Traffic Prediction Using Spatio-Temporal Data in Intelligent Transportation Systems: A Survey

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Abstract

In the evolving landscape of urban mobility, accurate traffic prediction is pivotal for enhancing intelligent transportation systems and fostering smart city development. This survey paper delves into the utilization of spatio-temporal data, deep neural networks, and machine learning techniques to advance traffic prediction models. Emphasizing the significance of these methodologies, the survey outlines the integration of temporal information and hypernetwork architectures as critical for urban planning and transportation efficiency. Key models like T-GCN and Auto-DSTSGN demonstrate superior performance in capturing spatial-temporal dependencies, significantly outperforming traditional methods. The paper also addresses challenges in data quality and real-time prediction, highlighting innovative approaches such as Loc-GCLSTM and xTP-LLM, which enhance prediction accuracy and provide explainable insights. By integrating diverse data sources and leveraging advanced algorithms, traffic prediction models contribute to optimizing urban mobility and supporting the development of sustainable, resilient smart cities. The survey concludes by underscoring the potential of these advanced frameworks to improve urban planning and transportation systems, ultimately enhancing the quality of life in urban environments. Future research directions include optimizing computational efficiency, integrating external factors, and exploring model adaptability to ensure robust and reliable traffic predictions.

1 Introduction

1.1 Significance of Traffic Prediction

Accurate traffic prediction is essential for the development of intelligent transportation systems, significantly improving urban mobility and transportation efficiency. As urbanization progresses, forecasting traffic conditions—such as speed and volume—becomes crucial for mitigating congestion and its economic repercussions [1]. Effective prediction models optimize traffic flow, facilitating resource allocation and infrastructure planning in complex urban settings.

Traditional traffic prediction methods often struggle with high computational demands and inadequate modeling of spatiotemporal patterns. Consequently, innovative approaches that leverage deep learning and advanced data analytics are necessary. By utilizing correlation information among spatiotemporal sequences, contemporary traffic prediction frameworks enhance the accuracy and reliability of forecasts, which are vital for the efficient management of urban transportation networks [2].

The incorporation of advanced predictive models into intelligent transportation systems not only improves urban mobility but also fosters the development of sustainable urban environments. As cities expand, robust traffic prediction models are crucial for supporting smart city initiatives and enhancing urban life quality [3]. Additionally, advancements in mobile Internet and positioning technologies have significantly improved traffic forecasting, highlighting its pivotal role in intelligent transportation systems [4].

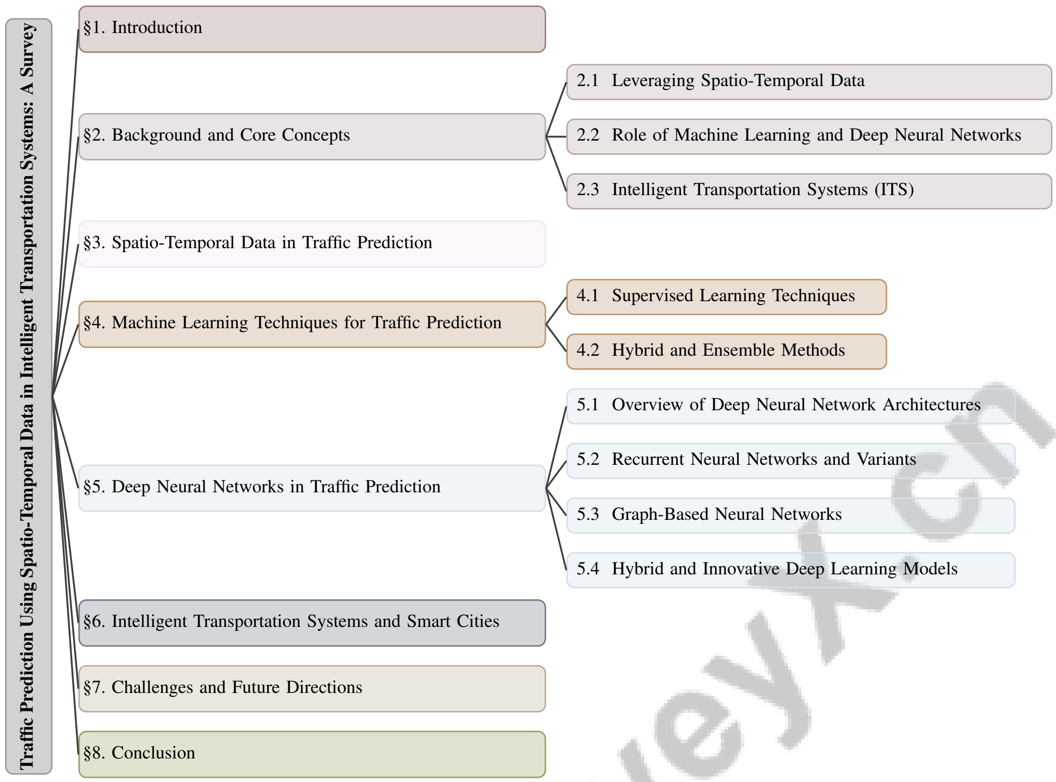

Figure 1: chapter structure

1.2 Structure of the Survey

This survey is structured to provide a thorough understanding of traffic prediction utilizing spatio-temporal data within intelligent transportation systems. The introductory section emphasizes the significance of traffic prediction and its impact on urban mobility and transportation efficiency. Following this, foundational concepts such as spatio-temporal data, machine learning, deep neural networks, and the framework of intelligent transportation systems are explored.

The survey then delves into spatio-temporal data in traffic prediction, focusing on data collection, processing, and integration techniques. This is succeeded by an examination of machine learning techniques, discussing both supervised learning and advanced hybrid methods. The section on deep neural networks investigates various architectures, including recurrent and graph-based networks, highlighting their efficacy in capturing complex traffic patterns.

Subsequently, the integration of intelligent transportation systems into smart city frameworks is analyzed, showcasing the advantages and applications of traffic prediction models in urban planning [5]. The survey concludes with a discussion on current challenges and future research directions, providing insights into the evolving landscape of traffic prediction technologies and their prospective advancements [6].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Leveraging Spatio-Temporal Data

Spatio-temporal data is key to accurately modeling urban transportation dynamics by integrating spatial and temporal dimensions, which traditional methods often overlook [7]. Techniques like the Bayesian Spatio-Temporal Graph Convolutional Network (BSTGCN) enhance predictive accuracy by learning graph structures from road networks and traffic data [1]. The CorrSTN model improves traffic flow forecasts by leveraging spatial and temporal dependencies through SCorr and TCorr representations, further enhanced by self-supervised learning [2, 8]. The STGNPP model integrates spatio-temporal graph learning with neural point processes to predict congestion events, showcasing the potential of these data types in complex traffic forecasting [7].

Static graph models often neglect dynamic spatial dependencies, necessitating approaches that account for temporal variations [9]. Social media features, particularly from platforms like Twitter, enhance traffic predictions by utilizing spatio-temporal data [10]. This data is also critical for capturing mobile traffic dynamics influenced by user mobility and device heterogeneity [11]. In contexts with limited historical data, techniques to mitigate overfitting are crucial, addressing challenges posed by numerous trainable parameters [12]. Models that integrate anomaly awareness improve prediction accuracy by accommodating unexpected events [13]. Novel data sources, like video camera streams, offer new methodologies for estimating traffic metrics [14].

The integration of spatio-temporal data with distributed deep learning solutions at base stations highlights the potential of Knowledge Transfer Learning (KTL) to enhance model performance [15]. These advancements are vital for developing robust traffic prediction models, crucial for optimizing urban mobility, reducing environmental impacts, and fostering intelligent transportation systems.

2.2 Role of Machine Learning and Deep Neural Networks

Machine learning and deep neural networks significantly enhance traffic prediction by managing the complexities of spatio-temporal data. Techniques like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) automatically extract relevant features, facilitating accurate traffic condition predictions. The integration of CNNs with RNNs for mobile traffic prediction at the edge, alongside Knowledge Transfer Learning (KTL), optimizes training processes and reduces energy consumption [15]. Recurrent Neural Networks, including Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), excel in modeling temporal dependencies crucial for forecasting traffic flow [5]. Advanced techniques like Transformers and XGBoost further enhance prediction accuracy by leveraging complex data patterns [5].

Graph-based models, such as 3D Temporal Graph Convolutional Networks (3D-TGCN), improve prediction accuracy through learned traffic patterns [16]. The Multi-Weight Traffic Graph Convolutional (MW-TGC) network effectively models spatio-temporal dependencies using multi-weighted adjacency matrices [17]. The Spatio-temporal Neural Structural Causal Model (STNSCM) employs causal graphs and counterfactual reasoning to enhance prediction accuracy, providing deeper insights into spatial and temporal relationships [18]. Innovative frameworks like CorrSTN incorporate correlation information into dynamic graph neural networks and attention mechanisms, significantly improving existing methods [2]. The DSTCGCN model employs a dynamic approach to capture spatial and temporal dependencies [9]. The Spatial-Temporal Hypergraph Neural Network (STHODE) method integrates spatial and temporal hypergraphs with ordinary differential equations to enhance modeling of spatio-temporal dependencies [4].

These models promise to enhance the reliability and effectiveness of traffic prediction systems, supporting the ongoing development of intelligent transportation systems and smart city initiatives by addressing challenges such as spatial and temporal heterogeneity [8].

2.3 Intelligent Transportation Systems (ITS)

Intelligent Transportation Systems (ITS) transform traffic management by utilizing advanced technologies to improve the efficiency and safety of transportation networks. ITS integrates components like sensors, communication technologies, and data analytics to enhance traffic management. By leveraging real-time transportation data, ITS predicts traffic flow patterns, optimizes urban planning, and improves vehicle routing, leading to significant congestion reductions. The application of artificial intelligence and edge computing within ITS allows for rapid and secure processing of heterogeneous data, addressing urban mobility complexities while promoting sustainable transportation solutions [19, 20, 21, 22, 23]. ITS is crucial in modern urban environments, where sophisticated solutions are essential to manage traffic complexities.

The integration of Machine Learning (ML) and Internet of Things (IoT) technologies within ITS frameworks has significantly advanced smart transportation systems, enabling real-time data collection and analysis [24]. By employing ML algorithms, ITS can predict traffic patterns and optimize traffic signals, reducing delays and improving overall traffic efficiency. ITS encompasses both

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supply-side strategies, like traffic management systems, and demand-side strategies, including user navigation and route optimization [25]. This dual approach ensures effective responses to varying demands and conditions, benefiting both traffic operators and commuters.

A critical aspect of ITS is its capability to model traffic states using various graph types, which are instrumental in understanding and forecasting traffic conditions [26]. These graph-based models enable accurate predictions and effective management strategies. ITS enhances operational efficiency and contributes to the evolution of smart cities by integrating advanced communication technologies, information processing, and control systems. This integration is optimized through AI-driven solutions that facilitate better urban planning, vehicle routing, and congestion management. As urban populations are projected to increase significantly by 2050, the implementation of ITS is vital for sustainable urban environments and addressing rapid urbanization challenges [22, 27]. ITS plays a crucial role in creating sustainable and resilient urban mobility solutions tailored to growing urban populations' needs.

3 Spatio-Temporal Data in Traffic Prediction

3.1 Data Collection and Processing

The collection and processing of spatio-temporal data are foundational for accurate traffic prediction models, requiring advanced methodologies to capture the intricate dynamics of traffic systems. Effective strategies involve deploying sensors and GPS systems to gather comprehensive historical traffic data, which is then processed using techniques like Dynamic Time Warping to compute time series similarities, crucial for understanding traffic patterns [16]. Preprocessing steps, such as binning GPS coordinates and timestamps, exemplify the meticulous approach needed for effective data handling [3].

As illustrated in Figure 2, the hierarchical structure of data collection and processing methodologies in traffic prediction models is depicted, highlighting key data collection techniques, modeling frameworks, and advanced techniques. Advanced modeling frameworks like the Spatio-Temporal Graph Neural Point Process (STGNPP) and the Bayesian Spatio-Temporal Graph Convolutional Network (BSTGCN) enhance predictive capabilities by modeling historical traffic states and adapting graph structures based on observed data, thus improving forecast accuracy [7, 1]. The Spatio-Temporal Self-Supervised Learning (ST-SSL) method refines data processing by constructing traffic flow graphs from historical data [8], while the Multi-Weight Traffic Graph Convolutional (MW-TGC) network uses multiple geometric characteristics to create weighted adjacency matrices, facilitating a nuanced understanding of traffic dynamics [17].

Dynamic graph neural networks, such as the CorrSTN model, employ multi-head attention mechanisms to capture complex spatio-temporal relationships, enhancing forecasting accuracy [2]. The Spatio-Temporal Neural Structural Causal Model (STNSCM) integrates causal modeling to predict traffic flow, showcasing the potential of advanced data processing techniques [18]. Empirical validation from real-world datasets, such as those from the Caltrans Performance Measurement System (PeMS), underscores the effectiveness of these methodologies in optimizing urban mobility and advancing intelligent transportation systems [4].

3.2 Integration of Diverse Data Sources

Integrating diverse data sources is vital for developing comprehensive traffic prediction models, enhancing the ability to capture the multifaceted nature of traffic systems. Incorporating various data types, such as online crowd query data and road intersection information, enables models to achieve a more nuanced understanding of traffic dynamics [28]. The Dynamic Graph Convolutional Recurrent Network (DGCRN) exemplifies this by generating dynamic graphs that adaptively reflect changes in traffic data, thereby improving prediction accuracy [29].

The combination of traffic density and weather data is essential for comprehensive traffic predictions, as these additional layers provide insights into external factors influencing traffic patterns [5]. However, maintaining consistency across diverse datasets poses significant challenges, particularly in multi-source environments [30].

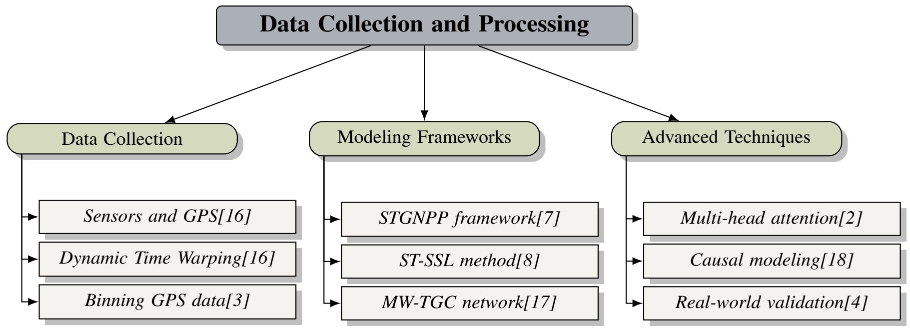

Figure 2: This figure illustrates the hierarchical structure of data collection and processing methodologies in traffic prediction models, highlighting key data collection techniques, modeling frameworks, and advanced techniques.

Advanced methodologies address these challenges through sophisticated data fusion techniques, such as the interactively- and integratively-connected deep recurrent neural network (I²DRNN), which harmonizes disparate data sources, including trajectories and traffic flow, into a cohesive framework. This approach enhances forecasting accuracy, particularly in scenarios with limited data or multiple transportation modes, improving representation and predictive capabilities of smart mobility systems [31, 32]. By leveraging diverse data inputs, integrated models provide a comprehensive basis for traffic prediction, optimizing urban mobility and supporting intelligent transportation systems.

3.3 Data Preprocessing and Feature Engineering

Data preprocessing and feature engineering are crucial for enhancing traffic prediction model performance, especially amidst the complexities of spatio-temporal data. The intricacies of deep learning models, while offering advanced predictive capabilities, can lead to overfitting, particularly in limited data scenarios [33]. This necessitates robust preprocessing techniques to mitigate overfitting and improve model generalization.

A significant challenge lies in effectively representing traffic data in graph structures, essential for capturing real-time traffic conditions [27]. The Dynamic Spatio-Temporal Graph-based Convolutional Neural Network (DST-GCNN) introduces a novel convolutional layer that captures both spatial and temporal dependencies, distinguishing it from traditional static methods [34]. This underscores the importance of adaptive preprocessing techniques that respond to evolving traffic patterns.

Feature engineering plays a vital role in extracting meaningful insights from raw data, enhancing model performance. Techniques such as statistical analysis and machine learning-based feature extraction improve the detection of road anomalies and aggressive driving behaviors [35]. The NodeTrans model illustrates the effectiveness of clustering-based mechanisms in identifying common spatial-temporal patterns [36].

Managing large and noisy datasets presents significant challenges for data preprocessing, necessitating strategies that address the volume and variability of traffic data [23]. The absence of a unified framework for accommodating varying data formats complicates the integration of diverse sources, affecting the effectiveness of existing techniques [30]. Innovative approaches are required to enhance data quality and consistency, ultimately leading to more accurate and reliable traffic predictions.

4 Machine Learning Techniques for Traffic Prediction

4.1 Supervised Learning Techniques

Supervised learning techniques are integral to traffic prediction, leveraging historical datasets to model and forecast traffic conditions with high accuracy. These methods excel in capturing spatio-temporal dynamics, enhancing predictive performance. The MTSP-DL framework, for instance, employs deep learning to predict future traffic speeds by managing temporal dependencies effectively [37]. Similarly, the ST-NN model uses historical taxi trip data to forecast travel time and distance, demonstrating practical efficacy [3].

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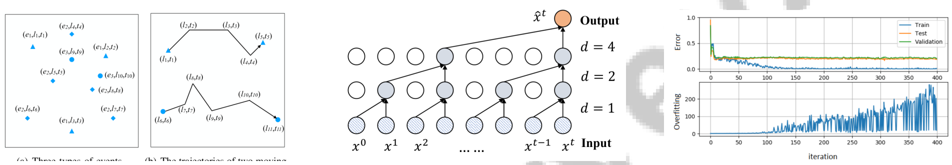
Recurrent Neural Networks (RNNs), particularly LSTM networks, are widely used due to their proficiency in capturing temporal dependencies, thus improving accuracy [5]. Integrating LSTM with models like Transformers and XGBoost further enhances performance by identifying complex patterns [5]. An edge-based framework by Petrella et al. shows improved accuracy and reduced energy consumption, highlighting supervised learning's efficiency [15].

Innovative models like TrafficGPT use generative AI for multi-scale traffic flow analysis [38]. The GSTF algorithm incorporates anomaly detection and multi-scale spatio-temporal feature fusion to enhance prediction accuracy [13]. The PHC algorithm utilizes parallel processing to improve accuracy through efficient data handling [39].

Advanced techniques, such as video data analysis, refine traffic predictions. For example, Yadav's method analyzes video feeds to yield accurate forecasts [14]. Huang's flexible integration frameworks adapt based on dataset attributes, showcasing supervised learning's versatility [30]. The STHODE method employs modular approaches for enhanced accuracy [4].

Recent advancements, including learnable filter modules and large language models, enhance model adaptability and robustness. These innovations filter noise and incorporate contextual information, improving prediction accuracy. Such progress is crucial for advancing intelligent transportation systems, enabling reliable forecasting and informed decision-making for transportation scheduling [30, 40]. By capturing complex spatio-temporal patterns, these models lay a solid foundation for optimizing urban mobility and developing smart cities.



(a) ERROR!!![41] (b) ERROR!!![40] (c) ERROR!!![42]

Figure 3: Examples of Supervised Learning Techniques

As shown in Figure 3, supervised learning techniques are crucial for analyzing and forecasting traffic patterns. Despite placeholder errors, references indicate diverse methodologies. For instance, Wang et al. explore deep learning frameworks for spatiotemporal data, while Zhu et al. enhance prediction accuracy through learnable models. Bejani and Ghatee focus on regularized deep networks for intelligent traffic systems, highlighting the versatility and effectiveness of these techniques [41, 40, 42].

4.2 Hybrid and Ensemble Methods

Method Name	Method Integration	Dynamic Relationship Capture	Application Versatility
FL-GCNs[43]	Kalman Filter	Dynamic Spatial-temporal	Intelligent Transportation Systems
MCTP[44]	Ensemble Learning Approach	Nonlinear Dependencies	Real-time Applications
GRNN[45]	Multiple Algorithms	Dynamic Relationships Capture	Intelligent Transportation Systems
SFA[46]	Genetic Algorithms	Single Vertex	Traffic Forecasting
FlashST[47]	Prompt-tuning Mechanism	Context Distillation	Various Traffic Prediction
ADIF[30]	Adaptive Algorithm	-	Various Data Types
SL[48]	Symbolic Regression Enhanced	Spatial Temporal Dependencies	Urban Traffic Prediction

Table 1: Overview of hybrid and ensemble methods for traffic prediction, highlighting their method integration, dynamic relationship capture, and application versatility. The table summarizes various models, such as FL-GCNs, MCTP, and GRNN, and their respective approaches to enhancing prediction accuracy and robustness in intelligent transportation systems.

Hybrid and ensemble methods enhance traffic prediction models' accuracy and robustness by leveraging multiple algorithms to address spatio-temporal data complexities. These approaches effectively capture dynamic traffic relationships, overcoming single-model limitations. FL-GCNs integrate deep learning with classical filtering, improving prediction accuracy and robustness by accommodating traffic flow dynamics [43].

Ensemble learning, as demonstrated by Li, reduces training error while capturing periodic patterns, illustrating the benefits of combining multiple models [44]. The GRNN exemplifies another ensemble method that effectively captures dynamic relationships across traffic networks [45].

GNNs are frequently employed within hybrid frameworks to improve accuracy, leveraging traffic data's spatial structure for precise modeling [23]. The SFA method innovatively addresses temporal gaps by designing perturbations without future information, showcasing a novel hybrid approach [46].

The FlashST framework introduces spatio-temporal prompt-tuning to adapt pre-trained models to various tasks, demonstrating hybrid methods' versatility [47]. The ADIF exemplifies hybrid approaches by using real-time data analysis to enhance model performance [30].

The SL method combines historical and current data to predict outflow traffic at urban junctions, illustrating hybrid techniques' practical applications [48]. The effectiveness of machine learning algorithms in applications like route optimization and accident detection underscores hybrid and ensemble methods' utility in intelligent transportation systems [24].

Hybrid and ensemble methods represent a pivotal advancement in traffic prediction, enhancing accuracy and reliability. By integrating diverse algorithms' strengths, these methods tackle short-term traffic flow forecasting complexities. Recent studies highlight ensemble approaches like adaptive boosting, modeling prediction as a matrix completion problem for efficient data analysis. Novel models like ALLSCP leverage temporal and spatial characteristics, achieving impressive accuracy rates in real-world scenarios. These advancements improve prediction outcomes and enable robust responses to fluctuating conditions, optimizing traffic management in Intelligent Transportation Systems [49, 44]. Such approaches are crucial for enhancing urban mobility and supporting intelligent transportation systems and smart cities. Table 1 presents a detailed comparison of hybrid and ensemble methods used in traffic prediction, emphasizing their integration techniques, ability to capture dynamic relationships, and application versatility.

5 Deep Neural Networks in Traffic Prediction

The adoption of deep neural networks (DNNs) has revolutionized traffic prediction by enabling the modeling of complex traffic patterns and dependencies. This section delves into various DNN architectures that have become pivotal in traffic prediction, highlighting their distinctive features and effectiveness in capturing intricate spatio-temporal relationships within traffic data.

5.1 Overview of Deep Neural Network Architectures

Deep neural network architectures have advanced traffic prediction by effectively modeling complex spatio-temporal dependencies. The ST-NN model exemplifies a unified DNN architecture that enhances prediction accuracy [3]. The STGNPP model excels in forecasting traffic congestion events, demonstrating its capability in capturing intricate spatiotemporal dependencies [7].

Convolutional Neural Networks (CNNs) are crucial for extracting spatial features from traffic data represented as tensor matrices, as shown by the DR method [11]. These features are further processed by Recurrent Neural Networks (RNNs) to capture temporal dependencies, essential for accurate traffic prediction. The integration of CNNs and RNNs facilitates comprehensive modeling of both spatial and temporal dimensions, as evidenced in scalable deep traffic flow prediction methodologies [16].

The 3D Temporal Graph Convolutional Networks (3D-TGCN) approach effectively captures spatial and temporal dependencies without relying on potentially inaccurate spatial information [16]. The DSTCGCN model combines an FFT-based attentive selector with a dynamic cross graph construction module, modeling dynamic spatial-temporal cross dependencies [9].

Graph-based architectures like the Bayesian Spatio-Temporal Graph Convolutional Network (BST-GCN) enhance prediction accuracy by learning a more accurate graph structure from traffic data while incorporating uncertainty [1]. The MW-TGC network utilizes graph convolution operations on traffic speed data to predict speeds based on historical data, demonstrating the utility of graph neural networks in traffic prediction [17].

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The STHODE method effectively models complex road network topologies and captures high-order temporal dependencies, significantly outperforming existing methods [4]. The ST-SSL framework employs self-supervised learning to model spatial and temporal heterogeneity, showing superior performance in traffic flow prediction [8]. Additionally, deep learning techniques applied to video data processing enhance traffic metric estimation, contributing to more accurate predictions [14].

These advancements highlight the critical role of DNN architectures in optimizing traffic prediction models, significantly contributing to intelligent transportation systems and enhancing urban mobility. By effectively capturing and analyzing complex spatio-temporal correlations in urban traffic data, these models, including the innovative ST-MetaNet, provide a robust framework that enhances prediction accuracy and supports the development of smart city infrastructures [50, 32].

5.2 Recurrent Neural Networks and Variants

Recurrent Neural Networks (RNNs) and their variants are vital in traffic prediction, adeptly capturing temporal dependencies in sequential data. These networks maintain internal memory, leveraging past information for accurate future predictions [51]. The Long Short-Term Memory (LSTM) architecture effectively captures long-term dependencies and periodic patterns, essential for predicting traffic accident risks and flow [52].

The CAConvLSTM model illustrates RNNs' application in vehicle-to-vehicle (V2V) channel predictions, showcasing their versatility in diverse predictive contexts [53]. The meta recurrent neural network approach dynamically models various spatial and temporal correlations, enhancing understanding of urban traffic dynamics [50]. The PARNN method combines RNNs with a discretized macroscopic traffic flow model, offering a 'grey-box' approach that integrates data-driven and model-based insights for improved prediction reliability [54].

Innovative architectures like the I2DRNN capture both short-term and long-term dependencies, enhancing predictive accuracy [31]. The HTVGNN captures dynamic spatial correlations and temporal dependencies, improving prediction accuracy, particularly in long-term forecasting scenarios [55].

Adaptive learning capabilities of RNNs are evident in models that utilize spatial and temporal patterns to predict traffic flow, as demonstrated by Chen et al.'s approach, which enhances accuracy by learning influences from various road segments [56]. The LOCALEGN model effectively leverages localized information, performing well with minimal data, making it suitable for cities with limited historical traffic data [57].

5.3 Graph-Based Neural Networks

Graph-Based Neural Networks (GNNs) have become powerful tools in traffic prediction, adeptly modeling complex spatial relationships in transportation networks. They excel in capturing dependencies between traffic nodes, providing a nuanced understanding of traffic dynamics compared to traditional methods [26]. GNNs effectively integrate spatial information from road networks, crucial for accurate traffic forecasting.

GNNs' flexibility in handling diverse graph structures makes them suitable for traffic prediction tasks. They model traffic states using various graph types, including road-level, region-level, and station-level graphs, which are essential for understanding and forecasting traffic conditions. This multi-level approach integrates diverse data sources, such as real-time regional knowledge, point of interest (POI) information, and historical traffic data, enhancing prediction accuracy and addressing exceptional circumstances in traffic patterns [30, 58]. Their ability to incorporate dynamic spatial correlations allows them to adapt to changing traffic patterns over time.

Recent advancements in GNN architectures, particularly multi-weighted adjacency matrices and dynamic graph construction modules, have significantly improved predictive accuracy by effectively modeling complex spatio-temporal dependencies. These innovations enable GNNs to capture intricate correlations in urban spatio-temporal data, crucial for applications in intelligent transportation systems and urban computing, thus improving forecasting capabilities across various domains such as traffic management, environmental monitoring, and public safety [23, 59, 60]. The integration of attention mechanisms within GNNs further enhances their ability to accurately predict traffic flow.

The advantages of GNNs over traditional methods are evident in their superior performance across various traffic prediction scenarios. By adeptly capturing intricate spatial and temporal relationships in traffic networks, GNNs enhance Intelligent Transportation Systems (ITS), facilitating improved traffic forecasting, vehicle control, and demand prediction, while optimizing urban mobility and contributing to smart city development. Recent studies underscore GNNs' superior performance in ITS applications, highlighting their potential to address complex urban traffic management challenges and enhance overall infrastructure efficiency [23, 61, 62, 63]. The ongoing evolution of graph-based neural networks in traffic prediction is expected to play a pivotal role in advancing the accuracy and reliability of predictive models.

5.4 Hybrid and Innovative Deep Learning Models

Hybrid and innovative deep learning models have emerged as transformative approaches in traffic prediction, integrating multiple methodologies to enhance forecasting accuracy. These models leverage the strengths of various deep learning techniques, capturing complex spatio-temporal dependencies and dynamic traffic patterns. The method proposed by Han et al. employs a regional spatio-temporal module alongside a road-level attention-based prediction model, illustrating an innovative approach to deep learning in traffic prediction [58]. This model effectively combines spatial and temporal insights to improve prediction accuracy.

The TEAM framework exemplifies innovation through its continual learning module, utilizing the Wasserstein metric to identify stable and changing nodes, facilitating efficient re-training and adaptation to new traffic data [64]. This continual learning approach ensures model robustness and adaptability to evolving traffic conditions.

The STPS model employs a multi-step training process to progressively refine model parameters, enhancing forecasting accuracy through iterative refinement [65]. The AHSTN model captures both node-level and cluster-level spatiotemporal correlations in an end-to-end manner, improving forecasting capabilities by leveraging spatial hierarchy [66].

The MegaCRN model learns adaptive graph structures reflecting dynamic traffic conditions, allowing accurate predictions even amid anomalies [67]. The RDAT method innovatively combines reinforcement learning with adversarial training to improve model performance, enhancing resilience to data variability and adversarial conditions [68].

NodeTrans introduces a hybrid approach by integrating spatial-temporal graph neural networks with a clustering-based transfer strategy, demonstrating the potential of transfer learning in enhancing traffic prediction models [36]. Zhou et al. highlight the hybridization of SARIMA with Bayesian learning to create a model capable of adapting to varying traffic conditions [69]. This hybrid model balances statistical and machine learning techniques, providing a robust framework for traffic prediction.

The MFGM model integrates multivariate, temporal, and spatial modeling to predict vehicle-related GCT flow with improved accuracy, showcasing the benefits of comprehensive data integration in traffic forecasting [70]. By incorporating multiple data dimensions, MFGM exemplifies the potential of holistic modeling approaches in enhancing traffic prediction accuracy.

These hybrid and innovative deep learning models represent significant advancements in traffic prediction, offering enhanced accuracy and reliability by leveraging the complementary strengths of multiple algorithms. These approaches are essential for improving urban mobility through intelligent transportation systems (ITS) and advanced technologies, addressing traffic congestion, enhancing infrastructure efficiency, and promoting sustainable urban development in light of projected urban population growth [22, 32, 25].

In recent years, the integration of advanced predictive frameworks has become increasingly vital in the realm of urban planning and transportation systems. These frameworks not only enhance the efficiency of transportation networks but also contribute to the development of sustainable urban environments. As depicted in Figure 4, this figure illustrates the hierarchical structure of intelligent transportation systems and smart cities, categorizing the benefits and integration of traffic prediction models. The visual representation underscores the multifaceted role these models play in optimizing urban planning and transportation systems, ultimately fostering a more sustainable and efficient urban landscape.

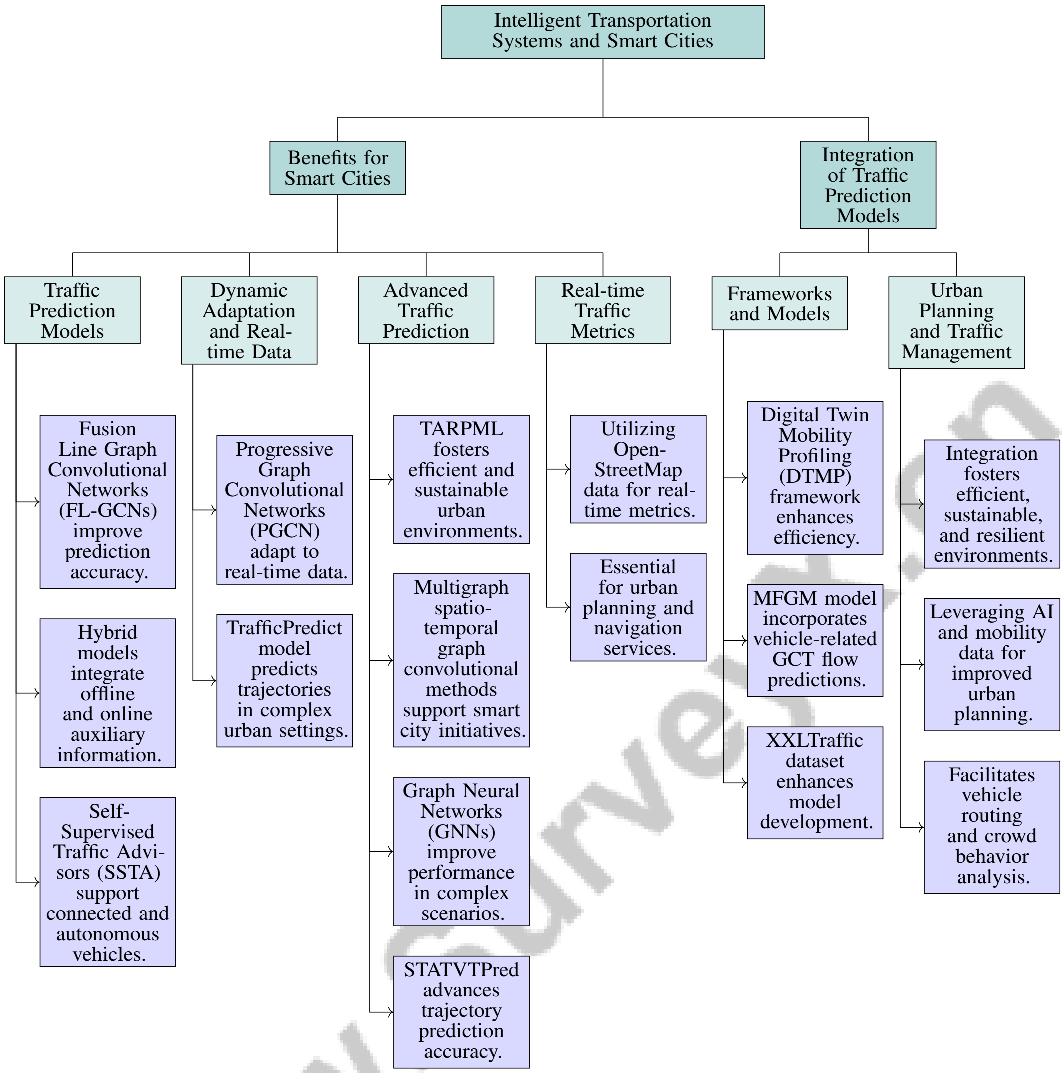

Figure 4: This figure illustrates the hierarchical structure of intelligent transportation systems and smart cities, categorizing the benefits and integration of traffic prediction models. It highlights the role of advanced predictive frameworks in enhancing urban planning, optimizing transportation systems, and supporting sustainable urban environments.

6 Intelligent Transportation Systems and Smart Cities

6.1 Benefits for Smart Cities

Traffic prediction is pivotal in advancing smart cities by enhancing urban planning and optimizing transportation systems. Advanced predictive models like Fusion Line Graph Convolutional Networks (FL-GCNs) significantly improve prediction accuracy, crucial for effective traffic management and urban mobility [43]. Hybrid models that integrate offline and online auxiliary information outperform traditional methods, offering valuable insights for urban planning and smart city initiatives [28]. The Self-Supervised Traffic Advisors (SSTA) framework further supports connected and autonomous vehicles by providing precise traffic predictions essential for smart infrastructures [71].

Progressive Graph Convolutional Networks (PGCN) dynamically adapt to real-time traffic data, enhancing their utility in urban planning and smart city development [72]. This adaptability is vital for addressing real-time traffic conditions and optimizing transportation networks. The TrafficPredict model aids in accurately predicting trajectories in complex urban settings, facilitating proactive traffic management [73].

Models like TARPML demonstrate the benefits of traffic prediction in fostering efficient and sustainable urban environments [52]. The use of multigraph spatio-temporal graph convolutional methods in practical applications highlights the potential of advanced traffic prediction in supporting smart city initiatives [74]. Graph Neural Networks (GNNs) enhance intelligent transportation systems by improving performance in complex traffic scenarios, ensuring reliable predictions [23]. The STATVTPred model exemplifies advancements in trajectory prediction accuracy, underscoring the role of predictive frameworks in enhancing urban mobility [75].

Frameworks utilizing OpenStreetMap data to provide real-time traffic metrics significantly bolster urban planning and navigation services, essential for the development of intelligent transportation systems [14]. Innovations in traffic prediction are crucial for creating efficient, sustainable, and resilient urban environments, advancing smart city objectives.

6.2 Integration of Traffic Prediction Models

Integrating advanced traffic prediction models into smart city infrastructure is essential for optimizing urban mobility and enhancing the efficiency of intelligent transportation systems. The Digital Twin Mobility Profiling (DTMP) framework exemplifies this integration, outperforming traditional techniques in traffic prediction and improving smart city frameworks [76]. By providing a virtual representation of urban transportation networks, DTMP facilitates real-time analysis and optimization, enabling proactive traffic management and congestion reduction.

The MFGM model's incorporation of vehicle-related GCT flow predictions illustrates the benefits of integrating advanced predictive frameworks into urban planning, enhancing prediction accuracy and supporting intelligent transportation solutions that adapt to urban dynamics [70]. Additionally, the XXLTraffic dataset addresses benchmark limitations by offering comprehensive data that enhances the development and integration of predictive models within smart city infrastructure [12].

These advancements highlight the critical need for integrating traffic prediction models into smart city frameworks, fostering efficient, sustainable, and resilient urban environments. By leveraging advanced predictive frameworks and intelligent transportation systems (ITS), smart cities can significantly improve their transportation networks, reducing congestion and enhancing urban mobility. With urban populations projected to increase by nearly 2.5 billion by 2050, integrating artificial intelligence and extensive mobility data is imperative for effective urban planning and traffic management. Such technologies facilitate improved vehicle routing and crowd behavior analysis while promoting sustainable transportation practices, addressing the challenges posed by rising vehicular traffic and the need for efficient mobility solutions in densely populated areas [22, 25].

7 Challenges and Future Directions

7.1 Challenges in Data Collection and Quality

The efficacy of traffic prediction models is heavily dependent on data collection and quality. Advanced models like the Dynamic Spatio-Temporal Graph Convolutional Network (DSTCGCN) face challenges of computational complexity and overfitting when dealing with extensive datasets [9]. This complexity is exacerbated by the resource-intensive nature of data processing, which often struggles with scalability [39]. Accurate traffic speed forecasting is further complicated by the intricate interactions among road segments and geometric features [17], necessitating sophisticated data collection methods. The Modifiable Areal Unit Problem (MAUP) introduces prediction instability due to spatial partition variations, complicating the characterization of global spatial dependencies [77].

Integrating diverse data sources, such as social media, is crucial for a holistic understanding of traffic patterns but poses challenges due to data heterogeneity [10]. Dependence on historical data can lead to inaccuracies, especially in irregular traffic scenarios or when data is scarce. The quality of input data and the selection of neighboring sensors significantly affect model performance [37]. Dynamic-control problems in deep reinforcement learning add to computational demands, risking overfitting and complicating quality data collection [39]. Capturing temporal conditions, such as traffic patterns and intersection waiting times, remains challenging [3]. Innovative data collection and processing methods are needed to improve data quality and consistency, ultimately leading to more accurate traffic predictions.

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7.2 Integration of External Factors

Incorporating external factors, such as weather conditions, into traffic prediction models is crucial for accurate forecasts. Weather significantly impacts traffic flow and congestion, and its absence in models like ST-ResNet can lead to suboptimal predictions [78]. Accurately modeling the dynamic nature of external factors poses a challenge for traditional models [79]. The lack of comprehensive datasets that include both traffic and external factors complicates integration, hindering model training across varying conditions.

The variability of external factors requires advanced modeling techniques to capture their influences across diverse scales and contexts. Recent studies show that integrating contextual information, such as weather and regional characteristics, through deep recurrent neural networks and graph-structured models enhances predictive accuracy by accommodating multi-scale dependencies and real-time interactions [30, 31, 58, 80]. Developing algorithms that seamlessly integrate diverse data sources is essential for accurately reflecting the effects of external factors in traffic predictions, further complicated by the need for real-time data processing to adapt to rapidly changing conditions.

7.3 Real-time Prediction and Scalability

Real-time prediction and scalability in traffic systems present significant challenges due to complex interactions and dynamic traffic conditions. Efficient integration and processing of real-time data are crucial for timely predictions [70]. Traffic networks' intricate spatio-temporal dependencies necessitate sophisticated models that handle large data volumes while maintaining computational efficiency.

Real-time prediction requires models that adapt quickly to changing conditions, often integrating data from various sources like sensors, GPS, and social media. The fusion of multimodal spatio-temporal data is challenging due to diverse formats and the need for advanced techniques to ensure consistency and accuracy. This involves merging data from different transportation modes, addressing data loss due to privacy or technical constraints, and adapting to historical and current traffic pattern variations. Effective data fusion must consider intricate relationships across multiple spatio-temporal scales and challenges presented by insufficient data in certain areas. Robust methods for seamless data fusion are critical for enhancing predictive analytics in smart mobility and intelligent transportation systems [81, 31, 32, 30]. Scalability is a key concern, as models must handle increasing data volumes without compromising performance.

Growing urban populations and traffic volumes emphasize the need for scalable solutions. Models must manage anticipated traffic demand growth by handling large-scale network complexities and delivering real-time insights through diverse data sources, such as textual information and roadway capacity attributes [12, 30, 82]. This requires efficient algorithms leveraging distributed computing resources for parallel processing to reduce computational bottlenecks.

7.4 Future Directions and Research Opportunities

Future research in traffic prediction will explore model adaptability, scalability, and diverse data source integration. Extending frameworks like Spatio-Temporal Self-Supervised Learning (ST-SSL) to a model-agnostic paradigm is a significant focus [8]. Optimizing neural architectures and hyperparameters, as seen in the Bayesian Spatio-Temporal Graph Convolutional Network (BSTGCN), can enhance performance across spatio-temporal forecasting tasks [1]. Investigating structural dynamics within transportation networks, incorporating long-term periodicity, and enhancing adaptive mechanisms in hypergraph construction are crucial for advancing traffic prediction methodologies.

Optimizing algorithms like Parallel Hierarchical Clustering (PHC) may improve computational efficiency and accuracy in traffic prediction [39]. Exploring additional partitioning methods and improving visual consistency in model analysis can enhance interpretability and usability [77]. Incorporating causal properties into modeling and refining correlation information extraction are vital for improving interpretability and accuracy in traffic forecasting. Enhancing model robustness to rare events and exploring applications in other transportation domains could yield valuable insights into traffic dynamics [18].

Integrating sophisticated data fusion techniques, particularly incorporating diverse sources like public transportation feeds and extensive historical datasets, holds substantial potential for improving traffic prediction accuracy. Leveraging methodologies such as large language models to process textual information and generate embeddings can effectively combine real-time data with historical patterns, addressing challenges related to exceptional circumstances and enhancing overall predictive performance. This approach facilitates the alignment of covariate distributions to manage shifts in data patterns, promoting a robust training framework that enhances adaptability in existing short-term traffic prediction models [30, 81]. Future research could refine these techniques and explore their application in real-time data integration scenarios, enhancing the adaptability and efficiency of traffic prediction models.

Addressing these research opportunities will lead to the development of adaptive and efficient models that meet the dynamic requirements of intelligent transportation systems (ITS). These advancements are crucial for alleviating traffic congestion, which has significant economic and environmental implications, such as increased travel time and fuel consumption. Leveraging emerging technologies and artificial intelligence, particularly in multivariate traffic time series modeling, will enhance prediction accuracy and improve urban mobility. Furthermore, these innovations will support the ongoing evolution of smart city initiatives by optimizing urban planning, facilitating effective vehicle routing, and ensuring safer, more sustainable transportation systems [19, 30, 22, 6, 61].

8 Conclusion

The exploration of traffic prediction using spatio-temporal data within intelligent transportation systems highlights the transformative role of advanced methodologies, such as deep neural networks and machine learning, in enhancing urban mobility and supporting smart city initiatives. The integration of temporal data and hypernetwork architectures emerges as a cornerstone for optimizing urban planning and transportation systems. Models like T-GCN exemplify the ability to effectively capture spatial and temporal dependencies, consistently outperforming traditional methods across various metrics and prediction horizons.

The criticality of recognizing dynamic spatial and temporal patterns is emphasized, with tools like STG4Traffic providing a standardized framework for performance evaluation and strategy development. The Traffic-Net system marks significant progress in traffic monitoring, achieving high accuracy and offering valuable insights into traffic dynamics and safety. Innovative approaches like Auto-DSTSGN advance prediction accuracy while maintaining computational efficiency, and decentralized prediction methods offer notable improvements over centralized systems in real-time congestion forecasting.

Despite ongoing challenges related to data quality and real-time prediction, models such as Loc-GCLSTM demonstrate superior capabilities in capturing complex spatial-temporal traffic patterns. Moreover, the xTP-LLM model underscores the potential of explainable AI in traffic forecasting, merging competitive accuracy with transparent predictive insights. These advancements collectively underscore the potential for future innovations, paving the way for more efficient, reliable, and intelligent transportation systems.

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