International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Review Of Traffic Congestion Prediction And Control Models: Insights From Spatio-Temporal Analysis And AI Methods

Prof. Bhasker Rao K [a], Laasya Vasanth [b], Neha U [c], Preeti Chand H H [d], Priyamvadha J Mahishi [e]

[a] Computer Science and Engineering, Associate Professor, Dayananda Sagar Academy of Technology & Management, Bengaluru, India.
[b] Computer Science and Engineering, Student, 4th Year, B.E, Dayananda Sagar Academy of Technology & Management, Bengaluru, India.
[c] Computer Science and Engineering, Student, 4th Year, B.E, Dayananda Sagar Academy of Technology & Management, Bengaluru, India.
[d] Computer Science and Engineering, Student, 4th Year, B.E, Dayananda Sagar Academy of Technology & Management, Bengaluru, India.
[e] Computer Science and Engineering, Student, 4th Year, B.E, Dayananda Sagar Academy of Technology & Management, Bengaluru, India.

ABSTRACT :

Accurate visitors forecasting is vital for sensible transportation systems (ITS) to optimize visitors control and concrete planning. This challenge explores a Spatio-Temporal Graph Convolutional Network (ST-GCN) that captures each spatial and temporal dependencies in street networks for visitors circumstance prediction. The proposed framework includes a dynamic ST-GCN incorporating graph convolutional networks (GCNs) for spatial members of the family and Gated Recurrent Units (GRUs) for temporal patterns. Unlike static graph-primarily based totally models, this dynamic framework introduces a two-circulate community with a waft prediction circulate and a graph prediction circulate to evolve to evolving visitors conditions. Additionally, the version leverages auxiliary information, together with climate and point-of-interest (POI) data, to decorate prediction accuracy. Experimental critiques on realinternational datasets exhibit that the ST-GCN outperforms conventional methods, imparting strong and correct visitors waft and velocity forecasts.

Keywords: Traffic Forecasting, Spatio-Temporal Graph Convolutional Network, Intelligent Transportation Systems, Dynamic Framework, Graph Convolutional Networks, Gated Recurrent Units, Auxiliary Data, Weather Data, Point-of-Interest, Traffic Flow Prediction.

1. INTRODUCTION :

Traffic congestion is a major problem in urban environments, leading to increased travel times, air pollution, and economic losses. To mitigate these challenges, intelligent transportation systems (ITS) rely on accurate traffic forecasting to optimize real-time traffic management and infrastructure planning. Accurate forecasting helps reduce traffic congestion, improve route planning, and increase overall transportation efficiency. Historically, traffic forecasting has relied on traditional statistical models such as autoregressive integrated moving average (ARIMA) and Kalman filters. While these models are effective for simple time series forecasting, they fail to capture the spatial dependencies and nonlinearities present in real-world traffic data [4].

The advent of machine learning (e.g., support vector machines) and deep learning techniques (e.g., convolutional neural networks (CNNs) and recurrent neural networks (RNNs)) has significantly improved the accuracy of forecasting. However, these methods have difficulty modeling the complex and dynamic spatial relationships inherent in road networks, which are inherently non-Euclidean [1],[2].

Graphical Convolutional Networks (GCNs) address these limitations by efficiently modeling non-Euclidean spaces such as road networks. By combining GCNs with temporal models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs), the Spatio-Temporal Graphical Convolutional Network (ST-GCN) provides a unified approach to capture spatial and temporal dependencies [2],[3].

This project proposes an improved dynamic ST-GCN framework:

1) Integrates dynamic graphical structures to reflect real-time changes in traffic conditions.
2) Leverage auxiliary data such as weather and POIs to improve forecast reliability.
3) Use a two-stream architecture for stream and graph prediction.

2. LITERATURE REVIEW :

Early Statistical Methods

Because they were quick and easy to simulate linear connections in time-series data, statistical models became rapidly popular in early traffic forecasting. The methods most used in early traffic forecasting were the Kalman Filter and the Auto-Regressive Integrated Moving Average (ARIMA). ARIMA models rest fundamentally on the assumption of stationarity, which claims that the statistical properties of a given data remain unchanged over time. These models utilize past data and errors to estimate future values. Short-term forecasts are an area in which ARIMA has shown promise as clearly applicable, while traffic patterns tend to be regular and steady [4]. In contrast, this works poorly even when non linearities emerge, as well as with complete modeling. For instance, Williams [4] applied seasonal ARIMA models to forecast motorways traffic and found such applicability for the short-term forecasts with consistent data patterns. Kalman filter, on the other hand, is a recursive estimation technique applied in dynamic systems for on-line prediction. It is instrumented to alter its forecasts as new observations arrive. The Kalman filter is a common procedure in real-time applications and is also very effective in systems with noisy data; however, its performance is not very good in nonlinear patterns and long-term dependencies [4]. Kalman filters can be used to predict traffic flow in cities. The updating capability of these filters allowed one to continuously improve the short-term prediction accuracy. Yet, neither can control the complexity, non-linearity, and dynamics associated with modern urban networks.

Machine Learning Approaches

As statistical methods have their own limitations, they gave way to machine learning (ML) models that can comprehend more complex patterns in traffic data. These have a greater on-the-fly learning advantage without attaching freedom to a predefined functional form and thus are more flexible and adaptable. Support Vector Machines (SVMs) are one of the popular machine learning models and are often referred to as supervised learning models. In regression purposes, model based SVMs were found most efficient because they get an optimal hyperplane having minimum error prediction. Also, they are excellent at building a model for a nonlinear relationship using kernel functions; however, they turn quite expensive in computation in large datasets and lack a mode for sequential data modelling [2]. For example, Zhu et al. [2] used SVMs to demonstrate traffic flow forecasting in urban cities where the method achieved a significant higher accuracy when compared to ARIMA, in scenarios where non linear patterns were exhibited. K-Nearest Neighbors (KNN) is another common ML algorithm that averages the traffic over historical points closest to one another to forecast future traffic states. KNN is intuitive and does not assume any particular distribution but it is inefficient with substantial dataset and sensitive to the value of k chosen as the number of neighbors. KNN models on short term traffic predictions have given very good firm results in local patterns of traffic [2], but beyond this, machine learning models face still great challenges representing temporal dependencies and very complex dependencies between traffic segments within the urban traffic network [2].

2.3 Deep Learning Techniques

Deep learning techniques have penetrated into the traditional and machine learning models to go beyond raw patterns and non-linear relationships while also capturing long-term dependencies from the traffic data, and thus enable applications capable of useful forecasting messages on traffic. In this aspect, CNNs are among the very pertinent deep learning techniques due to their structure in capturing spatial features as convolutional filters over the input data applied upon those [1]. CNNs are excellent in extracting local spatial dependencies and compressing data dimensions using pooling layers; however, they are primarily focused on Euclidean data such as grids and images. This makes them less powerful in modeling non-Euclidean road networks [2]. RNNs are thus the networks capable of processing the time series data while not being able to predict previously elapsed time because of their backward feed; rather they hold a hidden state which remembers the information from past time steps. It is worth noting that RNNs face a common problem known as the vanishing gradient problem; thus it causes them not to deduce long-term dependencies well, as mentionedby Dai et al. [1]. The forwarded enhancements involved Long Short Term Memory networks and Gated Recurrent Units. The gates like those of LSTM, including forget, input, output gates, or the reset and update gates in the GRU assist in learning to keep long-term dependencies and eliminiate fading gradients. As demonstrated by Dai et al. [1], LSTM models were found to be relatively good in comparison with traditional RNNs in urban environment travel time prediction [1]. Finally, Hybrid CNN-LSTM Models bring in the best features of both CNNs and LSTMs.

Graph Based Models

As naturally, urban traffic networks are not Euclidean; thus, researchers have turned toward graph-based techniques as the methods capable of modeling spatial dependencies in traffic networks. Graph Convolutional Networks (GCNs) bring up the traditional CNNs for processing graphs, where nodes represent road segments and edges their connectivity. As such, GCNs capture spatial relationships effectively for irregular data structured as graphs, making them relevant for modeling the complex-measured interconnection of urban road networks [3]. For many real problems, however, they work side by side with temporal models to include the complete capture of both spatial and temporal dependencies in traffic data. GCNs have mostly been used for predicting traffic flow by modeling road networks as graphs, which improves spatial accuracy involved in the model based on CNN, [2], [3]. Spatio-Temporal Graph Convolutional Networks (ST-GCNs) advance this technique further since they integrate GCNs with a temporal model such as RNN, LSTM, or GRU in order to add both spatial and temporal dynamics [2]. ST-GCNs have already shown superior performance in traffic speed prediction, jointly providing much better performance by connecting road segment and time dependency in a single model, thus enhancing the accuracy of its traffic forecast, [2], [3].

Dynamic Graph Models and External Factors

The significant aspect emphasized by recent studies is the dynamic update of the graph structure through which external contextual information is integrated to improve the accuracy of traffic forecasting. Dynamic Graph Models are an advanced approach that updates graph structures in real-time to traffic data, unlike the static graph-based models relying on shaping a fixed representation of the road network [2]. The major advantage of dynamic models is to better present in real time the dynamic considerations of traffic and accommodate the changes occurring in road networks, allowing for a more accurate and timely prediction [2]. For example, dynamic Spatio-Temporal Graph Convolutional Networks (ST-GCNs) continuously update the graph structure and adjust it to match real-time traffic data, thus allowing much more rapid and accurate traffic flow predictions, [2]. Another crucial aspect of improving prediction accuracy is to incorporate external factors such as weather conditions (rain, temperature) and points of interest (POI) data (e.g., proximity to restaurants, schools, or commercial areas). The Attribute-Augmented ST GCN (AST-GCN) model combines dynamic and static external attributes, such as information from weather and POIs, into a model to improve the accuracy of traffic forecasts [2]. For example, Zhu et al. [2] demonstrated that including external data such as weather and POIs improved traffic forecasting outcomes over models that were reliant only on traffic flow data [2].

3. FUTURE RESEARCH ASPECTS :

Future research in traffic congestion prediction and control can focus on merging data from multiple sources, such as social media, GPS, IoT sensors, and weather reports, to improve forecast accuracy and decision-making [3]. While explainable AI (XAI) will ensure interpretability for valuable insights, advanced AI approaches like transformers, federated learning, and reinforcement learning may enhance spatial-temporal modeling [2]. Personalization and dynamic adaptation, including real-time adaptive traffic controls and user-specific forecasts, offer opportunities for more customized and efficient solutions [5]. Environmental considerations such as integrating emissions data and analyzing weather impacts will make models more resilient and sustainable [5].

Although deployment problems will be resolved by scalable cloud and edge computing solutions, new technologies like connected infrastructure, driverless vehicles, and smart city systems have the potential to fundamentally alter traffic management strategies [5]. Ethical concerns of data privacy and bias mitigation must be carefully considered in order to uphold justice and trust [4]. Standardized datasets and simulation frameworks will facilitate model validation, and long-term analytics may help with trend forecasts and resilience planning for urban transportation. By addressing these areas, future research can advance the development of more intelligent, sustainable, and flexible transportation systems [5].

4. CONCLUSION :

ST-GCN is a dynamic Spatio-Temporal Graph Convolutional Network that models time-varying traffic data in both spatial and temporal dimensions. Compared to conventional models such as ARIMA and Kalman filters, it is clearly superior. The two-stream architecture (comprising flow and graph prediction streams) of this model dynamically adapts to realtime changes by incorporating external factors such as weather and POI data into consideration. The ST-GCN outperforms both static graph models and traditional models in terms of traffic flow and speed forecast accuracy and its adaptability to real time condition changes. It fits perfectly in the intelligent transport system (ITS) within which it supports real-time traffic forecasting, adaptive signal control, and urban planning. Data assimilation from external contributing factors makes a model perfect for dynamic traffic management in real-time traffic forecasting for navigation systems, traffic signal timing optimization, event-based traffic peak management, and guiding infrastructure and public transport development.

REFERENCES :

[1] Ma, C., Dai, G., & Zhou, J. (2021). Short-term traffic flow prediction for urban road sections based on time series analysis and LSTM_BILSTM method. IEEE Transactions on Intelligent Transportation Systems, 23(6), 5615-5624.

[2] Zhu, J., Wang, Q., Tao, C., Deng, H., Zhao, L., & Li, H. (2021). AST-GCN: Attribute-augmented spatiotemporal graph convolutional network for traffic forecasting. Ieee Access, 9, 35973-35983.

[3] Zhang, T., Xu, J., Cong, S., Qu, C., & Zhao, W. (2023). A hybrid method of traffic congestion prediction and control. IEEE Access, 11, 36471-36491.

[4] Williams, B. M., & Hoel, L. A. (2003). Modeling and forecasting vehicular traffic flow as a seasonal ARIMA process: Theoretical basis and empirical results. Journal of transportation engineering, 129(6), 664-672.

[5] Cornacchia, G., Lemma, L., & Pappalardo, L. (2024, October). Alternative Routing based on Road Popularity. In Proceedings of the 2nd ACM SIGSPATIAL Workshop on Sustainable Urban Mobility (pp. 14-17).

[6] Pareek, M. (2023). Evolutionary Strategies for Parameter Optimization in Deep Learning Models.

[7] Reddy, S. S., & Channegowda, N. (2021). Edge Boost Curve Transform and Modified ReliefF Algorithm for Communicable and Non Communicable Disease Detection Using Pathology Images. International Journal of Intelligent Engineering & Systems, 14(2).

[8] Kumar, N., Nandini, D. C., Raj, Adiga, S. G., Raja, M. A., & Anuhya, T. V. (2022). CONTROLLING MULTIPLE APPLICATIONS WITH HAND GESTURE USING CONVOLUTION NEUTRAL NETWORK. IJCRT - International Journal of Creative Research Thoughts (IJCRT), 10(4), c384–c389c384–c389.

[9] Kumar, N., Nandihal, P., Madhumala, R. B., Pareek, P. K., Nikshepa, T., & Sowmya, S. R. (2022, December). A Novel Machine Learning-Based Artificial Voice Box. In 2022 Second International Conference on Advanced Technologies in Intelligent Control, Environment, Computing & Communication Engineering (ICATIECE) (pp. 1-7). IEEE.

[10] Girish, N., & Nandini, C. (2023). Inter-frame video forgery detection using UFS-MSRC algorithm and LSTM network. International Journal of Modeling, Simulation, and Scientific Computing, 14(01), 2341013.

[11] Manjunath D.R., Selva Kumar S., Sai Shiva Sumanth Reddy, & Lohith J.J. (2024). Enhancing Personalized Learning based on AI-Driven Lesson Plan Generator Using Mistral-7B for Efficient Content Extraction and Summarization. In GRADIVA (Vol. 63, Number 06, pp. 34–50). Zenodo. https://doi.org/10.5281/zenodo.12578736

[12] Kumar, P. R., Meenakshi, S., Shalini, S., Devi, S. R., & Boopathi, S. (2023). Soil Quality Prediction in Context Learning Approaches Using Deep Learning and Blockchain for Smart Agriculture. In Effective AI, Blockchain, and E-Governance Applications for Knowledge Discovery and Management (pp. 1-26). IGI Global.

[13] Mathapati, M., Nandihal, P., Mishra, P., & Kotagi, V. (2023, November). Improvisation of QoS in SDN-Frame Work for UAV Networks Using Dijkstra Shortest Path Routing Algorithm. In 2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE) (pp. 1-7). IEEE.