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Enhancement of traffic forecasting through graph neural network-based information fusion techniques

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ABSTRACT

To improve forecasting accuracy and capture complex interactions within transportation networks, information fusion approaches are crucial for traffic predictions based on graph neural networks (GNNs). GNNs offer a potentially effective framework for capturing complex patterns and interactions among diverse elements, such as road segments and crossings, by considering both temporal and geographical dependencies. Although GNN-based traffic forecasting has recently been investigated in many studies, there is a need for comprehensive reviews that examine information fusion approaches for GNN-based traffic predictions, including an analysis of their benefits and challenges. This study addresses this knowledge gap and offers future insights into the potential advancements and developing fields of research in GNN-based fusion techniques, as well as their implications in urban planning and smart cities. Existing research demonstrates that the accuracy of traffic forecasting is substantially enhanced by information fusion techniques based on GNNs in comparison to more conventional approaches. By integrating information fusion methods with GNNs, the model is capable of capturing complex temporal and spatial relationships between various locations in a traffic network. Multi-source data integration benefits traffic forecasting models, including social events, weather conditions, real-time traffic sensor data, and historical traffic patterns. In addition, combining GNNs with other artificial intelligence (AI) methods like evolutionary algorithms or reinforcement learning could be an efficient strategy. With the potential to combine the best features of several methods, hybrid models could improve overall performance and flexibility in challenging traffic situations.

Abbreviations

ARIMA	Autoregressive integrated moving average
BNGC	Bus network graph convolution
BRB	Belief rule base
CNN	Convolutional neural network
DCRNN	Diffusion convolutional recurrent neural network
EAGTCN	Ensemble attention-based graph time convolutional networks
ETGCN	Evolution temporal graph convolutional network
FLP	Facility location problem
GAN	Generative adversarial network
GAT	Graph attention network
GC-GRU	Graph convolution gated recurrent unit
GCN	Graph convolution network
GLSTM	Graph long short-term memory
GNN	Graph neural network
GRU	Gated recurrent unit
HetGAT	Heterogeneous graph attention network
ISVR	Integrated spatial–temporal variational recurrent neural network
LSTM	Long short-term memory
MAE	Mean absolute error
MAS	Mean absolute error
MAPE	Mean absolute percentage error

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MIC Maximal information coefficient
MLP Multilayer perceptron
PEMS Performance measurement system
PVCGN Physical-virtual collaboration graph network
RAME Relative absolute mean error
RNN Recurrent neural network
RMSE Root mean squared error
ST Spatial–temporal
STGNN Spatial temporal graph neural network
STGGAN Spatial–temporal graph generative adversarial network
LightGBM Light gradient boosting machine
ST-MGCN Spatio-temporal multigraph convolutional network
STZINB Spatial–temporal zero-inflated negative binomial
SVR Support vector regression
TCN Temporal convolution network
TGCN Temporal graph convolutional network
TP Trajectory prediction
UAM Urban air mobility
WaveNet Waveform generative model
ZINB Zero-inflated negative binomial

1. Introduction

Modern transportation systems play a vital role in economic growth, urban development, and technological advancement [1]. The effectiveness of transportation networks influences the uninterrupted daily mobility of large populations in modern urban areas [2]. These systems are essential for tying human activity into physical space, impacting a range of technological, political, and socioeconomic domains at different geographical scales. An effective transportation infrastructure enhances a country's economic development and benefits individuals, companies, and the environment through measurable advantages [3]. Urbanization has given rise to several issues, including congestion on roads, increased demand for transportation, limited accessibility, and lower productivity. These issues can be resolved using traffic forecasting tools to make early interventions [4]. The adverse effects of traffic congestion on commute times, energy use, road safety, and environmental quality make it a major barrier to sustainable urban development. On modern transportation infrastructures, researchers have implemented intelligent transportation systems (ITSs), which are based on the fundamental concept of forecasting traffic patterns, to reduce traffic congestion [5]. Monitoring traffic conditions in the development of smart cities and intelligent transportation systems (ITS) uses sensors, transaction logs, surveillance footage, and global positioning system (GPS) data from smartphones [6]. Smart cities can now track and evaluate traffic in real-time due to the intelligent traffic monitoring system with real-time analysis for smart cities, specifically designed for personal computers. With robust data analysis methods and improved algorithms, the system provides precise and real-time traffic statistics [7]. In this case, this thorough approach to data collection enables reliable forecasting. Improving traffic forecasting has been a key focus for transportation system optimization in the dynamic field of urban mobility [8]. The complex relationships within traffic data are becoming more challenging for traditional forecasting approaches to capture as cities grow and traffic complexities rise.

To improve transportation efficiency and make well-informed modifications to urban traffic management, this predictive analysis is essential. Precise traffic forecasting is essential for the advancement of ITS since it greatly influences the choices made for effective traffic control in urban areas [4]. The traffic forecasting problem is more complex than traditional time series forecasting problems because it involves many highly dimensional data, including traffic light optimization, strategic opening or closing of lanes, or even catastrophes like road traffic collisions (RTC) [9,10]. In order to predict future changes in traffic flow, historical trends must be examined. Traditional techniques primarily concentrate on comprehending the time and space components of traffic data, ignoring significant facts about how traffic operates. Resolving this issue is important in raising the accuracy and usefulness of traffic forecasts in cities. The previous researchers mainly employed three categories of methodologies for forecasting future traffic conditions based on historical observations of traffic data. These approaches include conventional parametric approaches, encompassing stochastic and temporal methods such as autoregressive integrated moving average (ARIMA) [11]; machine learning techniques, exemplified by support vctor machine (SVM) [12]; and deep learning [13,14]. Artificial intelligence approaches exhibit superior performance compared to parametric methods, due to their adeptness in handling extensive datasets [15]. Parametric models also fail to deliver accurate results due to the stochastic and non-linear characteristics inherent in traffic flow [16]. To foresee congestion, it is necessary to handle a variety of data sources, including loop counters and floating car data. These data sets show complex, frequently sparse, incomplete, and high-dimensional spatiotemporal dependencies [17]. Real-time computation is imperative, necessitating incorporating external elements like weather conditions and road accidents for a comprehensive forecasting approach [18]. As a novel approach to solving these problems with higher accuracy, data integration techniques utilizing graph neural networks (GNNs) have emerged as a powerful deep learning tool that can evaluate big and complex datasets.

The growing importance of advanced deep learning approaches specific to graph structures is highlighted as the best approach to handle various natural language processing (NLP) problems beyond traditional data analysis techniques [19]. GNNs are specifically used for these tasks because the results are more accurate than other approaches. GNNs are highly effective in predicting traffic patterns because they utilize the inherently graphical structure of road networks [5]. This is accomplished by using non-Euclidean graph structures to represent partial connections efficiently. Utilizing GNN-based traffic prediction, a highly precise method, can effectively address the growing traffic challenges. This approach can assist in defining parameters, optimizing transportation systems, and mitigating traffic congestion [20]. Although the structural data of a graph is important for models based on GNN, not many studies have been conducted on this aspect. However, most GNN-based models ignore the connectivity information between the graphs and instead focus primarily on the structural information of the graphs [21]. Many researches on traffic forecasting have highlighted numerous challenges in getting higher accuracy using machine learning or deep learning approaches following the GNN method without thoroughly explaining how different information fusion techniques can help to overcome those challenges. Many studies have focused primarily on analyzing the difficulties and limitations related to traffic forecasting or investigating specific information fusion techniques for GNN-based traffic predictions without providing any future insights. Despite the extensive research on GNN-based traffic forecasting in recent years, there is a lack of comprehensive reviews on information fusion approaches for GNN-based traffic predictions, including their advantages and challenges. This study addresses the existing knowledge gaps and offers valuable insights into the potential improvements and emerging research areas in fusion methods based on GNNs. It also explores the implications of these methods in urban planning and smart cities.

2. Graph neural network

Graph neural networks (GNNs) are neural network topologies that function on graphs. A GNN architecture aims to train an embedding with neighborhood data [22]. Numerous issues can be resolved using this embedding, including node labeling, edge and node prediction, and more [23]. Stated differently, GNNs are a subset of deep learning techniques intended for graph-based data inference. They can carry out prediction tasks at the node, edge, and graph levels when applied to graphs. As a potent framework for analyzing complex correlations in graph-based data, GNNs have emerged as a key advancement in machine learning. Because of their remarkable expressiveness, which makes them useful models for various systems in natural science, social science, and other fields of study, graphs are becoming increasingly popular as tools for machine learning. Because of their exceptional performance in graph analysis, GNNs are often used as deep learning methods designed explicitly for the graph domain. GNNs have been developed to overcome the drawbacks of earlier techniques, such as the use of directed acyclic graphs with recursive neural networks (RvNNs) in the 1990s [24] and the following development of recurrent neural networks (RNNs) and feedforward neural networks. The historical background of neural networks for graphs is where GNNs originated.

2.1. Basic principles of GNN

A particular type of machine learning model called GNN is designed to operate on data arranged in graphs [25]. The fundamental ideas and techniques that allow for the efficient representation of and learning from graph-structured data are included in the GNNs' core principles. Apart from providing a valuable framework for learning from graph-structured data, the principles of GNNs are continuously enhanced to tackle problems in an extensive array of application domains. Graph-level predictions, link prediction, and node categorization are tasks that GNNs can perform effectively. They can also capture complex interactions and adjust to dynamic changes [26].

While CNNs excel at managing text and image data, GNNs are exceptionally skilled at handling the complexity of non-Euclidean structures, such as graphs. As GNNs can handle graph-structured data, they can do tasks like node categorization, link prediction, and clustering more efficiently and with a deeper grasp of relationships. They differ from other algorithms because of this capability. The integration of GNN layers, each utilizing a unique multilayer perceptron (MLP) on graph components, is a notable development in geometric deep learning. This modular technique allows learning of node embeddings, edge embeddings, and global-context vectors, which enhances the overall representation of the graph. With GNNs, the original network's connection remains unchanged. Hence, the generated graph retains its structure but gains new embeddings. This demonstrates the adaptability and effectiveness of GNNs in recognizing dynamic patterns in graph data [27].

2.2. Evolution and advancements in GNNs

GNNs have been playing a major role in the era of machine learning. The evolution and advancements in GNNs were discussed in financial time series price forecasting by Zhang et al. [28]. A type of deep learning model known as GNNs was developed expressly to work with graph-structured data, enabling efficient representation and gaining knowledge and understanding of the edges and nodes in the graph. The three-dimensional tensor used as the model input in the GNN price forecasting model was constructed based on a graph built utilizing a network of connected assets. In this graph, every node denoted an asset, and edges were produced by forming connections between assets using metrics like correlation or sector similarity. Each node had a feature set comprising various technical indicators and previous trading data. The node feature matrices were stacked along the temporal dimension to form the model's input. The GNN block, which combined a CNN or LSTM network and a graph convolution network (GCN), was the central element of the GNN paradigm. The CNN or LSTM network can be placed before the GCN for feature extraction. The CNN or LSTM aids in additional processing as the GCN uses the adjacency matrix to ascertain node associations and update node attributes. By modeling the relationships between various assets and utilizing data from related assets, the use of GNNs in price forecasting can potentially improve forecasting performance. Nonetheless, the study highlighted a number of difficulties with GNNs in this situation. Choosing suitable characteristics and carefully considering pertinent interactions while building the input graph in financial markets can be difficult. Since the adjacency matrix mostly depends on historical data, GNNs may also have issues with sparse historical data or abrupt changes in the market. Moreover, GNNs are characterized by high computational costs, particularly for extensive financial networks [28].

In the particular context of Parkinson's disease (PD), Zafeiropoulos et al. [29] carefully examined the development of GNNs. Graph generative networks (GGNs) and graph reinforcement learning networks (GRLNs) are two examples of the many varieties of GNNs thoroughly covered in this paper. Their functions in producing realistic representations of PD symptom progression and optimizing individual treatment options were explained. In order to provide an insightful understanding of the complex interactions between PD symptoms and underlying disease pathology, the research emphasized the critical role that GNNs play in utilizing the patient data that is now accessible for PD. It also tackled important issues in PD research, like the integration of electronic healthcare records (EHRs), model selection and validation, and data quantity and quality. Data privacy and confidentiality are prioritized in the proposed GNN-based PD monitoring and alerting approach, which heavily relies on systematically integrating diverse external data sources.

3. Information fusion techniques

The techniques of information fusion stretch back to the late 1980s and have undergone substantial evolution since then. These methods were first developed in the context of sensor fusion, mostly for military uses [30]. Nevertheless, information fusion approaches have grown rapidly, moving outside their original field of study to include a broad range of technological, sociological, and economic factors [31]. The most important aspect of information fusion approaches is their capacity to integrate and combine information or data from several sources to improve the output's overall quality, accuracy, and comprehensiveness. During this evolution, models such as the Joint Directors of Laboratories (JDL) emerged, which structured and arranged various techniques into levels and functions. Information quality is essential for assessing how well information fusion approaches work in various contexts [32]. The application of enhanced information is crucial when using information fusion approaches, especially in tracking and monitoring. The contrast between "information fusion" and "data fusion," where the former emphasizes the interpretation of data meaning and the latter the improvement of sensor-collected data, is a common example of this difference [31].

Information fusion methods have been shown to be flexible and adaptive in a variety of domains, including traffic forecasting, smart home scenarios, food quality evaluation, and Earth observation. In order to maximize text and video data fusion, specific modifications are required. It was stressed how important it is to have strong validation and analytical processes [33]. It has become a key instrument in Earth observation, allowing the integration of various data sources, even unusual ones like social media data. Even though using noisy and poorly labeled data for learning can be difficult, it is important to advance the studies [34]. Information fusion techniques went beyond traditional methods in the field of traffic prediction by merging several data streams using a multi-stream architecture. By utilizing attention processes, fully connected neural networks (FNN), gated recurrent unit (GRU) and GCN channels, Spearman rank correlation coefficients, and complete temporal, spatial, and contextual information, these techniques improved prediction accuracy [35]. These versatile information fusion techniques are still evolving, propelling decision-making and predictive modeling advances that hold promise for interdisciplinary breakthroughs [33–36].

3.1. Fundamentals of information fusion

The foundations of information fusion are defined by their cross-disciplinary nature and broad applicability [33]. Information fusion is an essential approach that may be applied to many different fields, such as image processing, data integration, monitoring and tracking, and decision-making support. The study by Gutiérrez et al. [33] highlighted the need for domain-specific modifications, stressing the distinct obstacles and prospects found in every application domain. The analysis of the many data sources used in information fusion reveals certain neglected categories—like text and video data—and suggests possible directions for further study. In addition, the paper clarified the significance of solid validation procedures and quantitative assessment measures, tackling present shortcomings in reproducibility and data accessibility. These foundations built the framework for a thorough comprehension of information fusion, highlighting its significance as an instrument for improving information quality in various fields and opening up new directions for research and standardization.

As reported by Salcedo-Sanz et al. [34], the principles of information fusion centered on the purposeful combination of various data sources to improve the comprehension and utilization of Earth observation. A key principle of Earth observation research is information fusion, which attempts to combine data from a variety of platforms, sensors, and most significantly, unorthodox sources like social media. The main goal is overcoming the challenges brought on by the Earth observation field's inherent heterogeneity, non-stationarity, and massive data. The importance of machine learning in information fusion is one of the paper's main points, as machine learning models show promise in drawing insightful conclusions from complex, multi-dimensional datasets. In the big data era, fusion entails merging data with varying resolutions, spectral and geographical properties, and addressing scalability difficulties. The principles also applied to the difficulties presented by unstructured data, which need innovations in natural language processing, unsupervised machine learning, and geographic data science. Furthermore, the study highlighted how critical it is to advance our grasp of underlying causal links using techniques like causal inference and strengthening our predictive capacities. Future information fusion research should explore the integration of domain knowledge, the use of probabilistic and differentiable programming, and the development of hybrid physics-aware machine learning models. These approaches should lead to significant developments in Earth observation applications and insights.

Information fusion principles are based on the methodical fusion of information and data from several sources in order to acquire more accurate and complete insights than can be obtained from separate channels [37]. The information fusion principles were used for new non-destructive analytical methods for food quality authentication in the context of the surveyed study. Preparing and separating food samples into calibration and validation sets was the first of several crucial processes. Complementary sensing systems then analyze these samples, producing digital data from several sources. There were various stages of information fusion: low-level fusion, which involves concatenating data; mid-level fusion, which employs feature engineering techniques like principal component analysis (PCA) and linear discriminant analysis (LDA); and high-level fusion, which combines judgments from several machine learning models. After that, the combined data was shaped for additional analysis that would produce a final result or choice. The efficacy of information fusion techniques was rooted in their capacity to improve precision in food quality determination through diverse sensors and analytical tools.

The systematic integration of data from various sources to produce a complete and accurate depiction of the underlying reality is at the heart of information fusion principles [36]. Information fusion's primary goal was to lessen the shortcomings and restrictions of the different data sources, increasing the overall dependability and usefulness of the combined information. A wide range of strategies were usually used in this process, such as knowledge-based, evidence-based, and probability-based approaches. Bayesian algorithms and other mathematical models were used by probability-based techniques to handle uncertainty and guarantee reliable data collecting. Evidence reasoning techniques, such as the Dempster-Shafer theory, offered a framework for dynamically allocating belief distributions and managing uncertainty. Conversely, knowledge-based approaches did not depend on particular distribution functions; instead, they used intelligent aggregation, machine learning, and fuzzy logic to glean valuable insights from imprecise huge data.

3.2. Role of information fusion in traffic forecasting

Innovative approaches in traffic forecasting are based on information fusion, which is essential for combining various data sources [35]. It facilitates the thorough integration of previous statistics, real-time information, and traffic factors, leading to a more profound comprehension of traffic dynamics [38]. This process includes the complex interactions between the temporal, geographical, and dynamical components of traffic conditions, going beyond simple data aggregation [39]. Information fusion stimulates the improvement of prediction models by efficiently combining and integrating disparate data sources. This significantly improves control systems, traffic management, and infrastructure planning.

The multi-stream feature fusion approach combines several datasets to improve traffic forecasting prediction accuracy. In the study by Li et al. [35], data was combined from multiple sources, deftly negotiating the complex network of spatial, temporal, and spatiotemporal factors, guaranteeing a thorough integration of information about traffic circumstances. An adaptive graph creation approach that dynamically illustrated the road sensor network captured complicated interactions between monitor stations and allowed real-time alterations during model training, highlighting its versatility. Spatial correlations within the non-linear structure of monitoring stations were effectively understood by components such as the GCN, resulting in excellent spatial feature extraction performance. Further contributions were made by the GRU and FNN, which extracted temporal characteristics and covered a variety of variables influencing traffic patterns, respectively.

Information fusion is a revolutionary approach that improves the accuracy and reliability of traffic predictions by utilizing many data sources. Its main objective is to organize and incorporate data from many sources efficiently, an essential component of traffic forecasting. Zhang et al. [38] included historical data, journey duration information, and traffic-related characteristics using a well-designed artificial neural network (ANN), namely a BP neural network model. This integration skillfully managed the uncertainties and nonlinearities inherent in traffic flow, enabling a thorough understanding of transportation network relationships. The study shed light on the shortcomings of conventional models, such as autoregressive models and linear statistical regression, in managing the stochastic character of actual traffic situations impacted by various variables, including weather, seasonal variations, accidents, and driver psychology. Combining an ANN with information fusion produced a more flexible and self-learning approach to navigating these uncertainties. Preprocessing was part of the BP neural network's fusion process to guarantee that the variables used for network learning were suitable. This allowed for accurate forecasting by finding patterns and correlations between trip time, amount of traffic, and historical traffic data. With the help of this coordinated approach, complex traffic patterns and fluctuations were more accessible to record, improving forecasting systems that support infrastructure design, giving travelers access to real-time traffic information, and improving traffic management and control systems. The model evaluation demonstrated the importance of information fusion, especially when compared to conventional methods, exhibiting higher accuracy and stability, mainly when used with the BP neural network. The effective coordination of many data sources, the empowerment of models to manage inherent uncertainties in traffic systems, and the eventual development of accurate and reliable forecasting systems for intelligent transportation were all made possible by information fusion. Combined with artificial neural networks, it significantly increased traffic management and control decision-making.

Due to information fusion, intelligent transportation systems (ITS) have significantly benefited from the increased accuracy and dependability of short-term traffic projections [39]. In this challenging environment, accurate predictions—achieved through information fusion techniques—were crucial for efficient traffic management and accident detection. To prevent or lessen catastrophic traffic events, the study emphasized the importance of precise short-term traffic projections. Conventional traffic prediction techniques used different data sources, which made it challenging to determine traffic conditions, mainly when the data was inaccurate or unlabeled. In order to increase forecast accuracy, the research presented a critical improvement: conditional information fusion in conjunction with anomaly detection. The study by Sun et al. [39] significantly improved anomaly detection for more accurate traffic forecasts by utilizing methods like the dynamic Poisson distribution and the Chi-square test, which leverage anomaly detection strategies based on density, distribution, and distance. The study is noteworthy for developing a day-week decomposition (DWD) method that takes into account both weekly and daily seasonality, hence boosting anomaly detection and tackling multi-seasonality and dynamic traffic variations. Through a 15.3 % improvement in estimations, the study highlighted the need for information fusion methods for improving traffic forecasts. By adding conditional information fusion, the study improved the prediction algorithm's adaptability to changing traffic conditions by introducing an ensemble technique based on k-nearest neighbors (kNN) regression. The study overcame the constraints of the current anomaly detection methods by highlighting the significance of preprocessing techniques like DWD in controlling the daily and weekly seasonality of traffic data.

4. Traffic forecasting problems

With the rapid increase in the world population, there is a rapid increase in traffic congestion, an increase in the need for transportation, poor accessibility, and decreased productivity owing to urbanization. Despite the continuous progress in science and technology, many major cities worldwide still lack sustainable means of transportation for passengers and freight. The annual costs of traffic congestion amount to billions and billions of dollars because of lost productivity, air pollution, and fuel loss, among many other reasons [40]. To curb these issues, Intelligent transport systems that depend on accurate traffic forecasts are being implemented [5,40–42]. Contemporary transportation infrastructures are built on the basis of traffic forecasts. It has proven valuable for road traffic control, vehicle routing, and trip planning [5]. Recurrent and convolution neural networks are two key examples highlighted when various widely used deep learning models are discussed, primarily to simulate temporal and spatial interdependence in traffic forecasting issues. Recent research has introduced GNNs to depict transportation systems in graph structures in conjunction with contextual data. These networks have proven effective in various traffic forecasting scenarios [42].

4.1. Road traffic speed

Predicting future traffic conditions requires accurate traffic speed forecasting, enhancing travel route optimization, traffic efficiency, and the robustness of smart transportation networks [9,43,44]. Reliable traffic speed forecasting can be significantly helpful in route planning and safe and efficient arrival at destinations for drivers. Road traffic management and individual travelers benefit from accurate traffic speed forecasting [44]. While most studies aim to improve speed prediction, they fail to take into account the importance of background information, which is dispersed all over an urban environment. Incorporating context information into traffic forecasts is further hampered by its complexity and diversity. Forecasting the traffic status for the future is still a challenge, though, because many complex aspects affect it. Current existing models often take into account the dependencies of the physically connected road segments and overlook the physically disconnected road segments [9,43]. However, the drawbacks of these deep learning forecasting processes highlight the inability to manage different crucial variables, including the number of similar lanes, toll data, and accident frequency. Additionally, there are instances of incompetence and variable performance on forecasting tasks when heterogeneous series are involved [45]. Researchers have proposed several innovative approaches to address these concerns, including hybrid models based on machine learning and deep learning. The outcomes confirm forecast accuracies through comparison analysis and improve the models' application, practicality, and reliability.

Addressing the challenge of accurate traffic speed prediction in sustainable smart cities based on deep GNNs (DGNNs), named STGGAN, was the primary emphasis of Sharma et al. [20]. The study assessed the effectiveness of the suggested model for real-time traffic-speed estimates and used GNNs to depict the connectivity of road segments as a graph. The model concentrated on correctly estimating short-term traffic flow on roadways in cities by using spatiotemporal data and graph structures, as per the framework highlighted in Fig. 1. The results showed high accuracy in predicting values of 96.67 % for PeMSD4 and 98.75 % for PeMSD8. The efficacy of the STGGAN approach was further proved by the computation of mean squared error (MSE), mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean square error (RMSE), which all showed a gradual drop in error values as one increased loop frequency [20]. The study thoroughly evaluated current cutting-edge models for estimating traffic flow. The proposed STGGAN-infused framework could consider the characteristics and structure of the road networks, incorporating edge features for directed arcs and achieving improved prediction accuracy compared to baseline models [20]. However, the main barrier to forecast accuracy was the

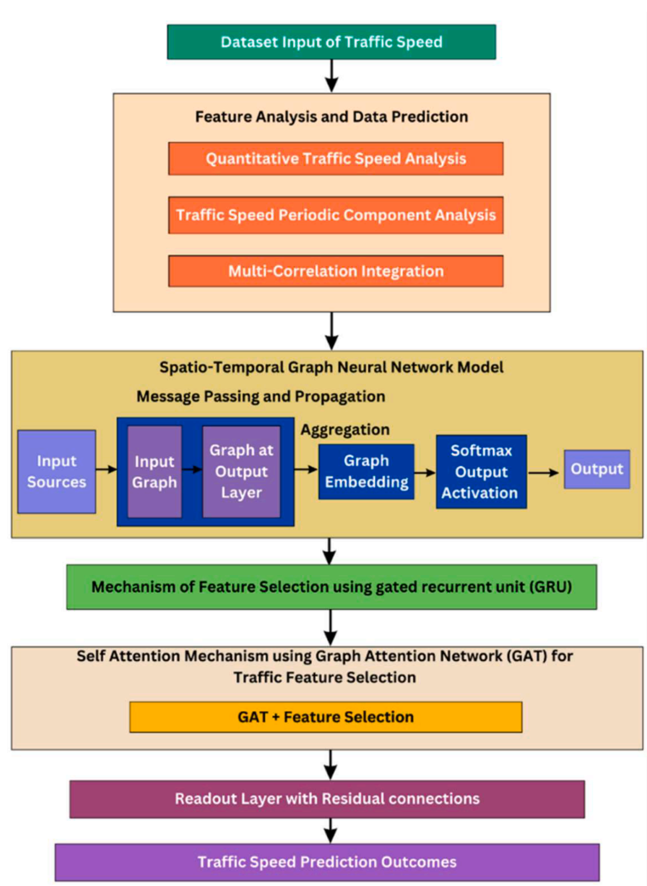

Fig. 1. Framework of the model for the STGGAN approach [20].

inherent complexity of interconnecting road segments [9,43]. Regardless, by addressing the geographical and temporal dependencies in data and illustrating the suitability of the suggested STGGAN model in sustainable smart cities, the work substantially contributed to the area of traffic-speed estimate.

A study by Lu et al. [46] addressed the complex problem of road speed prediction, a critical subtask in traffic flow forecasting, emphasizing identifying spatial–temporal correlations in road networks. The authors utilized RNNs to study GNNs and temporal relations, which were employed to incorporate graph-structured and node-attributed information. The authors constructed a novel graph LSTM (GLSTM) framework with a message-passing system for feature accumulation, a temporal-directed attributed graph to model complex traffic flow, and LSTM variations alongside a GNN block under the encoder-decoder structure for modeling spatial–temporal dependency. The study's findings revealed that the proposed GLSTM model could effectively use the traffic speed data and the latent graph structure of the road to estimate future roadway conditions. In comparison to other innovative baseline techniques, the experimental outcomes on real-life data sets from Xi'an and Beijing demonstrated how effectively GLSTM performed, with improvements of as much as 43.2 % in mean absolute percentage error (MAPE), 32.8 % in mean absolute error (MAE), and 23.1 % in root mean squared error (RMSE) [20]. The research also suggested that road network spatial topology should be taken into account, as the GLSTM performs better than basic deep learning techniques like MLP and LSTM, which do not take graph structure into account [46]. One of the challenges was the proposed GNN-based GLSTM's ability to describe graph structure more accurately than methods like diffusion convolutional recurrent neural network (DCRNN) and temporal graph convolutional network (T-GCN). However, the potential of GNNs with LSTM cells in addressing traffic prediction problems was demonstrated by the GLSTM's efficiency in successfully gathering graph structural attributes and enhancing prediction accuracy. The authors also emphasized the model's interpretability, showing how GLSTM can track road speed changes on specific segments, providing insights into traffic dynamics [6]. Future work is suggested to explore additional factors like weather and holidays, incorporate more road network properties, and use the proposed model in other spatial–temporal forecasting tasks, indicating a roadmap for further improvements and applications.

An alternate approach to the complex problem of traffic speed prediction in intelligent transportation systems was the application of a evolution temporal GCN (ETGCN), as proposed by Zhang et al. [47]. To accurately estimate traffic speed on road network graphs, the authors suggested combining the model with several graph structures and utilizing the GCN to describe spatial correlations while simultaneously learning spatial–temporal connections and their rapid advances. To achieve this, the proposed study introduced Multiple adjacency matrix fusion and the ETGCN cell. Multiple Adjacency Matrix Fusion involves a similarity-based attention method that fuses different adjacency matrices, namely content similarity, transportation neighborhood, and graph betweenness, to learn spatial dependencies. To capture both temporal and spatial dependencies, the ETGCN cell incorporated GCN, multiple adjacency matrix, and GRU fusion. The suggested approach's effectiveness in terms of space complexity and time was demonstrated by the computational complexity study. Its results successfully highlighted the superiority of the suggested ETGCN model when compared to other conventional methods, showcasing its ability to provide more accurate prediction results across various prediction horizons on large-scale datasets. Specifically, the ETGCN outperformed spatio-temporal deep learning methods, such as GMAN, TGCN, and ST-MGCN, as well as traditional models like ARIMA, ISVR, GCN, and LSTM, highlighting its capability to handle complex temporal and spatial data [11,20]. The difficulty, however, was with traditional models like ARIMA, ISVR, GCN, and LSTM in handling complex spatiotemporal data and the need for sophisticated methods like ETGCN. Overall, the comprehensive understanding of spatial–temporal learning of features for traffic speed predictions can be further improved, improving the potential of ETGCN in enhancing predictive accuracy in intelligent transportation systems.

To address the challenges in traffic speed prediction within intelligent traffic management systems, Jin et al. [45] overcame the limitations of existing deep learning models, specifically GNNs, GCN, WaveNet, and LSTM. To achieve this, the authors proposed an end-to-end model, HetGAT, that is hybrid, aiming to fuse spatiotemporal attributes with various relevant features like accident occurrences, the total number of lanes, and toll information for more effective traffic speed prediction. The methodologies used in the study involve the development of a heterogeneous graph attention network (HetGAT) incorporating a temporal dilated convolutional network (TCN) to simulate multi-scale temporal context impacts on traffic flow. Furthermore, the input temporal data were encoded using a weighted graph attention network (GAT), and the output speed sequences were predicted by a decoder using the freeway structure of the network. Based on a variety of datasets, the study's findings demonstrated HetGAT's superiority over deep prediction models and traditional sequence analysis methods in areas such as RMSE, MAPE, and MAE [20]. The proposed model effectively integrated spatio-temporal factors for prediction, outperforming other models in experimental evaluations and achieving enhanced performance in traffic speed prediction. However, there were potential limitations of machine-learning methods in handling spatial dependencies, particularly evident in datasets with simpler topologies like the G60 expressway. Regardless, the HetGAT model demonstrated consistent and superior performance to other methods for long-term and short-term traffic speed predictions, effectively capturing both temporal and spatial dependencies [49].

4.2. *Road traffic flow*

A considerable number of traffic flow data is gathered due to the quick deployment of traffic sensors, which shows how traffic flows have evolved and how traffic networks have gradually grown. The foundations for developing smart cities in the modern period are traffic flow analysis, forecasting, and management [50]. Precise and accurate predictions of traffic patterns throughout an entire city are essential for numerous spatiotemporal mining uses, including public risk assessment and intelligent traffic management [51]. Using massive traffic data and deep neural networks, we may better grasp the concealed connections hidden in complex transportation networks. The dynamics of traffic flow on a given road are dependent not only on sequential patterns in the time dimension but also on other roads in the space dimension [49,50]. While some efforts have been made to predict traffic flow, most need to be improved in how they can represent temporal and spatial connections. Since existing approaches mainly focus on analyzing the spatial–temporal connectivity of static networks, the challenge of efficiently developing learning models on network systems with expansions and developing trends has gotten fewer considerations than other approaches. Many previously suggested models cannot incorporate complex traffic transition consistency, which is multi-resolution and depends on time [49–51]. Hence, this section discusses new approaches to tackle these that have been proposed, such as infusing GNNs and deep learning to achieve greater efficiency and accurate forecasts.

Introducing a new traffic flow prediction method using spatial–temporal GNN (STGNN), Wang et al. [49] improved traffic flow analysis, prediction, and management for the development of smart cities. By adding a learnable positional attention system to efficiently collect data from nearby roads and a sequential element to model traffic flow dynamics, they addressed the shortcomings of previous methods in modeling spatial and temporal dependencies. This allowed them to take advantage of global and local temporal dependencies. Three primary components were implemented: a transformer layer to capture global temporal dependencies, a GRU layer for sequential temporal links, and a spatial GNN (S-GNN) layer to capture spatial interactions. The S-GNN layers employed GNN to transform and propagate information through traffic networks, addressing spatial relations between the roadways. A positional attention mechanism was introduced to model spatial dependencies. The temporal dependency was captured using GRU for local temporal information and a transformer layer for global temporal information [48]. The STGNN model outperformed traditional statistical methods, simple neural network models, and recently proposed spatial–temporal models in long and short-term traffic flow predictions. However, there is a strong need for careful consideration of the application scope, as the proposed model may not directly apply to different network structures or scenarios [51].

Using the vast amounts of traffic flow data gathered from the placement of sensors, Chen et al. [50] addressed the challenges of efficiently establishing frameworks for traffic networks that experience changing and growth patterns over time. To obtain precise forecasts along with high performance in the setting for building traffic networks, the authors, based on continual learning and GNNs, presented a streaming traffic flow forecasting framework called TrafficStream. The study demonstrated the proposed framework's ability to identify traffic patterns with high accuracy in an ongoing streaming network scene by validating it on an existing dataset, PEMS3-Stream, acquired in real-time by California Transportation Agencies. The findings showed that TrafficStream is more successful in achieving reduced prediction errors than conventional online training techniques like Expansible-STModel and Static-STModel. It performed almost the same as the higher bounds, including STSGCN, STGCN, and Retrained-STModel [50]. The proposed framework continued to provide accurate and consistent forecasts, continually picking up emerging traffic patterns and maintaining what was already known. Efficiency analyses reveal that TrafficStream maintains high efficiency while achieving accurate predictions, making it suitable for real-world applications. The potential for catastrophic forgetting in incremental training methods like Expansible-STModel acts as a possible weakness. Moreover, the increased training time of Retrained-STModel and STGCN may pose challenges [16,22]. Regardless, the study effectively provided a solution, TrafficStream, that efficiently addressed evolving traffic patterns, showcasing its potential for practical deployment in streaming traffic flow forecasting scenarios.

A transportation emission monitoring and forecasting system was developed by Yao et al. [54] to address the growing pollution caused by urban transportation. The authors' primary objective was to anticipate the evolution of traffic emissions, focusing on accurate traffic flow projections for urban roadways. Their proposed framework, ensemble attention-based graph time convolutional networks (EAGTCN), employed deep learning techniques. Specifically, it integrated GCN to capture global spatial patterns and time convolution net (TCN) to capture temporal patterns. The model utilized spatial ensemble attention, as illustrated in Fig. 2, handled complex spatial correlations in traffic networks and was crucial for capturing dynamic heterogeneous spatial correlations among nodes in traffic networks, enhancing the model's predictive capabilities [8,15]. Experimental results on real-world datasets demonstrated that EAGTCN outperformed other strong baselines in terms of accurate traffic flow predictions, especially in long-term forecasting situations. The model addressed the difficulties caused by the non-Euclidean topology framework of transportation networks and produced better prediction results with less processing costs. The key strength of this study is the improvement of accuracy over existing models, followed by the incorporation of EAGTCN. However, one of its areas for improvement is the limited exploration of external factors influencing urban traffic flow [55].

By putting out a strategy comprising RNN-GCN and belief rule base (BRB) for data fusion, Zhu et al. [52] conducted their study to improve traffic flow forecasting for intelligent transport in smart cities. Using BRB for data fusion, the authors combined many indicators for traffic flow to build a novel traffic flow forecast model that included saturation and speed data, followed by RNN-GCN for capturing time correlations and a topology graph for final traffic flow predictions. The study,

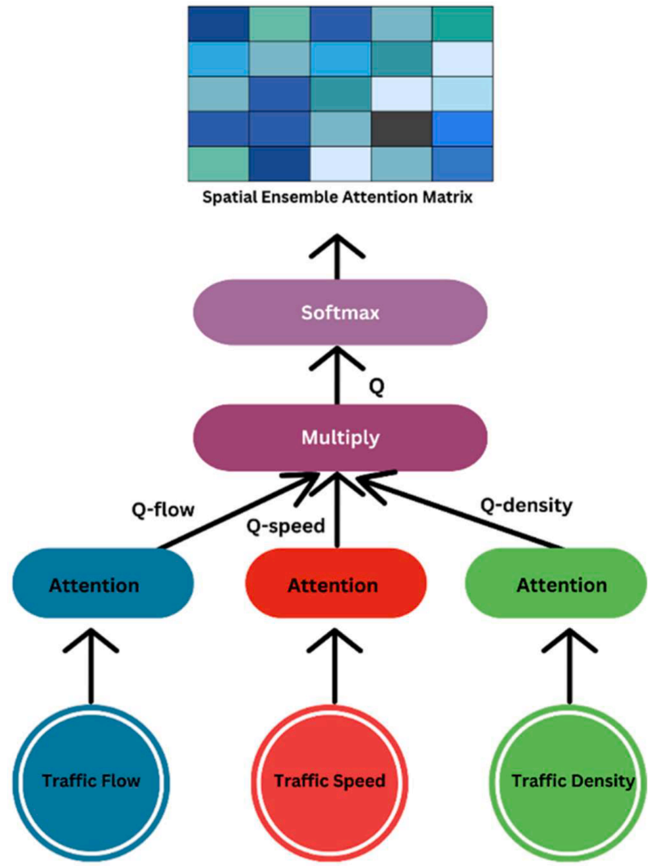

Fig. 2. Structure highlighting the spatial ensemble attention layer [54].

however, should have considered the time attention mechanism in obtaining temporal correlation through the RNN model [20]. The traffic flow fusion model, which is BRB-based, introduced a belief rule base for data fusion with a structured model reasoning process involving rule matching and activation weight calculation. A unique neural network structure was used by the RNN-GCN-based Traffic Flow Forecasting Model to solve the correlation of acquisition time that is important for traffic flow forecasting, demonstrating effectiveness through decreased MAE and RAME and increased accuracy over training times [6,9]. The suggested method performed better than conventional time series analysis techniques, shedding light on an improved accuracy in modeling nonlinear and complex traffic data. The study advanced intelligent transport systems by offering a thorough framework for traffic flow forecasting using BRB and RNN-GCN.

4.3. Road traffic demand

Traffic demand forecasting is emerging as a major component of intelligent transportation systems (ITS). A fundamental work in transportation is scheduling resources, which is crucial and helpful in predicting traffic demand and estimating travel demand from the point of origin to the end of destination [56,57]. Traffic demand over time may be inferred from the number of cars using specific portions of the sensors and the frequency of pick-up cabs in a given region. Accurate traffic demand forecasting can help develop smart cities and lessen traffic bottlenecks. Intelligent mobility infrastructures are the primary sources of large-scale traffic data, such as speed, occupancy, and flow. These infrastructures also ensure that big data is used to allow smart mobility in cities [58]. Deep learning models that fuse temporal and spatial learning have demonstrated remarkable potential in raising prediction accuracy [56,57]. While spatiotemporal deep learning models demonstrate considerable potential to improve the accuracy of predictions, sparsity and uncertainty issues in different implementation matrices have only been partially addressed in a few research [56]. Traffic demand prediction is still a challenging problem given that demand is very dynamic and contextual impacts are complicated. To handle this issue, several studies based on GNN are put forward. Nevertheless, many earlier studies considered spatial dependency a static graph, and their inference process is complex to understand [58].

By inventing the spatial–temporal zero-inflated negative binomial GNN (STZINB-GNN), Zhuang et al. [56] addressed sparsity and uncertainty concerns in fine-grained Origin-Destination trip expectation matrices for modes of transportation. The authors used temporal convolution networks and diffusion to make a temporal and spatial connection, which they then included in a model that parameterizes the distributions of probabilities of travel requests. The zero-inflated negative binomial (ZINB) distribution was used methodologically by the STZINB-GNN to explain the observed sparsity and overdispersion in real-world data. The model used a new method for constructing the O–D graph, taking O–D pairings as vertices and using a temporal convolutional network for temporal dependencies and a diffusion graph convolution network with spatial correlations [9,17]. The study demonstrated STZINB-GNN's superiority against comparable designs, particularly its tight confidence intervals, high spatial–temporal resolutions, high accuracy, and easily interpreted characteristics. There was, however, an increase in the difficulty of parameter learning for Negative Binomial distribution due to the presence of zeros in real-world data and the model's performance degradation under coarser spatial–temporal resolutions. Regardless, the study provided a robust framework for uncertainty quantification in sparse travel demand prediction, offering improved accuracy and interpretability over existing models.

A successful combined prediction model was built to account for both traffic flows and travel demand by Yuan et al. [48] to implement across all city regions for a future time interval. To achieve this, the authors identified three essential properties: inter-traffic correlations, temporal periodicity, and region-level correlations. These properties captured spatial dependencies, time-of-day patterns, and the dynamic relationships between traffic flows and travel demands [17,18,20]. The future spatiotemporal information encoding module, the past traffic sequence encoding module, the graph-based correlation encoding module, and the final estimate module comprise the four modules that comprise the comprehensive neural network model called DeepTP, as mentioned in the study. To capture the necessary qualities, DeepTP included several efficient encodings and embeddings, such as inter-traffic correlation calculations, region embeddings, and temporal periodicity embeddings. The model used GNNs, fully connected neural networks, and sequence encoding models like GRU to handle diverse data relationships [48]. The study successfully developed and validated the DeepTP model through various real-dataset based experiments. When it came to forecasting travel requests and traffic flows, the proposed approach outperformed several baseline techniques, including GBRT, Historical Average, DMVST, ARIMA, ST-Meta, and MGCN. It outperformed existing methods with its robustness in predicting travel demands and traffic flows [11,20]. Additionally, DeepTP exhibits efficiency in terms of memory usage, training time, and online prediction compared to models like MGCN and ST-Meta. A few difficulties faced during the study were handling sparse traffic data and ensuring efficient predictions across diverse city regions. One area for improvement was the dependence on the node2vec graph embedding method for initializing temporal embedding matrices. However, the proposed DeepTP model's strengths effectively address inter-traffic correlations, temporal periodicity, and region-level correlations.

By determining the most significant number of individuals who can benefit from urban air mobility (UAM) in an urban area, with an emphasis on daily commuters, the study by Bulusu et al. [59] evaluated the target audience for UAM as a multifaceted substitute and justified the investment of the public. The authors' analysis of traffic demand determined the location, quantity, and distribution of vertiport demands, which considered variables including adaptability to save vertiport transfer times and traveling time. A traffic demand forecasting method examined 300,000 cross-bay commuting trips in the San Francisco Bay Area. The method involved gathering trip information, speculating on transfer durations and vertiport-to-vertiport transit speeds, and formulating the issue using an uncapacitated facility location problem (FLP) formulation, similar to a k-means method used in Matlab. Assumptions about aircraft operations, capacity constraints, and cost justification were also integral to the process. The findings showed that, even in cases of traffic congestion, around 45 % of demand—commuters who place a high value on time—could benefit by using UAM, and over 90 % could benefit given the ideal mix of transfer times and commuter flexibility. The analysis provided insights into the feasible vertiport combinations, showing a potential mode shift to UAM for a substantial portion of the population during congested hours. The study acknowledges the limitation of not considering commuter willingness to pay and suggests that affordability assessment would need further research. Despite these limitations, the study's strengths include a systematic traffic demand analysis method, application to a real-world scenario, and visualization tools providing valuable insights for network design research, policy-making, and UAM value proposition.

4.4. Station-level passenger (subway/railway/bus/bike) flow

A short-term passenger flow forecast is necessary to manage real-time traffic networks, react swiftly to crises, select routes considering crowd density, and modify service schedules over time [53]. Accurate real-time metro passenger flow forecast is essential for better demand management and operational efficiency [60]. Bus transportation, among other public transportation, can help ease traffic congestion and reduce the use of private vehicles and gasoline [53]. The four-stage technique, consisting of travel generation, distribution, mode split, and assignment, has been the most widely used method for predicting passenger flow [61,62]. It is being implemented as a technique using macrolevel prediction. Deep learning algorithms have been used in a few recent research to try to forecast passenger flow. These methods are becoming more common, given the development of real-time data collecting, information dissemination platforms, and transportation network complexity. GNNs, a novel deep learning technique that demonstrates graph dependency by transferring messages between its nodes, are also gaining popularity [53]. However, the complicated temporal and geographical distributions of the metro passenger flow data frequently affect the prediction performance [60]. Furthermore, earlier techniques that either overlooked the metro systems' topological data or learned about it through their physical topology found it challenging to thoroughly study the passenger evolution patterns [55].

Addressing the shortcomings of metro passenger flow considering the short-term forecasting methods was the main emphasis of Zhang et al. [63]. They highlighted the significant time-space complexity, poor accuracy, and ambiguous contributing elements. The study aimed to formulate the data-driven, multi-input, single-output regression prediction issue as a short-term metro passenger flow forecast. In order to obtain greater accuracy and reduced space-time costs in projecting metro station passenger flow, the authors presented an approach based on ST-LightGBM that took transfer passenger flow into account. Using past information as a starting point [48], the problem was first transformed into a regression prediction problem as part of the study's thorough methodology. Significant impact characteristics were found using the maximal information coefficient (MIC) feature selection technique, and these features were then used to form a short-term framework for forecasting metro passenger flow. The light gradient boosting machine (LightGBM) technique served as the foundation for the proposed model (Fig. 3), known for its efficiency and speed, and incorporates spatial transfer features to enhance accuracy [63]. Based on data from Xiamen City's Lianban metro station, the study's

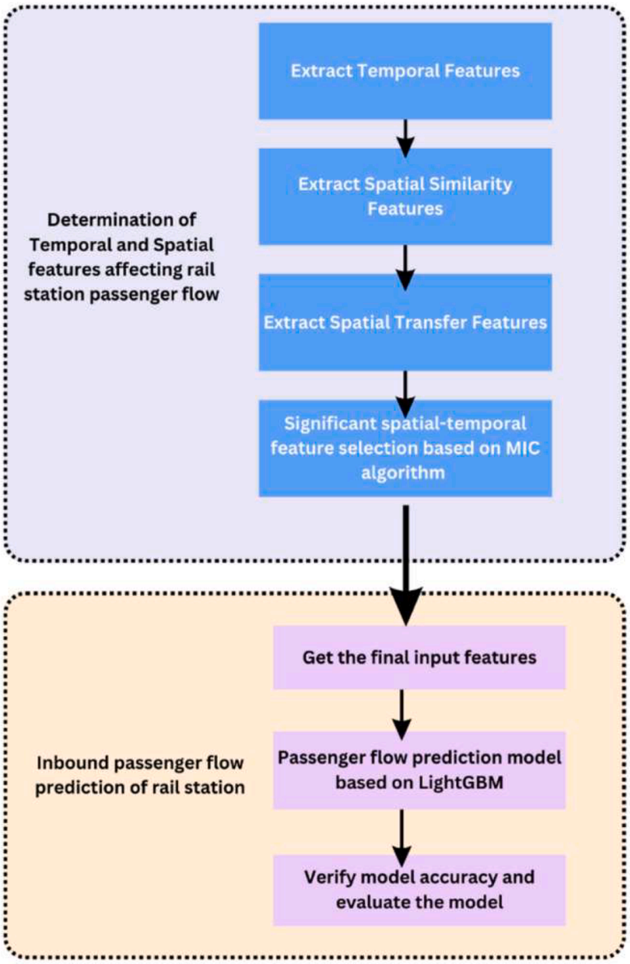

Fig. 3. The proposed ST-LightGBM passenger flow forecast method's framework [63].

experimental findings showed that the suggested approach performed better in prediction accuracy than SARIMA, SVR, and backpropagation networks. The method considered spatial–temporal features comprehensively, mainly accounting for transfer passenger flow, leading to higher efficiency and accuracy in predicting inbound passenger flow at metro stations [63]. The proposed method was supported in terms of scalability, applying to various metro stations [60], conventional bus stations, and BRT stations in different cities. Its drawbacks, however, are its incapacity to forecast at the station level as opposed to the city- or line-level and its limited to forecasting when under the effect of crises. The complexity of feature extraction, especially for spatial transfer features, posed a challenge. Despite these challenges, the suggested approach exhibits excellent prediction effectiveness and precision, making it a viable strategy for short-term passenger flow forecasting in rail transit stations.

The challenges in metro ridership prediction were addressed by Chenz et al. [55] by introducing a unified physical-virtual collaboration graph network (PVCGN). The PVCGN modeled the metro system as a blend of real and virtual graphs with customized designs to capture complicated ridership patterns efficiently. The study's methodologies included building a physical network based on the metro system's realistic topology and creating similarity and correlation graphs influenced by passenger movement between stations. To develop spatial–temporal representations, these complimentary graphs were integrated into a graph convolution GRU (GC-GRU), and the global development tendency was captured by a fully connected GRU (FC-GRU). With GC-GRU and FC-GRU, the final prediction model was a seq2seq framework [55]. The study outcomes demonstrated how effective the suggested PVCGN is in predicting metro ridership at the station level. Comprehensive tests conducted on two sizable measures (Hangzhou Metro and Shanghai Metro) validated the model's ability to predict future metro ridership sequentially. There were, however, potential limitations in handling external factors like weather and holidays [46], which could impact ridership. Additionally, the periodic nature of ridership evolution was acknowledged, suggesting a potential area for improvement. Regardless, the higher performance of PVCGN over other models revealed the creative method of merging real and virtual graphs to capture ridership patterns fully.

The research performed by Baghbani et al. [53] addressed the important problem of predicting short-term passenger flow in bus networks. The study was designed to develop a neural network model called the bus network graph convolutional LSTM (BNG-ConvLSTM) to improve real-time management, emergency response, and route suggestions. The objectives included the GNN approach to effectively get spatial dependencies in transportation networks and utilize the unique integration of graph-based convolutional and LSTM components for both temporal and spatial forecasting of passenger flows. The LSTM component dynamically recorded the temporal relationships in the passenger flow information. The proximity matrix, bus network graph, and adjacency matrix were among the inputs used by the model. Spatial feature extraction relies heavily on the bus network graph convolution (BNGC) operation, a product of an adjacency matrix, a bus network proximity matrix, and a trainable weight matrix [53]. The BNG-ConvLSTM approach performed better for short-term passenger flows network-wide forecasts in terms of scalability and resilience compared to various well-liked deep-learning techniques. The integration of graph-based convolution and LSTM components [46] further contributed to a unique modeling framework not found in the existing literature. At the station level, the suggested model demonstrated exceptional proficiency in identifying temporal and spatial correlations within network-wide passenger flows, providing a noteworthy breakthrough in short-term passenger flow forecasting [53]. However, the study acknowledged that further research is needed to enhance the model by considering additional factors such as weather [10,26], construction, and bus-related variables. While the BNG-ConvLSTM model demonstrates superior performance, it comes with a trade-off in terms of computation time, requiring more time per epoch compared to other models like MLP and CNN. Future research is needed to incorporate additional factors and data sources for a more comprehensive and realistic modeling of short-term passenger flows. The key findings and methodologies surveyed in the present study are summarized in Supplementary Table 1.

5. Information fusion approaches for GNN-based traffic predictions

Information fusion significantly improves the efficiency of traffic predictions based on GNNs and offers a comprehensive method for handling the complexity of urban transportation systems [64]. The ability of information fusion to integrate various data sources provides a thorough and detailed understanding of the factors influencing traffic dynamics. This process involves multiple levels of integration, including feature-level, graph-level, multi-modal, and spatial–temporal fusion. One of the main benefits of information fusion is the increase in prediction accuracy in GNN-based traffic predictions [35,65]. Information fusion also makes better generalization possible by enabling the model to apply learned patterns to various scenarios. Additionally, information fusion improves generalization by allowing GNN models to adapt learned patterns to different scenarios.

5.1. Integrating GNNs with information fusion

A potential strategy to improve prediction accuracy and capture complex spatial dependencies in traffic forecasting models is to combine GNNs with information fusion. Given the interdependent character of traffic networks, GNNs are ideal for modeling complicated relationships within graph-structured data. The integrated models (Fig. 4) are able to successfully detect underlying patterns and predict traffic dynamics because they combine various data sources, including real-time traffic data, historical patterns, and contextual features. With the GNN's data propagation capabilities, spatial dependencies can be included, leading to a more complete picture of traffic flow. Both the model's ability to adapt to changing traffic patterns and the accuracy of short-term predictions are improved by this integration. An intelligent transportation system that is both efficient and dependable can be developed through the ongoing investigation and improvement of GNN-based traffic forecasting models.

To increase the capacity of GNNs, recent research on traffic prediction has focused on integrating multiple data sources through multi-process information fusion. To address the complex nature of traffic dynamics in metropolitan areas, fusion involves combining data from various sources or processes. GNNs are highly effective at maintaining spatial dependencies within transportation systems, which makes them suitable for traffic prediction tasks [20]. However, to increase their predictive accuracy and robustness, researchers have looked into multi-process fusion strategies. One approach is temporal fusion, in which time-dependent variations in traffic conditions are taken into account by integrating the temporal dynamics of traffic patterns into GNNs [66]. Furthermore, road network spatial arrangements are integrated into GNN architectures through spatial fusion techniques, which capture the innate spatial dependencies between various locations [65]. In practical terms, traffic management, intelligent transportation system development, and urban development rely on information fusion in GNN-based traffic predictions. It provides precise and up-to-date data to decision-makers, enabling them to develop more effective and responsive traffic management plans that, in turn, promote safer and more sustainable public transportation.

5.1.1. *Multi-source data fusion*

Enhanced levels of security and alertness in contemporary production vehicles have been made possible by advancements in vehicular perception systems over the past ten years. In order to bridge the perception gaps that individual sources' sensors experience, collaborative perception combines sensor data from several sources. One crucial area of collaborative perception studied by Thornton et al. [67] was the simultaneous association of objects detected by several vehicles. This task was critical because inaccurate object association led to overlooked or replicated detections, which could cause drivers to drive recklessly. For this task, the study proposed a GNN model with an average precision (AP) of 0.882 in a problematic virtual environment with 25 simultaneous, mobile, and unique viewpoints. The model obtained an AP of 0.998 in a more straightforward real-world scenario with two static views, demonstrating that this model could also be easily applied to real-world scenarios. The study's strength was the development of an efficient automated labeling pipeline to manage the substantial volume of data that needed to be labeled. Further research should be done on other real-world factors that affect collaborative perception, such as highly mobile environments, dynamic network availability, and models' vulnerability to adversarial attacks and other malicious activity.

One crucial mission in graph data mining is the prediction of spatiotemporal data. Spatial prerequisites are typically captured by immediately combining features of nearby local vertices in a fixed graph, as is the case with typical spatiotemporal data prediction techniques. By building a feature graph in which the adjacency matrix was continuously generated through DNS, Wang et al. [68] recommended a novel multigraph-based dynamic learning framework that included a novel dynamic neighbor search (DNS) mechanism established to model global dynamic associations between vertices. Following that, there was an additional reduction in the over-smoothing problem with the suggested adaptive heterogeneous representation (AHR) module. The proposed multi-graph fusion block integrated the feature graph and origin graph after they had been introduced into the AHR modules. Furthermore, a differential vertex representation (DVR) module utilized differential information to simulate temporal trends. Employing six practical spatiotemporal records from various cities and domains, thorough experiments demonstrated the outstanding forecasting performances of the recommended multigraph-based dynamic learning structure. This verified the robust efficiency of the proposed framework and its superior generalization ability. However, the need for frequent updates to the multiple graphs may limit the model's ability to adapt to changing traffic dynamics and increase computational complexity, which will affect the model's practicality and responsiveness in scenarios with dynamic traffic.

5.1.2. *Multi-modal forecasting*

In order to improve the precision and comprehensiveness of GNN-based traffic predictions, multi-modal predicting incorporates data

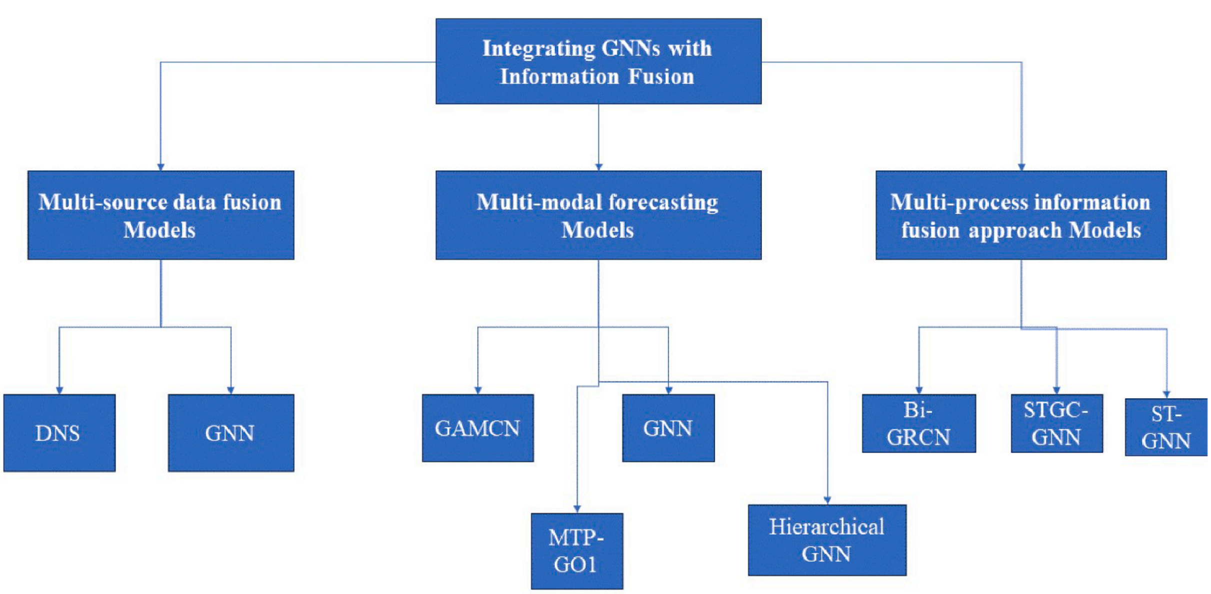

Fig. 4. GNNs integration with information fusion.

from multiple data modalities, including traffic flow, speed, and meteorological conditions. Multi-modal forecasting considers various factors at once to provide a more comprehensive picture of the traffic environment. by using multiple data sources. A graph and attentive multi-path convolutional network (GAMCN) model was presented by Qi et al. [69] as an approach to forecasting future traffic parameters, including speed, for a given road network. The primary emphasis of the model was on the temporal and spatial variables that impact traffic conditions. To represent the spatial factors, a variation of the GCN called the LPGCN was employed to embed the vertices of a road network graph into a latent space where vertices with correlated traffic conditions are close to one another. Further, to model the temporal factors, a multi-path CNN was employed to understand the combined effect of different configurations of previous traffic conditions on future traffic conditions. Evaluations of real-world traffic datasets showed that GAMCN performed better than existing models in terms of time efficiency at around 23.4 % and traffic prediction errors at around 18.9 %. These results made the proposed model highly effective for application in real-world scenarios. With only minor code modifications, TensorFlow distributed training APIs, which distribute training samples among computing units like GPUs, could speed up GAMCN training. However, the time and memory requirements for training GNNs could be high.

GNNs have shown great promise in traffic prediction for autonomous vehicles. This is mainly due to their powerful interconnected predictive bias, which makes multi-agent forecasting possible, allowing for simultaneous predictions for multiple targets. Significant characteristics of the graph-based probabilistic multi-agent trajectory with neural ODEs (MTP-GO) model proposed by Westny et al. [70] included the implementation of a spatiotemporal architecture with specifically built graph gated frequent cells that maintained salient inter-agent communication during the prediction process. The model was designed to be flexible enough to adjust to the constantly changing environment while keeping forecasts reliable for every agent in the scene at the time of prediction, regardless of potential shortages of historical data. To calculate physically possible trajectories that captured the naturally smooth and limited nature of physical motion, the model integrated a dynamic motion model using neural ODEs. The model computed multimodal probabilistic predictions by combining an extended Kalman filter with a mixture density output, which allowed it to capture the inherent uncertainty and multidimensional nature of traffic. One of MTP-GO's most important contributions was its interaction comprehension, which could be linked to the model's capacity to maintain the graph during prediction. Furthermore, the addition of neural ODEs provided the model with important extension properties that enhanced generalization beyond observed data and allowed it to obtain the fundamental variation constraints associated with different road users. MTP-GO underwent evaluations on several naturalistic traffic data sets, showing potential in real-world traffic scenarios and surpassing current methods in various performance metrics.

One of the key developments propelling the transition to smooth and secure transportation is multi-modal mobility (MMM). To maintain the autonomous operation of various modalities while maintaining a comprehensive view of the MMM network, Saeedi et al. [71] proposed a segmentation method. Following the region's division into a uniform collection of hexagon-shaped cells, features related to various modes of transportation were extracted. Segmentation can be considered a means of sharing information among different modes and integrating local data for analysis. A GNN-based model was also implemented to encode the features and network structure into lower dimension embedding. The evaluation of the clustering approach on an open multimodal real-world dataset showed that each group of cells had a similar demand pattern. The study's strength was its understanding of demand patterns, which could help with macro and micro decision-making for the transportation system. Nevertheless, the study did not assess the suggested model using a dataset that comprised ride-hailing and private transportation services.

To simulate the connections of heterogeneous traffic attendees, such as cars, pedestrians, and riders, in conjunction with LSTM to forecast their routes, a hierarchical GNN framework was proposed by Li et al. [72]. The proposed framework consisted of two modules with two GNNs for trajectory prediction (TP) and interactive events recognition (IER). The IER module can identify when the ego vehicle interacts with other drivers or pedestrians on the road. The TP module is designed to predict the interactive trajectory and take the recognized results as input. Furthermore, LSTM and GNN were used to carry out the multi-step prediction in the TP module. The suggested hierarchical framework was validated by the naturalistic driving data collected from the metropolitan environment. The hierarchical GNN framework demonstrated exceptional performance in identifying interactive events and predicting dynamic behaviors, as demonstrated by comparisons with cutting-edge techniques. In terms of average displacement error (ADE) and final displacement error (FDE), the suggested framework performed better than alternative baseline techniques. By including a category layer for every kind of participant, the proposed framework solved this issue and achieved 91–98 % accuracy in IER recognition. Combining the benefits of maneuver-based and interaction-aware methods, the recommended hierarchical framework outperformed traffic-predicted GNN in prediction performance.

5.1.3. Multi-process information fusion approaches

Bidirectional-graph recurrent convolutional network (Bi-GRCN), an innovative spatio-temporal model, was proposed by Jiang et al. [73] to predict the traffic flow based on a GNN that took into account the importance of the structure and the correlation of traffic flow data considering the time dimension. To capture the distinctive features of the model, the spatial dependence between traffic flow data and traffic roads was the primary objective of the GCN. The Bi-GRU was employed to simultaneously analyze historical and prospective information, accounting for the traffic flow data's temporal dependence throughout its time-series period. Bi-GRCN executed better in accuracy and traffic prediction performance than GCN and GRU, indicating the model's capacity to predict medium- and long-term traffic flow in addition to short-term traffic flow. Additionally, Bi-GRCN proved to be more successful in traffic prediction than the conventional techniques of historical average (HA), ARIMA, and SVR. However, other elements that might affect traffic prediction, like the weather, weekdays, holidays, and traffic accidents, weren't taken into consideration.

A spatial–temporal Granger causality framework was proposed by He et al. [74] to model spatial geographic variation in the road network. Compared to the local and steadfast connectivity produced by the spatial distribution of the road network, the recommended spatial–temporal causality accomplished better in the range of 45-min and 60-min long-term predictions because it was capable of capturing the long-range dependence and approximated the relationship of dynamic traffic flow transmission from the long-term observed traffic flow. Following the final analysis, a directional causal relationship was discovered that precisely complemented the source-node and target-node of an actual traffic system. At the individual node prediction level, the proposed model improved the prediction over all horizons for intersectional, boundary, and distant nodes. This illustrated the effectiveness of the GDTi transfer capture method compared to a spatial graph.

High-coverage detection devices assist road users in planning their routes and avoiding blockages in traffic; nevertheless, employing this data comes with unique challenges, such as dynamic temporal association and dynamic spatial coherence brought on by variations in road conditions. Le et al. [75] suggested the novel model DetectorNet to improve the implementation of spatial–temporal graph-based traffic prediction. By applying various modules, including the Multi-view Temporal Attention module, DetectorNet could accurately predict traffic flow by taking into account not only the initial static data but also the dynamic connection of the road structure. Furthermore, the outcomes of two publicly available dataset experiments and comparing four ablation experiment results demonstrated that DetectorNet outperformed the eleven sophisticated baselines in effectiveness. The recommended multi-view temporal consideration module and the dynamic spatial graph convolutional network enhanced the learning of the spatial correlation of multiple traffic scenarios and the temporal correlation of different views, respectively. However, there may be challenges, such as complex spatial–temporal correlation, with the detector network-based traffic prediction problem. A comparison is made in Table 1 between the identified challenges and benefits of the information fusion approaches. The studies incorporating GNNs with information fusion have been summarized in Supplementary Table 2.

5.2. Case studies and real-world applications

GNN-based traffic prediction models have been effectively used by several cities as part of their smart city projects. Singapore is a remarkable case study since it optimized its public transportation infrastructure by implementing a GNN-based traffic prediction system [76]. The GNN model reliably forecasts traffic conditions over multiple road segments and crossings by evaluating real-time traffic flow data from several sources, such as GPS-enabled cars and traffic sensors. By rearranging traffic and dynamically adjusting traffic signal timings, the system interacts with the city's Intelligent Transportation Systems (ITS) to enhance general traffic flow and lessen traffic congestion.

Table 1
Strengths and shortcomings of the information fusion techniques for GNN-based traffic predictions.

Performance	Multi-source data fusion	Multi-modal forecasting	Multi-process information fusion
Strengths	- Data quality and reliability are enhanced by merging information from different sources.	- The predicted phenomenon becomes understood more thoroughly when multiple modalities are utilized.	- Enables data incorporation at different processing stages, facilitating flexibility in response to various scenarios.
	- It strengthens the system's ability to handle anomalies, outliers, and missing information from specific sources.	- In complex systems, in particular, better predictions can be achieved by combining data from several modalities.	- Facilitates scalability through the incorporation of supplementary processes as required.
	- Enables a more holistic comprehension of the situation by incorporating various points of view.	- Having redundancy in multiple modalities can help reduce the risks of uncertainties in each modality.	- Capable of maximizing efficiency by combining the best features of various fusion methods (e.g., fusion at the decision level).
Shortcomings	- It can be computationally intensive and technically difficult to integrate data from different sources.	- Information integration from various modalities necessitates advanced algorithms and methodologies.	- Using fusion algorithms correctly at each processing stage can be demanding and complex.
	- Data management becomes more challenging when dealing with various resolutions, formats, and semantics.	- Proficiently interpreting and integrating information from various modalities requires expertise in several fields.	- The potential for increased computational burden arises from the requirement for numerous fusion processes.
	- Depends substantially on the accessibility and availability of various data sources.	- Data synchronization and alignment across various modalities are not always easy to achieve.	- Final fused outputs may be less interpretable if integrated across several processes.

Techniques for forecasting and simulating highway traffic are essential for automated transportation systems. For a variety of traffic forecasting challenges, deep-learning-based techniques have recently become the standard of the industry. Nevertheless, these techniques necessitate a substantial volume of training data, which must be gathered over an extended duration. To estimate short-term traffic volumes on an expressway network, Mallick et al. [77] developed TL-DCRNN, a transfer learning strategy for the diffusion convolution RNN based on graph partitioning. The fundamental roadway network was divided into multiple areas by TL-DCRNN by restricting geographically specific patterns. The spatiotemporal traffic characteristics were subsequently examined as a function of the traffic state and the network connection. The efficacy of TL-DCRNN was then demonstrated by using the trained model to predict traffic on inaccessible portions of the highway network structure, employing a year's worth of traffic data from California obtained from the Caltrans Performance Measurement System. Furthermore, transfer learning between the Los Angeles and San Francisco regions may be accomplished by the model trained using the TL-DCRNN technique. Regardless of being implemented in an area that was not observed during training, TL-DCRNN surpassed standard techniques utilized in large-scale traffic forecasting, such as autoregressive model incorporated moving average, feed-forward neural network, support vector regression spatiotemporal graph convolutional network, and fully connected LSTM. These findings provided compelling proof that even in a shortage of substantial historical data, researchers and practitioners might start implementing cutting-edge forecasting techniques like TL-DCRNN in their regions. Through enhanced forecasting at lower infrastructure development costs, this innovative capability allowed practitioners to use modern facilities techniques trained on datasets obtained from other sources, enabling a wide range of transportation system operations. Graph-partitioning-based transfer learning for traffic prediction may face challenges and lead to inadequate partitioning because traffic patterns are dynamic.

Brimos et al. [78] investigated how to use cutting-edge deep learning algorithms to exploit traffic open-government data (OGD). This study showed that real-time traffic data from the Greek open-data portal and OGD for generating models that accurately predicted traffic flow were two necessary resources to construct more sophisticated GNN algorithms. These algorithms were diffusion convolutional RNN (DCRNN) and temporal GCN (TGCN). Nevertheless, the quality and quantity of the data used to train GNNs significantly affected their effectiveness. OGD presented a unique chance to access enormous volumes of data from numerous sources. Moreover, the accessibility of OGD from various governments and nations made it possible to develop more thorough models that can be applied to predicting traffic patterns in various locations and weather scenarios. Ultimately, historical traffic data was employed in most traffic projection investigations at short intervals, usually every five or fifteen minutes. However, the primary focus of this study was on the Greek OGD traffic data case, which collected traffic data hourly. The application of OGD in deep learning scenarios was a strong point of the study. This could result in the development of more robust and consistent traffic-forecasting deep learning algorithms as well as the provision of innovative and useful public services to the public and private sectors.

Table 2 presents a list of case studies and real-world applications that demonstrate the use of information fusion approaches for traffic predictions based on GNNs.

Multiple models concentrating on spatial and temporal feature processing and spatial–temporal fusion were discussed in the surveyed studies. The common factors and strategies used across these models are summarized in Table 3.

Table 2
Summary of case studies and real-world applications.

Case studies/ application	Study	Objective	Outcome	Advantages	Disadvantages
Automated transportation System (USA)	Mallick et al. [77]	Estimation of short-term traffic volumes on an expressway network	TL-DCRNN surpassed common techniques utilized in large-scale traffic forecasting	- Permitted a variety of transportation system - Sustainable and cost-effectively through better forecasting	The dynamic nature of traffic patterns may cause difficulties and result in inefficient partitioning.
Smart city (India)	Sharma et al. [20]	The interaction of road sections and real-time traffic speed evaluation	The experiment's results validated 96.67 % and 98.75 % prediction accuracy values for the PeMSD4 and PeMSD8 datasets.	Demonstrated exceptional proficiency in preserving spatial dependencies and complex relationships for traffic prediction.	Sensitivity to graph structures, scalability issues, and high computational requirements
Public service (Greece)	Brimos et al. [78]	Forecasting Traffic Flow	Accurately predicted traffic flow employed to develop more sophisticated GNN algorithms.	By utilizing OGD in deep learning scenarios, more robust and consistent traffic forecasting algorithms were developed.	Complicated temporal dependencies that may lead to limited interpretability and overfitting.

Table 3
Common factors and strategies used for spatial and temporal processing and spatial–temporal fusion.

Spatial feature processing	Temporal feature processing	Spatial–temporal fusion
- Integration of different methods, including pooling layers and skip connections, to maintain spatial information and effectively manage different scales.	- Utilization of methods such as GRU or LSTM to model temporal dynamics.	- Temporal and spatial features are integrated at various phases of the model's architecture.
- Implementing efficient architectures for spatial feature extraction, such as DenseNet, ResNet, or Inception.	- Attention mechanisms are considered in order to suppress noise and emphasize pertinent temporal features.	- The process of learning feature representations that incorporate temporal and spatial information through a combined training of temporal and spatial components.
- Use of CNNs for extracting spatial features from input data or images.	- Capturing sequential patterns and temporal dependencies in data by integrating RNNs, TCNs, or transformers.	- Using fusion modules or layers to efficiently combine temporal and spatial features.

6. Challenges and benefits associated with GNN-based traffic forecasting

GNNs offer several benefits in traffic forecasting, as presented in Table 4. One significant advantage is their ability to depict complex spatial interdependencies characteristic of traffic networks. The complicated interrelationships between different road segments can be effectively represented by GNNs, which conceptualize roadways as nodes and traffic flow as edges in a graph. The utilization of GNNs in this manner facilitates more accurate predictions of travel durations and congestion trends [49]. By employing this approach, GNNs are capable of discerning spatial hierarchies and interdependencies, such as the repercussions of congestion in a particular area on neighboring regions. Furthermore, GNNs exhibit exceptional compatibility with dynamic and ever-changing traffic conditions, which empowers them to adapt to road infrastructure variations promptly. Graph neural networks (GNNs) are exceptionally efficient tools for improving the accuracy of traffic forecasts due to their capacity to integrate spatial and temporal data.

The utilization of GNNs for traffic forecasting presents a series of obstacles (Table 4). A notable obstacle that may arise is the ever-changing nature of traffic networks, which can result in fluctuations in the structure of the graph due to road closures, accidents, or abrupt changes in demand. The computational challenge of adapting GNNs to these dynamic graphs necessitates ongoing model retraining to achieve optimal performance [79]. In addition, significant challenges related to scalability emerge in the context of complicated and massive traffic networks, thereby demanding hardware resources and algorithms that operate efficiently. An additional issue is the interpretability of GNN-based models [80]. Their complex architecture may obscure the reasoning behind particular predictions, thereby questioning the forecasts' accuracy and trustworthiness. To overcome these obstacles, continuous research endeavors are necessary to improve the resilience, expandability, and comprehension of GNNs to facilitate traffic forecasting applications that are both efficient and trustworthy.

Table 4
Benefits and challenges of using GNNs in traffic prediction.

Aspect	Advantages	Challenges
Scalability	Capable of adapting extensive and complicated traffic networks.	Sufficient resources and efficient algorithms are necessary to achieve scalability.
Interpretability	Improves the interpretation of complicated traffic patterns.	GNNs are frequently considered as models with limited interpretability, often referred to as "black-box" models.
Spatial dependency modeling	Effectively represents complicated spatial relationships within traffic networks.	The computational demands associated with coping with dynamic structures in graphs can be significant.
Relations with external factors	Takes into account external variables such as weather conditions and events.	Efficient incorporation of external variables should be ensured for reliable forecasts.
Transferability	Has the potential to be modified and applied to various geographic locations.	The process of generalizing data across various regions may present certain challenges.
Temporal dependency modeling	Successfully models the temporal dynamics associated with traffic patterns.	Typical GNNs may encounter difficulties in effectively capturing dependence over time.
Training efficiency	Highly effective training approaches enhance scalability.	The computational requirements for training large-scale GNNs can be substantial.
Noise and anomaly resistance	Able to detect anomalies while remaining robust to erratic input data.	Anomalies must be managed in real-time, and the system must be resilient to noise.
Edge weights and feature design	Allows for the weights and features of edges to be learned.	Optimization of edge weights and features may be challenging to determine.
Scattered data and sampling	Supports traffic data that is sparse and has irregular sampling.	Must effectively address any missing or insufficient information.

7. Future insights

Future traffic forecasts indicate a positive trend toward enhancing fusion methods employing GNNs. It is expected that the integration of GNNs with supplementary technologies, including conventional traffic models and sophisticated data analytics, will result in traffic predictions that are more precise and resilient. Future studies will potentially center on GNN architectures to successfully manage the complex and continuously changing features inherent in traffic networks. This will address concerns about temporal dependencies, scalability, and the capacity to adapt to real-time changes. Applying GNNs for traffic forecasting can substantially revolutionize urban planning and accelerate the progress of smart cities. GNNs have the potential to assist in the forecasting of traffic congestion patterns, the optimization of traffic flow, and the overall improvement of transportation efficiency. In addition to their application in traffic management, GNNs have far-reaching implications for urban planning strategies, encompassing energy optimization, sustainable development practices, and infrastructure design. With its ongoing development, GNN-based traffic forecasting is to be found to influence the development of smart cities significantly, fostering urban environments that are more intelligent and resilient.

7.1. Potential enhancements in GNN-based fusion methods

Advancements in GNN-based fusion techniques for traffic forecasting can significantly enhance the precision and flexibility of predictive models. An area that requires considerable enhancement is the integration of varied data sources into GNN frameworks. This would enable the incorporation of components such as public transportation schedules, weather conditions, and special events. By utilizing multimodal fusion, a greater understanding of the complicated interactions that impact traffic patterns can be achieved, thereby improving the model's ability to represent discrete relationships across the urban transportation network. Furthermore, the integration of GNNs with conventional traffic models offers a potentially effective strategy to capitalize on the respective advantages of each paradigm. Hybrid models, which integrate the spatial dependency capturing capabilities of GNNs with the established principles of conventional traffic engineering, provide an in-depth perspective that enhances the reliability and accuracy of traffic predictions.

Temporal dynamics constitute an additional crucial element that promises improvement in fusion methods based on GNNs. The advancement of methods that efficiently represent and forecast temporal dependence, considering fluctuations across various time scales, can substantially enhance the accuracy of traffic predictions. In addition, an increasing emphasis is being placed on the ability to adapt in real time. Efforts are being made to develop fusion methods that can dynamically modify the structure of the graph to account for changing traffic conditions. The model's capacity to adapt guarantees its continued efficacy within dynamic circumstances, including but not limited to road closures, accidents, and sudden changes in demand. With the progression of these advancements, fusion methods based on GNNs have the potential to significantly impact the domain of traffic forecasting, thereby contributing to the development of more robust and effective urban transportation systems.

7.2. Emerging areas of research and application

The emerging fields of study involving traffic forecasting using GNNs are distinguished by various innovative techniques designed to tackle the complex issues posed by urban transportation systems. Improving the ability of GNN architectures to process dynamic graph structures in real-time is a primary objective. Researchers are investigating approaches to dynamically modify the graph representation in response to evolving traffic conditions. This ensures the model remains alert to unexpected changes, such as road closures or accidents. In addition, an increasing number of stakeholders and decision-makers are concerned with the interpretability of GNNs in traffic forecasting. It is critical to understand the reasoning behind model predictions to establish reliability. Investigating explainable AI methods within GNN frameworks is emerging as a critical area of study, illuminating the complex interactions and characteristics that contribute to precise traffic forecasts.

GNNs are discovering innovative applications that extend beyond conventional traffic forecasting circumstances. A noteworthy domain refers to incorporating GNNs into smart city endeavors, wherein these models make valuable contributions to urban planning and development strategies. GNNs possess the capability to optimize the flow of traffic, mitigate congestion, and improve the overall efficiency of transportation within smart cities. In addition, scholars are investigating the potential of GNNs to mitigate environmental sustainability issues by optimizing traffic management to decrease energy consumption and emissions. With the ongoing development of smart city infrastructure, integrating GNNs with real-time data streams is crucial in developing more resilient and adaptable urban transportation systems. The expanding scope of GNN-based traffic forecasting is exemplified by these emerging research and application domains, which transcend conventional prediction tasks and adopt an integrated approach to developing more innovative, environmentally friendly cities.

7.3. Implications for urban planning and smart cities

The transformative potential of GNN-based traffic forecasting for smart cities and urban planning is immense, as it enables the development of more sustainable and efficient urban environments and the optimization of transportation systems. By providing precise forecasts of traffic patterns, GNNs significantly contribute to urban planning by empowering city planners to make well-informed decisions regarding traffic management and infrastructure development. By capturing complicated spatial relationships in traffic networks, GNNs enable the detection of critical traffic bottlenecks, which facilitates the implementation of targeted interventions to mitigate congestion and enhance the overall traffic flow. This insight is of immense value in improving road networks, developing streamlined public transportation routes, and strategically situating critical urban facilities.

GNN-based traffic forecasting is of the utmost importance in smart cities as it significantly improves the intelligence and responsiveness of urban infrastructure. GNNs contribute to developing adaptive traffic management systems that respond promptly to changing conditions by utilizing real-time data streams and dynamic adaptability. This enhances the efficiency of residents' daily transportation and contributes to achieving sustainability targets by reducing emissions and energy usage. Incorporating GNNs into smart city initiatives is consistent with a more comprehensive goal of developing technologically advanced urban environments that are also adapted to the requirements of their inhabitants. With the ongoing evolution of smart cities, the effects of traffic forecasting utilizing GNNs transcend immediate transportation issues and assist in the development of urban environments that are more habitable, resilient, and sustainable.

8. Conclusions

Graph neural network (GNN)-based information fusion techniques provide an advanced and efficient way to capture the complex dynamics found in urban transportation systems. The model can identify complex patterns by combining temporal and geographical dependencies in a graph structure, leading to higher forecasting accuracy than existing techniques. Based on the importance of GNN-based traffic forecasting, the present work comprehensively reviewed information fusion approaches for enhancing GNN-based traffic predictions along with their benefits and challenges. It also provided future insights on the potential enhancements and emerging research areas in GNN-based fusion methods and their implications in urban planning and smart cities. GNNs have proven to be effective in identifying spatial dependencies across traffic networks. An essential result is the capacity to simulate the impact of traffic conditions at one location on adjacent locations. Integrating information fusion techniques with GNNs improves the model's ability to comprehend complex spatial connections, resulting in more precise traffic predictions. GNN-based information fusion can potentially increase the resilience and efficiency of urban transportation systems, as evidenced by the observed gains in forecasting accuracy. By providing a solid framework for developing adaptable models that can handle the changing difficulties of contemporary urban mobility, many previous researches offer significant insights to transportation authorities and urban planners. The potential for revolutionizing the field of traffic forecasting is apparent when sophisticated deep learning methods are combined with transportation analytics. Innovative solutions are needed to keep up with the continual evolution of urban surroundings. The development of intelligent and adaptive traffic management systems in the future will be greatly influenced by additional study and improvement of these methods.

CRediT authorship contribution statement

Shams Forruque Ahmed: Writing – original draft, Supervision, Investigation, Formal analysis, Conceptualization. **Sweety Angela Kuldeep:** Writing – original draft, Formal analysis. **Sabiha Jannat Rafa:** Writing – original draft, Investigation. **Javeria Fazal:** Writing – original draft, Software, Formal analysis. **Mahfara Hoque:** Writing – original draft, Formal analysis. **Gang Liu:** Writing – review & editing, Investigation. **Amir H. Gandomi:** Writing – review & editing, Supervision.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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Supplementary materials

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