AI-Powered Real-Time Urban Traffic Congestion Prediction Using Distributed Big Data Processing

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Abstract
Urban traffic congestion remains a major challenge in rapidly expanding cities, impacting mobility, fuel consumption, and environmental sustainability. With the rise of big data and real-time information from sensors, GPS, and IoT devices, there is tremendous potential to build smarter traffic management systems. This paper explores how deep learning models can be used to predict traffic congestion in real time, highlighting architectures such as Convolution Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and Transformers. Deep learning offers greater accuracy and scalability than conventional machine learning techniques by automatically extracting significant features from intricate spatial and temporal traffic data. We also look at how big data technologies like Apache Spark and Kafka manage the rapid ingestion and processing of traffic data. The most recent advancements, widely used datasets, deployment tools, major obstacles, and potential future directions for integrating deep learning-based real-time traffic prediction in smart city systems are all thoroughly reviewed in this survey.

Keywords: Intelligent Transportation Systems (ITS), Time Series Forecasting, Urban Traffic Management, Deep Learning, Spatiotemporal Modeling, LSTM, CNN, GNN, Transformers, Big Data Analytics, Real-Time Data Streams, Apache Spark, Apache Kafka, Traffic Congestion Prediction.

1. Introduction

Many cities frequently experience traffic congestion as a result of the sharp increase in vehicle usage brought on by urbanization and rapid population growth. In addition to lengthening commutes, these delays increase fuel consumption, air pollution, and financial losses. Because real-world traffic is unpredictable, traditional traffic control systems that rely on set rules or simple statistical models frequently fail.

New opportunities for smarter traffic have been made possible by recent advancements in big data and DL. To improve prediction accuracy, this system combines deep learning and machine learning methods. In order to provide dynamic traffic insights, it takes into account variables such as weather, past traffic patterns, and current incidents. Cities can manage enormous datasets thanks to distributed big data processing, which guarantees scalability.

These days, a variety of sources, such as loop detectors, GPS-enabled cars, mobile devices, surveillance cameras, and Internet of Things sensors, are continuously producing real-time traffic data. Although these data streams offer insightful information, managing them is challenging due to their size, speed, and diversity.

Compared to older ML methods, DL is better at extracting useful features from messy, high- dimensional data like images, sensor logs, or GPS traces. For instance, LSTMs are excellent for analyzing traffic sequences over time, CNNs perform well with traffic camera video feeds, and GNNs aid in more precise traffic network modeling at the road segment level.

This survey provides a comprehensive overview of existing methods for DL and big data platforms-based real-time congestion prediction. The various model types, infrastructure tools, datasets, deployment strategies, evaluation techniques, and important research gaps are all covered. Cities now have more potent tools to create effective, scalable, and responsive traffic systems as artificial intelligence and real-time data become essential components of urban mobility. However, platforms that can handle the speed and complexity of contemporary

traffic data are necessary to fully utilize these technologies.

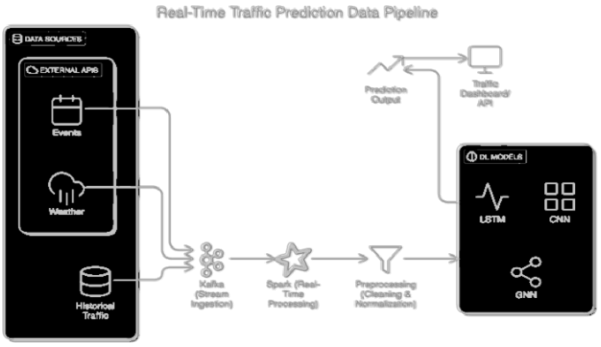

FIGURE 1. General Architecture for Real-Time Traffic Congestion Prediction Using Bigdata and Deep Learning

Managing quick, real-time traffic data streams now requires the use of big data platforms like Apache Spark and Kafka. These tools allow for highly accurate congestion forecasting and the detection of intricate spatiotemporal patterns in traffic flow when paired with sophisticated ML and DL algorithms, such as SVM, RF, KNN, Linear Regression, and LSTM.

This survey provides a comprehensive overview of the latest techniques for real-time traffic congestion prediction using artificial intelligence and big data. It looks at the primary uses, tools, formulas, and structures that underpin modern intelligent traffic systems. Additionally, it highlights the main challenges, open research areas, and possible directions for developing scalable, real-time, AI-powered traffic prediction systems that meet the needs of smart city infrastructure.

2. Literature Review

Noureen Zafar et al. [1] proposed a hybrid DL model combining GRU and LSTM, applied to city-wide traffic data collected from various sources. For tasks like map matching, handling sparse data, eliminating outliers, modifying zero-speed values, mapping segments using Open Street Map (OSM), and also created a custom data pipeline with algorithms. Tests demonstrated that the suggested model performs better than alternative techniques at forecasting traffic conditions. By combining a variety of data inputs with OSM, including traffic load, GPS signals, weather, and special events, the study created a hybrid feature space. Road conditions were categorized as smooth, congested, and highly congested using an ETA- based congestion index. The GRU-LSTM model led DL approaches with the highest accuracy, while RF performed best among ML techniques. The authors came to the conclusion that when used to address arterial road congestion, DL techniques provide more accurate and dependable results than traditional ML

Jesús Mena-Orej et al. [2] carried out a detailed comparison of several modern neural network models for traffic prediction. Using real-world traffic data, tested different architectures under the same conditions, covering both smooth-flowing and congested traffic scenarios. One key insight from the research is that strong performance during normal traffic doesn't always translate to effective predictions when congestion arises. The study underlines the need to evaluate prediction models specifically in congested conditions to truly understand the reliability. It also shows that combining spatial and temporal traffic information yields better results than relying on time-based data alone, particularly during heavy traffic. Moreover, models designed with error feedback referred to as error recurrent models consistently delivered better accuracy across different traffic states compared to those without such feedback.

Saurabh Pratap Singh Rathore et al. [3] proposed an AI-based system aimed at predicting and managing traffic congestion. The system tracks traffic conditions in real time by using continuous streams of data from IoT devices, including GPS, inductive loop sensors, and images. CNN and LSTM models are combined to create traffic forecasts. Furthermore, the integration of Geographic Information System (GIS) technology facilitates dynamic traffic control and supports spatial analysis. This gives drivers alternate routes to help them avoid

traffic and enables real-time traffic signal adjustments. According to preliminary testing, these intelligent traffic management systems can significantly enhance traffic flow and lessen gridlock in big cities. The integration of self-driving cars and reinforcement learning techniques are among the future opportunities covered in the paper, along with issues like data privacy and system scalability. The system makes use of IoT sensor data that replicates real-world traffic situations.

Malathi et al. [4] introduced a smart system for tackling traffic congestion by combining advanced congestion detection with adaptive traffic signal control. The system uses AI to analyze a range of data sources including real-time traffic flow, road conditions, and historical trends to accurately identify congestion patterns. Machine learning algorithms then assess these patterns to dynamically optimize signal timings based on traffic volume, queue lengths, and delays.

Simulation results showed that the system performs exceptionally well, achieving an accuracy of 94.89%, precision of 97.40%, recall of 96.38%, and an F1 score of 96.76%. These strong results demonstrate its ability to detect congestion reliably while minimizing false alarms. By integrating these cutting-edge techniques, the system significantly improves traffic flow, reduces travel times, and enhances the overall driving experience. The Intelligent Traffic Congestion Identification and Signal Switching System offers a fresh and effective approach to managing urban traffic challenges. Its real-time analysis capabilities enable precise detection of congested areas, which is crucial for adjusting signal timings efficiently. Thanks to its adaptability and automation, this solution stands out as a practical tool for easing congestion and boosting transportation efficiency for commuters.

Hongsuk Yi et al. [5] developed an automated machine learning framework designed to optimize hyper parameters for traffic prediction models, focusing mainly on major highways. Acknowledging the difficulties involved in training deep learning models—especially the time- consuming and expert-driven process of tuning hyper parameters. This framework uses techniques like Bayesian optimization and meta-learning to make the search for the best hyper parameters more efficient. By combining Hypernet with LSTM networks, the approach effectively captures the temporal patterns in traffic data, leading to improved predictions of highway congestion. The main goal is to automate much of the training process, reducing the need for manual adjustments and boosting model accuracy across various traffic datasets.

Humayun Kabir et al. [6] introduced an Intelligent Traffic Management System (ITMS) that uses IoT technology to address urban traffic congestion, a major challenge for growing cities. The system collects real-time traffic data—such as vehicle counts, speeds, and lane occupancy— through sensors installed at key intersections. A central control unit processes this information and dynamically adjusts traffic signals, allocating green light durations based on the actual flow of vehicles. This strategy aims to improve traffic movement, reduce congestion, and boost overall efficiency. The study highlights benefits like shorter travel times, better air quality, and increased safety for both pedestrians and drivers. It also compares fixed and adaptive signal timings across different traffic scenarios, demonstrating the effectiveness of real-time traffic signal regulation in busy urban areas.

Mouna Zouari Mehd et al. [7] proposed a congestion prediction method using a supervised approach based on differential entropy and convolution neural networks. Their model incorporates various traffic-related parameters including location, date, day of the week, time, special road conditions, and holidays. Validated on the City Pulse dataset, which contains vehicle traffic records, their approach achieved accurate congestion predictions for multiple traffic nodes. The system aims to help prevent congestion by suggesting alternative routes to drivers. Simulation results confirm the model's strong prediction accuracy across the different nodes analyzed.

Kavitha et al. [8] proposed an IoT-based traffic control system that uses RFID technology alongside Arduino microcontrollers to improve emergency vehicle movement. The system detects emergency vehicles through RFID tags and dynamically adjusts traffic signals to create

a clear path for them. Implemented with RFID receivers and Arduino controllers, this setup allows real-time traffic signal management. Early tests showed a significant decrease in emergency vehicle transit times. While

the system shows promise for enhancing urban traffic management and emergency response, it also faces challenges such as potential interference from other RFID devices and dependence on the reliability of the RFID and Arduino components.

Yuan-yuan Chen et al.[9] explored the use of publicly available on line data to provide real- time traffic information. They collected traffic conditions from web-based map services and employed a stacked LSTM model to learn and predict traffic patterns. Their experiments demonstrated that the stacked LSTM out performed traditional models like multilayer perceptrons, decision trees, and support vector machines. The study also reviewed four categories of open data platforms—web maps, social media, local events, and weather websites—and confirmed the viability of online open data as a valuable source for traffic condition monitoring.

Leixiao Li et al. [10] introduced MF-TCPV, a system that integrates multi-source, heterogeneous traffic data using Data-X and Data-V technologies for congestion prediction and visualization. They proposed a deep learning prediction model called LSTM-SPRVM, which combines deep learning, machine learning algorithms, and Spark parallelization to forecast traffic congestion levels. In this system, congestion is categorized into six levels based on factors such as average speed, road occupancy, and traffic density using a fuzzy comprehensive evaluation. Experimental results showed that MF-TCPV accurately predicts congestion and visualizes the results effectively, with LSTM-SPRVM outperforming other deep learning models in prediction accuracy.

Naveen et al. [11] developed a model to predict and visually represent traffic congestion using both machine learning and deep learning techniques. Their approach begins with exploratory data analysis (EDA) to understand data distribution and patterns through descriptive statistics, correlation analysis, and visualizations. They then apply manifold learning methods to reduce dataset complexity while preserving important information. Feature importance techniques help identify key factors influencing traffic volume predictions. The model offers insights into traffic patterns and congestion levels, presenting visualizations based on time, day, and month to highlight congestion hotspots. Project emphasizes how data analysis and feature extraction can aid traffic regulation. The Route Rover system, driven by machine learning, shows promise for enhancing travel efficiency and reducing congestion, although its success depends on the quality of real-time data and scalability. With further refinement, Route Rover could become a valuable tool for optimizing routes and easing traffic problems.

Supriya Tel Sang et al. [12] introduced a fresh approach to traffic control that enhances urban signal systems by integrating machine learning techniques. Their study focuses on improving vehicle flow and reducing congestion through data collection and vehicle detection methods aimed at optimizing traffic signals. By dynamically adjusting signal timings, the system significantly boosts overall traffic efficiency. The model also prioritizes emergency vehicles, improving public safety and emergency response times. The successful results underline how machine learning can revolutionize traffic management and contribute to smarter metropolitan planning and infrastructure development.

Chunyao Zhong et al. [13] proposed a congestion warning framework based on a "data + model" approach. Their method observes that traffic flow sharply increases and speeds drop around congestion events. By analyzing real traffic data, they determine stable speed and flow ranges before and after congestion and select an appropriate traffic flow model to describe relationships between key traffic parameters. Using the slope changes in this model's graph, the framework identifies early warning points within a range defined by historical data, enabling timely congestion alerts.

Suthaharan Satkunarajah et al. [14] developed a model that dynamically adjusts traffic light schedules at four-way intersections in real time, responding to changing traffic densities. The study focuses on two scenarios: light and heavy traffic. Simulations reveal that their adaptive approach out performs traditional fixed-time traffic control methods. Specifically, their proposed green signaling method, with a total cycle time of 40 seconds, achieves better traffic flow than the conventional fixed schedule of 20 seconds per road. This strategy shows clear potential for reducing delays and easing congestion in traffic management systems.

Tianrui Zhang et al. [15] introduced a traffic state prediction approach that combines improved particles warm

optimization (IPSO) with a radial basis function (RBF) and a feature fusion model integrating LSTM and SVM. This hybrid model demonstrated superior performance in predicting urban traffic conditions. To tackle congestion, the study also proposed a traffic allocation-based control method for managing congested sections. Using VISSIM simulations, this method was shown to outperform other traffic control schemes. The work bridges traffic prediction and control theories with intelligent algorithms, identifying key factors that influence traffic states and offering solutions for both prediction and congestion management.

Binghua Nie et al. [16] developed a traffic flow control simulation using a fuzzy control algorithm to regulate highway traffic conditions. The study compared various control strategies—including no control, ALINEA, and fuzzy control—using real data from the Xibao Expressway. Results indicated that fuzzy control provides smoother and more stable traffic flow, with faster response times than ALINEA. While the fuzzy control rules are flexible and can be easily adapted, their effectiveness depends heavily on expert knowledge, which could lead to incomplete or redundant rules. Overall, fuzzy control showed promise in improving traffic operation and reducing highway congestion.

Shyam Shankaran et al. [17] proposed an Adaptive Traffic Control System(ATCS) that adjusts traffic signal timings dynamically based on real-time traffic demand. The system combines hardware—such as sensors for traffic density estimation—and software that analyzes current traffic flow data. Compared to conventional sensors, their model measures queue lengths at intersections more precisely by using camera-based monitoring and image processing. The ATCS has unique features to prioritize emergency vehicles and shortens signal cycle times. By using fewer cycles than fixed-timing systems, this method improves traffic stability at four-way intersections, lowers noise and air pollution, and uses less fuel. To further improve traffic management, future improvements might include solar-powered equipment, LED display boards, synchronized citywide signals, AI-driven image analysis, and high-resolution night- vision cameras.

Yu Zheng et al. [18] explored diverse data sources in Intelligent Transportation Systems (ITS) and proposed a scalable big data analysis framework using distributed computing and parallel processing. The system efficiently processes large-scale traffic data in real time, offering critical decision support for intelligent traffic control. Experimental evaluations demonstrated

the framework's scalability and effectiveness in data preprocessing. The study emphasizes that accurate traffic flow prediction enhances signal timing, congestion management, and road efficiency. However, challenges such as handling the increasing scale and complexity of data remain, highlighting the need for continued research in scalable big data processing.

TABLE 1. Comparison table for literature Review

Reference	Methodology/Model	Data Sources/ Features	Key Contributions	Limitations
[1]	Hybrid GRU-LSTM, Random Forest	GPS, weather, OSM, ETA index, traffic load, conditions	GRU-LSTM outperformed classical models; handles sparse data well	Not suitable for non-linear non-sequential data; data sparsity still a challenge
[2]	DNNs vs Error Recurrent Models	Real traffic data under varied conditions	Error recurrent models outperform DNNs;real- time latency spatiotemporal modeling improves accuracy	Doesn't- address edge deployment or
[3]	CNN+LSTM,GIS+ Reinforcement Learning (future)	IoT sensor data (GPS, images, loop sensors), GIS	Real-time traffic rerouting using GIS; integration of CNN + LSTM for spatial-temporal prediction	Future scope (RL,GIS) is not implemented; hardware integration challenges

[4]	ML classification + Adaptive Signal Control	Traffic flow, queue length, past congestion	Achieved 94.89% accuracy; optimizes traffic flow via adaptive signals	Data set limited to one location; lacks real-time responsiveness
[5]	Auto ML + Hyper net + Bayesian Optimization	Highway traffic datasets	Auto-optimized LSTM configurations; reduces training effort	Requires significant computational resources; less interpretable
[6]	IoT-based Intelligent Traffic System	Sensor data: vehicle count, speed, lane occupancy	Real-time dynamic signal control; improves air quality and safety	Requires reliable sensor networks; not ML-based
[7]	CNN+ Differential Entropy	City Pulse dataset: date/time, location, road status	Effective supervised prediction; driver rerouting suggestion feature	Limited to static dataset; may not adapt to unseen conditions
[8]	IoT with RFID and Arduino	RFID sensors for emergency vehicles	Real-time priority for ambulances; simple hardware integration	Interference issues with RFID; no predictive component
[9]	Stacked LSTM + Online Learning	Web maps, weather, events, social media	Dynamic learning on test data; performs better than MLP, DT, SVM	Lacks deployment details; online learning increases model complexity
[10]	LSTM-SPRVM+MF-TCPV Platform	Data-X, Data-V, Spark; heterogeneous traffic data	Multi-level classification; high accuracy and visualization	Requires advanced infrastructure (Spark, Data-V); limited scalability for small cities
[11]	ML + DL with EDA	Time, day, month, visual EDA	Strong visual and statistical analysis; model integration	No real-time testing; lacks comparison with DL models
[12]	ML-enhanced Dynamic Signal Timing	Live traffic and vehicle detection	Real-time emergency handling; efficient signal control	Not scalable; lacks cloud or edge deployment strategy
[13]	Data-driven Congestion Warning Framework	Speed-flow pre-and post-congestion	Early congestion detection via speed-flow shift modeling	Only work spost-congestion; not proactive
[14]	Video Surveillance + Sensor-based Prioritization	CCTV footage, ultrasonic + IR sensors	Emergency vehicle detection and signal override	Requires costly camera infrastructure; lacks predictive ML models
[15]	YOLOv3 + LSTM + YOLOv5 for congestion severity	CCTV traffic images	Visual classification of congestion levels; ML-based severity detection	Real-time latency and large GPU requirements
[16]	Wireless Sensors + Dynamic Signal Control	Wireless node data	Real-time green light optimization; adaptive based on vehicle flow	Sensor nodes prone to failure; limited area coverage
[17]	ANN, SVM, KNN Comparison	Speed, travel time, vehicle count	ANN outperformed SVM and KNN; good for small-scale prediction	Dataset not disclosed; limited scalability
[18]	IoT Sensors + Traffic Priority System	Sound sensors, vibration sensors, IR	Priority for emergency vehicles and adaptive signaling	No ML/AI usage; less accurate compared to DL methods

3. PROPOSEDMETHODOLOGY

The goal of the proposed system is to develop a robust framework for predicting traffic congestion in real time using multiple deep learning architectures. Unlike traditional approaches that depend on static datasets, this system incorporates API-driven live traffic data collection and dynamic evaluation of models. The methodology is structured into five main phases: Data Acquisition, Preprocessing, Feature Engineering, Model Design and Training, and Evaluation and Deployment.

A. Data Acquisition

Traffic-related data is collected in real-time from publicly available APIs such as Tom Tom, HERE Maps, Google Maps API or Open Traffic. These APIs provide dynamic information including:

- Current speed S_c
- Free Flow speed S_f
- Travel time T
- Geo graphic coordinates
- Jam factor or traffic flow indicates (if available)

In cases where a congestion index C_i is not provided, it is computed using the formula:

$$C_i = 1 - \frac{S_c}{S_f}$$

Where:

- S_c = current observed speed
- S_f = free-flow or Ideal speed
- $C_i \in [0,1]$, with higher values indicating greater congestion.

B. Data Preprocessing

Theacquireddataisstructuredandcleanedtoremovenoiseandinconsistencies.Thefollowing steps are applied:

a. Missing Value Handling: Forward fill or linear interpolation isused.
b. Normalization: Features are scaled using Min-Max normalization:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

c. Time stamp Alignment: Timestamps are converted to a uniform time zone and format.
d. Sequence Framing: A sliding time window approach is used to create sequences for temporal prediction. For a window of size w:\

$$X_t = \{x_{t-w+1}, \ldots, x_t\}, \qquad y_t = C_{i,\, t+1}$$

C. Feature Engineering

Along with primary features, derivative features such as speed variability, hour of the day, weekday/weekend flag, and weather data (optional) are considered to enrich model input.

$$Speed\ Variability = \frac{\sigma(S_c)}{\mu(S_c)}$$

Where:

- $\sigma(S_c)$ is the standard deviation of current speed
- $\mu(S_c)$ is the mean speed over the window

D. Deep Learning Models Explored

Multiple deep learning models are evaluated to determine the most effective architecture for predicting congestion in real time. These include:

a) Long Short-Term Memory(LSTM)
b) Gated Recurrent Unit(GRU)
c) Convolution Neural Networks(CNN) for time-series
d) Transformer-based models (e.g., Temporal Fusion Transformer)
e) Hybrid Models(e.g., CNN-LSTM)

Each model is trained using the processed time-series data to predict either:

- A continuous congestion index
- Or a congestion class(e.g., low, medium, high) The training loss function depends on the output type:

- For Regression:

$$L_{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

- For Classification:

N

$L_{CrossEntropy} = -\sum_{i=1} y_i \log(\mathcal{y}_i)$

E. Model Evaluation and Deployment

- Mean Absolute Error(MAE)
- Root Mean Squared Error(RMSE)
- Classification Accuracy(if applicable)
- F1-Score
- Inference time(for real-time feasibility)

The best-performing model is deployed in a real-time prediction pipeline. Live sequences are passed to the model, and outputs are visualized via:

- Traffic Heat maps
- Time-series charts

4. Expected Results

Theproposedreal-timetrafficcongestionpredictionsystemisdesignedtoyieldseveralkey outcomes:

- Accurate Congestion Forecasting:

Deep learning models such as LSTM, CNN, and GNN are expected to achieve high prediction accuracy by capturing complex spatiotemporal patterns in traffic data. Prior studies report F1- scores above 95% for similar configurations [1], [4].

- Real-Time Responsiveness:

With Apache Kafka and Spark, the system can handle high-velocity data streams and deliver sub- second latency in inference, making it suitable for live urban traffic environments.

- Multi modal Input Integration:

The system can process diverse sources including GPS, IoT sensors, weather data, and camera feeds. Features like speed variability, time-of-day, and congestion indices enhance model learning.

- Actionable Outputs:

Outputs include a congestion index and class labels (e.g., low, medium, high), visualized via heat maps and alert dashboards to assist in traffic rerouting and control.

- Evaluation Metrics:

Performance is assessed using RMSE, MAE, accuracy, and inference time. The system is expected to match or surpass benchmarks reported in related literature [2], [3].

5. Conclusion

This project aims to develop a real-time traffic congestion prediction system utilizing deep learning techniques and dynamic traffic data sourced from public APIs. The primary goal is to accurately forecast congestion levels in urban environments, offering timely insights to improve traffic management and optimize routing decisions.

The proposed framework consists of a comprehensive pipeline including real-time data acquisition, preprocessing, feature engineering, model training and evaluation, and system deployment. Traffic data such as current speed, free-flow speed, and travel time are continuously gathered from platforms like the Tom Tom API, forming the basis of the dataset. The congestion index is calculated and used as the prediction target.

Multiple deep learning architectures, including LSTM, GRU, CNN, and Transformer models, are explored to capture the temporal patterns inherent in traffic data. Both regression and classification methods are tested, depending on whether the model predicts a continuous congestion index or discrete congestion categories.

Thorough experiments are conducted to identify the model that balances high prediction accuracy with fast real-time inference. Results are presented through a user-friendly dashboard that features congestion alerts, traffic heat maps, and predictive analytics.

The system offers valuable applications in smart city initiatives, urban traffic monitoring, emergency response coordination, and navigation services, ultimately contributing to reduced travel times, enhanced safety, and a better commuting experience.

References

1. Zafar, N., Haq, I.U., Sohail, H., Chughtai, J.-U.-R., & Muneeb, M. (2022). Traffic prediction in smart cities based on hybrid feature space. *IEEE Access*, 10, 134333– 134347. https://doi.org/10.1109/ACCESS.2022.3231448

2. Mena-Oreja, J., & Gozalvez, J. (2020). A comprehensive evaluation of deep learning- based techniques for traffic prediction. *IEEE Access*, 8, 91188–91224. https://doi.org/10.1109/ACCESS.2020.2994415

3. Rathore, S.P.S., Farhaoui, Y., Nagpal, T., M., T., Aniebonam, E.E., & Kaushik, P. (2025). AI-driven traffic congestion management: A predictive analytics approach for smart cities. In *Proc. IEEE Int. Conf. Interdisciplinary Approaches in Technology and Management for Innovation*. https://doi.org/10.1109/IATMSI64286.2025.10985513

4. Malathi, M.D., Alaswad, F., Aljaddouh, B., Ranganayagi, L., & Sangeetha, S.R. (2025). AI-powered traffic management: Improving congestion detection and signal regulation. In *Proc. Int. Conf. Multi-Agent Systems for Collaborative Intelligence*, 899– 904. https://doi.org/10.1109/ICMSCI62561.2025.10894186

5. Yi, H., & Bui, K.-H.N. (2021). An automated hyper parameter search-based deep learning model for highway traffic prediction. *IEEE Transactions on Intelligent Transportation Systems*, 22(9), 5486–5495. https://doi.org/10.1109/TITS.2020.2987614

6. Kabir, M.H., & Islam, M.S. (2024). Enhancing traffic flow and reducing congestion: A smart city approach with an IoT-based intelligent traffic management system. In *Proc. 4th Int. Conf. on Innovations in Science, Engineering and Technology (ICISET)*. https://doi.org/10.1109/ICISET62123.2024.10939106

7. Mehdi, M.Z., Kammoun, H.M., Benayed, N.G., Sellami,D., & Masmoudi, A.D. (2022). Entropy-based and CNN-based traffic congestion prediction. *IEEE Access*, 10, 16123– 16133. https://doi.org/10.1109/ACCESS.2022.3149059

8. Kavitha, K.P., Teja, K.P., Rahul, R.S.G., Charan, K.S., Reddy, K.R.K., & Reddy, V.S.C (2024). IoT-based traffic control system for emergency vehicles. In *Proc. Int. Conf. on Intelligent Algorithms for Computational Intelligence Systems (IACIS)*. https://doi.org/10.1109/IACIS61494.2024.10721837

9. Chen, Y., Lv, Y., Li, Z., & Wang, F.-Y. (2016). Long short-term memory model for traffic congestion prediction with online open data. In *Proc. IEEE 19th Int. Conf. Intelligent Transportation Systems*. https://doi.org/10.1109/ITSC.2016.7795601

10. Li, L., Lin, H., Wan, J., Ma, Z., & Wang, H. (2020). MF-TCPV: A machine learning and fuzzy comprehensive evaluation-based frame work for traffic congestion prediction and visualization. *IEEE Access*, 8, 227113–227125. https://doi.org/10.1109/ACCESS.2020.3043582

11. N.S., M.P.S., Sanketh, G.,M.G.J., & Kannadaguli, P. (2024). Route Rover: AI-enabled traffic congestion prediction and route optimization for Indian urbanites. In *Proc. Int. Conf. Recent Advancement sin Science, Engineering and Technology (ICRASET)*, 1–7. https://doi.org/10.1109/ICRASET63057.2024.10895019

12. Telsang, S., et al. (2024). Traffic management and signal manipulation system using machine learning. In *Proc. 5th IEEE Global Conf. for Advancement in Technology (GCAT)*, 1–6. https://doi.org/10.1109/GCAT62922.2024.10923974

13. Zhong,C., Huang, Q., An, Z., Luo, S., Meng, H., & Wei, Y. (2023).Research on traffic congestion warning method based on data modeling. In *Proc. IEEE 8th Int. Conf. Intelligent Transportation Engineering (ICITE)*, 242–247. https://doi.org/10.1109/ICITE59717.2023.10733878

14. Satkunarajah, S., & Puvanendran, R. (2023). Simulation-based traffic management model to minimize the vehicle congestion in traffic signals. In *Proc. 5th Int. Conf. on Advanced Computing (ICAC)*. https://doi.org/10.1109/ICAC60630.2023.10417520

15. Zhang, T., Xu, J., Cong, S., Qu, C., & Zhao, W. (2023). A hybrid method of traffic congestion prediction and control. *IEEE Access*, 11, 36471–36489. https://doi.org/10.1109/ACCESS.2023.3266291

16. Nie,B., &Ma, B. (2023). Highway traffic flow control model and simulation based on fuzzy control. In *Proc. 3rd Int. Conf. on Computer Science, Electronics, Information Engineering, and Intelligent Control Technology (CEI)*, 847–853. https://doi.org/10.1109/CEI60616.2023.10528133

17. Shankaran, S., & Rajendran, L. (2021). Real-time adaptive traffic control system for smart cities. In*Proc. Int. Conf. on Computer Communication and Informatics (ICCCI)*, 1–6. https://doi.org/10.1109/ICCCI50826.2021.9402597

18. Zheng, Y. (2024). Scalable big data analysis and processing technology for intelligent traffic control. In *Proc. IEEE 3rd World Conf. on Applied Intelligence and Computing (AIC)*, 448–453. http.org/10.1109/AIC.2023.74

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