



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.

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Chapter 1: Introduction

1.1 Problem Definition

Urban traffic congestion has become one of the most pressing challenges facing modern cities, particularly at signalized intersections where uneven traffic demand and fixed-time signal plans often result in substantial queue buildup. As vehicle volumes continue to increase, traditional signal timings struggle to accommodate dynamic fluctuations in traffic flow, leading to delays, excessive idle time, and reduced overall network efficiency. Persistent congestion at critical approaches not only disrupts daily mobility but also increases fuel consumption, contributes to environmental pollution, and undermines the economic productivity of urban areas.

Although many congestion patterns occur during predictable peak periods, accurately identifying which specific intersection movements will experience heavy pressure and determining how signal timings should adjust in response remains a complex task. Conventional traffic analysis methods typically rely on static averages or predefined rules that fail to capture the nonlinear, time-dependent interactions between neighboring intersections. These limitations prevent timely interventions and contribute to avoidable traffic buildup.

This creates a strong need for intelligent congestion-forecasting systems capable of learning from high-resolution detector data and recognizing early indicators of queue formation. By leveraging advanced machine learning and deep learning models, it becomes possible to predict approaching congestion and proactively modify signal timings such as extending green time for heavily loaded approaches to prevent excessive accumulation and improve traffic throughput. Developing such predictive and adaptive mechanisms is essential for achieving more efficient, responsive, and sustainable urban traffic management within the framework of smart city initiatives.

1.2 Thesis Objectives

This thesis aims to develop an intelligent AI-driven framework capable of predicting congestion at individual traffic-signal approaches and using these predictions to support

adaptive signal-timing strategies that reduce queue buildup and improve intersection performance. To accomplish this, the study is guided by the following objectives:

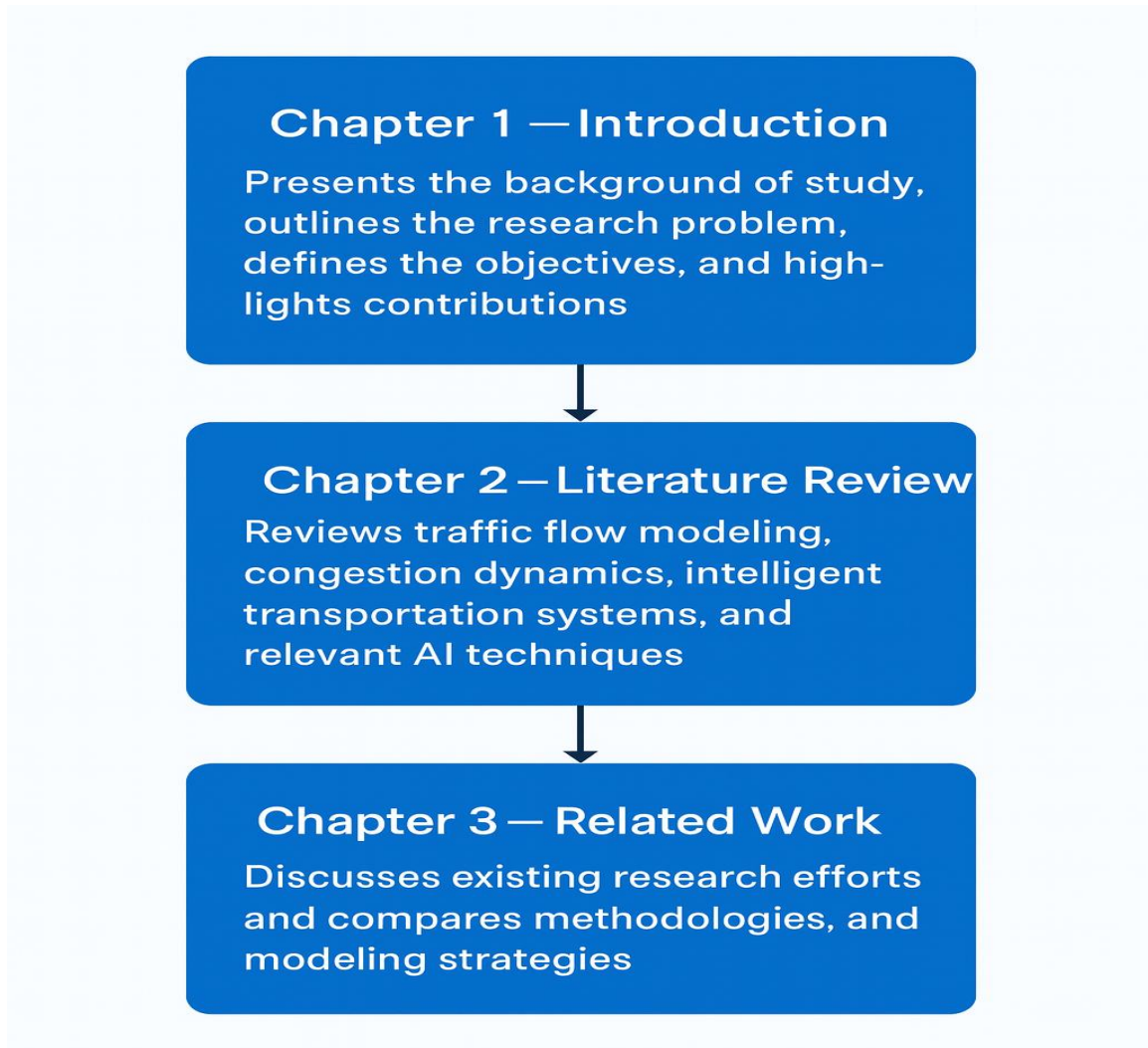
- Conduct an exploratory analysis of high-resolution traffic detector data to identify temporal and spatial patterns associated with congestion formation, and to determine which signal approaches are most prone to recurring bottlenecks.
- Develop a short-term congestion-prediction model using advanced machine learning and deep learning techniques capable of capturing nonlinear traffic behavior and forecasting congestion likelihood for each individual signal movement.
- Implement feature engineering and selection methods to enhance model accuracy, reduce noise, and ensure that the learned patterns reflect meaningful operational factors influencing congestion at signalized intersections.
- Evaluate the predictive model using appropriate performance metrics, such as accuracy, precision, recall, and F1-score for classification tasks, ensuring that the system reliably identifies emerging congestion under different traffic conditions.
- Visualize key traffic insights through heatmaps, temporal profiles, and approach-level flow analyses to better understand peak periods, detector behaviors, and the underlying drivers of queue accumulation.
- Propose a conceptual integration of the prediction model with adaptive signal control, demonstrating how forecasted congestion can inform proactive adjustments such as extending green time for heavily loaded approaches to prevent excessive queue growth and improve overall intersection efficiency.

1.3 Thesis Contributions

This thesis provides several important contributions to the field of AI-enabled traffic management and congestion mitigation, particularly in the context of intelligent signalized intersections:

- **Development of a congestion-prediction framework:**
The study introduces a complete data-driven pipeline capable of forecasting short-term congestion levels for individual traffic-signal approaches using refined detector-based traffic data. The framework incorporates structured feature engineering and selection processes that enhance predictive accuracy and overall model stability.
- **Real-world applicability and operational relevance:**
All analyses and model experiments are conducted using actual traffic-detector volumes collected from functioning signalized intersections. This ensures that the proposed approach aligns with practical traffic-control challenges and can be readily adapted to existing or future smart-city traffic management systems.
- **Improved interpretability through analytical insights:**
By applying visualization techniques and feature importance evaluations, the study offers clear insight into how temporal patterns, approach-specific behaviors, and intersection characteristics influence congestion formation. These insights enhance model transparency and support informed decision-making by traffic engineers and planners.
- **Foundation for AI-driven adaptive signal control:**
A key contribution of this work is establishing a conceptual bridge between congestion prediction and dynamic signal-timing adjustment. The proposed framework demonstrates how forecasted congestion can guide proactive green time reallocation extending the green phase for heavily loaded approaches to prevent excessive queue buildup.
- **Scholarly and methodological advancement:**
The study enriches existing literature by showing how modern machine learning and deep learning techniques can outperform static planning tools and traditional traffic models. It also provides a reproducible and well-documented methodology that can serve as a building block for future research in spatio-temporal modeling, reinforcement learning based signal control, or integrated smart mobility systems.

1.4 Thesis Organization



Chapter 2 Overview

2.1 Introduction to Traffic Congestion Forecasting

Traffic congestion forecasting has become a critical component of modern intelligent transportation systems, particularly as cities strive to manage increasing traffic demand and improve the operational efficiency of signalized intersections. Traditional forecasting methods, which relied primarily on statistical models and linear assumptions, offered early insights into traffic behavior but proved insufficient for capturing the highly dynamic, nonlinear, and time-dependent nature of congestion formation especially at intersections where traffic patterns can shift rapidly within short intervals.

The emergence of advanced sensing technologies including loop detectors, adaptive traffic-signal devices, and widespread IoT-based infrastructure has enabled the collection of rich, high-resolution traffic data across multiple movements at each intersection. At the same time, advances in machine learning and deep learning have introduced powerful modeling tools capable of learning complex spatial and temporal relationships within traffic networks. These algorithms are particularly effective at identifying early indicators of congestion, forecasting future traffic pressure on individual signal approaches, and supporting proactive traffic-management strategies.

Within this context, congestion forecasting is not only a tool for understanding traffic conditions but also a foundational element for adaptive signal control, where predicted congestion can guide dynamic adjustments to green-time allocation. This shift from reactive to predictive traffic management forms the backbone of emerging smart city initiatives, enabling more efficient mobility, reduced delays, and improved intersection performance.

2.2 Classical Machine Learning Methods

Early research on traffic congestion forecasting made extensive use of classical machine learning techniques applied to structured traffic detector data. These studies focused primarily on modeling short-term fluctuations in vehicle flow by leveraging historical

detector readings, time-of-day features, and basic roadway characteristics. Algorithms such as logistic regression, naïve Bayes, support vector machines (SVM), and decision trees were commonly used to classify congestion states or predict traffic volume within upcoming intervals. Among these, decision tree based models often demonstrated superior performance due to their ability to capture interactions among mixed feature types while preserving interpretability an important factor for traffic engineers.

As research progressed, more advanced classical models such as random forests and k-nearest neighbors (KNN) were introduced. Random forests, in particular, gained popularity for their robustness and ability to handle noisy, high-variance traffic datasets by aggregating predictions across multiple decision trees. Despite their practical advantages and relatively strong accuracy, classical machine learning methods exhibited significant limitations in realistic traffic management scenarios.

Most classical models lack the capacity to represent nonlinear temporal dependencies patterns that evolve minute by minute and spatial relationships between movements at adjacent approaches or interconnected intersections. These limitations are critical because congestion frequently forms through propagation effects across the network rather than isolated fluctuations. Consequently, classical machine learning methods provided useful baselines but were insufficient for forecasting congestion in complex, high density urban settings. These shortcomings ultimately encouraged the transition toward deep learning and spatio temporal models capable of capturing the intricate dynamics necessary for predictive and adaptive signal control.

2.3 Deep Learning Approaches

Deep learning has significantly advanced the field of traffic congestion forecasting by providing models capable of learning complex, nonlinear behaviors that traditional methods often fail to capture. Early progress in this domain highlighted the effectiveness of recurrent neural networks particularly Long Short Term Memory (LSTM) architectures in modeling short-term traffic dynamics. LSTM based models excel at capturing temporal dependencies within detector readings, enabling them to learn how traffic conditions evolve across successive time intervals. As a result, many studies have shown that LSTM

architectures outperform classical machine learning techniques in short term congestion prediction tasks.

Building upon the strengths of LSTM networks, researchers introduced hybrid models such as Convolutional Neural Network–LSTM (CNN–LSTM) architectures. These frameworks combine spatial feature extraction with temporal sequence modeling, allowing the system to detect localized variations in traffic flow while simultaneously learning broader temporal patterns. CNN–LSTM models have demonstrated substantial improvements in forecasting accuracy, especially in settings involving multiple approaches at the same intersection or closely spaced intersections where congestion dynamics are spatially correlated.

In addition to deep neural architectures, ensemble approaches such as gradient-boosted trees (e.g., XGBoost) have been explored to identify influential predictors like peak-hour intensity, approach-specific flow patterns, and signal-timing characteristics. Although not inherently designed for sequential learning, these models often deliver competitive results and are frequently integrated with deep learning components to enhance prediction performance.

The most notable advancements in recent years have emerged from spatiotemporal deep learning, particularly through graph-based neural networks. Models such as the Spatio-Temporal Graph Convolutional Network (STGCN), Temporal Graph Convolutional Network (T-GCN), and various graph-attention frameworks explicitly represent the traffic network as a graph where intersections serve as nodes and roadway links act as edges. By jointly modeling spatial relationships between intersections and temporal variations in traffic flow, these models offer highly accurate forecasts that closely reflect how congestion propagates across an urban network. Such capabilities make graph-based neural networks especially well-suited for intelligent traffic signal systems that rely on predictive insights to adjust green times and mitigate developing congestion.

2.4 Hybrid and Optimized Models

Recent developments in traffic congestion forecasting have increasingly shifted toward hybrid learning frameworks and optimization-enhanced models. These approaches aim to address the shortcomings of conventional deep learning or classical machine learning techniques when used independently, particularly in scenarios where traffic dynamics exhibit strong spatial dependencies, nonlinear relationships, and rapid temporal fluctuations across multiple signal approaches.

One prominent line of research integrates deep neural networks with metaheuristic optimization algorithms. Studies have shown that training models such as Artificial Neural Networks (ANNs) or LSTMs using evolutionary optimizers including Genetic Algorithms, Particle Swarm Optimization, and other swarm intelligence techniques can substantially improve model convergence and robustness. These optimization methods help fine-tune hyperparameters more effectively, enabling neural networks to better handle noisy detector data and high variance urban traffic conditions.

At the same time, more advanced hybrid architectures have emerged that explicitly fuse spatial and temporal learning mechanisms. CNN–RNN combinations, and particularly CNN–LSTM models, leverage convolutional layers to extract spatial traffic features from detector grids or road segments, while recurrent layers capture temporal movement patterns and flow progression. This feature-fusion approach has demonstrated consistently superior performance, with many studies reporting reduced forecasting error and improved prediction accuracy compared with models relying on spatial or temporal learning alone.

The versatility of these hybrid and optimization driven frameworks makes them especially appealing for applications involving predictive signal control, where accurate short-term congestion forecasts are essential for adjusting green-time durations and balancing traffic loads across competing movements at intersections.

2.5 Use of Real-World Datasets

Research on traffic congestion forecasting depends fundamentally on real-world datasets collected from operational transportation systems, as these datasets provide the granular and context specific information necessary for modeling congestion at individual signal approaches. Many studies draw upon traffic measurements obtained from loop detectors, adaptive traffic-signal controllers, connected vehicle systems, and other IoT-enabled sensing infrastructures. Prominent examples include datasets from the California Performance Measurement System (PeMS), the Victorian Transport Data Repository, and open-data platforms maintained by various urban transportation agencies. These sources typically offer high resolution observations such as traffic volumes, speeds, occupancy levels, detector activations, and sometimes signal timing records captured at regular intervals across multiple intersections.

Preprocessing such datasets is a critical step in ensuring model reliability. Common procedures include correcting inconsistent detector readings, reconstructing missing intervals, and mitigating abrupt spikes caused by sensor errors or unusual events. Researchers also generate temporal features including hour of day, day of week, and peak-period indicators to capture cyclical mobility patterns that strongly influence congestion formation. Additionally, categorical descriptors such as detector IDs, approach movements, or intersection classifications are usually transformed into numerical representations through encoding or embedding techniques. These preprocessing steps help create a structured and learnable dataset suitable for machine learning and deep learning models aimed at forecasting congestion and supporting adaptive signal-control applications.

2.6 Research Gaps and Opportunities

Although machine learning and deep learning have contributed substantially to advances in traffic congestion forecasting, several critical research gaps continue to limit the effectiveness and real-world applicability of existing models:

- **Limited integration of real-time traffic data:**
Many forecasting models rely predominantly on historical detector readings and do not

incorporate live data streams from IoT sensors, adaptive traffic controllers, or connected vehicles. This reduces their value for real-time traffic management and weakens their ability to support predictive signal-timing adjustments when congestion begins to form.

- **Insufficient modeling at the multi-intersection level:**

A significant share of prior studies concentrates on single intersections or isolated roadway segments. Such approaches overlook the interconnected nature of urban traffic systems, where congestion often propagates between adjacent approaches and across multiple signalized junctions. This restricts model generalizability for network-wide traffic control.

- **Underexploration of hybrid and ensemble deep learning models:**

While initial efforts involving CNN–LSTM hybrids, graph-based neural networks, and attention mechanisms have demonstrated strong potential, opportunities remain to investigate more advanced hybrid or ensemble architectures that may offer improved robustness and higher predictive accuracy under diverse traffic conditions.

- **Limited translation from prediction to actionable control:**

Much of the existing literature focuses solely on forecasting congestion without extending the findings toward operationally meaningful strategies. Few models explicitly connect their predictions to adaptive signal-control decisions such as dynamic green time reallocation, predictive phase sequencing, or prioritization of congested movements.

These gaps highlight the need for forecasting frameworks that:

- incorporate near–real-time traffic data,
- operate effectively across interconnected urban networks,
- leverage advanced hybrid and ensemble deep learning methods, and
- directly support data-driven, predictive traffic signal control aimed at preventing queue buildup and improving intersection performance.

2.7 Conclusion

The reviewed body of research demonstrates the substantial progress achieved through artificial intelligence, deep learning, and hybrid modeling techniques in forecasting traffic congestion across urban road networks. Prior studies confirm that predictive accuracy improves significantly when models are designed to capture both temporal patterns and

spatial interactions within intersection-level traffic data. These advancements highlight the growing potential of AI-driven methods to support more informed and efficient transportation management.

Building on these insights, this thesis adopts a refined predictive framework trained on real-world detector data to better anticipate congestion at individual signal approaches. The proposed direction addresses several gaps identified in earlier literature, including the need for enhanced feature selection, improved model transparency, and a stronger alignment between prediction models and practical traffic-control requirements. By integrating these components, this work lays the foundation for developing intelligent, data-driven strategies that can proactively adjust signal timings such as extending green phases for heavily loaded movements to mitigate congestion before it escalates.

Ultimately, the findings from this research aim to support the long-term vision of adaptive, AI-enabled traffic management systems capable of improving mobility, reducing delays, and enhancing the overall performance of smart urban transportation networks.

Chapter 3 Related Work

3.1 Introduction

Accurate forecasting of traffic congestion has become a central research focus due to its direct impact on urban mobility, economic productivity, and the overall efficiency of transportation systems. Over the past decade, advancements in sensing technologies and data availability have enabled researchers to develop a wide spectrum of models, ranging from early statistical approaches to increasingly sophisticated AI-driven and spatiotemporal frameworks. These techniques have progressively improved the ability to capture the dynamic, nonlinear, and network-dependent nature of traffic flow.

3.2 History

The development of traffic congestion forecasting has progressed substantially over the past several decades, reflecting advancements in both transportation engineering and computational modeling. Early studies primarily relied on statistical and rule-based approaches, including linear regression, autoregressive time-series models such as ARIMA, and probabilistic methods. These techniques were used to analyze historical traffic volumes, identify peak-period patterns, and estimate congestion levels based on fixed relationships between time of day, roadway characteristics, and traffic demand. While informative, these models were limited in their ability to handle nonlinear fluctuations or rapidly changing conditions within urban networks.

During the 2000s, the emergence of machine learning introduced a new wave of predictive capabilities. Models such as decision trees, support vector machines (SVMs), k-nearest neighbors (KNN), and logistic regression were increasingly adopted for congestion classification and short-term traffic prediction. These algorithms offered improved accuracy and flexibility compared with traditional statistical methods, yet they still struggled with high-dimensional data and with the complex temporal-spatial dependencies that characterize real-world traffic behavior.

The past decade has marked a significant shift toward deep learning approaches. Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and hybrid CNN-RNN architectures have begun to dominate the field due to their superior ability to learn sequential patterns and capture spatiotemporal dynamics. These models have benefited from the growing availability of real-time traffic measurements,

sensor networks, and connected vehicle data, enabling them to represent congestion propagation more accurately across multiple intersections.

More recent advancements have integrated optimization algorithms—such as Genetic Algorithms, Particle Swarm Optimization, and other nature-inspired techniques—to enhance model training, feature selection, and parameter tuning. In addition, the incorporation of explainable AI (XAI) frameworks, including SHAP and LIME, has improved model transparency by identifying the factors most influential in congestion formation. Together, these innovations have driven the field toward more robust, scalable, and operationally relevant solutions capable of supporting intelligent traffic management and adaptive signal control in modern smart cities.

3.3 Previous Studies on Traffic Congestion Forecasting

Recent advances in artificial intelligence have led to a wide range of models designed to predict traffic congestion across urban road networks. The following studies represent influential contributions to the field, covering classical machine learning, deep learning, hybrid spatiotemporal models, and physics-informed approaches.

Katambire et al. (2023) compared the performance of ARIMA and LSTM models for short-term traffic-flow prediction at the Muhima Junction in Rwanda. Using MAE, MAPE, and RMSE as evaluation metrics, the LSTM model consistently outperformed ARIMA, demonstrating lower forecasting errors and stronger suitability for adaptive traffic-signal control applications.

Muhammed et al. (2024) introduced a hybrid GAT–Bi-LSTM–Attention architecture for multi-horizon traffic-speed prediction on the PeMSD4 and PeMSD7 freeway datasets. The full GAT–Bi-LSTM–Attention model achieved $MAE \approx 0.19$, $RMSE \approx 0.43$, and $MAPE \approx 9.7\%$ on PeMSD4—substantially outperforming simplified variants without GAT, bidirectional LSTM, or attention modules. The study highlights the effectiveness of combining graph-based spatial modeling with temporal learning for complex road networks.

Topilin et al. (2025) proposed a CPO–CNN–LSTM–Attention hybrid model optimized using the Crested Porcupine Optimizer (CPO). Tested on Paris urban traffic data, the model

achieved RMSE values ranging from 17.35 to 19.83 and MAE between 13.98 and 14.04. The approach demonstrated strong predictive performance on dense, congestion-prone corridors, validating the integration of CNN spatial filters, LSTM temporal modeling, and attention mechanisms.

Chen and Fan (2021) applied an XGBoost model to predict freeway travel time using probe-vehicle data. After extensive hyperparameter tuning, XGBoost outperformed standard Gradient Boosting models in accuracy and computational efficiency. The results confirmed that tree-based ensemble methods are highly effective for congestion-related travel-time forecasting.

Li et al. (2025) introduced a Physics-Informed DeepONet (PI-DeepONet) that incorporates traffic-flow conservation laws and the Greenshields fundamental diagram into the learning process. Experiments on real-world traffic datasets showed improvements in MAE and RMSE of up to 24.17% and 27.84%, respectively, compared with state-of-the-art baselines. The model demonstrated increased ability to capture shockwaves and congestion propagation over space and time.

Sakib (2025) evaluated multiple tree-based models—Decision Trees, Random Forest, Gradient Boosting, XGBoost, and LightGBM—on highly heterogeneous, congested road conditions in Dhaka using Google Maps travel-time data. Random Forest achieved the lowest RMSE, MAE, and MAPE, in addition to the highest R^2 . SHAP analysis revealed that “travel time 15 minutes prior” was the most influential feature, demonstrating the importance of explainable AI techniques in understanding traffic-flow dynamics.

These studies collectively highlight the diversity of modeling approaches, the importance of spatial-temporal learning, and the ongoing shift toward hybrid and interpretable AI techniques in traffic-flow forecasting.

3.4 Comparative Summary Table

Table summarizes representative quantitative findings from recent studies on traffic congestion forecasting, highlighting the diversity of models and their reported performance.

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 forecasting, several notable research gaps remain:

Limited integration of real-time sensor data:

Many models rely exclusively on historical data, reducing applicability to live traffic-control systems that require rapid response.

Insufficient network-level modeling:

Several studies focus on individual intersections or short road segments, limiting the ability to generalize congestion dynamics across multi-intersection networks.

Underuse of ensemble deep learning and hybrid approaches:

While early results from CNN-LSTM and GNN models are promising, comprehensive ensemble deep learning frameworks remain understudied.

Lack of operational deployment pathways:

Few studies present end-to-end systems that integrate prediction with actionable control strategies such as adaptive signal timing or rerouting.

Limited interpretability in complex models:

Although explainable AI (XAI) has begun to emerge, many deep models still function as black boxes, making it difficult for transportation engineers to trust and operationalize them.

These gaps underscore the need for models that are not only accurate but also interpretable, scalable, and compatible with real-world smart-city infrastructures

3.6 Model Candidates for the Proposed Traffic Prediction System

Based on the findings of the reviewed literature and the analytical requirements of intelligent traffic management systems, two advanced AI architectures have been identified as suitable candidates for the congestion-prediction component of the proposed framework. These models have demonstrated strong performance in previous studies and align with the project's aim of enabling adaptive signal control to mitigate congestion across urban intersections.

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

The STGCN model is specifically designed to capture both spatial dependencies between interconnected intersections and temporal variations in traffic flow. By representing the road network as a graph and applying graph convolutional operations, STGCN effectively models how congestion propagates across nearby traffic signals. Its ability to integrate spatial and temporal learning makes it a strong candidate for predicting 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 learning temporal dynamics. This hybrid approach has shown high predictive accuracy in short-term traffic forecasting tasks while maintaining lower computational complexity than graph-based methods. Its modular structure also makes it flexible and easier to implement during the early development phase.

Both models are aligned with the objectives of this project, and each offers distinct advantages depending on the structure of the available dataset and the computational constraints of the intended deployment environment. The final model selection will be determined in the next phase of the project, following a deeper analysis of the dataset and performance requirements during the implementation stage of the predictive framework.

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