated by the desire to capture sentiment information, leverage the capabilities of GNNs in modeling complex dependencies, enhance interpretability, and improve the performance of various tasks in graph-structured data. This integration has the potential to provide deeper insights and more accurate predictions in domains where sentiment plays a crucial role. Table 2 describes the literature that integrates sentiment analysis with GNNs in different domains. By harnessing the capabilities of GNNs to model graph-structured data and integrating techniques from sentiment analysis, researchers have achieved performance improvements in tasks such as graph classification and prediction.

4.2. Integrating GNNs with stock prediction for enhanced performance

The integration of GNNs with stock prediction has emerged as a compelling area of research harnessing the power of graph structures to enhance forecasting accuracy and capture complex relationships within financial markets. Recent studies have explored diverse approaches to leveraging GNNs for stock prediction, focusing on key themes that encompass graph representation learning, temporal dependencies, attention mechanisms, external data integration, portfolio optimization, and hybrid modeling. One primary focus of this research is the effective representation of stock relationships within a graph. GNNs, which are designed to operate on graph-structured data, prove adept at capturing dependencies among stocks by treating them as nodes and relationships as edges. By propagating information across this graph, GNNs learn latent features that contribute to stock price movements. Researchers have proposed various architectures for tailoring GNNs to the unique characteristics of financial market data.

Temporal aspects play a crucial role in stock prediction, given the sequential nature of price movements. To address this, researchers have extended GNN architectures to incorporate temporal dependencies. Recurrent GNN models, which explicitly incorporate temporal aspects, facilitate the modeling of changing relationships among stocks across various time intervals, thereby improving the models' capability to capture dynamic market trends. Attention mechanisms have also been integrated into GNNs to selectively focus on influential stocks during information propagation. This approach enhances the models' ability to prioritize relevant information, contributing to improved prediction accuracy. Additionally, the integration of external data sources, such as news sentiment and social media trends, enriches the feature set and provides a broader market context for GNN-based models.

Beyond stock prediction, GNNs have found applications in portfolio optimization and risk management. By considering the interconnectedness of stocks in a portfolio, GNNs contribute to the design of diversified investment strategies while managing risk effectively. Some studies explore hybrid models that combine GNNs with traditional time-series models or statistical approaches. Ensemble techniques, leveraging predictions from different models, are also considered to enhance overall performance.

Despite these promising advancements, challenges persist, including data quality, interpretability, and the nonstationary nature of financial markets. Ongoing research endeavors aim to refine GNN architectures, explore novel applications, and address these challenges. The integration of GNNs in stock prediction represents a dynamic and evolving field with the potential to revolutionize financial decision-making by revealing intricate patterns and dependencies within the complex landscape of financial markets. Table 3 examines the current literature on the integration of GNNs for enhancing stock price prediction analysis, providing a comprehensive analysis of existing research in this domain.

4.3. Integrating sentiment analysis with GNNs for enhanced stock prediction

The incorporation of sentiment analysis with GNNs has garnered much interest in recent years as a possible method for improving stock prediction. Sentiment analysis is the process of extracting and examining the sentiment conveyed in written material, such as news stories,

Table 2
Literature that integrates sentiment analysis with GNNs in different domains.

Paper	Summary of work	Proposed model	Limitations
[82]	Graph Attention Networks (GATs) introduce masked self-attentional layers, enabling nodes to weigh their neighborhood features differently without costly operations or upfront knowledge of the graph structure, addressing challenges of spectral-based GNNs. GAT models achieve state-of-the-art results across Cora, Citeseer, Pubmed citation network datasets, and protein – protein interaction datasets, showcasing applicability to both inductive and transductive graph problems.	GATs	GATs face practical challenges in handling larger batch sizes, and potential interpretability issues, while extension to graph classification and incorporation of edge features for broader problem applicability are areas for future exploration.
[83]	The study introduces a theoretical framework assessing the expressive power of GNNs for capturing diverse graph structures. The results reveal limitations in popular GNN variants, prompting the development of a provably most expressive GNN architecture, validated empirically for state-of-the-art performance on graph classification benchmarks.	GNN	The study does not explore architectures beyond neighborhood aggregation, leaving the potential of more powerful graph learning frameworks unexplored.
[84]	The Personalized review generation (PRG) model uses a Capsule Graph Neural Network (CapsGNN) and a heterogeneous knowledge graph (HKG) to generate informative reviews that align with user preferences. It enhances user preferences at both aspect and word levels, confirmed by real-world datasets.	CapsGNN	The evaluation has only utilized three datasets that possess aligned entity–item connection. Need to incorporate additional forms of external knowledge, such as WordNet, into the PRG job.
[85]	A neural recommendation model was introduced that integrates review content and user–item graphs for improved user and item representation learning, using a Multiview framework and a hierarchical graph neural network (HAGNN), validated on four datasets.	HAGNN	Only the adjacent nodes in the user–item graph are utilized. Additional variations of GNNs should be investigated to further boost user learning. Require investigation into the integration of diverse user and item data to enhance recommendation systems. Require optimization of the computational expense of the method to enhance the practicality of this approach.
[86]	The work discusses the use of probabilistic theory and differential equations in machine learning models, specifically for understanding latent variable learning from observations, and suggests the use of GNNs in subspace learning.	Differential Equations-GNN (DE-GNN), Probabilistic-GNN (PI-GNN)	The provided information is deficient in terms of particular details regarding potential limitations such as generality and applicability, computational complexity, and sensitivity to hyperparameters.
[87]	The Attentional-graph Neural Network based Twitter Sentiment Analyzer (AGN-TSA) model, a neural-network-based Twitter sentiment analysis, incorporates tweet-text and user-connection information, employing a three-layer structure and unique loss functions. Experiments show a 5% performance improvement.	AGN-TSA	Require clarification on the concepts of hyperparameter sensitivity, interpretability, and temporal dynamics.
[88]	Multi-Level Graph Neural Network (MLGNN) was used for text sentiment analysis, overcoming limitations of GNNs by incorporating local and global features and integrating a scaled dot-product attention mechanism.	ML-GNN	The work lacks the practical relevance and scalability of the paradigm.
[89]	The Sentiment Transformer Graph Convolutional Network (ST-GCN) is introduced in this work, presenting a deep neural network that models sentiment corpus as a graph. It learns document and word embeddings, showcasing superiority over existing models in sentiment analysis	TGTCN	It is necessary to extend the ST-GCN architecture by incorporating inductive factors and explore the utilization of dynamic neighborhood aggregation operators to enhance classification performance.
[90]	The improvement in aspect-level sentiment analysis is achieved by the Convolutional Attention Neural Network - Syntax-based Graph, Semantic-based Graph, and Context-based Graph (CANN-SSCG) model. This model constructs three heterogeneous graphs: syntax-based, semantic-based, and context-based. By combining these into an SSC graph, it applies a CANN algorithm for sentiment analysis.	CANN-SSCG	Need to implement contextual analysis. Can be tested on fake news detection on a social network.
[91]	Sentiment analysis is enhanced by reshaping dependency trees into aspect-oriented trees and introducing a relational graph attention network (R-GAT) in the paper, resulting in improved aspect-opinion connections and performance.	R-GAT, R-GAT+ Bidirectional Encoder Representations from Transformers (BERT)	Require clarification on the concept of constrained evaluation metrics, difficulties encountered in real-world applications, and the issue of annotation uniformity.
[92]	The study introduces a novel neural network approach for sentiment polarity identification in sentence representations, outperforming existing techniques and establishing a new state-of-the-art in aspect-based sentiment classification combining dependency trees with a convolution over dependency tree (CDT) model and employing Bi-LSTM and graph convolutional network (GCN) to improve sentence representations with contextual and dependency information.	Aspect-Level Sentiment Analysis-Bidirectional Long Short Term Memory (ASP-BiLSTM), ASP-GCN, CDT	The research lacks the considerations such as the robustness to noisy data, dependence on aspect vectors, and the associated computational costs.

(*continued on next page*)

Table 2 (*continued*).

[93]	Multilevel Semantic Relation-enhanced Learning Network (MSRL-Net) is proposed for aspect-based sentiment analysis. It enhances semantic representations by leveraging word and sentence relations, showcasing superior performance in accuracy, Macro-F1, and AUC over BERT across multiple datasets	MSRL-Net	Did not explore knowledge graphs to discover organized commonsense knowledge and did not investigate a human-interpretable learning technique.
[94]	A novel approach for Aspect-Based Sentiment Analysis (ABSA) is presented, employing graph Fourier transform-based networks. The approach achieves high accuracy on SemEval-2014 datasets and demonstrates competitive results on e-commerce domain datasets.	STGNN, STGNN-GRU	The study is limited by its exclusive use of BERT for sentence encoding, potential challenges in achieving optimal results across diverse datasets without comprehensive hyperparameter tuning, and the unexplored application of the proposed approach in tasks such as sequence tagging or natural language generation.
[95]	The study presents a novel approach using a graph neural network (GNN) combined with Long short-term memory (LSTM) for sentiment analysis of Weibo comments, achieving remarkable performance with 95.25% accuracy and 95.22% F1 score, demonstrating its effectiveness in handling non standardized text data.	GNN-LSTM	The limitation of this study lies in its specific focus on sentiment analysis for user comments on social platforms like Weibo, potentially limiting the generalizability of the GNN-LSTM model to other types of textual data or platforms. Additionally, the study does not extensively explore the scalability and adaptability of the model to accommodate the dynamic nature and evolving trends in user expressions on social media
[96]	The paper presents a tree-based sentiment analysis method on Stanford Sentiment Treebank, utilizing graph convolutional and recurrent neural networks for improved accuracy and efficiency.	Graph recurrent neural network (GRNs)	The study's limitation lies in its focused application of graph neural networks to enhance tree-LSTMs for sentiment analysis, with potential constraints on generalizability and scalability to diverse linguistic contexts or NLP tasks.
[97]	Syntactic edge-enhanced graph neural network model for sentiment analysis is presented, utilizing GNN in Natural Language Processing, with the best sentiment classification performance achieved in business, politics, and research.	A syntactic edge-enhanced graph neural network model	The suggested work needs to elucidate the real-world applicability and influence of syntactic information, as well as the impact of the attention process.
[98]	A brain-inspired multifeature hierarchical graph attention model (MH-GAT) for sentiment analysis is introduced in the article, achieving a 5.17% accuracy improvement compared to previous methods, with a focus on incorporating structural, semantic, and positional contextual information.	MH-GAT	The proposed MH-GAT model for sentiment analysis may face challenges in scaling to larger datasets or domains with diverse linguistic characteristics.
[99]	A novel implicit sentiment analysis model utilizing a graph attention convolutional neural network was introduced, addressing challenges in implicit sentiment by incorporating attention mechanisms with orthogonal and score constraints. The proposed model achieves an F value of 88.16%, surpassing benchmark models	GACNN	The study did not explore the impact of external knowledge on implicit sentiment analysis and could benefit from further investigation into incorporating semantic information like part of speech and dependency relationships in graph neural network-based sentiment analysis models.
[100]	The Heterogeneous Aspect Graph Neural Network (HAGNN) a heterogeneous graph neural network, effectively captures intersentence relationships, improving aspect-based sentiment analysis performance across various datasets.	HAGNN	The proposed HAGNN model effectively learns pattern knowledge from interactions between sentences and aspect categories but may face challenges related to scalability and computational complexity in large-scale datasets.
[101]	Deep dependency-aware graph convolutional networks (DA-GCN) model was introduced for sentiment analysis, utilizing interactive relations, multihead attention, and grammar information to improve its effectiveness and advancement.	DA-GCN	Potential complexity and computational cost of incorporating word-to-word dependencies and multiple conditional random fields, which may hinder scalability and efficiency in large-scale applications.
[102]	The aspect-based sentiment analysis is enhanced by the SenticNet-based graph convolutional network (Sentic GCN), a graph convolutional network, which outperforms existing methods by learning dependency information from contextual and aspect words.	Affective GCN, Sentic GCN, Sentic GCN-D, Sentic GCN-BERT	The key limitation of Sentic GCN model is its reliance on external knowledge from SenticNet, which may introduce biases or inaccuracies in affective information, impacting the model's generalization across diverse datasets and domains.
[103]	The proposed aspect-specific and language-agnostic discrete latent opinion tree model, leveraging aspect-to-context attention scores and syntactic distances, offers competitive performance and interpretability for aspect-based sentiment classification, eliminating the reliance on external dependency parsers.	dotGCN	The proposed method's reliance on reinforcement learning and attention-based regularization may pose challenges in terms of training stability and convergence.
[104]	The Disentangled Linguistic Graph Model (DLGM) improves transparency and performance in aspect-based sentiment analysis by disentangling linguistic properties, reducing redundancy, and incorporating cross-linguistic routing.	DLGM can improve performance and transparency.	The proposed model may face challenges in scalability and generalization to diverse linguistic contexts and datasets.
[105]	The incorporation of syntactic awareness using a graph attention network on dependency tree structures, along with the integration of external pretraining knowledge from the BERT language model, enhances the effectiveness of aspect-level sentiment classification.	Syntax-Aware Graph ATtention Network (SAGAT).	The proposed SAGAT model for aspect-level sentiment classification may have limitations in scalability and generalizability to diverse datasets and domains.
[106]	The Bert-TextLevelGCN model, combining BERT pretraining with TextGCN, efficiently classifies sentiments in public opinion text, aiding government response to social violence events and improving public opinion analysis.	Bert-TextLevel GCN based on BERT pretraining and improved TextGCN.	The limitation of the study lies in the extended training time due to the large number of parameters and layers in the BERT model, resulting in prolonged duration for model training.

Table 3
Research that incorporates GNNs into the analysis of stock price prediction for improved performance.

Paper	Summary of work	Models/Algorithms used	Limitations
[9]	The novel framework combines ChatGPT's graph inference with graph neural networks for stock movement forecasting, outperforming benchmarks and demonstrating higher portfolio returns and reduced volatility. This highlights ChatGPT's potential for dynamic network inference from temporal textual data in finance.	LSTM, ChatGPT's graph inference and GNN	Limitations include reliance on limited input features and basic network structures, potential sample bias from focusing on the DOW 30 companies, and scope for incorporating sentiment analysis and more sophisticated architectures for enhanced predictive accuracy.
[10]	The visibility method is employed to transform stock price data into a graph structure, allowing a graph neural network to learn the overall topological structure, thereby effectively capturing the long-term dependency property and showcasing successful forecasting of future stock trends.	The integration of the GNN and visibility graphs	The limitations include the need for exploration of alternative methods to model long-term dependency, the potential improvement in labeling functions, and the consideration of cross-information among stocks for enhanced predictive capabilities.
[11]	Machine learning in financial market predictions is explored in the paper, with a focus on Japanese Nikkei 225 stock prices over a 20-year period. GNNs and company knowledge graphs are employed to mimic investor decision-making processes, demonstrating significant improvements over benchmarks and baseline LSTM models.	GNNs and company knowledge graphs	The preliminary nature of the trials raises questions over the ability to scale and maintain the effectiveness of adding firm relations knowledge graphs under various market conditions. Although there is potential, the difficulty of interpreting and explaining complicated graph-based predictions has limits that need to be carefully considered when applying them to financial decision-making.
[13]	The study introduces StockPool, a finance-specific graph pooling technique for short-term stock price movement forecasting, outperforming existing methods on the S&P 500, and enhancing performance with uncorrelated GNN models.	GNN with a finance-specific graph pooling technique called StockPool	Evaluating the trade-off between computing efficiency and model accuracy poses a challenge, and the incorporation of various types of data, such as fundamental data, may introduce complexities that impact the model's performance.
[14]	A method for improving stock price prediction by incorporating information from related corporations is introduced in the study. Real market investment facts and node embedding techniques are employed, leading to improved accuracy in Mainland China stock market data.	DeepWalk+LSTM, node2vec+LSTM, LINE+LSTM, GCN.	The utilization of information from affiliated companies for stock forecasting may face obstacles pertaining to the accessibility and precision of data. The efficacy of the suggested solutions could be impacted by the ever-changing and intricate structure of corporate relationships, which might restrict their applicability.
[15]	The study introduces the Relation-aware Dynamic Attributed Graph Attention Network (RA-AGAT) for stock prediction and recommendation, utilizing financial market graph properties and correlations. Experiments on China A-share market data demonstrate its effectiveness.	RA-AGAT	The model's performance may face challenges when incorporating diverse data types, including fundamental data, and integrating real-world financial market linkages, investor sentiment, and domain expertise into the GNN-based framework may present complexities.
[107]	The Stock Sequence Array Convolutional Neural Network (SSACNN), a novel convolutional neural network framework, is introduced in this article. It is designed to enhance stock trading prediction accuracy by utilizing historical prices and leading indicators, demonstrating potential applicability in real financial markets.	SSACNN	The SSACNN approach, effective with five Taiwanese and American firms, may not apply to a wider range of equities due to potential market shifts or economic shocks, and its dependability in dynamic trading scenarios is uncertain.
[108]	A framework for forecasting stock prices using interconnected stocks is introduced in this study. The model utilizes a variational autoencoder and a hybrid approach (GCN-LSTM) to effectively capture spatial and temporal signals, outperforming baselines and demonstrating potential for time-series prediction.	Variational autoencoder (VAE) and GCN_LSTM	The GCN-LSTM framework, despite its superior performance on stock price data, may struggle to capture subtle market interactions during rapid fluctuations. It requires careful assessment of its generalizability and hyperparameter fine-tuning.
[109]	A novel stock trend prediction method is introduced in this paper, utilizing a Graph Convolutional Feature-based Convolutional Neural Network (GC-CNN) model. The approach integrates individual stock and market information, showcasing superior performance on six Chinese stocks.	Improved graph convolutional network (IGCN) and a Dual-CNN are designed to construct GC-CNN	The study lacks specification on data duration, potential metaheuristic algorithm implementation, and the incorporation of investor sentiment, enterprise association networking data, industry background, shareholder structure, and IPO positioning, limiting its comprehensiveness and potential performance improvement.
[110]	The study introduces a deep learning approach to stock price prediction, combining it with related stocks and mutations. It uses ConvLSTM for target stock features, knowledge graph for related stocks, and GCN for mutation detection.	Convolutional LSTM, knowledge graph mining, and GCN	The model's performance near mutation points remains a challenge, and incorporating additional information types, such as market indicators and news data, may lead to potential degradation in predictive accuracy.
[111]	The study uses a novel hierarchical architecture called Hierarchical Graph Neural Network (HGNN) to predict stock type using a stock relation graph. The method improves accuracy by 3.54% and average return ratio of SSE and SZSE by 18.57% and 8.75%, respectively.	Hierarchical Graph Neural Network (HGNN)	The proposed approach may face challenges in handling extreme market conditions or unforeseen events, requiring further investigation into its robustness and adaptability across various market scenarios.
[112]	The paper introduces the Spectral Temporal Graph Neural Network (StemGNN), a method that enhances multivariate time-series forecasting accuracy by capturing interseries correlations and temporal dependencies in the spectral domain. It learns interseries correlations automatically and is tested on ten real-world datasets.	Spectral Temporal Graph Neural Network (StemGNN)	The applicability of StemGNN's time complexity reduction may be limited, and its effectiveness across various datasets and practical scenarios, such as product demand forecasting and budget analysis, could vary.

(*continued on next page*)

Table 3 (*continued*).

[113]	The paper introduces the Graph Transformer Network (GTN) for Volatility Forecasting (VF), a multivariate approach combining limit order book data and relational data to predict short-term realized volatility in stock markets. Experiments on 500 S&P 500 index stocks show superior performance compared to other benchmarks.	GTN-VF	The study's effectiveness may be constrained by the specific types of relational data considered, and its applicability to diverse relational contexts beyond the explored ones requires further investigation.
[114]	The PriceExploration-Network (PE-Net) excels in stock price trend prediction by effectively leveraging temporal and cross-sectional information in price data. It outperforms state-of-the-art models in both accuracy and AUC, showcasing its effectiveness on real-world S&P 500 constituents.	Price Exploration-Network (PE-Net) utilizing temporal and cross-sectional data employing clustering and GAT architecture	The proposed PE-Net model may face challenges in capturing complex market dynamics and information beyond historical price data, potentially limiting its ability to predict stock prices accurately in rapidly changing market conditions.
[115]	Attention-based graph learning kernel network (AGKN), a novel framework for stock price prediction, demonstrates superior performance over state-of-the-art methods, achieving up to 4.3% lower error in experiments on Chinese stock market data. The model effectively integrates dynamic spatial correlations, temporal correlations, and hidden correlations between stocks, showcasing its potential in capturing complex market dynamics.	Attention-based graph learning kernel network (AGKN)	The proposed AGKN model, while demonstrating effectiveness, may face challenges in scalability and generalization to diverse market conditions, warranting further exploration and evaluation across a broader range of datasets and market scenarios.
[116]	The proposed Hierarchical Attention Network for Stock Prediction (HATS) effectively leverages relational data, selectively aggregates information from different relation types, and outperforms existing methods in predicting both individual stock prices and market index movements, demonstrating the significance of considering diverse relation types in stock market prediction.	Hierarchical Attention Network for Stock Prediction (HATS)	The definition of the corporate network neighborhood in this study, based on direct edges or meta-paths with at most 2 hops, could be further improved, and the reliance on a single database (WikiData) for creating the company network may limit the generalizability of the findings.
[117]	The LSTM-GCN model, a neural network-based stock return prediction method, outperforms baseline methods on Eurostoxx 600 and S&P 500 datasets, capturing complex topological structures and temporal dependencies.	LSTM-GCN model	The study's focus on previous stock performance as node attributes may limit the model's flexibility in predicting market dynamics, and its generalizability is questionable due to differences in performance across datasets.
[118]	The proposed stock trend forecasting framework effectively mines concept-oriented shared information from both predefined and hidden concepts, improving forecasting performance by simultaneously utilizing shared and individual stock information. Experimental results demonstrate the framework's efficiency, and investment simulations indicate higher returns compared to baselines.	**S**hared **I**nformation for **S**tock **T**rend forecasting (HIST)	The study's reliance on Twitter demographics may introduce bias and limit applicability. Although mood dimensions improved DJIA predictions, retrospective analysis doubts model's future market predictions. More research and real-time validation needed.

social media posts, and financial reports. GNNs excel at capturing and analyzing intricate relationships and interdependencies among entities that are represented in a graph structure. An essential obstacle in sentiment analysis is the embedding of inherent connections between phrases in the semantic significance of a document. The incorporation of sentiment analysis into GNNs presents a significant opportunity to improve stock prediction. By integrating sentiment research into the examination of financial data, such as stock prices and trading volumes, it becomes feasible to capture the influence of market moods on stock movements. Due to their capacity to represent intricate connections and interdependencies, GNNs can proficiently encapsulate the interrelatedness of multiple aspects that impact stock values, including sentiment-related data. The combination of sentiment analysis and GNNs is a recently developed and growing field; however, there is already some related research on sentiment analysis and stock prediction. The objective of this research is to enhance the precision and dependability of stock prediction models by combining the advantages of sentiment analysis and GNNs. This work aims to enhance the analysis of graph-structured financial data by adding sentiment conveyed in textual data. In pursuing this objective, the study aims to provide a comprehensive and nuanced understanding of the elements influencing stock prices. Table 4 provides a comprehensive list of the literature that employs sentiment analysis and GNNs for the purpose of predicting stock prices.

4.4. Limitations and challenges of existing sentiment analysis approaches

Existing sentiment analysis approaches for stock prediction face several limitations and challenges. These limitations are discussed based on the provided references.

1. Several studies have reported conflicting results regarding the predictive capabilities of sentiment analysis for stock market prediction. While sentiment analysis has shown promise in various applications, its effectiveness in predicting stock market movements is still an open problem [125].

2. The dynamic and volatile nature of stock markets poses challenges for accurate stock prediction [23]. Sentiment analysis models need to adapt to changing market conditions and capture evolving sentiment patterns in real time.

3. Sentiment analysis relies on textual data from sources such as social media, news articles, and online forums. However, these sources often contain noise, sarcasm, irony, and ambiguous language, which can affect the accuracy of sentiment analysis [126].

4. Sentiment lexicons play a crucial role in sentiment analysis by providing sentiment scores for words and phrases. However, existing sentiment lexicons may not adequately cover the domain-specific language used in financial and stock market contexts [126]. This can lead to inaccurate sentiment analysis results.

5. Sentiment analysis approaches may struggle to capture nuanced sentiment expressions, such as subtle changes in sentiment or sentiment shifts over time [23]. These nuances are important in stock prediction, as they can indicate changing market trends and investor sentiment.

6. While sentiment analysis provides valuable insights, relying solely on sentiment analysis for stock prediction may overlook other important factors, such as fundamental analysis, market trends, and economic indicators [125]. Integrating sentiment analysis with other data sources and analysis techniques can lead to more robust stock prediction models.

7. Standardized evaluation metrics are necessary to gauge the effectiveness of sentiment analysis models in the specific domain of stock prediction. Uniform assessment criteria would allow for equitable

Table 4
Literature that uses sentiment analysis and GNNs for enhanced stock prediction.

Paper	Summary of Work	Proposed model	Limitations
[8]	The study presents a database of transaction data, news texts, and graphical indicators that uses relational dimensions for indicator embedding to shed light on stock market indicator information mining. The study uses graph convolution aggregation with metapath-based analysis to fuse multisource heterogeneous graph data and classify complex financial graph data to predict stock market price fluctuations and understand interindicator relationships.	Msub-GNN	The suggested model may fail to capture implicit semantics and interrelationships across indicator nodes, restricting its use of rich semantic information in multisource heterogeneous network data. Stock market trend prediction may benefit from subgraph node relationship study and numerous attention techniques for semantic information mining from diverse indicators.
[12]	The application of spatial–temporal graph neural networks (ST-GNN), including Graph WaveNet, MTGNN, and StemGNN, to predict share prices on the Johannesburg Stock Exchange (JSE) is explored, revealing Graph WaveNet's superior performance in capturing intrashare and intershare dependencies. The study marks one of the early applications of ST-GNNs in share price prediction, demonstrating their effectiveness over short and medium-term horizons compared to LSTM and other approaches.	ST-GNN	Generalization to other stock markets and consideration of external factors affecting stock prices beyond temporal dependencies remain unexplored aspects in this study.
[119]	The study introduces RA-AGAT, an attributed graph attention network model, leveraging correlation information and time series characteristics to recommend high return ratio stocks in the financial sector. RA-AGAT surpasses previous methods in predicting and recommending stock return ratio in the real China A-share market, demonstrating the practicality and applicability of graph models in finance.	RA-AGAT	Integration of real-world connections, assessment of the dynamic and fluctuating nature of the stock market, and advancement in utilizing heterogeneous information networks in financial markets pose challenges.
[120]	A model for predicting stock price movement is introduced, utilizing knowledge graphs from financial news. The effectiveness of knowledge graph embedding for classification tasks in stock prediction is demonstrated, showcasing improved performance compared to traditional methods, emphasizing the utility of knowledge graphs in business decision-making.	Knowledge Graph	The study lacks an in-depth analysis of the impact of external factors on stock price movements, such as market sentiment, economic indicators, and geopolitical events, which could influence prediction accuracy.
[121]	The MAC method outperforms state-of-the-art baselines in stock price movement prediction, Sharpe Ratio, and trading income backtesting using numerical features, market-driven news sentiments of target and related stocks, and a pretrained sentiment classifier and GCN. An embedding feature generator pretraining improves news sentiment representation, while a GCN improves stock price prediction.	Combined GCN and BiLSTM	The suggested model lacks a fake news detection mechanism, creating a weakness. The model's accuracy may also be affected by financial news' figurative language, highlighting the need for better computational language understanding.
[122]	Dynamic attributes-driven graph attention networks incorporating sentiment (DGATS) model integrates sentiment, transaction, and text data with dynamic attributes-driven graph attention networks, incorporating Kronecker product-based tensor fusion, LSTM, and temporal attention networks to capture short and long-term transition features for improved stock price prediction performance on real datasets.	DGATS	The suggested model may struggle with temporal stock market features. The model's preconfigured graphs may not fully capture intramarket dependencies, suggesting it could improve in adjusting to dynamic market situations.
[123]	The article offers a stock knowledge graph creation method that quantifies stock linkages and creates a distance adjacency matrix to improve price trend prediction. Combining Concept Drift (CD) with GCNs and using historical stock prices improves prediction accuracy, achieving optimal performance on a large stock dataset and ensuring robustness and stability for more reliable investment returns.	Knowledge graph (KG), GCN, K-means, community detection (CD)	The model's reliance on prior stock prices may hinder its ability to respond to rapidly shifting market circumstances not captured in the training data. Additionally, the study's use of a large stock dataset may limit its applicability to diverse market conditions, particularly smaller or niche markets with different characteristics and dynamics.
[124]	The paper introduces a multimodality graph neural network (MAGNN), a multimodality graph neural network, addressing lead–lag effects in financial time series forecasting by integrating historical prices, raw news text, and knowledge graph relations. MAGNN exhibits superior performance across 3714 stocks and is successfully deployed in a major Chinese financial service provider, meeting industry regulations.	MAGNN	The MAGNN model's effectiveness is contingent on the quality and completeness of input data, with potential limitations in sparse or unreliable information. Its generalizability to global financial markets may be constrained by regional variations in market dynamics and regulations. Real-world validation is specific to the Chinese financial industry.

comparisons among various methodologies and expedite progress in the discipline.

Therefore, existing sentiment analysis approaches for stock prediction face limitations and challenges related to predictive capabilities, the dynamic nature of stock markets, noise and ambiguity in textual data, domain-specific sentiment lexicons, capturing nuanced sentiment, overreliance on sentiment analysis alone, and the lack of standardized evaluation metrics. Addressing these challenges is crucial for improving the accuracy and effectiveness of sentiment analysis in stock prediction.

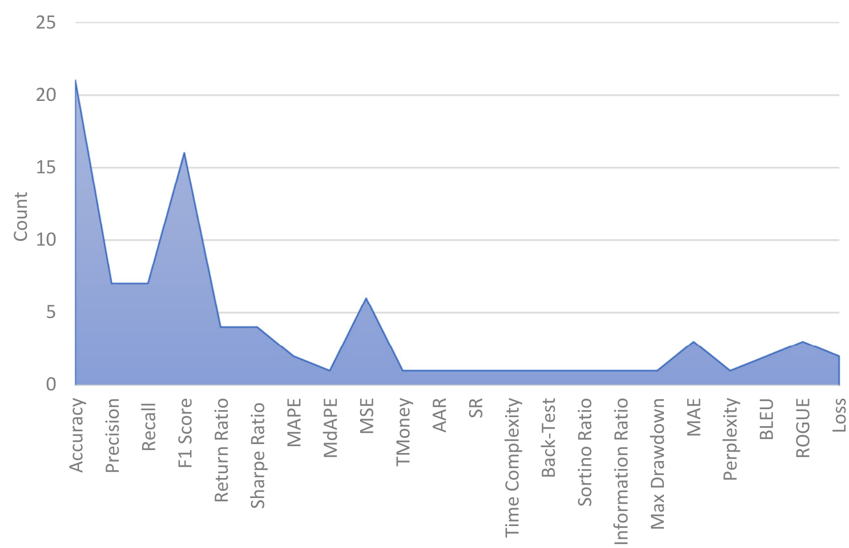

Fig. 10. Usage of different evaluation metrics.

4.5. Research on different evaluation metrics

When assessing the performance of GNNs, it is clear that their effectiveness is impeded by many issues. First, GNNs rely heavily on the structure of the graph on which they are trained. This can make it harder for them to work with new data and situations. Moreover, the task of optimizing hyperparameters for GNN models is frequently time-consuming and demanding, resulting in the consumption of valuable resources and a heightened susceptibility to overfitting the training data. To fully realize the capabilities of GNNs in areas such as natural language processing and financial prediction, it is crucial to create algorithms that are more efficient and scalable and capable of addressing these limitations. By strengthening the generalizability of GNNs, they can be more able to handle varied datasets and react to changing market situations.

Fig. 10 provides insight into how various evaluation metrics are utilized across different research articles to assess the performance of prediction models. These metrics include both classification metrics, which evaluate the accuracy of movement predictions, and regression metrics, which measure the accuracy of stock or index price predictions. Understanding and effectively utilizing these evaluation metrics are crucial steps toward advancing the capabilities of GNNs in predictive tasks.

5. Discussion

5.1. Exploration possibilities, challenges, and limitations

This section highlights the various obstacles and opportunities that researchers and practitioners may encounter as they work on integrating sentiment analysis with GNNs for enhanced stock prediction. It is essential to recognize the potential impact of addressing these challenges and to inspire future research efforts. The quality and dependability of sentiment data from multiple sources require robust data gathering methods, sentiment label validation, and irrelevant information filtering. For accurate sentiment analysis, researchers must investigate preprocessing, sentiment lexicons, and aggregation methods for unstructured and noisy social media text data. Since financial decision support systems need interpretability to generate confidence and comprehend decision-making, researchers should study how sentiment affects GNN-based predictions. Researchers should incorporate transfer learning, ensemble models, or macroeconomic indicators to make sentiment-GNN hybrid models more robust and generalizable across varied stock markets. Morally risky sentiment-driven financial models may encourage market manipulation. Researchers must discover techniques to reduce these dangers and maintain financial market ethics. To make accurate and timely predictions in dynamic markets, researchers should investigate ways to seamlessly integrate real-time sentiment data with previous stock data. Sentiment analysis, market news, and geopolitical events improve stock prediction, but feature extraction, alignment, and information fusion are difficult tasks requiring effective methods. To optimize sentiment-GNN models for large financial datasets, researchers should investigate graph sampling, parallel processing, and hardware acceleration. Researchers must guarantee that financial market AI models comply with rules, privacy laws, and decision-making transparency to achieve effectiveness.

5.2. The superiority of GNNs

GNNs have several advantages over contemporary models for predicting stock prices. These benefits include:

1. Capturing complex dependencies: GNNs excel at capturing complex dependencies and relationships in data, especially in stock prediction, by modeling intricate relationships between equities, sectors, and investors using graph structures [9].
2. Incorporating sentiment analysis: GNNs can incorporate sentiment analysis into their prediction process, thereby capturing the impact of market sentiment on stock prices and producing more accurate forecasts by leveraging sentiment-related features and scores.
3. Handling dynamic and evolving data: GNNs excel at managing dynamic stock market data, capturing temporal dependencies and evolving patterns, and updating predictions continuously with recurrent or temporal architectures [127].
4. Handling missing or incomplete data: Frequently, stock market data are absent or incomplete, which impacts prediction models. GNNs can manage this by leveraging adjacent nodes and enhancing the accuracy of their predictions through message passing [128].
5. Interpretable predictions: GNNs improve the interpretability of stock price forecasts by disclosing learned representations and node importance, allowing for a greater comprehension of the factors influencing stock prices and more informed investment choices [129].

5.3. Improving stock prediction with sentiment analysis and GNNs: difficulties and limitations

Integrating sentiment analysis with GNNs for enhanced stock prediction presents challenges, including difficulties in modeling evolving relationships and potential limitations in generalization. Despite these challenges, the approach yields valuable insights into dynamic market trends. Sentiment analysis is dependent on textual data obtained from sources such as news stories, social media, and financial reports. However, these data can be inconsistent and susceptible to interference from factors such as noise, disinformation, and prejudice. GNNs are very responsive to the accuracy of the underlying graph data and may not exhibit perfect alignment with fluctuations in the stock market. Acquiring a substantial dataset is a demanding task when training GNNs. Stock markets are subject to multiple influences, and GNNs may encounter difficulties in adjusting to changing conditions. The intricate structures of GNNs contribute to their reduced interpretability, and incorporating sentiment analysis with GNNs could heighten the risk of overfitting. Adhering to ethical principles and meeting regulatory criteria are crucial for achieving strong performance. Moreover, GNNs can need significant processing resources, thereby restricting their implementation in real-time scenarios or environments with limited resources. To address these problems, it is necessary to thoroughly analyze the particular application scenario, implement strong data preprocessing techniques, perform feature engineering, and continuously monitor and change the model to accommodate evolving market conditions.

5.4. Future research scope

There is a growing interest in deploying GNNs in various domains, including the stock market, due to their rapid development. The applicability of GNNs in predicting stock market trends was explored using financial news sentiment data. However, several avenues can be pursued in the future to further enhance the accuracy and efficacy of GNNs in the stock market. This subsection offers future directions for interested scholars, in addition to a potential outlook, to present them with a fresh perspective. The directions are outlined below:

1. Future research on GNNs should focus on scalable models to address computational efficiency challenges in large-scale graphs, enabling efficient handling of massive graphs.
2. Future research should concentrate on enhancing the interpretability and interpretability of GNN-based models, as their black-box character renders them inappropriate for sensitive domains such as finance and healthcare. The interpretability of GNNs in the stock market is essential for future research, as their results are promising but difficult to interpret. The development of visualization techniques could increase confidence in forecasts.
3. In robotics, gaming, and recommendation systems, combining GNNs with reinforcement learning could improve performance.
4. Future research on fraud detection and risk management could be bolstered by integrating GNNs into real-world applications such as financial forecasting.
5. Exploring the application of GNNs in finance beyond stock market trends provides optimistic insights into credit risk analysis, fraud detection, and portfolio optimization, thereby improving their capabilities and limitations.
6. Research suggests incorporating additional financial data, such as technical indicators and macroeconomic data, into the GNN model to better comprehend market trends.
7. Alternative graph structures, such as social networks, stock correlations, and industry-level networks, should be explored to gain a deeper understanding of the relationships between entities in the stock market.

6. Conclusions

In conclusion, this survey research article provides a comprehensive overview of the application of GNNs in conjunction with sentiment analysis for stock prediction. Through an exploration of the literature, the article highlights the advantages and potential of integrating GNNs and sentiment analysis in this domain. GNNs offer distinct advantages over traditional models in stock price prediction. By capturing complex dependencies and relationships in data, GNNs can effectively model the intricate interdependencies between stocks, sectors, or investors. Moreover, their ability to incorporate sentiment analysis allows them to leverage market sentiment as a valuable factor in predicting stock prices. The survey covers various approaches and techniques used for sentiment analysis and stock prediction via GNNs. Different graph structures, such as stock networks and investor networks, and the methodologies employed to incorporate sentiment analysis into these networks have been discussed. The article also examined the challenges associated with data collection, preprocessing, and annotation, as well as the evaluation metrics and performance benchmarks used for assessing GNN-based stock prediction models.

Furthermore, the article has emphasized the ability of GNNs to handle dynamic and evolving data, adapt to changes in the graph structure, and address missing or incomplete information. This flexibility and robustness make GNNs well suited for stock prediction tasks in real-world scenarios. Importantly, GNNs provide interpretability, allowing researchers and practitioners to gain insights into the learned representations and understand the factors influencing stock prices. This interpretability enhances transparency and aids in making informed investment decisions. While this survey research article has provided valuable insights, there are still areas that require further exploration. Future research should focus on addressing these limitations and open research questions, including the development of more sophisticated GNN architectures, refining sentiment analysis techniques, and investigating the impact of incorporating additional data sources.

Therefore, the integration of GNNs with sentiment analysis is a promising approach for improving stock prediction accuracy. By leveraging the power of GNNs and harnessing the information embedded in sentiment data, researchers and practitioners can enhance their understanding of the stock market and make more informed investment decisions in an increasingly complex and dynamic financial landscape.

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Data availability

Data will be made available on request.

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