



Predicting and Mitigating Urban Traffic Congestion Using Artificial Intelligence

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Abstract

Traffic congestion continues to pose a major challenge for modern urban environments, particularly at signalized intersections where vehicle queues can accumulate rapidly during peak periods. This project proposes an AI-enabled framework designed not only to predict congestion levels across multiple traffic-signal approaches, but also to support adaptive signal-control strategies that dynamically adjust green-time allocations for the most congested movements. By identifying which approaches are likely to experience high traffic pressure before the congestion fully develops, the system aims to reduce queue buildup and enhance overall intersection performance.

The study utilizes real traffic-volume data collected from smart signal detectors. The data preprocessing stage includes cleaning inconsistent records, reconstructing missing intervals, and extracting temporal and flow-based features critical for understanding intersection-level dynamics. Various analytical methods were applied to uncover recurring congestion patterns and to highlight traffic movements that frequently become bottlenecks. Machine learning and deep learning models including LSTM-based architectures and advanced tree-based algorithms were trained to forecast short-term congestion states, demonstrating high predictive accuracy across evaluation metrics.

A series of visual analytics, such as temporal heatmaps, movement-level flow profiles, and day-to-day variation charts, were employed to validate the learned patterns and provide operational insights. Results show that incorporating detailed detector-level measurements and temporal structure significantly enhances model performance. The proposed framework provides practical value for smart city applications by enabling data-driven, proactive adjustment of signal timings to relieve congestion before it escalates. This work lays the foundation for future developments, including real-time deployment, integration with IoT-based traffic sensors, and fully adaptive AI-controlled signal systems.

List of Publications

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List of Abbreviations

- **AI:** Artificial Intelligence
- **ANN:** Artificial Neural Network
- **ARIMA:** Autoregressive Integrated Moving Average
- **BiLSTM:** Bidirectional Long Short-Term Memory
- **CNN:** Convolutional Neural Network
- **CPO:** Crested Porcupine Optimizer
- **DT:** Decision Tree
- **DeepONet:** Deep Operator Network
- **F1-score:** F1 Measure
- **GBM:** Gradient Boosting Machine
- **GAT:** Graph Attention Network
- **GRU:** Gated Recurrent Unit
- **IoT:** Internet of Things
- **ITS:** Intelligent Transportation Systems
- **KNN:** k-Nearest Neighbors
- **LightGBM:** Light Gradient Boosting Machine
- **LSTM:** Long Short-Term Memory
- **MAE:** Mean Absolute Error
- **MAPE:** Mean Absolute Percentage Error
- **ML:** Machine Learning
- **MLP:** Multi-Layer Perceptron
- **PeMS:** Performance Measurement System
- **PI-DeepONet:** Physics-Informed Deep Operator Network
- **R²:** Coefficient of Determination
- **RF:** Random Forest
- **RMSE:** Root Mean Square Error
- **RNN:** Recurrent Neural Network
- **SHAP:** SHapley Additive exPlanations
- **STGCN:** Spatio-Temporal Graph Convolutional Network
- **SVM:** Support Vector Machine
- **XAI:** Explainable Artificial Intelligence
- **XGBoost:** Extreme Gradient Boosting

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Chapter 1: Introduction

1.1 Problem Definition

Urban traffic congestion has become one of the most critical challenges facing modern cities, particularly at signalized intersections where traffic demand fluctuates rapidly across different approaches and time periods. Fixed-time or semi-actuated signal plans often fail to respond effectively to these dynamic conditions, leading to queue buildup, increased travel delays, excessive fuel consumption, and elevated emissions. These effects collectively reduce the efficiency and sustainability of urban transportation networks and negatively impact economic productivity and quality of life.

Although congestion patterns often recur during peak hours, accurately predicting which specific signal approaches will experience excessive demand remains a complex task. Traditional traffic analysis methods typically rely on historical averages, static thresholds, or rule-based logic, which are insufficient for capturing nonlinear and time-dependent interactions between traffic movements and neighboring intersections. As a result, congestion is frequently detected only after queues have already formed, limiting the effectiveness of reactive traffic-control measures.

Recent advances in data availability from traffic detectors, adaptive signal controllers, and intelligent transportation systems have created opportunities for more proactive congestion management. By leveraging artificial intelligence (AI) and machine learning techniques, it is possible to learn complex traffic patterns from high-resolution data and anticipate congestion before it fully develops. Such predictive capabilities are essential for enabling adaptive signal-control strategies that can dynamically adjust green-time allocations to mitigate congestion and improve intersection performance (Medina-Salgado et al., 2022; Rahmani et al., 2023).

1.2 Thesis Objectives

The primary objective of this thesis is to develop an AI-driven framework for predicting traffic congestion at signalized intersections and to demonstrate how such predictions can support adaptive traffic signal control. To achieve this objective, the study focuses on the following specific goals:

- To analyze real-world traffic detector data and identify temporal and movement-level patterns associated with congestion formation.
- To explore machine learning and deep learning techniques suitable for short-term congestion prediction in urban traffic environments.
- To apply feature engineering and selection methods that enhance predictive accuracy while maintaining interpretability.
- To evaluate congestion-prediction performance using standard classification metrics such as accuracy, precision, recall, and F1-score.
- To provide analytical and visual insights that support proactive traffic-management decisions at signalized intersections.

These objectives align with the broader goal of improving urban mobility through data-driven and intelligent transportation systems.

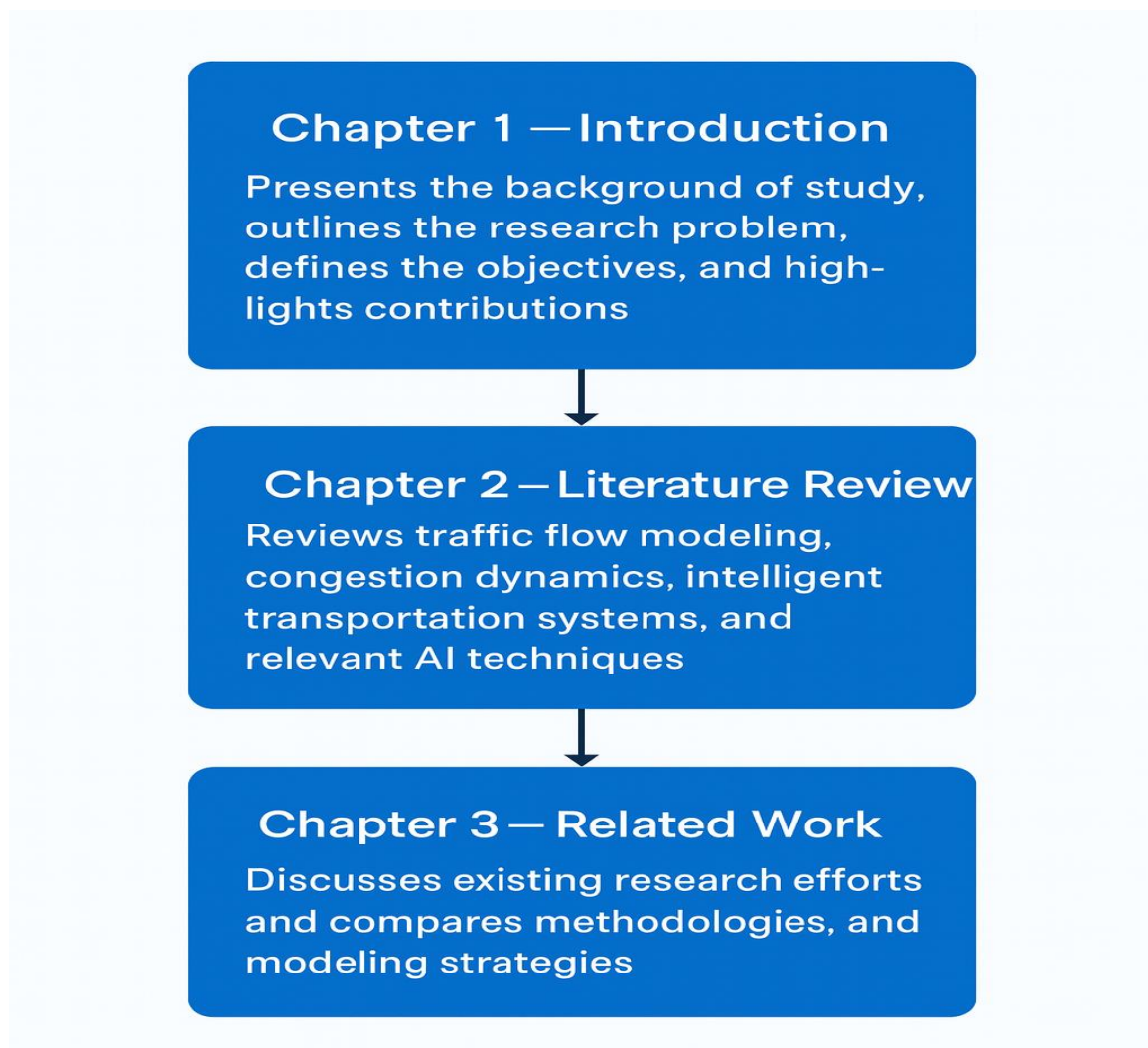
1.3 Thesis Contributions

This thesis contributes to the field of AI-enabled traffic management by proposing a structured and reproducible framework for predicting traffic congestion at signalized intersections using real-world detector data. The framework is designed to capture short-term congestion dynamics at the approach level, providing a practical foundation for intelligent traffic analysis.

In addition, the study emphasizes the integration of congestion prediction with traffic signal control concepts. Rather than treating congestion forecasting as an isolated analytical task, the proposed approach demonstrates how predicted congestion levels can support adaptive signal-timing strategies, such as proactive green-time reallocation for heavily loaded approaches to prevent excessive queue buildup.

From an academic perspective, this work synthesizes recent advances in machine learning, deep learning, and hybrid modeling techniques within the context of urban traffic congestion forecasting. By organizing and contextualizing these approaches, the thesis establishes a clear conceptual basis for future research, including extensions toward real-time deployment, network-level coordination, and reinforcement learning-based traffic signal control.

1.4 Thesis Organization



Chapter 2 Overview

2.1 Introduction

Traffic congestion forecasting has become a fundamental component of modern intelligent transportation systems, particularly as urban areas continue to experience rapid growth in traffic demand. At signalized intersections, traditional traffic management strategies based on static signal plans and historical averages often fail to respond effectively to short-term fluctuations in traffic flow. These limitations reduce the ability of traffic authorities to manage congestion proactively and efficiently.

Recent developments in data availability, sensing technologies, and computational methods have enabled the application of machine learning and deep learning techniques to traffic congestion forecasting. Unlike conventional approaches, data-driven models are capable of learning complex temporal patterns and nonlinear relationships directly from large-scale traffic data. As a result, these models have demonstrated improved adaptability and forecasting performance in short-term traffic prediction tasks.

Within this context, AI-based congestion forecasting is increasingly viewed as a key enabler for adaptive traffic signal control and smart city applications. By predicting congestion before it fully develops, such systems can support proactive traffic-management strategies, improve intersection performance, and contribute to more efficient and sustainable urban mobility.

2.2 Classical Machine Learning Methods

Early research on traffic congestion prediction relied heavily on classical machine learning algorithms applied to structured traffic datasets. Commonly used models include logistic regression, decision trees, support vector machines (SVM), and k-nearest neighbors (KNN). These techniques were primarily employed to classify congestion states or predict short-term traffic volumes based on historical detector data and basic temporal features.

Among classical approaches, decision tree–based models and random forests received particular attention due to their robustness and interpretability. Random forests, in particular, are effective in handling noisy traffic data by aggregating predictions from multiple decision trees, which helps reduce overfitting and improve generalization. Despite these advantages, classical machine learning models generally struggle to capture complex temporal dependencies and spatial interactions between adjacent intersections, which limits their effectiveness in highly dynamic urban traffic environments (Liu et al., 2025).

2.3 Deep Learning Approaches

Deep learning techniques have significantly advanced traffic congestion forecasting by enabling models to learn nonlinear and time-dependent traffic patterns directly from data. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) architectures, are widely used due to their ability to model sequential data and capture temporal correlations in traffic flow. As a result, LSTM-based models have demonstrated superior performance compared with traditional machine learning methods in short-term congestion prediction tasks.

To further enhance predictive performance, hybrid deep learning models such as Convolutional Neural Network–LSTM (CNN–LSTM) architectures have been introduced. These models combine convolutional layers for spatial feature extraction with recurrent layers for temporal modeling, allowing them to capture both localized traffic variations and broader temporal trends. Hybrid frameworks are especially effective in scenarios involving multiple traffic movements and closely spaced intersections.

More recently, graph-based deep learning models have gained prominence in traffic forecasting research. By representing traffic networks as graphs, spatiotemporal graph neural networks can jointly model spatial dependencies between intersections and temporal traffic evolution, providing a more realistic representation of congestion propagation in urban networks (Rahmani et al., 2023).

2.4 Hybrid and Optimized Models

Hybrid and optimization-enhanced models have emerged as an effective approach to overcoming the limitations of standalone machine learning and deep learning techniques. These approaches often integrate neural networks with metaheuristic optimization algorithms, such as genetic algorithms or swarm-based methods, to improve parameter tuning and training efficiency. Optimization techniques help enhance model convergence and robustness, particularly when dealing with noisy and high-variance traffic data (Kashyap et al., 2022).

In addition, hybrid architectures that fuse multiple learning mechanisms, such as CNN–RNN or CNN–LSTM frameworks, have shown strong potential in traffic congestion forecasting. By jointly leveraging spatial pattern recognition and temporal sequence learning, these models consistently outperform single-structure models in terms of prediction accuracy and stability. Their flexibility makes them particularly suitable for congestion forecasting systems intended to support adaptive traffic signal control (Topilin et al., 2025).

2.5 Use of Real-World Datasets

The effectiveness of traffic congestion forecasting models depends heavily on the quality and relevance of the datasets used for training and evaluation. Most studies rely on real-world traffic data collected from operational transportation systems, including loop detectors, adaptive traffic signals, and IoT-based sensing infrastructures. Well-known data sources include the California Performance Measurement System (PeMS) as well as open-data platforms provided by urban transportation authorities.

In this study, real-world traffic volume data obtained from signalized intersections are used to support congestion prediction and analysis. Specifically, the dataset is sourced from the Traffic Signal Volume Data repository provided by the Department of Transport and Planning, Victoria, which offers high-resolution detector-based traffic counts collected from operational traffic signal systems (Department of Transport and Planning, 2025). Such

datasets provide detailed temporal and movement-level information that is essential for modeling congestion dynamics at signalized intersections.

Preprocessing real-world traffic data is a critical step in model development. Common procedures include handling missing values, correcting inconsistent detector readings, removing outliers, and generating temporal features such as time of day and day of week. These steps ensure that the resulting datasets accurately reflect traffic dynamics and are suitable for machine learning and deep learning applications (Zhu et al., 2019).

2.6 Research Gaps and Opportunities

Despite significant progress in AI-based traffic congestion forecasting, several research gaps remain. Many existing models rely primarily on historical data and do not fully integrate real-time traffic streams, limiting their applicability in operational traffic management systems. In addition, a large proportion of studies focus on isolated intersections or short road segments, which restricts the ability to generalize predictions across interconnected urban networks.

Furthermore, although hybrid and graph-based deep learning models have demonstrated promising results, their practical deployment remains limited due to computational complexity and interpretability challenges. These gaps highlight the need for forecasting frameworks that are accurate, scalable, interpretable, and capable of supporting predictive traffic signal control in real-world environments (Rahmani et al., 2023; Liu et al., 2025).

2.7 Conclusion

This chapter reviewed the main methodological approaches used in traffic congestion forecasting, ranging from classical machine learning techniques to advanced deep learning and hybrid models. The literature demonstrates that AI-based approaches significantly outperform traditional methods when applied to complex and dynamic traffic environments.

Building on these insights, this project focuses on developing a congestion forecasting framework grounded in real-world traffic data and informed by recent advances in machine learning and deep learning. The reviewed research provides a strong theoretical foundation for the subsequent chapters, which aim to explore how predictive models can support intelligent and adaptive traffic signal management.

Chapter 3 Related Work

3.1 Introduction

Traffic congestion forecasting has attracted growing research interest due to its direct impact on urban mobility, economic productivity, and environmental sustainability. As urban populations and vehicle ownership continue to increase, traditional traffic management strategies have struggled to cope with rapidly changing traffic conditions, particularly at signalized intersections. These limitations have motivated the exploration of more advanced, data-driven approaches capable of capturing the complex dynamics of urban traffic systems.

In response to these challenges, researchers have proposed a wide range of traffic congestion forecasting methods, evolving from early statistical and analytical models to modern machine learning, deep learning, and hybrid approaches. Each generation of models has sought to improve predictive accuracy, adaptability, and robustness by better representing temporal variations, nonlinear relationships, and spatial dependencies within traffic networks.

This chapter reviews key developments in traffic congestion forecasting, tracing the progression of methodologies from classical techniques to advanced artificial intelligence-based models. By examining prior studies and their reported findings, the chapter highlights how existing research has addressed congestion prediction and establishes the relevance of these approaches to the objectives of the proposed study.

3.2 Historical Development of Traffic Congestion Forecasting

Early research on traffic congestion forecasting was primarily grounded in statistical and analytical methods. Classical techniques such as linear regression, autoregressive integrated moving average (ARIMA), and probabilistic models were widely employed to analyze historical traffic volumes and identify recurring peak-period patterns. Although these approaches provided useful baseline insights into traffic behavior, their effectiveness was limited by an inability to capture nonlinear relationships and rapid temporal fluctuations that are characteristic of urban traffic systems (Zhu et al., 2019).

During the early 2000s, the introduction of machine learning marked a significant shift in congestion forecasting research. Models including decision trees, support vector machines

(SVM), k-nearest neighbors (KNN), and logistic regression offered greater flexibility by learning complex relationships directly from traffic detector data. These methods improved predictive accuracy compared with purely statistical models; however, they continued to face challenges related to high-dimensional feature spaces and the modeling of long-term temporal dependencies (Medina-Salgado et al., 2022).

In the past decade, deep learning approaches have become increasingly prominent in traffic forecasting studies. Recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, demonstrated superior performance in modeling sequential traffic data and capturing temporal dependencies over extended horizons. More recently, spatiotemporal and graph-based neural networks have been introduced to explicitly represent spatial relationships between intersections and roadway segments. These models enable a more realistic representation of congestion propagation across urban networks, reflecting both spatial interactions and temporal evolution of traffic conditions (Rahmani et al., 2023).

3.3 Previous Studies on Traffic Congestion Forecasting

A substantial body of recent research has demonstrated the effectiveness of artificial intelligence techniques for predicting traffic congestion and traffic flow under varying conditions. Katambire et al. (2023) compared ARIMA and LSTM models for short-term traffic-flow prediction at an urban intersection and reported that LSTM consistently outperformed ARIMA in terms of MAE, MAPE, and RMSE. Their findings underscored the importance of temporal learning for congestion-related forecasting tasks.

Muhammed et al. (2024) proposed a hybrid Graph Attention Network–Bidirectional LSTM–Attention (GAT–Bi-LSTM–Attention) model for multi-horizon traffic-speed prediction using freeway datasets. The study demonstrated that incorporating spatial dependencies alongside temporal attention mechanisms significantly enhanced forecasting accuracy compared with simpler deep learning architectures.

Tree-based ensemble methods have also shown strong performance in congestion-related prediction tasks. Chen et al. (2021) applied an XGBoost model to predict travel time using real-world probe-vehicle data and achieved superior accuracy and computational

efficiency compared with traditional gradient boosting models. These results highlighted the suitability of ensemble learning approaches for handling heterogeneous and noisy traffic datasets.

More advanced hybrid and physics-informed approaches have recently emerged. Li et al. (2025) introduced a physics-informed Deep Operator Network (DeepONet) that integrates traffic-flow conservation principles into the learning process. Their experimental results demonstrated notable improvements in prediction accuracy and an enhanced ability to capture congestion propagation over both space and time.

In addition, Sakib (2025) evaluated multiple tree-based machine learning models, including Decision Trees, Random Forest, Gradient Boosting, XGBoost, and LightGBM, under highly congested urban traffic conditions. The study found that Random Forest achieved the best overall performance, while explainable AI tools such as SHAP provided valuable insights into the factors influencing congestion, thereby improving model interpretability.

Overall, these studies indicate a clear trend toward hybrid, spatiotemporal, and interpretable AI-based models for traffic congestion forecasting. However, much of the existing literature focuses primarily on predictive accuracy, with limited emphasis on directly linking congestion forecasts to operational traffic-control strategies such as adaptive signal timing. This gap motivates the need for integrated frameworks that combine accurate prediction with practical traffic management applications.

3.4 Comparative Summary Table

The following table presents a comparative summary of representative quantitative findings from recent studies on traffic congestion forecasting. It highlights the diversity of modeling approaches applied in the literature and summarizes their reported performance and key contributions.

Study	Model	Key Findings
Katambire et al.(2023)	LSTM vs. ARIMA	Compared ARIMA and LSTM for short-term traffic-flow forecasting at Muhima Junction (Rwanda). Using MAE, MAPE

		and RMSE as evaluation metrics, the LSTM model achieved lower errors than ARIMA and was selected as the best-fitting model for monthly traffic-flow prediction, supporting its use for adaptive traffic-signal control.
Muhammed et al. (2024)	GAT-Bi-LSTM-Attention	Proposed a hybrid GAT-Bi-LSTM-Attention model for multi-horizon traffic-speed prediction on PeMSD4/PeMSD7 freeway datasets. The full model (GAT-Bi-LSTMA) achieved MAE ≈ 0.19 , RMSE ≈ 0.43 and MAPE $\approx 9.7\%$ on PeMSD4—substantially better than ablated variants without Bi-LSTM, attention or GAT—showing the benefit of combining graph-based spatial modeling with bidirectional LSTM and temporal attention.
Topilin et al. (2025)	CPO-CNN-LSTM-Attention (Hybrid Deep Model)	Developed a Crested Porcupine Optimizer (CPO)-CNN-LSTM-Attention model for urban traffic-flow forecasting on Paris road data. The hybrid architecture achieved RMSE in the range 17.35–19.83 and MAE about 13.98–14.04, outperforming comparison models and demonstrating strong short-term prediction performance for congestion-prone urban corridors.
Chen & Fan (2021)	XGBoost (Tree-Based Gradient Boosting)	Used an XGBoost model to predict freeway travel time from probe-vehicle data. After hyperparameter optimization, XGBoost delivered higher prediction accuracy and efficiency than a standard Gradient Boosting model, indicating that boosted decision-tree ensembles are effective for congestion-related travel-time forecasting on freeways.
Li et al. (2025)	Physics-Informed DeepONet (PI-DeepONet)	Introduced a physics-informed Deep Operator Network for traffic-state estimation, embedding the traffic-flow conservation law and the Greenshields fundamental diagram into the learning process. Experiments on real-world traffic data showed that DeepONet and PI-DeepONet improved MAE and RMSE by up to about 24.17% and 27.84%, respectively, compared with state-of-the-art baselines, while better capturing congestion propagation in space and time.
Sakib (2025)	Tree-Based ML + XAI (DT, RF, GBM, XGBoost, LightGBM + SHAP)	Evaluated five tree-based models for travel-time prediction under heterogeneous, highly congested traffic conditions in Dhaka (Bangladesh) using Google Maps travel-time data. Random Forest achieved the lowest RMSE, MAE and MAPE and the highest R^2 among the models. SHAP analysis showed that “travel time 15 minutes prior” was the most influential predictor, followed by earlier travel times and section length, highlighting the value of explainable ensemble models for congestion-related travel-time prediction.

3.5 Research Gaps Identified from Prior Studies

Despite significant progress in AI-based traffic congestion forecasting, several research gaps remain evident in the existing literature. Many studies rely primarily on historical traffic data and do not incorporate real-time sensor streams, which limits their applicability in operational traffic-control environments (Liu et al., 2025).

Moreover, a large proportion of prior research focuses on isolated intersections or short roadway segments, overlooking congestion propagation across interconnected urban networks. Although hybrid and spatiotemporal deep learning models have demonstrated promising results, their practical deployment within adaptive signal-control systems remains limited. These gaps underscore the need for predictive frameworks that are accurate, interpretable, scalable, and directly connected to traffic-signal control decisions.

3.6 Model Candidates for the Proposed Traffic Prediction System

Based on the reviewed literature and the analytical requirements of intelligent traffic management systems, two advanced AI architectures are identified as promising candidates for the congestion prediction component of the proposed framework. These models have been widely adopted in prior studies and align with the project's objective of supporting adaptive signal control to mitigate congestion at urban intersections.

(1) Spatio-Temporal Graph Convolutional Network (STGCN)

The STGCN model is designed to capture both spatial dependencies among interconnected intersections and temporal variations in traffic flow. By representing the road network as a graph and applying graph convolutional operations, STGCN enables effective modeling of congestion propagation across nearby traffic signals. Its integrated spatiotemporal learning capability makes it a suitable candidate for forecasting emerging congestion and supporting proactive signal-timing adjustments.

(2) CNN-LSTM Hybrid Model

The CNN-LSTM architecture combines convolutional layers for extracting spatial patterns from traffic-flow sequences with LSTM layers for modeling temporal dynamics. This hybrid approach has demonstrated strong performance in short-term traffic forecasting tasks while maintaining relatively lower computational complexity compared with graph-based models. Its modular structure also provides flexibility, making it appropriate for early-stage development and experimentation.

Both architectures are consistent with the objectives of this study, with each offering distinct advantages depending on data characteristics and computational constraints. The final model selection will be determined in subsequent project phases following further analysis of dataset properties and performance requirements during implementation.

3.7 Conclusion

This chapter presented a comprehensive review of related work in the field of traffic congestion forecasting, highlighting the evolution of methodologies from early statistical and machine learning approaches to advanced deep learning, hybrid, and physics-informed models. The reviewed studies demonstrate that artificial intelligence-based techniques significantly outperform traditional methods in capturing the complex temporal and spatial dynamics of urban traffic systems.

The literature analysis shows a clear shift toward spatiotemporal and hybrid modeling frameworks, such as CNN-LSTM architectures, graph-based neural networks, and optimization-enhanced models, which offer improved predictive accuracy and robustness. In addition, recent studies emphasize the growing importance of model interpretability through explainable AI techniques, enabling better understanding of the factors influencing congestion.

Despite these advancements, the review also identified several limitations in existing research, including limited integration of real-time traffic data, insufficient consideration of network-level congestion propagation, and a weak connection between congestion prediction and practical traffic-signal control strategies. These gaps highlight the need for predictive frameworks that are not only accurate, but also scalable, interpretable, and operationally relevant.

Building on the insights gained from the reviewed literature, this study focuses on developing a congestion prediction framework tailored to real-world traffic signal data and aligned with the requirements of adaptive signal control. The next chapter builds upon this foundation by describing the proposed methodology, dataset characteristics, feature engineering process, and model development steps used to address the identified research gaps.

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