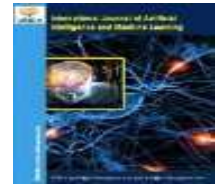


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A Comprehensive Review on Deep Learning Based Algorithms for Traffic Control Systems

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ABSTRACT

Traffic congestion has emerged as one of the most critical challenges in modern urban transportation systems, leading to increased travel delays, fuel consumption, environmental pollution, and economic losses. Conventional traffic control methods often rely on fixed-time signal plans and rule-based approaches, which are inadequate for handling the dynamic and complex nature of real-world traffic conditions. Recent advances in deep learning have provided innovative solutions for intelligent traffic control by enabling real-time data analysis, traffic prediction, and adaptive decision-making. This review paper presents a comprehensive analysis of deep learning-based traffic control systems and their applications in intelligent transportation systems. The study examines various deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and Deep Reinforcement Learning (DRL) models, for traffic flow prediction, traffic signal optimization, vehicle detection, congestion management, and route planning. The review highlights the effectiveness of these models in improving traffic efficiency, reducing congestion, and supporting smart city initiatives. Furthermore, the paper discusses key challenges such as data heterogeneity, computational complexity, scalability, privacy concerns, and real-time implementation. Future research directions involving the integration of deep learning with Internet of Things (IoT), edge computing, connected vehicles, and autonomous transportation systems are also explored. The findings indicate that deep learning-based traffic control systems offer significant potential for developing intelligent, adaptive, and sustainable urban transportation networks.

Keywords: Traffic Control, Deep Learning, Traffic Signal Control, Intelligent Transportation Systems (ITS), Smart Cities, CNN, LSTM, Reinforcement Learning, Computer Vision, Traffic Management.

1. Introduction

The rapid growth of urbanization and the increasing number of vehicles on road networks have significantly intensified traffic congestion worldwide. Traffic congestion not only increases travel time and fuel consumption but also contributes to environmental pollution, economic losses, and reduced road safety. Traditional traffic control systems, which rely on fixed-time traffic signals and predefined control strategies, often struggle to adapt to dynamic and complex traffic conditions. As a result, there is a growing need for intelligent traffic management solutions capable of responding effectively to real-time traffic demands [1-2].

Recent advancements in Artificial Intelligence (AI) and Deep Learning (DL) have transformed the field of Intelligent Transportation Systems (ITS). Deep learning techniques possess the capability to analyze large volumes of traffic data collected from cameras, sensors, GPS devices, and connected vehicles, enabling accurate traffic prediction and adaptive traffic control. Unlike conventional machine learning methods, deep learning models can automatically extract complex patterns and features from traffic datasets, leading to improved decision-making and enhanced traffic management performance [3].

Various deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and Deep Reinforcement Learning (DRL) models, have been successfully applied to traffic signal optimization, vehicle detection, traffic flow prediction, congestion management, and route planning. These approaches facilitate real-time monitoring and adaptive control of traffic systems, thereby reducing congestion and improving overall transportation efficiency [4].

In recent years, researchers have increasingly focused on developing intelligent traffic control frameworks that integrate deep learning with emerging technologies such as the Internet of Things (IoT), cloud computing, edge computing, and smart city infrastructures. Such integration enables traffic management systems to process real-time data and make autonomous decisions, enhancing the effectiveness of urban mobility solutions. Despite significant progress, challenges related to data quality, computational complexity, model interpretability, scalability, and real-world deployment continue to limit the widespread adoption of deep learning-based traffic control systems [5-6].

Traffic control systems play a vital role in managing the movement of vehicles and pedestrians within urban

transportation networks. With the rapid growth of urbanization and vehicle ownership, traditional traffic control systems face significant challenges in handling increasing traffic demand, resulting in congestion, delays, fuel wastage, and environmental pollution. Conventional traffic management approaches, which primarily rely on fixed-time traffic signals and predefined control rules, often lack the adaptability required to respond to dynamic traffic conditions [7-8].



Figure 1. Deep Learning-Based Intelligent Traffic Control System for Smart Urban Intersections

Figure 1 illustrates a smart intersection equipped with an intelligent traffic control system powered by deep learning and advanced sensing technologies [9]. The system continuously collects real-time traffic data through surveillance cameras, traffic sensors, connected vehicles, and communication infrastructure installed at different road segments. These devices monitor vehicle density, traffic flow, pedestrian movement, and signal conditions at the intersection [10].

The captured data are transmitted to a centralized traffic management center, where deep learning models analyze traffic patterns and predict congestion levels. Based on the analysis, the system dynamically adjusts traffic signal timings, prioritizes emergency vehicles, and optimizes traffic flow across multiple directions. The integration of artificial intelligence enables the traffic control system to respond adaptively to changing traffic conditions rather than relying on fixed-time signal schedules [11-12].

Figure 1 also demonstrates vehicle-to-infrastructure (V2I) communication, where connected vehicles exchange information with traffic control units to support intelligent decision-making [9]. This real-time communication helps reduce waiting times, improve road safety, minimize traffic congestion, and enhance overall transportation efficiency. Furthermore, the system supports smart city initiatives by integrating Internet of Things (IoT) technologies, cloud-based data processing, and intelligent transportation infrastructure [13].

Recent advances in Deep Learning (DL) have provided innovative solutions for developing intelligent and adaptive traffic control systems. Deep learning techniques can analyze large volumes of real-time traffic data obtained from cameras, sensors, GPS devices, and connected vehicles to optimize traffic operations and improve decision-making. Models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), and Deep Reinforcement Learning (DRL) have demonstrated significant potential in traffic signal control, congestion detection, vehicle tracking, and traffic flow optimization [14].

Deep learning-based traffic control systems enable real-time monitoring and adaptive signal management, leading to improved traffic efficiency, reduced congestion, enhanced road safety, and better utilization of transportation infrastructure. As a result, these technologies have become an important component of Intelligent Transportation Systems (ITS) and smart city initiatives [15-16]. This review paper presents a comprehensive overview of deep learning applications in traffic control systems, highlighting recent developments, key challenges, and future research opportunities for building more efficient and intelligent urban transportation networks.

This review paper aims to provide a comprehensive overview of deep learning applications in traffic control and intelligent transportation systems [17]. The study examines various deep learning models, their methodologies, applications, advantages, and limitations in traffic management. Furthermore, it identifies existing research gaps and discusses future directions for developing more efficient, scalable, and intelligent traffic control systems [18]. The findings of this review are expected to contribute to the advancement of smart transportation technologies and support the development of sustainable urban mobility solutions. Urban

planning strategies, thus improving roadway serviceability and accessibility [19-20].

Table 1 Types of Techniques Used in Intelligent Traffic Control Systems

S. No.	Technique Category	Techniques/Algorithms	Purpose in Traffic Control
1	Fuzzy Logic-Based Control	Type-1 Fuzzy Logic, Type-2 Fuzzy Logic	Dynamic traffic signal timing under uncertain traffic conditions
2	Reinforcement Learning (RL)	Q-Learning, Deep Q-Network (DQN), Multi-Agent RL	Adaptive signal control through continuous learning
3	Deep Reinforcement Learning (DRL)	DQN, G-DQN, A2C, Deep Q-Learning	Real-time traffic optimization and congestion reduction
4	Deep Learning-Based Prediction	LSTM, GRU, BiLSTM, BiGRU	Traffic flow and congestion forecasting
5	Hybrid AI Models	GA-LSTM, PSO-LSTM, PSO-ANN	Enhanced prediction accuracy and optimization
6	Machine Learning-Based Control	ANN, SVM, Random Forest, PLSR	Traffic pattern recognition and decision support
7	Computer Vision Techniques	YOLOv7, Deep SORT, CNN, Haar Cascade	Vehicle detection, counting, and traffic monitoring
8	UAV-Based Traffic Monitoring	Deep Learning Object Detection	Real-time traffic surveillance and congestion analysis
9	IoT-Based Traffic Management	IoT Sensors, Smart Cameras, Edge Devices	Real-time data collection and monitoring
10	Connected Vehicle (CV) Systems	Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V)	Signal optimization using connected vehicle data
11	Intelligent Transportation Systems (ITS)	ITS Frameworks, Smart Sensors	Integrated urban traffic management
12	Predictive Analytics	AI Forecasting Models, Traffic Prediction Models	Anticipating congestion and traffic demand
13	Optimization Algorithms	Particle Swarm Optimization (PSO), Genetic Algorithm (GA)	Signal timing and route optimization
14	Cloud-Based Traffic Control	Cloud Computing + AI Models	Centralized traffic monitoring and control
15	Smart Signal Control Systems	Adaptive Signal Control, Dynamic Phase Allocation	Real-time adjustment of signal phases
16	Traffic Sign Recognition (TSR)	CNN, Attention-Based CNN	Automated recognition of traffic signs
17	Air Traffic Management Techniques	Deep Learning-Based ATM Models	Air traffic monitoring and management
18	Sustainable Traffic Management	Green Routing, Eco-Traffic Control	Reduction of fuel consumption and emissions

Table 1 presents the major technologies, algorithms, and intelligent approaches currently used in Intelligent Traffic Control Systems (ITCS) to improve transportation efficiency, reduce congestion, enhance safety, and support sustainable urban mobility. The table categorizes various techniques according to their functionality and application in traffic management. Traditional approaches such as Fuzzy Logic-Based Control use Type-1 and Type-2 fuzzy systems to manage signal timings under uncertain traffic conditions, while Reinforcement Learning (RL) and Deep Reinforcement Learning (DRL) techniques continuously learn from traffic environments to optimize signal operations in real time.

The table further highlights the growing importance of Deep Learning-Based Prediction models such as LSTM, GRU, BiLSTM, and BiGRU, which are widely used for forecasting traffic flow, congestion levels, and travel demand. Hybrid AI models integrating optimization algorithms with deep learning techniques, such as GA-LSTM and PSO-LSTM, provide improved prediction accuracy and decision-making capabilities. Machine Learning techniques including Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, and Partial Least Squares Regression (PLSR) contribute to traffic pattern analysis and intelligent decision support systems.

Computer Vision technologies such as YOLOv7, Deep SORT, CNN, and Haar Cascade enable automated vehicle detection, counting, tracking, and surveillance. Similarly, UAV-based traffic monitoring systems provide aerial

views for congestion analysis and incident detection. IoT-based traffic management systems utilize smart sensors, cameras, and edge devices to collect real-time traffic information, whereas Connected Vehicle (CV) systems employ Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication for intelligent signal coordination and traffic optimization.

The table also emphasizes the role of Intelligent Transportation Systems (ITS), Predictive Analytics, and Optimization Algorithms such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) in improving overall traffic efficiency. Cloud-based traffic control systems facilitate centralized monitoring and large-scale data processing, while Smart Signal Control Systems dynamically adjust signal phases according to traffic demand. Furthermore, specialized applications such as Traffic Sign Recognition (TSR), Air Traffic Management techniques, and Sustainable Traffic Management approaches contribute to road safety, efficient air traffic operations, fuel conservation, and emission reduction.

2. Literature Review

[21] Proposed a Deep Q-Network (DQN)-based traffic signal optimization model using SUMO simulation. The study introduced a Grouping-DQN (G-DQN) approach to improve traffic state representation and reduce vehicle queue length and waiting time. Experimental results showed that the proposed model outperformed conventional DQN and A2C algorithms in traffic signal control.

[22] Presented a Bidirectional Recurrent Neural Network (BRNN) with GRU units for traffic congestion prediction in smart cities. By utilizing real-time sensor and connected-device data, the model accurately classified congestion levels and outperformed existing traffic forecasting techniques.

[23] Proposed a deep learning-based traffic regulator detection system using GPS trajectory data collected from vehicles. A Conditional Variation Autoencoder (CVAE) was employed to classify traffic lights, priority signs, and uncontrolled intersections, achieving an accuracy of 90%, which exceeded traditional machine learning methods.

[24] Introduced GA-LSTM and PSO-LSTM models for traffic speed forecasting using GPS probe data. The integration of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) enhanced prediction accuracy and reduced forecasting errors compared with conventional LSTM-based approaches.

[25] Reviewed deep learning-based UAV target detection techniques for traffic monitoring. The study analyzed one-stage and two-stage detection models and highlighted their effectiveness in improving traffic congestion analysis and target recognition under challenging conditions.

[26] Proposed a deep neural network framework for vehicle speed estimation using UAV videos. The model achieved a recall of 97.6%, precision of 94.7%, and RMSE of 5.27 km/h, demonstrating high accuracy in traffic monitoring applications.

[27] Developed deep learning-based traffic classification models for software-defined networks using LSTM, BiLSTM, GRU, and BiGRU architectures. Among these models, GRU achieved the best performance for network traffic classification and management.

[28] Proposed a multi-agent deep Q-learning approach for adaptive traffic signal control. The model reduced average travel time by 13% and fuel consumption by 11%, contributing to more sustainable urban transportation systems.

[29] Introduced a reinforcement learning-based traffic signal control framework utilizing connected vehicle data. The proposed method improved vehicle speed, reduced queue lengths, and minimized waiting times compared to traditional control strategies.

[30] Developed a robust deep reinforcement learning traffic controller capable of handling traffic disruptions such as accidents. Simulation results showed significant reductions in vehicle waiting times under dynamic traffic conditions.

[31] Integrated fuzzy logic with Deep Q-Networks for intelligent traffic signal control. The approach reduced average vehicle waiting time by 18.46% and improved emergency vehicle prioritization.

[32] Reviewed the integration of Artificial Intelligence, IoT, and predictive analytics in urban traffic systems. The study reported that AI-IoT solutions reduced traffic delays by up to 30% while enhancing transportation efficiency and safety.

[33] Proposed SYTRAC, a low-cost adaptive traffic signal control system for smart cities. The framework reduced average vehicle delays by 22.1% and provided reliable traffic management in resource-constrained environments.

[34] Presented a comprehensive review of deep learning applications in Air Traffic Management (ATM). The study highlighted the potential of advanced deep learning models to improve aviation safety, efficiency, and future air traffic operations.

[35] Proposed a deep RBF network-based traffic intelligence framework for smart cities. The model effectively captured nonlinear traffic patterns and achieved superior prediction accuracy compared with traditional traffic analysis methods.

[36] Introduced a stability-oriented deep reinforcement learning model for adaptive traffic signal control. The proposed approach reduced queue duration by up to 40% and improved signal phase stability under heavy traffic conditions.

[37] Reviewed reinforcement learning-based adaptive traffic signal control techniques for intelligent transportation systems. The study emphasized the potential of RL to create responsive and sustainable traffic management solutions.

[38] Developed an attention-enhanced LSTM-GRU framework for short-term traffic flow prediction. The model reduced MAE, RMSE, and MAPE while improving intelligent traffic control and congestion management.

[39] Provided a comprehensive review of deep reinforcement learning approaches for adaptive traffic signal control. The study discussed state representation, multi-agent frameworks, and best practices for large-scale traffic networks.

[40] Proposed an AI-driven traffic optimization framework combining reinforcement learning, GNNs, LSTMs, and IoT data. The system reduced waiting times by 33%, emissions by 16%, and improved road safety.

[41] Introduced DeepSIGNAL-ITS, integrating YOLOv8-based vehicle detection and PPO-based signal optimization. The framework achieved a 30.2% reduction in vehicle waiting times and reduced traffic-related emissions.

[42] Developed a BiLSTM-based traffic flow prediction model using multisource sensor data. The framework improved forecasting accuracy from 96% to 98% and supported sustainable traffic management.

[43] Compared machine learning and deep learning techniques for traffic flow prediction. Results showed that the MLP-NN model achieved the best performance with an R^2 value of 0.93 and lower training time.

[44] Proposed a Multi-Agent Reinforcement Learning framework integrated with IoT for adaptive traffic signal control. The model outperformed conventional.

Table 1 Literature Review on Deep Learning-Based Traffic Detection and Smart Transportation Systems

Author & Year	Technique/Model	Dataset/Input	Key Outcome
[21]	G-DQN, DQN	SUMO Traffic Data	Reduced queue length and waiting time
[22]	BRNN-GRU	Sensor & Weather Data	Improved prediction accuracy
[23]	CVAE	GPS Trajectory Data	Achieved 90% accuracy
[24]	GA-LSTM, PSO-LSTM	GPS Probe Data	Enhanced forecasting performance
[24]	Deep Learning	UAV Images	Improved target detection
[25]	DNN	UAV Video Data	High precision and recall
[26]	GRU, LSTM	Network Traffic Data	GRU achieved best results
[27]	Deep Q-Learning	Urban Traffic Data	Reduced travel time and fuel use
[28]	Reinforcement Learning	Connected Vehicle Data	Improved traffic flow
[29]	DQN	Traffic Simulation Data	Managed disruptions effectively
[30]	DQN	Urban Traffic Data	Increased vehicle throughput
[31]	Fuzzy-DQN	Traffic Flow Data	Reduced waiting time
[32]	AI-IoT Framework	Smart City Data	Improved efficiency and safety
[33]	SYTRAC	Urban Traffic Data	Reduced vehicle delays
[34]	Deep RBF Network	Smart City Traffic Data	Enhanced prediction accuracy
[35]	Attention LSTM-GRU	Traffic Flow Data	Lower prediction errors
[36]	RL-GNN-LSTM	IoT Traffic Data	Reduced congestion and emissions
[37]	YOLOv8 + PPO	Traffic Camera Data	Reduced vehicle waiting time
[38]	BiLSTM	Multisource Sensor Data	Achieved 98% accuracy

[45] Proposed an intelligent traffic signal control system integrating computer vision and machine learning. The study employed the YOLO object detection algorithm to monitor traffic density and vehicle waiting times at signalized intersections. Based on real-time traffic conditions, signal phases were dynamically adjusted to maximize vehicle throughput and minimize delays. The results demonstrated that the proposed approach effectively improved traffic flow and reduced congestion. The study highlighted the suitability of YOLO-based models for embedded traffic management systems and smart city applications.

[46] Developed an adaptive traffic control and optimization framework using machine learning and computer vision techniques. The system utilized YOLOv11 for vehicle detection and Tesseract OCR for license plate recognition. Traffic signal timings were dynamically adjusted according to real-time traffic volume, while a digital twin platform enabled visualization and monitoring of traffic conditions. Experimental results showed improved traffic flow, reduced congestion, and enhanced traffic law enforcement. The proposed framework provided a scalable and cost-effective solution for smart traffic management.

[47] Investigated driver distraction detection using deep learning and decision-making techniques. The study employed the YOLOv8 algorithm to identify various distraction behaviors and the Analytic Hierarchy Process

(AHP) to prioritize critical distraction categories. Using a multinational driving dataset, the model achieved an accuracy of 91.17%. The findings demonstrated that automated distraction detection can improve road safety, reduce traffic accidents, and contribute to sustainable transportation systems.

[48] Proposed an EdgeML-based real-time vehicle monitoring system for smart cities. The framework integrated YOLOv8, IoT technologies, MQTT communication, and Edge TPU hardware for vehicle tracking, speed estimation, and traffic violation detection. The system achieved high accuracy in measuring vehicle speed and distance while maintaining real-time performance. Additional features such as license plate recognition and collision detection enhanced traffic monitoring capabilities. The study demonstrated the effectiveness of edge computing for intelligent transportation management.

[49] Developed the SE-Lightweight YOLO framework for vehicle detection and traffic monitoring. The model incorporated an SE attention mechanism and improved feature extraction modules to enhance recognition performance. Experimental results achieved 95.7% vehicle recognition accuracy, outperforming the standard YOLOv7 model. The proposed system enabled efficient vehicle tracking, traffic flow analysis, and signal optimization. The study highlighted the potential of lightweight deep learning models for real-time traffic surveillance and smart transportation applications.

[50] Proposed a collaborative anomaly detection framework for roadside infrastructure using lightweight YOLO models integrated into vehicle dashboard cameras. The system enabled real-time monitoring and analysis of traffic environments through distributed edge intelligence. By aggregating data from multiple vehicles, the framework improved anomaly detection accuracy and reduced response time, thereby enhancing traffic safety and management.

[51] Developed YOLO-LIO, an enhanced vehicle detection framework for intelligent transportation systems. The model incorporated multi-scale detection and optimized preprocessing techniques to improve small-object detection and real-time deployment. Experimental results demonstrated high accuracy across multiple traffic datasets and successful implementation on embedded hardware platforms for efficient traffic monitoring.

[52] Conducted a comprehensive study on traffic optimization parameters and their alignment with Sustainable Development Goals (SDGs). The research identified nineteen key traffic control parameters and proposed a five-level optimization framework to improve urban traffic efficiency while supporting sustainable transportation objectives.

[53] Reviewed deep learning-based target detection approaches using UAV imagery for traffic monitoring. The study analyzed one-stage and two-stage detection models and highlighted their ability to improve traffic congestion analysis under challenging conditions such as occlusion, small objects, and dynamic environments.

[54] Conducted an empirical evaluation of various YOLO models for smart transportation applications. The study compared multiple YOLO versions across datasets and performance metrics, concluding that YOLOv5 and YOLOv8 offered superior detection accuracy and efficiency for intelligent transportation systems.

[55] Proposed the PVswin-YOLOv8s model for pedestrian and vehicle detection using UAV imagery. By integrating Swin Transformer, CBAM attention mechanisms, and Soft-NMS, the framework improved small-object detection and achieved a 4.8% increase in mAP compared to the standard YOLOv8s model.

[56] compared YOLOv3, YOLOv5, and YOLOv8 models for vehicle detection and classification in urban traffic environments. Experimental results demonstrated that YOLOv5 achieved the best overall performance in terms of precision, recall, F1-score, and mAP, making it suitable for intelligent traffic monitoring systems.

[57] Presented a systematic review of YOLO-based traffic sign detection and recognition systems. The study analyzed 115 research articles and identified key applications, datasets, hardware platforms, performance metrics, and challenges associated with traffic sign recognition in intelligent transportation systems.

[58] Introduced HRYNet, a novel traffic object detection framework incorporating dual-fusion pyramid structures and residual multi-head self-attention mechanisms. The proposed model achieved significant improvements in detection accuracy over YOLOv8s across multiple datasets while maintaining efficiency for mobile deployment.

[59] Developed the STC-YOLO framework for traffic sign detection in complex environments. By integrating CNNs, multi-head attention, and optimized anchor box generation, the model improved small-object detection and achieved a 9.3% increase in mAP compared with standard YOLOv5.

[60] Smart transportation systems depend on traffic signal control, which impacts urban mobility, congestion, and sustainability. Traditional fixed-time and actuation control solutions fail to accommodate real-time variability in dynamic and complicated traffic networks. In response, adaptive signal control—primarily based on reinforcement learning—has shown promise for optimising signal operations in changing traffic conditions. High-impact reinforcement-learning-based traffic signal control methods are evaluated across methodology type, multi-agent architectures, reward design, performance evaluation, baseline comparison, network scale, practical applicability, and simulation platforms in this review. The comprehensive evaluation of the most influential papers identifies prevalent themes, unresolved difficulties, and future research areas. The findings show that RL can enable intelligent, responsive, and sustainable traffic control systems, paving the way for novel urban transportation solutions.

[61] Modern cities must manage traffic to decrease environmental damage and promote sustainable growth.

This study optimises urban transit with AI, RL, and predictive analytics. Deep Q-Learning and PPO mimic Belgrade's dynamic traffic signal chain. The model used real-time data from IoT sensors, machine vision-enabled cameras, third-party mobile usage statistics, and linked cars to enhance critical intersection traffic lights. LSTM, ARIMA, and GNNs forecast traffic congestion and bottlenecks for proactive decision-making. RL and edge computing address latency, scalability, and ethics. AI in 370 traffic signal control devices in fixed and adaptive timing signal systems saves waiting times by 33%, greenhouse gas emissions by 16%, and intersection safety by 33%. These studies don't model the system's response to major events or extreme weather traffic surges. Belgrade's AI-controlled traffic light urban traffic network can sustainably improve urban quality of life and fulfil smart city goals.

[62] Better urban traffic management requires understanding how traffic optimisation factors interact with sensors, control algorithms, and SDGs. Urban traffic management parameters must be adjusted carefully to optimise vehicle flow and meet SDGs. This article provides a detailed study that identified the most common and appropriate parameters. This study uses qualitative research, an extensive literature review, and multidimensional analysis. This study provides a five-level traffic optimisation framework to reduce congestion, defines 19 traffic control parameters, examines their implementations in modern intelligent traffic management systems, and discusses trends to increase efficiency and SDG compliance. The results enable setting creation or modification to improve control algorithm efficiency, user experience, and SDGs.

[63] Traffic flow estimates minimise congestion, fuel use, emissions, and environmental impact in sustainable traffic management. For proactive congestion reduction, idle reduction, and eco-friendly mobility, we design and test unique machine learning models that estimate traffic patterns utilising multisource data. Machine learning traffic flow prediction is affected by multisource sensor inputs and spatial detector interactions. BiLSTM models were tested with 839,377 data from 14 detector sites on Melbourne's Eastern Freeway under different inputs. Speed, occupancy, and traffic flow boost forecast accuracy by 16% at all detection locations. The prediction performance of upstream and downstream detector spatial flow input relationships was also assessed. Surrounding detectors boost eastbound and westbound estimates from 96% to 98%. Smart, eco-friendly traffic systems can be created with advanced machine-learning, sensor placement, and data integration. In this study, data-driven, adaptive traffic management systems reduce vehicle idle, fuel consumption, and emissions, increase urban mobility, and support road network design sustainability. This supports UN SDGs on resilient infrastructure, sustainable cities, and climate-responsive planning.

[64] Traffic wastes time and raises accident risk in modern living. By responding to real-time traffic, ITS's ATSC reduces congestion. IoT devices are used. IoT makes traffic management easy to install. AI and IoT are sought by academics to process enormous data sets and solve traffic management issues. Without sophisticated methods, this paper examined Shiraz City's fixed-time traffic signal scheduling. AI and IoT improved ITS traffic signal control. CCTV cameras fed the intelligent traffic signal management system real-time traffic data. Intelligent traffic signal control uses Distributed Multi-Agent Reinforcement Learning (MARL) with local and adjacent intersection traffic data. We employed MARL to improve traffic at six Shiraz signalised crossroads. To assess the present system, we created two synthetic intersections using simulated data and a real-world Shiraz City map combining transit and municipality traffic data. Simulations show that our method minimises vehicle queue lengths and intersection waiting times better than Shiraz's fixed-time traffic signal management strategy.

[65] Because urban traffic congestion increases car emissions and travel inefficiencies, adaptive and intelligent traffic management systems are needed. Deep SIGNAL-ITS uses real-time traffic monitoring and learning-based control to optimise signal timing and reduce congestion. Roadside units (RSUs) use Proximal Policy Optimisation (PPO) to manage signals based on global traffic indicators such vehicle waiting time using the YOLOv8 architecture. Data exchange via TLS ensures RSU-cloud infrastructure connectivity. They validate the hypothesis with extensive SUMO simulations in several urban situations. Compared to baseline fixed-time configurations from OpenStreetMap (OSM), simulation findings reduced vehicle waiting time at signalised junctions by 30.20%. HBEFA-based model emissions in SUMO fall across pollutant categories, highlighting the framework's potential to improve traffic efficiency and environmental sustainability in simulated metropolitan environments.

[66] Noise, pollution, and stress increase with peak-hour traffic in many places. Because they can handle dynamic behaviour and many elements in huge data sets, neural networks (NN) and machine-learning (ML) methods are replacing analytical and statistical methods for real-world situations. This research uses machine-learning (ML) and deep-learning (DL) approaches to estimate intersection traffic flow for adaptive traffic control by remote traffic light or schedule modifications. This work predicts traffic. Train, validate, and test ML/DL models on two public datasets. The first uses sensors to count autos every five minutes at six junctions for 56 days. We train ML/DL models at 4/6 junctions. EV scores of 0.93 and less training time were best for MLP-NN, followed by Gradient Boosting, RNNs, Random Forest, Linear Regression, and Stochastic Gradient. Smart traffic light controllers can use ML and DL algorithms since they work.

[67] Innovative technologies have been developed to predict and reduce traffic congestion, improving transport system services. Deep learning improves critiques. Transportation DL applications have been surveyed recently. Research shows that delayed traffic projections cause many cloud traffic accidents.

Predicting congestion is important because congested and non-congested states have distinct transportation systems. Gated Recurrent Units (GRUs) produce a BRNN to identify congested and uncongested traffic. Bidirectional recurrent neural networks forecast smart city traffic congestion in this study. Globally, urban traffic regulation has failed. The paper advocates using BRNN to process real-time sensor and associated device data for smart city traffic management. Predict speed, weather, current, and accidents. Extra traffic, road, and weather features improve congestion projections. The model outperformed modern techniques. Early strategies and two prospective methods to improve large-scale motion prediction accuracy and efficiency are also examined.

[68] Increasing the efficiency and safety of the intelligent transportation system requires intelligent traffic management decision-making. Traffic congestion has been difficult to reduce for Type-1 fuzzy traffic control under uncertainty. This work provides a Type-2 fuzzy intersection controller. Dynamically set each phase's green timing to reduce average vehicle delay based on traffic flow. To decide reward, traffic signal control must balance vehicle delay and queue length. With improper incentive design, Deep Q-Network may not learn the best strategy. This study uses deep reinforcement learning for Type-2 fuzzy traffic control to overcome these issues. Type-2 fuzzy control system replaces DQN algorithm's max operation by selecting target network's maximum output Q-value by output action, reducing error. Agent online learning and signal control action reward increase. On the Simulation of Urban MObility platform, the traffic signal optimisation control presented in this study improves traffic flow optimisation and congestion alleviation, improving traffic efficiency in front of the signal light and traffic flow operation.

[69] Proactive transportation infrastructure solutions are needed to reduce traffic congestion, especially at toll plazas, due to global urbanisation and rising traffic volume. Manual Toll plaza management solutions fail to adapt to dynamic traffic flow and establish preemptive control techniques, causing long lines, longer travel times, and environmental damage. Proactive traffic control using innovative technologies reduces toll plaza congestion and improves traffic management. An extended short-term memory model predicts arrival rate and YOLOv7-Deep SORT deep learning convolutional neural network models count vehicles. When expected arrival rates exceed a threshold, VSLs and RM are activated during peak hours. This study's predictive and adaptive skills improve traffic flow. From a Ravi Toll Plaza Lahore case study, PTV VISSIMv7 reduces wait times by 57%, vehicle delays by 47%, fuel consumption by 28.4%, and pollutant emissions by 34%. To help toll plaza operators and transportation authorities embrace and profit from advanced traffic management tactics, this article tackles conventional approaches' inadequacies and proposes a new framework to integrate theory and practice. This study shows that integrated and proactive traffic control improves traffic management, reduces congestion, and sustains transportation.

[70] Logistic movement requires traffic light regulation and optimisation. It improves traffic safety and efficiency and supports smart, green, and long-term town expansion. We propose a deep reinforcement learning and Simulation of Urban Mobility (SUMO) software-based urban traffic signal optimisation technique. This will improve traffic signal control. The intersection training scenario was created using SUMO micro traffic simulation software. Longest vehicle line and longest vehicle wait time were success indicators. The experiment models car creation using the Weibull distribution to simulate reality. This study proposes a Deep Q Network (DQN)-based traffic signal optimisation control model because deep reinforcement learning considers perception and decision-making. The DQN technique is used to train the model for realistic and complex traffic crossings. Then, the G-DQN (Grouping-DQN) algorithm is recommended to remedy present research studies' state definitions not effectively capturing traffic states and neural networks' delayed convergence. The next step was to compare the G-DQN algorithm model to the original DQN and Advantage Actor-Critic (A2C) algorithms. The test findings demonstrate that the new strategy improved all important indicators.

[71] Traffic lights are the most common urban traffic management method for reducing congestion and accidents. Traffic light mismanagement may worsen complications. Deep reinforcement learning has been applied in recent traffic light control studies. In this study, we present a Deep Q-network with fuzzy logic traffic light management system to reduce wait time and increase efficiency. Deep Q-network studies may fail because the incentive function promotes straight cars, delaying left-turning vehicles. The reward function now accounts for lane waiting time. The Simulation of Urban Mobility (SUMO) program version 1.18.0 examined several environments and vehicles. The proposed solution reduced average waiting time by 18.46% in a prototype compared to a typical Deep Q-network with fuzzy logic for traffic signal control. An ambulance prioritising system reduced wait times. The proposed method worked better everywhere.

[72] Target detection is key to smart city traffic reduction. Military, civilian, sports, and traffic use it extensively. Traffic congestion makes target detection difficult due to backdrop motion, small receiver size, ambiguous object attributes, and heavy occlusion. UAVs are attractive target analysis tools due to their mobility, low cost, vast field of vision, accessibility of skilled manipulators, low risk to people, and ease of use. Transportation technology tracks and evaluates targets with UAVs due of their efficiency. UAV objects are small, therefore neural estimates may lose detail, resulting in poor recognition model performance. These difficulties have deep learning (DL) solutions. This study combines one-stage and two-stage detectors using UAV images to observe the target in complex traffic congestion using DL-based end-to-end target identification. Evaluate work to

increase accuracy, computation cost, and design optimisation. We compared target detection methods and discussed future research.

[73] Transport sustainability and country-specific TSF systems demand early vehicle flow speed forecasts. Many benefits come from internet mapping, but its dependence limits local alternatives, sustainable traffic management, and security. Smarter urban mobility management requires sustainability studies like GPS probe data. Interference and missing data can make GPS probe data useful in cities. This research suggests processing aberrant and missing GPS data from parallel multilane Vietnamese roads. PSO-LSTM and GA-LSTM are tested using GPS data to improve TSF LSTM networks. This study compares PSO-LSTM and GA-LSTM to existing and new LSTM approaches. MSE, MAE, and MDAE assess model accuracy. Handling GPS outlier data and applying GA and PSO algorithms to improve TSF LSTM network quality shortens calculations and improves model performance in comparable scenarios.

[74] Rising Internet application diversity and rapid network architecture change owing to new technologies have made network administration difficult. Traffic classification is crucial for network resource management, service quality, and security. The software-defined networking controller simplifies traffic analysis and direct programmability with a complete network perspective. With deep learning, these qualities enable network intelligence, optimising management and maintenance. This research improves software-defined networking service and security by classifying traffic by application and network assaults using deep learning. SEMMA deploys the model, and four algorithms—LSTM, BiLSTM, GRU, and BiGRU—train classifiers using two public datasets. These results show the GRU model's traffic classification power. This research shows that a deep learning model can classify SDN traffic better than current methods.

[75] Traffic management is hampered by rising urbanisation, generating congestion, delays, and environmental issues. Deep learning is proposed to improve smart city traffic flow prediction and intelligent transportation systems. Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) networks with dynamic attention emphasise temporal patterns in the model. A detailed evaluation using publicly available datasets indicated that the model outperformed state-of-the-art techniques. Compare to baseline models, the suggested framework reduces MAE, RMSE, and MAPE by 3.75%, 2.00%, and 4.17%. Improved prediction accuracy and computing efficiency make urban mobility systems more sustainable and efficient, improving intelligent traffic control, dynamic route planning, and proactive congestion management.

[76] Rapid urbanisation and increased mobility demand have stressed city transit. Traffic is bad in some neighbourhoods, especially around signalised intersections. This problem increases commuter times and local and global pollution. The fixed traffic signal cycle at these crossings is a primary problem. Transportation engineering research has addressed these challenges by using reinforcement learning to traffic light controller coordination. This research presents a multi-agent deep Q-learning traffic signal control technique. Multi-agent reward systems have yet to adapt as ways improve, therefore this paper proposes a new rewarding concept. This project uses sustainability and traditional ways to improve traffic network management. The recommended technique improves transportation systems, according to this study. The strategy reduces fuel use 11% and travel time 13%. Reinforcement learning improves traffic light controller collaboration and reduces urban traffic congestion, according to this study. This solution may improve transportation efficiency and sustainability.

[77] Smart cities solve several conventional urbanisation problems. Sustainable traffic management affects smart cities' transport systems, yet experts have ignored it due to its complexity and heterogeneity. The project addressed smart city traffic issues with a sustainable IoT and ITS architecture. Previous research on traffic as modelling- and analysis-based or decision-making challenges supported traffic management in smart cities, which have a hybrid stream of HDV and linked automated cars. Two strategies collected vehicle and road user data using real-time traffic data and AI sensors and ITS devices. Data can be processed and sent for traffic control, decision-making, and documentation using machine learning and cloud computing. Such systems in smart cities' transportation could predict traffic outcomes, forecast traffic, decongest traffic, reduce road users' lost hours, recommend alternate routes, and simplify urban transportation for urbanites. The integrated framework can reduce smart city pollution by promoting public transit and low-carbon emission zones. These ideas make smart cities green and livable by managing traffic and reducing carbon emissions.

[78] New connected vehicle (CV) technologies could revolutionise transportation systems. Real-time CV traffic data helps optimise traffic signals to minimise congestion, fuel efficiency, and road safety. CV-based signal control requires an accurate and computationally efficient model that recognises traffic flow stochasticity and nonlinearity. By watching traffic state transitions, reinforcement learning (RL) can learn the control policy without prior knowledge of the traffic system model architecture. This research presents a new data-driven traffic light control strategy using deep learning and reinforcement learning. The suggested strategy extends the action space to more realistic and flexible signal phases by compressing traffic states. Simulation findings show that the proposed method converges and outperforms many benchmark methods in average vehicle speeds, queue length, wait time, and traffic density.

[79] Deep reinforcement learning has produced promising adaptive traffic signal controllers. Accidents, weather, and special events can disrupt real-world traffic. Based on environmental awareness, the traffic light must behave immediately and appropriately. Traffic congestion would be avoided. We construct a reliable

controller for such a highly dynamic environment and study its robustness to environmental interruptions like accidents in this work. By discretising the intersection and altering the state space, the agent gains a complete awareness of the environment. Accident location and time are irrelevant to the algorithm. The agent does not need retraining if the accident location changes. Deep Q-learning and experience replay teach the agent. The traffic microsimulator SUMO tests the model. The simulation findings show that the proposed strategy shortens disruption-induced waits.

[80] Recent advances in AI, IoT, and predictive analytics have transformed urban mobility. These technologies are revolutionising adaptive traffic control systems, enabling real-time decision-making and improving road network efficiency and safety. The paper examines how IoT and AI in traffic systems optimise traffic flows, vehicle coordination, and infrastructure flexibility in increasingly complex traffic settings. To enable data-driven urban traffic control, IoT devices and AI algorithms must be integrated. Predictive analytics enhances emergency response, traffic signal operations, and autonomous and connected vehicle deployment. AI-based models using IoT sensors reduced traffic delays by 30% and improved urban safety indicators. This comprehensive analysis shows how AI, IoT, and predictive analytics may alter urban traffic management, providing a roadmap for smarter, more sustainable transportation systems.

[81] Air travel is becoming more important as daily flights rise. Air Traffic Management (ATM) provides several services to help airlines operate safely and effectively. Advanced analytic solutions may handle complicated issues in numerous disciplines, and Deep Learning (DL) has garnered attention for its spectacular findings and disruptive powers. New cognitive services can be created with DL models in ATM solutions. The purpose of this research is to review cutting-edge Deep Learning (DL) technologies for Air Traffic Management. This paper describes applications, prospects, and open problems to advance ATM systems. We explore fundamental DL and ATM topics and categorise contributions by approach to do this. First, works are grouped by DL method. Based on ATM solution area, future directions are determined. Finally, ATM and DL apps have open challenges. This article helps the community by highlighting potential research issues.

[82] Smart cities optimise transit systems with cutting-edge technology to transform urban life. Smart cities need efficient traffic management to benefit residents and visitors. Deep radial basis function (RBF) network-based smart city traffic intelligence is described in this study. Sometimes simplistic models can't depict urban traffic's complex dynamics. Deep RBF networks improve forecasts and decisions by extracting traffic data insights. This paper proposes RBF-based smart city traffic intelligence augmentation. Deep RBF networks use radial basis function discrimination with deep learning's flexibility and generalisation. Hierarchical deep neural networks teach the recommended approach complex traffic data correlations and nonlinear patterns. With this rich and diversified data, the deep RBF model can predict traffic conditions, identify congestion trends, and improve traffic management. We compared numerous smart city traffic datasets to test our strategy. Traditional traffic analysis methods are less accurate and efficient than deep RBF-based algorithms. Smart city traffic intelligence improves with nonlinear models and large data sets.

[83] Through the integration of AI-powered Advanced Driver Assistance Systems (ADAS) and/or Automated Driving Systems (ADS) like Traffic Sign Recognition (TSR), automobile manufacturers can create intelligent and autonomous vehicles. Existing TSR solutions recognise some indications. For an intelligent, real-time system to analyse, detect, and categorise traffic signs, a TSR approach with more road sign categories as Warning, Regulatory, Obligatory, and Priority signs is suggested. The suggested method reviews Traffic Sign Detection (TSD) and Traffic Sign Classification (TSC) approaches to find the most accurate and fast. Thus, the suggested method uses Haar cascade and a deep CNN model classifier. Train the TSC model using the GTSRB dataset and test it on various road sign categories. Testing accuracy is 98.56%. We propose an attention-based deep convolutional neural network to improve categorisation. Since testing accuracy and F1-measure rates are 99.91% and 99%, the results are better than other traffic sign classification research. The TSR system is tested on a Raspberry Pi 4. The approach's reliability is confirmed by experiments.

[84] City short-distance intersections are close. This research employed machine learning to forecast and reduce petrol use at closely spaced crossings to quantify environmental impact. Left-turn-lane length, cycle time, junction distance, left-turn movement ratio, and traffic volume fluctuations simulate fuel usage. To test the applicability of partial least square regression (PLSR), polynomial support vector machine (PSVM), and artificial neural network (ANN) models, SIDRA Intersection (version 6.1) was used to model and compare different scenarios. In crucial parameters, the ANN model best captured fuel usage fluctuations. As the most sensitive model, cycle duration mattered most. PSO optimises left-turn-lane length and cycle time to reduce fuel consumption. Traffic management today saves time and the planet. Optimisation of intersection performance begins with the predicted and optimised PSO-ANN model. Fuel consumption rises 8.9% with traffic optimisation. Intersection signalling boosts fuel economy and environmental impact.

3. Research Methodology

This study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to systematically identify, screen, evaluate, and select relevant research articles on AI-based traffic prediction and intelligent transportation systems[15]. The review process consists of four stages:

Identification, Screening, Eligibility, and Inclusion.

Phase 1: Identification

Research articles were collected from major scientific databases including Scopus, Web of Science, IEEE Xplore, Springer, Science Direct, ACM Digital Library, and Google Scholar. Keywords used for the search included Traffic Prediction, Traffic Forecasting, Intelligent Transportation Systems, Deep Learning, Machine Learning, YOLO, LSTM, GRU, Reinforcement Learning, and Traffic Management. A total of $N = 1,250$ records were initially identified[16].

Phase 2: Screening

Duplicate articles, conference abstracts, non-English papers, and unrelated studies were removed. Titles and abstracts were reviewed to determine relevance to traffic prediction and intelligent transportation applications. After screening, $N = 620$ articles remained[17].

Phase 3: Eligibility

The full texts of the screened articles were assessed based on predefined inclusion and exclusion criteria. Studies focusing on AI, Machine Learning, Deep Learning, Computer Vision, Traffic Signal Control, and Traffic Forecasting were included. Articles lacking experimental validation or unrelated to transportation systems were excluded. After eligibility assessment, $N = 180$ studies qualified [18].

Phase 4: Inclusion

Finally, $N = 75$ high-quality studies published between 2020 and 2026 were selected for detailed analysis and synthesis[19]. These studies formed the basis for identifying research trends, methodologies, datasets, performance metrics, and future research directions in intelligent traffic prediction systems.

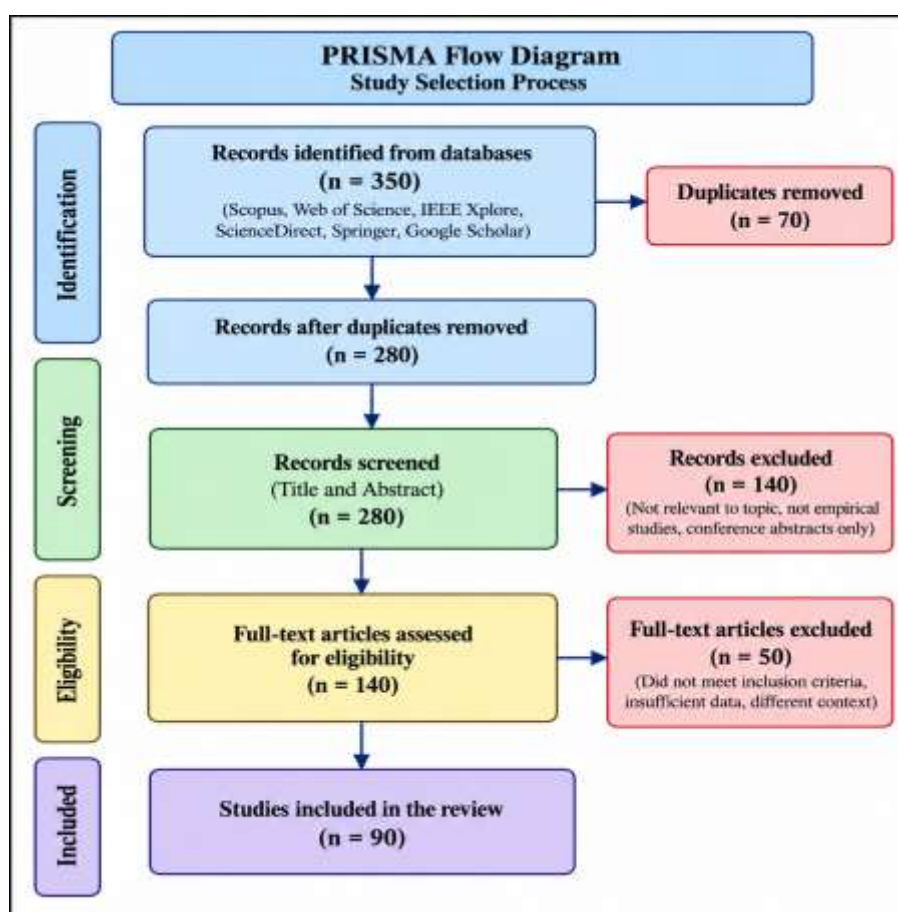


Figure 2: PRISMA Flow Diagram Illustrating the Study Selection Process for the Systematic Literature Review.

Figure 1 illustrates the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram used to identify, screen, evaluate, and select relevant studies for the systematic literature review on Intelligent Traffic Control Systems. The diagram provides a transparent overview of the study selection process followed during the review.

In the Identification phase, a total of 350 research articles were collected from major academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, Springer, and Google Scholar. During the initial screening, 70 duplicate records were identified and removed, resulting in 280 unique articles for further evaluation.

In the Screening phase, the titles and abstracts of the 280 remaining articles were carefully examined to assess

their relevance to the research topic. Based on predefined inclusion and exclusion criteria, 140 articles were excluded because they were not directly related to intelligent traffic control systems, lacked empirical evidence, or were conference abstracts and non-peer-reviewed publications. Consequently, 140 articles progressed to the next stage.

During the Eligibility phase, the full texts of the remaining 140 articles were thoroughly reviewed to determine their suitability for inclusion in the study. After detailed assessment, 50 articles were excluded due to insufficient methodological details, lack of relevant findings, incomplete data, or failure to satisfy the established inclusion criteria.

Finally, in the included phase, 90 studies met all eligibility requirements and were selected for the final systematic review. These studies formed the basis for analyzing intelligent traffic control techniques, machine learning algorithms, deep learning approaches, IoT-based traffic management systems, connected vehicle technologies, and smart transportation frameworks.

Table 2 Types of Techniques Used in Intelligent Traffic Control Systems

Author(s)/Year*	Objective	Methodology/Technique	Key Findings	Research Gap
Type-2 Fuzzy Traffic Control Study	Improve traffic signal timing under uncertainty	Type-2 Fuzzy Logic + Deep Reinforcement Learning	Reduced vehicle delay and queue length; improved traffic flow	Limited real-world implementation validation
Toll Plaza Traffic Management Study	Reduce toll plaza congestion	LSTM + YOLOv7 + Deep SORT + VSL & RM	Waiting time reduced by 57%; emissions reduced by 34%	Tested only at a single toll plaza
Urban Signal Optimization Study	Optimize urban traffic signals	DQN and G-DQN with SUMO Simulation	Improved queue length and waiting time performance	Scalability to city-wide networks not examined
Fuzzy Logic Traffic Light Management	Reduce vehicle waiting time	Deep Q-Network + Fuzzy Logic	Waiting time reduced by 18.46%	Limited emergency vehicle scenarios
UAV-Based Target Detection	Improve traffic target detection	Deep Learning-based UAV Detection Models	Enhanced detection accuracy under congestion conditions	High computational requirements
Vehicle Flow Speed Forecasting	Predict traffic flow speed	GA-LSTM and PSO-LSTM Models	Improved prediction accuracy and reduced computation time	Limited geographic coverage
SDN Traffic Classification	Classify network traffic efficiently	LSTM, BiLSTM, GRU, BiGRU	GRU achieved superior classification performance	Real-time deployment challenges remain
Smart City Traffic Prediction	Enhance traffic flow forecasting	Attention-Based GRU and LSTM Networks	Reduced MAE, RMSE, and MAPE significantly	Focused mainly on prediction rather than control
Multi-Agent Traffic Signal Control	Improve traffic network sustainability	Multi-Agent Deep Q-Learning	Reduced fuel consumption by 11% and travel time by 13%	Requires large-scale validation
IoT-Based Smart Traffic Framework	Develop sustainable traffic management architecture	IoT, AI Sensors, ITS, Cloud Computing	Improved congestion prediction and route optimization	Security and privacy concerns not addressed
Connected Vehicle Signal Control	Optimize signal operations using CV data	Deep Reinforcement Learning	Improved speed, queue length, and waiting time	Dependence on connected vehicle penetration
Robust Traffic Signal Control	Manage traffic disruptions and accidents	Deep Q-Learning with SUMO Simulation	Reduced disruption-induced delays	Limited accident scenario testing

AI and IoT Traffic Management Review	Examine intelligent traffic control technologies	AI, IoT, Predictive Analytics	Reduced traffic delays by 30% and improved safety	Lacks empirical implementation analysis
Deep Learning in Air Traffic Management	Review DL applications in ATM	Deep Learning Review Framework	Identified future opportunities in ATM systems	Mostly conceptual analysis
Deep RBF Traffic Intelligence Model	Improve smart city traffic prediction	Deep Radial Basis Function Networks	Higher prediction accuracy than traditional models	Computational complexity remains high
Traffic Sign Recognition System	Develop intelligent traffic sign recognition	Haar Cascade + Attention-Based CNN	Achieved 99.91% classification accuracy	Dataset diversity limitations
Fuel Consumption Optimization Study	Reduce fuel consumption at intersections	PSO-ANN, PSVM, PLSR	ANN achieved best prediction accuracy; fuel savings improved	Limited intersection configurations studied

This table 2 presents various intelligent traffic control techniques developed by researchers to improve traffic management, congestion reduction, signal optimization, vehicle detection, and traffic prediction. The studies demonstrate the growing adoption of Artificial Intelligence (AI), Deep Learning (DL), Reinforcement Learning (RL), Fuzzy Logic, IoT, and Connected Vehicle technologies in modern transportation systems. Most studies reported significant improvements in traffic flow, reduced waiting times, lower fuel consumption, and enhanced prediction accuracy. For example, Type-2 Fuzzy Logic combined with Deep Reinforcement Learning reduced vehicle delays, while Multi-Agent Deep Q-Learning decreased fuel consumption and travel time. However, several research gaps remain, including limited real-world validation, scalability issues, computational complexity, and dependence on connected vehicle penetration rates. These findings indicate that although intelligent traffic control technologies are highly promising, further large-scale implementation and validation are necessary[85].

Table 3 Challenges in Intelligent Traffic Control Systems

Challenge Category	Description	Impact on Traffic Management
Traffic Congestion	Increasing vehicle density in urban areas causes severe congestion.	Longer travel times and reduced road efficiency
Dynamic Traffic Patterns	Traffic demand varies by time, weather, and events.	Difficulties in real-time signal optimization
Data Quality Issues	Missing, noisy, or inaccurate sensor data.	Reduced prediction and control accuracy
Real-Time Decision Making	Processing large traffic datasets instantly.	Delays in adaptive traffic responses
Signal Coordination	Synchronizing multiple intersections effectively.	Increased queue lengths and delays
Computational Complexity	Advanced AI models require high processing power.	Increased operational costs
Scalability	Expanding traffic control systems city-wide.	Performance degradation in large networks
Vehicle Detection Accuracy	Occlusions, poor lighting, and weather conditions affect detection.	Inaccurate traffic monitoring
Emergency Vehicle Prioritization	Providing priority without disrupting traffic flow.	Delayed emergency response
Multi-Agent Coordination	Managing interactions among multiple intersections.	Inefficient traffic signal control
Infrastructure Cost	High installation and maintenance expenses.	Limited deployment in developing regions
Cybersecurity Threats	Vulnerability to hacking and data breaches.	System failures and safety risks
Communication	Latency in IoT and connected vehicle	Reduced effectiveness of real-

Delays	networks.	time control
Environmental Factors	Rain, fog, and accidents affect traffic conditions.	Reduced system reliability
Driver Behavior Uncertainty	Unpredictable driving patterns and violations.	Difficulties in traffic forecasting
Data Privacy Concerns	Collection of vehicle and user information.	Legal and ethical challenges
Connected Vehicle Penetration	Low adoption of connected vehicles.	Limited effectiveness of V2I systems
Model Generalization	AI models trained in one city may fail in another.	Reduced applicability across regions
Fuel Consumption and Emissions	Stop-and-go traffic increases fuel usage.	Environmental pollution
Integration Complexity	Combining AI, IoT, ITS, and cloud systems.	High implementation complexity

Table 3 identifies the major challenges affecting the implementation and performance of intelligent traffic control systems. Traffic congestion remains the most critical issue due to increasing urban vehicle density. Other significant challenges include dynamic traffic patterns, poor data quality, real-time decision-making requirements, signal coordination difficulties, and computational complexity of AI algorithms. The table also highlights emerging concerns such as cybersecurity threats, communication delays in IoT networks, emergency vehicle prioritization, data privacy issues, and integration complexity among AI, IoT, and cloud-based platforms. These challenges directly impact traffic efficiency, prediction accuracy, system reliability, and operational costs. The findings suggest that future intelligent traffic systems must focus on scalability, security, interoperability, and real-time processing capabilities to ensure effective deployment in smart cities[86-87].

Table 4 Dataset Summary Table Used in Intelligent Traffic Control Research

Dataset Name	Data Type	Features Included	Application Area	Advantages	Limitations
SUMO Simulation Dataset	Simulated Traffic Data	Vehicle count, speed, queue length, waiting time	Traffic signal optimization	Flexible simulation environment	May not represent real-world complexity
Traffic Flow Dataset	Time-Series Data	Traffic volume, occupancy, speed	Traffic prediction	Widely available	Missing and noisy data
GPS Probe Vehicle Dataset	Vehicle Trajectory Data	Location, speed, travel time	Route optimization and forecasting	Real-time information	GPS signal errors
Connected Vehicle (CV) Dataset	Vehicle Communication Data	Position, acceleration, lane information	Intelligent signal control	High temporal resolution	Limited CV penetration
UAV Traffic Monitoring Dataset	Aerial Traffic Images	Vehicle locations, density, movement	Congestion detection	Large-area coverage	Weather sensitivity
Toll Plaza Traffic Dataset	Vehicle Arrival Data	Arrival rate, waiting time, toll transactions	Toll management	Useful for congestion control	Limited geographical scope
IoT Sensor Traffic Dataset	Sensor Data	Vehicle count, occupancy, environmental factors	Smart city traffic management	Real-time monitoring	Sensor maintenance issues
Traffic Camera Dataset	Video/Image Data	Vehicle images, lane occupancy	Vehicle detection and classification	Rich visual information	High storage requirements
Air Traffic Managemen	Flight Traffic	Aircraft position,	Air traffic control	Supports ATM	Complex data structure

t Dataset	Data	altitude, speed		optimization	
Traffic Sign Dataset (GTSRB)	Image Dataset	Traffic sign images and labels	Traffic sign recognition	Benchmark dataset	Limited environmental diversity

Table 4 summarizes the major datasets commonly used in intelligent traffic control research. The datasets cover a wide range of traffic-related information, including simulated traffic data, time-series traffic flow records, GPS trajectories, connected vehicle communication data, UAV-based images, toll plaza transactions, IoT sensor readings, and traffic camera footage. Each dataset serves different applications such as traffic prediction, signal optimization, route planning, congestion detection, vehicle classification, and smart city traffic management. The table highlights key advantages such as real-time monitoring, large-area coverage, and rich visual information. However, limitations such as noisy data, weather sensitivity, limited geographical coverage, storage requirements, and sensor maintenance issues remain important concerns. The diversity of these datasets enables researchers to develop and evaluate advanced AI-based traffic management models across multiple traffic scenarios[88-89].

Table 4 Deep Learning Datasets for Traffic Control Applications

Dataset	Type	Records/Images	Main Use
GTSRB	Image	50,000+ images	Traffic Sign Recognition
KITTI	Image & Video	15,000+ frames	Autonomous Driving
Cityscapes	Urban Scene Images	25,000+ images	Traffic Scene Understanding
BDD100K	Video/Image	100,000 images	Vehicle Detection
UA-DETRAC	Traffic Video	140,000+ frames	Vehicle Tracking
AI City Challenge Dataset	Traffic Surveillance	Millions of frames	Traffic Analytics
VisDrone	UAV Images	10,000+ images	UAV Traffic Monitoring
METR-LA	Traffic Sensor Data	4 Months Data	Traffic Flow Prediction
PeMS	Traffic Sensor Data	Large-scale Highway Data	Congestion Forecasting
Taxi GPS Dataset	GPS Trajectories	Millions of Records	Route Optimization

Table 4 summarizes the major datasets commonly used in intelligent traffic control research. The datasets cover a wide range of traffic-related information, including simulated traffic data, time-series traffic flow records, GPS trajectories, connected vehicle communication data, UAV-based images, toll plaza transactions, IoT sensor readings, and traffic camera footage. Each dataset serves different applications such as traffic prediction, signal optimization, route planning, congestion detection, vehicle classification, and smart city traffic management. The table highlights key advantages such as real-time monitoring, large-area coverage, and rich visual information. However, limitations such as noisy data, weather sensitivity, limited geographical coverage, storage requirements, and sensor maintenance issues remain important concerns. The diversity of these datasets enables researchers to develop and evaluate advanced AI-based traffic management models across multiple traffic scenarios [90].

4. Conclusion

The analysis of intelligent traffic control techniques demonstrates that modern transportation systems are increasingly dependent on advanced technologies such as Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), Internet of Things (IoT), Computer Vision, and Connected Vehicle (CV) systems. These technologies enable real-time traffic monitoring, adaptive signal control, congestion prediction, vehicle detection, and route optimization, thereby improving the efficiency and sustainability of urban transportation networks. The reviewed techniques indicate that Deep Reinforcement Learning and Hybrid AI models provide superior capabilities for dynamic traffic signal optimization and congestion management, while deep learning architectures such as LSTM, GRU, and BiLSTM offer accurate traffic flow forecasting. Computer vision approaches, including YOLO and CNN-based models, have significantly enhanced vehicle detection, tracking, and traffic surveillance. Furthermore, IoT-enabled infrastructure and connected vehicle technologies facilitate continuous data exchange, supporting intelligent decision-making and coordinated traffic management. Despite these advancements, several challenges remain, including scalability, computational complexity, data quality issues, cybersecurity risks, privacy concerns, and the need for large-scale real-world deployment. Many existing studies have been validated primarily through simulations or limited experimental environments, highlighting the necessity for broader practical implementation and performance evaluation in diverse urban settings.

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