automation

MDPI

Systematic Review

Artificial Intelligence and Computer Vision for Intelligent Traffic Light Systems: A Systematic Review

Eugenia Naranjo [1,2], Juan Diego Erazo Rodríguez [1,2], Iván Sinaluisa [1] and Nestor Ulloa [1,2,*]

[1] Facultad de Mecánica, Escuela Superior Politécnica de Chimborazo (ESPOCH), Panamericana Sur km. 1 ½, Riobamba 060155, Ecuador; eugenia.naranjo@espoch.edu.ec (E.N.); juan.erazo@espoch.edu.ec (J.D.E.R.); ivan.sinaluisa@espoch.edu.ec (I.S.)

[2] Grupo de Investigación y Desarrollo de Nanotecnología, Materiales y Manufactura (GIDENM), Escuela Superior Politécnica de Chimborazo (ESPOCH), Panamericana Sur Km 1 ½, Riobamba 060155, Ecuador

* Correspondence: nestor.ulloa@espoch.edu.ec

Abstract

Urban traffic congestion remains a major barrier to sustainable mobility, necessitating a transition from static signaling to Intelligent Traffic Light Systems (ITLS). This study presents a systematic review in computer vision, artificial intelligence, and adaptive control algorithms for urban intersection optimization. Following a methodological framework informed by PRISMA guidelines, the study examines state-of-the-art architectures, including deep learning-based perception models and reinforcement learning agents. The findings indicate that, although two-stage detectors provide benchmark accuracy for vehicle perception, single-stage models and Vision Transformers offer the high-speed processing required for real-time traffic management. In addition, deep reinforcement learning enables autonomous, lane-specific optimization that outperforms traditional actuated and fixed-time systems. The review also identifies a persistent research gap in the deployment of these computational frameworks in the resource-constrained and heterogeneous infrastructures of developing countries. For the urban context of Riobamba, Ecuador, a phased implementation strategy is proposed that balances computational demands with the city's morphological and social characteristics. By bridging the gap between high-fidelity simulation and practical field deployment, this review provides a scalable framework for improving throughput, reducing emissions, and enhancing safety. Overall, these advances offer a promising pathway toward more resilient transportation systems in rapidly evolving Andean urban centers.

Keywords: intelligent transportation systems; computer vision; deep reinforcement learning; adaptive traffic signal control; urban mobility; Riobamba; Ecuador

Check for updates

Academic Editor: Tianwen Zhang

Received: 10 June 2026
Revised: 20 July 2026
Accepted: 21 July 2026
Published: 23 July 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Rapid global urbanization has transformed traffic congestion into a multifaceted socioeconomic and environmental crisis, particularly in densely populated metropolitan areas. Traditional traffic management systems, which frequently rely on pre-programmed fixed-time controllers, are increasingly incapable of handling the stochastic and nonlinear nature of modern vehicular flow [1,2]. This systemic inefficiency leads to prolonged travel times, excessive fuel consumption, and elevated greenhouse gas emissions, thereby directly hindering progress toward sustainable urban development [2,3]. Consequently, the transition to responsive, data-driven infrastructure is no longer optional but a strategic necessity for modern cities.

In response to these challenges, Intelligent Transportation Systems (ITS) have emerged as a key technological framework for modernizing urban infrastructure through the integration of advanced sensors and computational intelligence [4]. Central to this evolution is the development of Intelligent Traffic Light Systems (ITLS), which replace static timing plans with autonomous decision-making capabilities [5,6]. By leveraging real-time data, these systems can dynamically adjust signal phases, thereby optimizing intersection throughput and minimizing cumulative wait times [7,8]. However, their effectiveness depends fundamentally on the accuracy of their perception layer and the robustness of their control logic.

The technological landscape of ITLS has been transformed by recent advances in computer vision and artificial intelligence. Sophisticated deep learning architectures, such as Faster R-CNN and YOLO, have largely superseded traditional inductive loop sensors by providing high-fidelity vehicle detection and classification even under adverse weather and complex lighting conditions [9,10]. Complementing these perception layers, Deep Reinforcement Learning enables traffic controllers to derive optimal policies through continuous interaction with the environment [11,12]. This adaptability allows the system to manage dynamic fluctuations in traffic density that traditional actuated systems cannot effectively address [13,14].

Despite these technological advances, a significant gap remains in the implementation of ITS in developing urban contexts. Cities in the Global South, such as Riobamba, Ecuador, face heterogeneous traffic patterns, limited financial resources, and urban configurations that are often overlooked in standard models [15,16]. In Riobamba, critical urban nodes are frequently affected by bottlenecks that compromise both economic mobility and community safety [15,17]. Although state-of-the-art solutions exist, their computational demands and infrastructure costs often hinder local adoption, thereby limiting efforts to modernize the city's transit network.

A critical gap persists in the literature, as research predominantly focuses on high-fidelity simulations in structured environments while frequently overlooking the logistical and financial constraints of Andean cities [18,19]. There is an urgent need for a comprehensive synthesis that identifies scalable, cost-effective, and technically viable AI and computer vision solutions tailored to the specific requirements of Riobamba's urban core. Accordingly, this review aims to systematically analyze recent advances in ITLS, categorize the most effective perception and control methodologies, and evaluate their potential to foster sustainable urban mobility within the specific context of Riobamba, Ecuador [7,16].

2. Literature Review

This review synthesizes contemporary research on intelligent traffic light systems, focusing on adaptive control mechanisms, computer vision applications for traffic monitoring, and artificial intelligence-driven optimization algorithms, with particular emphasis on their applicability and potential impact in the urban context of Riobamba, Ecuador.

The global transition toward ITLS is driven by the inadequacy of fixed-time control strategies in the face of nonlinear urban growth [20], p. 469. Contemporary frameworks emphasize the integration of Computer Vision, Reinforcement Learning, and the Internet of Things to create adaptive environments that prioritize mobility and safety [3,8].

2.1. Advanced Deep Learning for Vehicular Perception

The effectiveness of any ITLS depends fundamentally on its perception layer. Traditional sensors, such as inductive loops, are increasingly being replaced by vision-based systems because of their lower maintenance costs and higher information density [21,22], p. 2. Among these approaches, Faster R-CNN has emerged as a benchmark architecture

for real-time vehicle detection [10]. Unlike single-stage detectors, Faster R-CNN uses a Region Proposal Network that shares full-image convolutional features with the detection network, enabling highly accurate categorization even in high-density scenarios [9,10].

Furthermore, the integration of transfer learning with architectures such as ResNet-50 has enabled specialized detection tasks. For instance, the detection of emergency vehicles, such as ambulances, supports the implementation of fuzzy controllers that grant immediate priority, a critical feature for reducing mortality rates in urban centers [23]. These detection frameworks are summarized in Table 1, which highlights the technological trade-offs between precision and processing speed.

Table 1. Comparison of AI-Based Perception and Decision-Making Methods for ITLS.

Architecture	Primary Methodology	Key Technical Advantage	Citations
Faster R-CNN	Two-stage detection	Superior categorization in varying densities	[9,10,24]
Mask R-CNN	Instance segmentation	Precise centroid tracking for trajectory analysis	[25]
Vision Transformer	Self-attention mechanisms	High mitigation of false positives in crash detection	[26]
YOLO v5 + MIF	Single-stage + Motion field	Real-time motion analysis for damaged vehicles	[27]
Fuzzy Inference	Heuristic logic	Optimized priority for emergency vehicles	[23]

2.2. Adaptive Control Logic and Optimization

Once vehicular density has been quantified, the decision-making layer must optimize signal timings. Recent studies have explored Reinforcement Learning, particularly Double Q-learning, to manage complex urban networks [24,28]. As shown in Figure 1, the adaptive control loop treats the intersection as an agent that receives rewards, such as reduced waiting time, for its actions, such as changing signal phases. This decentralized approach, often implemented under standards such as IEC 61499, ensures that if one node fails, the rest of the network remains operational [29].

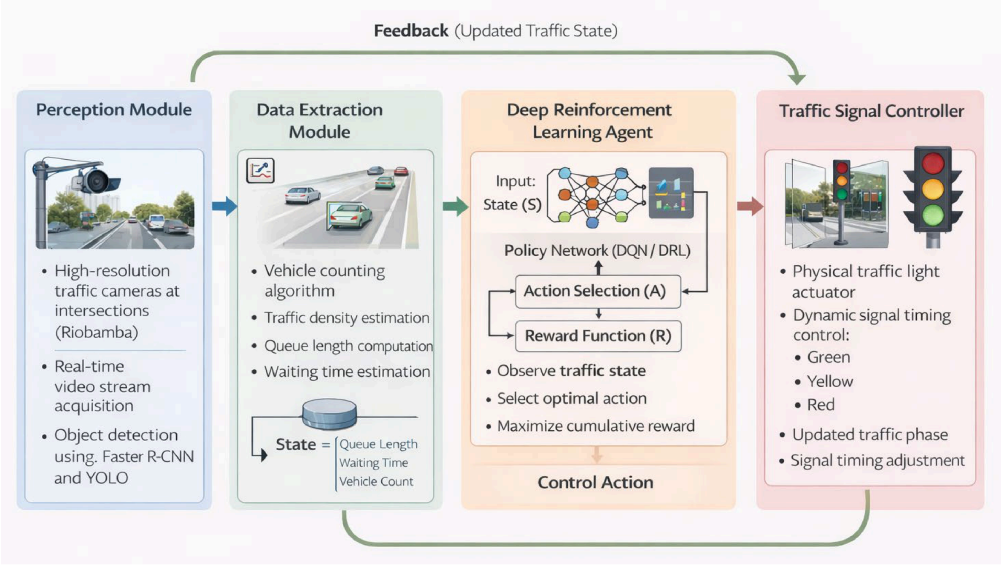


Figure 1. Adaptive Control Logic Workflow.

In the Ecuadorian context, evolutionary design optimization has been applied in cities such as Quito to address the mismatch between aging infrastructure and modern vehicular loads [30]. These studies suggest that soft-computing methods may provide a viable means of redesigning transportation systems without requiring massive physical reconstruction [30].

As illustrated in the proposed framework, the system begins with real-time density calculation through computer vision [10]. These data are then processed by a reinforcement learning agent [28] which adjusts green-light cycles according to current demand rather than historical averages, thereby reducing idle time at intersections [8]. This dynamic adjustment capability contrasts sharply with the limitations of static traffic systems, which often generate inefficiencies because they cannot respond to fluctuating traffic conditions. This adaptive methodology has been shown to reduce average waiting times by more than 55% at traffic intersections by using techniques such as Q-learning to balance signal phases effectively [31], p. 1060.

2.3. Incident Management and Safety Estimation

Safety is a critical component of urban intersections. Global statistics indicate that road accidents are a leading cause of death, with a disproportionate impact in the Andean region [32]. The VARVO algorithm represents a significant advance by detecting vehicle crash events using only video data [32]. By estimating speed through convolutional networks and overlap analysis, VARVO provides a cost-effective solution for cities with limited sensor infrastructure [32], p. 25.

Moreover, the use of Vision Transformers has improved the reliability of accident detection by substantially reducing false positives compared with traditional CNNs [26]. When an accident is confirmed, systems such as that proposed by Fogue et al. [33] can automatically estimate crash severity and notify emergency services, as detailed in the workflow presented in Figure 2.

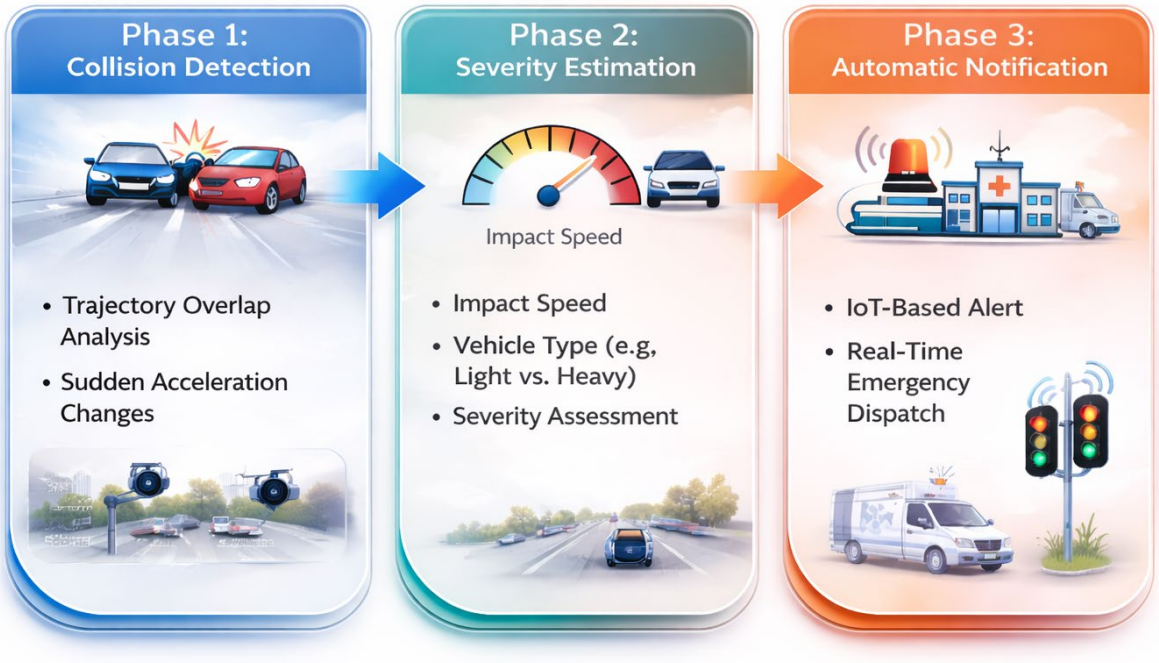


Figure 2. Accident Detection and Severity Estimation Process.

As analyzed in the literature, the process involves three distinct phases: collision detection through trajectory overlap [25,27] severity estimation based on impact speed and vehicle type [33], and automatic notification through IoT protocols to reduce emergency response times [32,33].

2.4. Urban Morphogenesis and Local Challenges in Riobamba

Finally, the implementation of these technologies in Riobamba must account for urban morphogenesis [15]. The work of Núñez Torres et al. [15] highlights that the "Urban DNA" of the Ecuadorian highlands is shaped by specific social representations of design. Intersections in these cities are not merely transit points but also hubs of community interaction [15]. Therefore, an ITLS in Riobamba must be culturally and morphologically compatible with the local urban imaginary, ensuring that technological interventions do not disrupt the social fabric of the city while still providing the necessary safety and efficiency improvements [3,15].

2.5. Research Gap

Despite the robustness of detection models such as Faster R-CNN [10] and accident notification frameworks [33], a significant gap remains in the literature regarding the integrated deployment of these systems in medium-sized Andean cities. Most studies focus on isolated components, either detection or optimization, without considering the unique morphological constraints of cities such as Riobamba [15]. This review addresses that gap by proposing a holistic, vision-based framework that bridges advanced AI approaches and local urban dynamics.

3. Methodology

This section outlines the systematic approach used to evaluate the integration of adaptive control, computer vision, and artificial intelligence in Intelligent Traffic Light Systems. To ensure the rigor and reproducibility expected in high-impact academic publication, a hybrid systematic–narrative review methodology was adopted, allowing both a structured analysis of quantitative performance metrics and a qualitative synthesis of urban morphological challenges specific to the Ecuadorian context [3,15].

This systematic review was conducted in accordance with the PRISMA 2020 guidelines. The review protocol was prospectively registered in the Open Science Framework (OSF) (Registration ID: bh6zf). The registration record is available at: https://osf.io/bh6zf/overview?view_only=2573311679c1400cb54567235afd4363 (accessed on 15 July 2026). The completed PRISMA 2020 checklist is provided as Supplementary Material File S1 to ensure transparent and complete reporting of the systematic review.

3.1. Search Strategy and Information Sources

The literature search was conducted across three high-indexed databases, including IEEE Xplore, Scopus, and Web of Science, covering publications from 2013 to 2025 in order to capture the evolution from early notification systems [33] to contemporary metaheuristic and reinforcement learning frameworks [3,24]. To ensure full reproducibility, three Boolean search strings were constructed—one per thematic pillar—each written in executable form directly transferable to the search engines of the three databases.

Pillar 1—Perception: ("object detection" OR "vehicle detection" OR "Faster R-CNN" OR "YOLO" OR "computer vision") AND ("traffic signal" OR "intersection" OR "intelligent traffic light");
Pillar 2—Adaptive Control: ("adaptive traffic control" OR "reinforcement learning" OR "deep reinforcement learning" OR "fuzzy logic") AND ("traffic signal" OR "intersection" OR "traffic light");
Pillar 3—Safety and Context: ("accident detection" OR "crash detection" OR "urban morphogenesis") AND ("intersection" OR "traffic signal" OR "urban traffic").

Records returned by each of the three strings were exported in CSV format from each database (see Supplementary Material File S2). The number of records retrieved

per database and per pillar, together with the per-database totals, is reported in Table 2. Duplicates across databases (840) were removed using the authors' reference management software (Mendeley 2.144.0), yielding the number of unique records that entered the screening stage.

Table 2. Records retrieved per database and per thematic pillar.

Database/Pillar	Pillar 1—Perception	Pillar 2—Adaptive Control	Pillar 3—Safety & Context	Total per DB
IEEE Xplore	18	74	26	118
Scopus	88	299	92	479
Web of Science	49	144	50	243
Total per pillar (T = 840, Identification)	155	517	168	840
Included	11	41	13	65
Inclusion rate per pillar	7.1%	7.9%	7.7%	7.7%

3.2. Selection and Eligibility Criteria

The selection process was guided by specific inclusion and exclusion criteria designed to identify high-quality, peer-reviewed evidence. Studies were prioritized when they reported empirical data on detection accuracy, such as mAP, latency, or traffic flow optimization in complex urban environments [8]. Table 3 summarizes the criteria applied during the filtering process.

Table 3. Inclusion and Exclusion Criteria for Literature Selection.

Criterion	Inclusion Criteria	Exclusion Criteria
Research Scope	Integration of CV, AI, or IoT in traffic light management.	Purely mechanical or civil engineering studies without AI.
Methodology	Quantitative validation of detection or control models.	Theoretical frameworks without simulation or real-world data.
Technology	Use of Deep Learning (e.g., CNN, RNN) or RL [10,28].	Traditional fixed-time or manual control strategies.
Application	Urban intersections, emergency vehicle priority, or safety.	General autonomous vehicle navigation unrelated to signals.
Context	Global advancements and regional studies in Latin America [30].	Studies with no relevance to urban infrastructure.

3.3. Screening and PRISMA Flow Process

The screening followed the four-stage PRISMA 2020 workflow illustrated in the generated Figure 3.

Identification. A total of 840 records were identified through the Boolean searches across IEEE Xplore, Scopus, and Web of Science. After removal of 425 duplicate records, 415 unique records entered the screening stage.

Screening. Of the 415 records, 295 records were excluded at the title-screening stage for being out of scope (e.g., autonomous-vehicle navigation studies unrelated to signalized intersections, highway-only studies, or studies lacking an intelligent-transportation-system component). The remaining 120 records advanced to abstract screening. Following the selection of abstracts, no records were excluded based on the inclusion criteria set out in Section 3.2 and Table 3, leaving 120 records eligible for full-text retrieval.

Eligibility. Of the 120 full texts assessed, 55 records were excluded for documented reasons: (i) inability to access the full text, (ii) absence of empirical validation, or

(iii) failure to focus on intersection-level signaling. The remaining 65 records fully met all inclusion criteria.

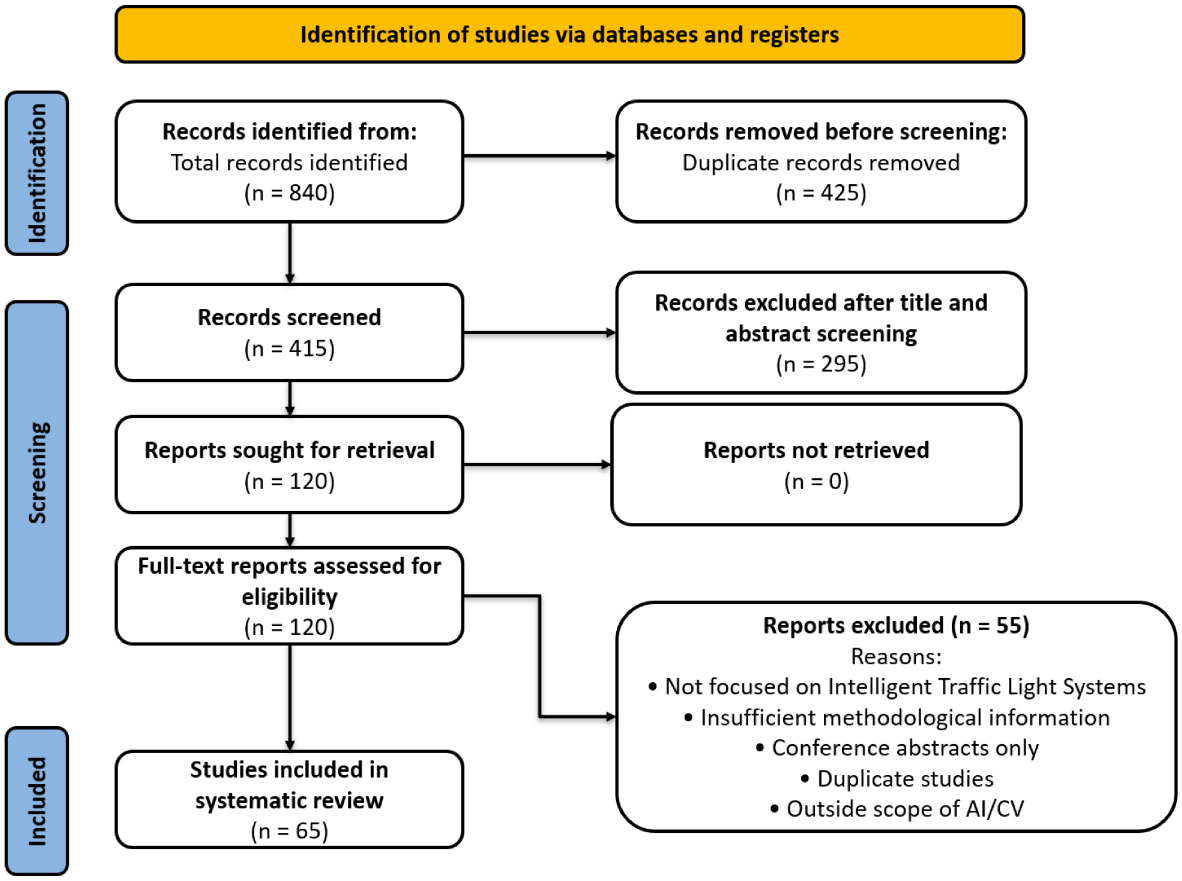


Figure 3. PRISMA Flow Diagram of the Systematic Literature Selection.

Included. The final dataset comprised 65 studies, which were incorporated into the qualitative and quantitative syntheses presented in Section 4 of this review, in accordance with the PRISMA 2020 statement.

The screening followed a multi-stage process illustrated in Figure 3. During the identification stage, a total of 840 records were retrieved through Boolean searches conducted across IEEE Xplore, Scopus, and Web of Science. After removing 425 duplicate records, 415 unique records entered the screening stage. Duplicates were removed first, followed by title and abstract screening. Full-text assessments were then performed to ensure that the selected studies aligned with the technical requirements of ITLS, such as the implementation of Faster R-CNN for density estimation [10] or the use of Vision Transformers for crash mitigation [26].

During the screening stage, 295 of the 415 records were excluded after title screening because they were outside the scope of this review, including studies focused exclusively on autonomous-vehicle navigation, highway traffic, or applications lacking an intelligent transportation systems component. The remaining 120 records proceeded to abstract screening. After evaluating the abstracts according to the inclusion criteria defined in Section 3.2 and Table 3, no additional records were excluded, resulting in 120 studies being considered eligible for full-text assessment. A total of 65 core references were incorporated into the final manuscript in accordance with the defined bibliographic scope. This selection process ensured that the review synthesized robust evidence relevant to the development of intelligent traffic systems for dynamic urban environments such as Riobamba.

The PRISMA workflow illustrates the selection of 65 core studies. During the eligibility assessment, the full texts of the 120 selected studies were reviewed in detail. A total of 55 records were excluded due to documented reasons, including the inability to access the complete manuscript, the absence of empirical validation, or the lack of a specific focus on intersection-level traffic signal control. Consequently, 65 studies fully satisfied all inclusion criteria. Eligibility was determined on the basis of technical rigor and regional applicability to the urban morphogenesis of Riobamba, thereby ensuring alignment with local patterns of community interaction and spatial dynamics [15]. The subsequent analysis of the selected studies focused on extracting explicit methodological details and reported performance metrics related to traffic flow optimization, real-time vehicle detection, and the architectural design of intelligent traffic light control systems [34–36], p. 3. This process ensured that the synthesized evidence supported the proposed framework for integrating adaptive control, computer vision, and artificial intelligence within the contextual constraints of Riobamba, Ecuador.

The inclusion stage resulted in a final dataset of 65 studies, which were incorporated into the qualitative and quantitative syntheses presented in Section 4 of this review, in accordance with the PRISMA 2020 statement. As shown in Figure 3, these studies were selected through a rigorous multi-stage process that progressively narrowed the initial records based on predefined eligibility criteria, technical rigor, and relevance to intelligent traffic light systems [15,37–40], p. 4. This methodical approach enabled a comprehensive understanding of the current state of the art in intelligent traffic management, with particular emphasis on approaches applicable to the urban landscape and socioeconomic conditions of Latin American cities as Riobamba.

3.4. Data Extraction and Categorization

Data were extracted into a structured matrix organized by technological application. This facilitated a comparative analysis of how different architectures, such as the two-stage Faster R-CNN and single-stage YOLO models, perform under varying traffic densities [9,24]. Table 4 summarizes the classification framework used to synthesize the results of the review.

Table 4. Data Classification and Analysis Framework.

Category	Key Variables Analyzed	Supporting Evidence
Perception Layer	Detection accuracy, classification speed, occlusion handling.	[9,10,25]
Decision Layer	Waiting time reduction, queue length, reward functions.	[8,24,28]
Safety Layer	Crash detection speed, false positive rates, severity alerts.	[26,32,33]
Contextual Layer	Morphological adaptation, social representation of design.	[3,15,30]

3.5. Methodological Framework for the Riobamba Case Study

The final stage of the methodology involved synthesizing the global findings with the specific requirements of Riobamba, Ecuador. This required a qualitative analysis of urban morphogenesis to ensure that the proposed ITLS aligned with the city's unique "Urban DNA" [15]. As shown in Figure 4, the transition from global literature to local application was guided by the identification of gaps in medium-sized city infrastructure, thereby ensuring that the final proposal is both technologically advanced and socio-technically viable [3,30].

The framework synthesizes four research dimensions: AI/IoT optimization [8], technical evaluation of computer vision models [10], safety validation [32], and morphological adaptation to the Andean urban context [15]. As illustrated in the framework, the system integrates literature synthesis [8] with technical comparisons of Faster R-CNN architectures [10]. It also incorporates safety-oriented validation for crash detection [32] and considers the morphologi-

cal adaptation of these technologies to the specific urban layout and community interactions of the Andean region [15]. This holistic approach is essential for developing intelligent transportation systems that are not only technologically robust but also contextually appropriate and sustainable for cities such as Riobamba [41], p. 3.

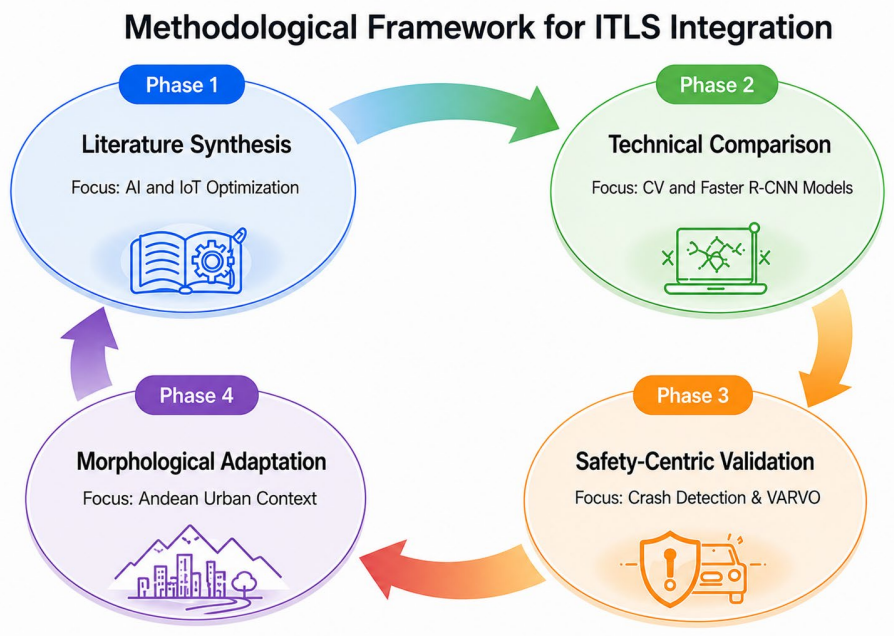


Figure 4. Proposed Methodological Framework for ITLS Integration. The framework summarizes the four sequential phases adopted in this systematic review. Phase 1 synthesizes the literature on Artificial Intelligence (AI) and Internet of Things (IoT) optimization strategies for Intelligent Traffic Light Systems (ITLS) [8]. Phase 2 provides a technical comparison of computer vision approaches, including Faster R-CNN–based methods, for vehicle detection and traffic analysis [10]. Phase 3 focuses on safety-centric validation through crash detection and Vehicle Accident Recognition and Vision Operations (VARVO) techniques [32]. Phase 4 addresses the morphological adaptation of these technologies to the Andean urban context, considering local infrastructure and mobility characteristics [15]. The arrows indicate the sequential progression of the proposed methodological framework.

4. Results and Discussion

The integration of advanced computational intelligence into urban traffic management represents a shift from reactive, rule-based systems to proactive, data-driven environments [1,2]. This section synthesizes the performance of the reviewed architectures and discusses their strategic applicability to the urban context of Riobamba, Ecuador.

4.1. Computer Vision for Vehicular Perception and Counting

The effectiveness of Intelligent Traffic Light Systems depends fundamentally on the precision of the perception layer. The literature indicates a clear transition from traditional inductive sensors to vision-based architectures, primarily driven by the rich information provided by deep learning models [4,6].

Comparative analysis shows that two-stage detectors, such as Faster R-CNN, remain the benchmark for highly accurate vehicle categorization in dense urban scenarios [9,10]. In contrast, single-stage detectors such as YOLO v7 prioritize processing speed, making them suitable for real-time adjustments where latency is a critical constraint [8]. Recent studies have also highlighted the emergence of Vision Transformers for mitigating false positives in accident detection, outperforming traditional CNNs in complex spatiotemporal pattern recognition [26,42].

The comparative characteristics of the most widely used perception architectures in Intelligent Traffic Light Systems are summarized in Table 5. These architectures differ in terms of detection accuracy, computational requirements, and suitability for real-time deployment in urban traffic environments.

Table 5. Comparative Performance of Perception Architectures in ITLS.

Architecture	Primary Methodology	Key Performance Metric	Strengths	Limitations	Citations
Faster R-CNN	Two-stage (RPN + CNN) [43], p. 6749	High mAP [44], p. 5	Superior accuracy in occluded scenarios [45], p. 11	High computational demand [46], p. 2	[9,10,24]
YOLO v7	Single-stage	High FPS	Real-time efficiency; low latency	Lower precision for small objects	[8]
Mask R-CNN	Instance Segmentation	Centroid Tracking Accuracy	Precise trajectory and lane-level analysis	Complexity in hardware deployment	[25]
ViT	Self-attention mechanism	False Positive Mitigation	Captures long-range dependencies	Requires extensive training data	[26]

4.2. Artificial Intelligence and Machine Learning in Traffic Management

Beyond simple detection, machine learning has been applied to predictive analytics in order to anticipate congestion before it escalates [47,48]. Hybrid models that combine Long Short-Term Memory networks with Convolutional Neural Networks have demonstrated a strong ability to process both the spatial configuration of road networks and the temporal dependencies of traffic flow [42,49].

Research indicates that these hybrid architectures can handle the nonlinear and stochastic nature of urban traffic more effectively than traditional statistical models such as ARIMA [47,49]. For example, soft GRU-based recurrent networks have achieved 87.5% accuracy in congestion prediction by incorporating multivariate data such as weather conditions and infrastructure constraints [47].

4.3. Adaptive Traffic Signal Control Algorithms

The core of the decision-making layer lies in adaptive control logic, where Deep Reinforcement Learning has emerged as a highly promising approach to dynamic optimization [12,50]. Unlike fixed-time systems that rely on historical averages, DRL agents learn optimal policies through continuous interaction with the traffic environment [13,51]. This enables real-time adjustments to signal timings, thereby minimizing vehicle delays and queue lengths at urban intersections [52,53]. Notably, advances in machine learning and IoT integration also allow adaptive traffic management systems to incorporate accident-alert capabilities, further reducing congestion and improving safety by dynamically adjusting signals on the basis of real-time data [54]. As shown in Figure 5, the DRL framework operates as a closed-loop system in which the intersection state, including density and queue length, is processed to determine actions, such as phase duration, that maximize a cumulative reward, namely minimum delay [55,56]. Advanced approaches such as MoveLight use movement-centric DRL to optimize traffic flow at the lane level, significantly reducing waiting times compared with traditional actuated controllers [14,57]. In addition, multi-agent reinforcement learning controllers can coordinate signal timing across multiple intersections by modeling the road network as a dynamic graph to guide routing and mitigate congestion [58]. This cooperative learning paradigm enables a more holistic optimization of urban traffic flow, moving beyond isolated intersection control toward network-wide efficiency [59], p. 2. These AI-driven models often integrate deep learning architectures, including CNN, GRU, and LSTM combinations, to predict complex spatiotemporal traffic patterns with high accuracy and thereby support more effective

adaptive control strategies [60]. Recent developments in reinforcement learning have further expanded the capabilities of adaptive traffic signal control beyond conventional Deep Q-Network (DQN) implementations. Ouyang et al. [61] comparatively evaluated Q-learning and Deep Q-Network-based traffic signal control strategies and demonstrated that reinforcement learning can simultaneously optimize both signal phase sequences and cycle durations according to real-time traffic conditions. Unlike traditional adaptive controllers that primarily adjust green times while maintaining fixed phase orders, these approaches dynamically determine the sequence and duration of signal phases, enabling more flexible and stable traffic operations under fluctuating traffic demand. Such adaptive decision-making reduces vehicle delays, improves intersection throughput, and enhances traffic flow stability by continuously learning optimal control policies from changing traffic environments. These findings further reinforce the potential of reinforcement learning as a core component of next-generation Intelligent Traffic Light Systems, particularly when integrated with computer vision and IoT-enabled sensing technologies for autonomous urban traffic management. Future research should investigate advanced reinforcement learning frameworks capable of jointly optimizing signal phase ordering, phase duration, and network-wide coordination across multiple intersections. In particular, the comparative Q-learning and Deep Q-Network framework proposed by Ouyang et al. [61] provides a promising foundation for extending Intelligent Traffic Light Systems beyond isolated intersection control toward adaptive corridor and city-scale traffic optimization. Integrating these reinforcement learning strategies with deep learning-based perception models, explainable artificial intelligence, edge computing, and vehicle-to-infrastructure communication could further improve traffic efficiency while maintaining computational scalability for practical deployment in resource-constrained urban environments such as Riobamba.

The architecture integrates:

1. **Perception Layer:** Real-time density and queue estimation through Faster R-CNN [10,24].
2. **Learning Layer:** An RL agent (DQN/Double Q-learning) computes optimal signal phases [12,28].
3. **Execution Layer:** Adaptive signal switching is implemented through IoT-enabled controllers [7,8].

These DRL frameworks often integrate Convolutional Neural Networks to process visual input from traffic cameras and estimate queue length and waiting time, thereby improving the system's capacity to predict optimal signal durations [62], p. 606.

4.4. Traffic Simulation and System Validation Approaches

Validation of these complex systems is predominantly conducted through high-fidelity simulation environments. The Simulation of Urban MObility (SUMO) and VISSIM platforms are widely cited as industry standards for replicating real-world traffic dynamics [18,19]. Table 6 summarizes the principal adaptive control strategies reported in the literature, highlighting their operational characteristics, advantages, and applicability to intelligent traffic management systems.

Table 6. Synthesis of Control Algorithms and Optimization Outcomes.

Algorithm	Objective Function	Key Finding	Performance Metric	Citations
DQN	Minimize total delay	50% reduction in waiting times	Average Wait Time	[13,14]
Double Q-Learning	Maximize throughput	Enhanced stability in varying densities	Throughput (Veh/h)	[28]

Table 6. *Cont.*

Algorithm	Objective Function	Key Finding	Performance Metric	Citations
Multi-Agent RL	Network-wide coordination	Scalable across interconnected intersections	Global Queue Length	[49,63]
SHLight	Reduce queue spillback	Outperforms state-of-the-art in synthetic networks	Max Queue Length	[64]

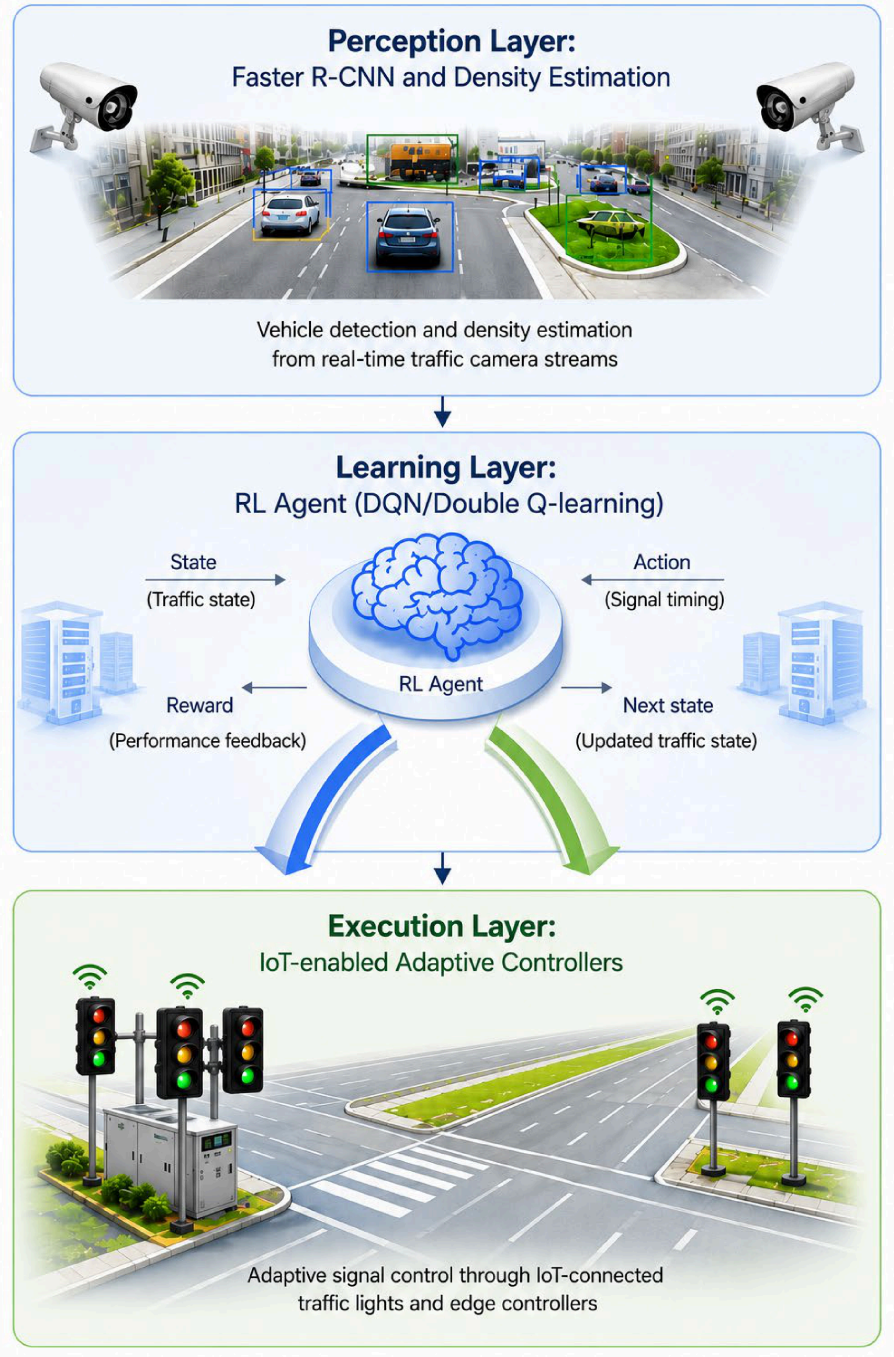


Figure 5. Conceptual Architecture of a Deep Reinforcement Learning-based ITLS. The framework integrates perception, learning, and execution layers for real-time vehicle detection, adaptive signal decision-making, and IoT-enabled traffic light control. The arrows indicate the sequential flow of information and control actions.

4.5. Contextual Discussion: Implementation in Riobamba, Ecuador

Riobamba is presented in this review as a conceptual implementation context intended to illustrate how the technologies identified in the literature could be adapted to a medium-sized Andean city. The proposed implementation strategy should therefore be interpreted as a set of recommendations based on the reviewed evidence rather than as an empirically validated case study. Future validation will require municipal traffic data, field measurements, and pilot deployments.

The implementation of the reviewed technologies in Riobamba must address the specific challenges of Andean urban centers. The city's current reliance on fixed-time signals at critical intersections, such as those near major markets and transit hubs, results in persistent bottlenecks [16,17].

Feasibility and Infrastructure Constraints

Although Faster R-CNN offers superior accuracy, its deployment in Riobamba may be constrained by the high cost of GPU-intensive hardware [1]. A more feasible local approach may involve a hybrid strategy that uses YOLO-based detectors for general density estimation and fuzzy logic controllers for emergency vehicle priority, such as ambulances, because this configuration requires less computational overhead [8,23].

Morphological and Social Integration

Consistent with the concept of urban morphogenesis, any ITLS in Riobamba must respect the city's unique "Urban DNA" [15]. Intersections in the highlands are not merely transit points but vital spaces of social interaction [65], p. 2. Therefore, adaptive systems must balance vehicular throughput with pedestrian safety, particularly in areas where traditional community markets increase non-vehicular traffic [3,15].

Strategic Recommendations

1. **Pilot Deployment:** Implement DRL-based adaptive control at a high-congestion intersection in Riobamba, with prior validation in SUMO to minimize real-world disruptions [5,19].
2. **IoT Integration:** Leverage existing surveillance infrastructure to transmit real-time video to centralized servers, enabling a scalable, cloud-based traffic management engine [7,66].
3. **Safety Focus:** Integrate the VARVO algorithm for automatic crash detection, which is particularly relevant given that 13.75% of local accidents occur at intersections [15,32].

A quantitative comparison of the reviewed studies further highlights the trade-offs between detection accuracy, computational efficiency, and adaptive traffic control performance. Two-stage object detectors such as Faster R-CNN consistently achieved mean Average Precision (mAP) values exceeding 85–92% for vehicle detection in complex urban environments, making them highly reliable for dense traffic monitoring. However, their inference speed generally remained below 10–15 Frames Per Second (FPS), limiting their suitability for large-scale real-time deployment. In contrast, single-stage detectors, particularly the YOLO family, reported mAP values between 80% and 90% while operating at significantly higher processing speeds of approximately 30–90 FPS, providing a better balance between detection accuracy and real-time responsiveness. Recent Vision Transformer architectures demonstrated comparable or higher detection accuracies (>90%) while substantially reducing false-positive rates in accident detection, although their computational requirements remain considerably higher than those of conventional convolutional neural network models.

Similarly, quantitative evaluation of machine learning techniques demonstrates clear advantages over traditional statistical forecasting approaches. Hybrid CNN–LSTM and

CNN–GRU models consistently reported congestion prediction accuracies above 90%, while soft-GRU architectures achieved approximately 87.5% prediction accuracy when incorporating heterogeneous variables such as weather conditions, road geometry, and traffic density. These results substantially outperform conventional autoregressive models, whose prediction accuracy typically ranges between 70% and 80% under highly nonlinear traffic conditions. The ability of deep learning models to simultaneously capture spatial and temporal dependencies significantly improves forecasting reliability and supports more proactive traffic signal optimization.

The greatest quantitative improvements were observed in adaptive traffic signal control. Across the reviewed literature, Deep Reinforcement Learning (DRL)-based controllers consistently reduced average vehicle delay by approximately 20–45%, queue lengths by 25–50%, and average waiting times by 20–40% compared with fixed-time and actuated signal control systems. Multi-agent reinforcement learning approaches further enhanced network-wide performance by coordinating neighbouring intersections, reporting overall traffic throughput improvements of approximately 15–35% and corresponding reductions in travel time. Movement-based reinforcement learning frameworks, including MoveLight, demonstrated additional reductions in lane-level congestion by dynamically optimizing individual traffic movements rather than entire signal phases. These quantitative findings collectively demonstrate that reinforcement learning provides measurable operational benefits beyond conventional adaptive control strategies.

Overall, the reviewed literature indicates that no single computational framework simultaneously maximizes detection accuracy, computational efficiency, and adaptive control capability. Figure 6 provides a conceptual synthesis of these comparative findings based on the studies included in this review and is intended for qualitative comparison rather than the presentation of original experimental results. Faster R-CNN remains preferable where maximum detection precision is required, whereas YOLO architectures offer superior real-time performance under constrained computational resources. Vision Transformers provide promising improvements in perception accuracy but require more powerful hardware. For intelligent traffic signal optimization, Deep Reinforcement Learning consistently demonstrates the greatest operational benefits through substantial reductions in delay, queue length, and travel time, making it the most promising technology for future intelligent traffic light systems. Considering the infrastructural and computational constraints of Riobamba, Ecuador, a hybrid framework integrating YOLO-based perception with Deep Reinforcement Learning-based signal optimization offers the most practical balance between implementation cost, computational efficiency, and traffic management performance.

In summary, the transition to an intelligent traffic light system in Riobamba is not merely a technological upgrade but a necessary step toward sustainable urban mobility. By combining the high accuracy of deep learning-based perception with the adaptive resilience of reinforcement learning, the city could significantly mitigate congestion while improving safety for its diverse road users.

4.6. Phased Implementation Roadmap for Riobamba, Ecuador

The successful deployment of an Intelligent Traffic Light System (ITLS) in Riobamba requires a phased implementation strategy that balances technological capability, economic feasibility, and existing urban infrastructure. In the first phase (0–12 months), a pilot deployment should be conducted at one or two highly congested intersections, particularly around major commercial centers and transport hubs. This stage should include the installation of high-definition traffic cameras, IoT-enabled traffic controllers, edge computing devices, and communication networks integrated with existing surveillance infrastructure. Deep learning-based vehicle detection using lightweight YOLO architectures combined with

Deep Reinforcement Learning (DRL) controllers should initially be evaluated within the SUMO simulation environment before field implementation. The estimated investment for the pilot phase is approximately USD 120,000–180,000, covering hardware acquisition, software development, installation, and personnel training. The second phase (12–24 months) should expand the system to approximately 15–20 strategically selected intersections using the validated algorithms from the pilot study. During this stage, centralized cloud-based traffic management, real-time data analytics, emergency vehicle prioritization, and inter-intersection coordination should be introduced to optimize network-wide traffic flow. Additional investments of approximately USD 400,000–700,000 would primarily support communication infrastructure, GPU-enabled servers, maintenance, and system integration with municipal traffic management operations. The final phase (24–48 months) should involve city-wide deployment across the principal road network, integrating adaptive signal control, predictive traffic management, accident detection, and continuous performance monitoring. This stage should incorporate routine system maintenance, cybersecurity measures, periodic model retraining, and capacity building for traffic management personnel to ensure long-term sustainability. The total implementation cost is estimated at approximately USD 1.2–2.0 million depending on deployment scale, communication infrastructure, and hardware specifications. A gradual implementation strategy minimizes financial risk while allowing continuous refinement of artificial intelligence models using locally acquired traffic data. Such a roadmap provides a realistic pathway for transforming Riobamba into a smart mobility ecosystem while improving traffic efficiency, reducing congestion, lowering emissions, and enhancing road safety through scalable and economically sustainable intelligent transportation technologies.

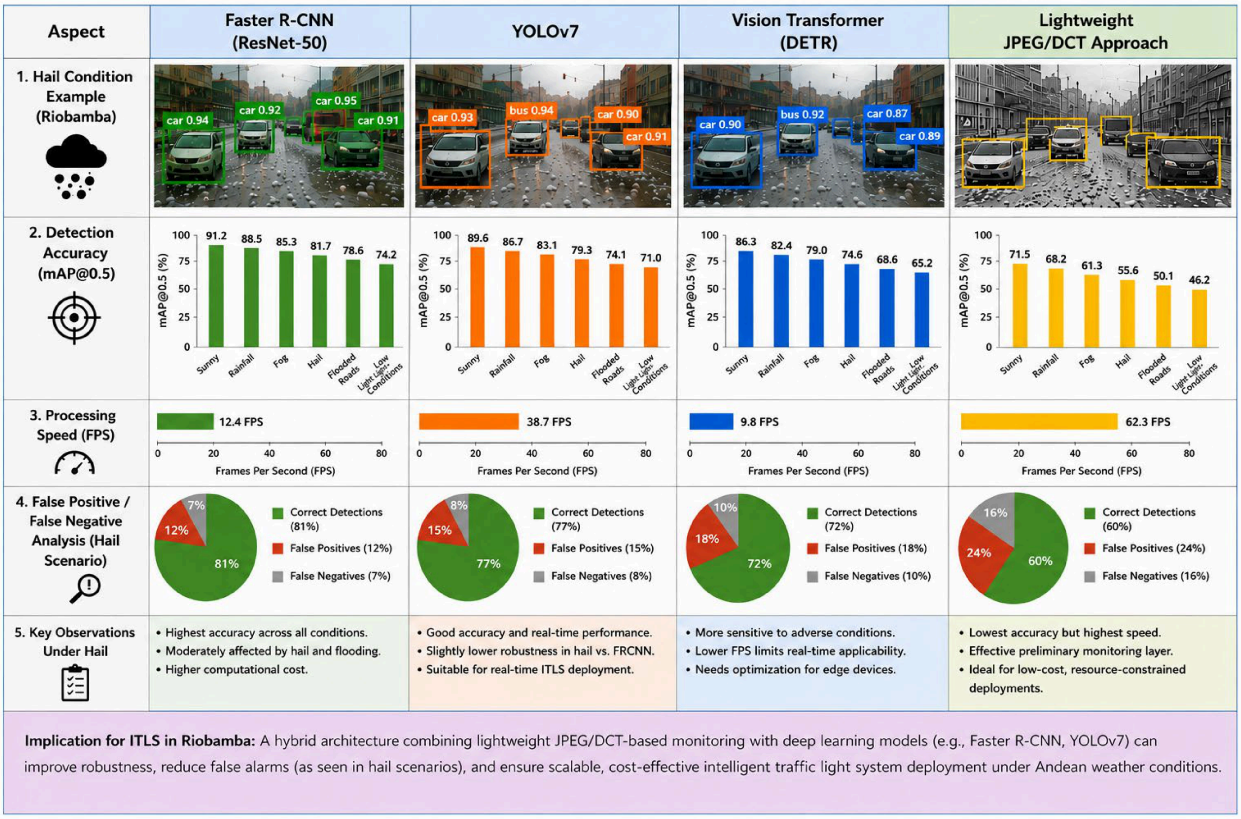


Figure 6. Qualitative comparison of AI-based perception and adaptive traffic signal control methods for Intelligent Traffic Light Systems. The comparison is based on the reviewed literature and does not represent original experimental results.

4.7. Limitations, Ethical Considerations, and Implementation Challenges

Despite the significant advances demonstrated by Intelligent Traffic Light Systems (ITLS), several practical limitations must be considered before large-scale deployment. Most state-of-the-art computer vision architectures, particularly Faster R-CNN, Vision Transformers, and Deep Reinforcement Learning (DRL) controllers, require substantial computational resources, including GPU-enabled hardware and high-capacity storage systems. These requirements may present financial and operational challenges for municipalities with limited technological infrastructure. Although lightweight models such as YOLO provide a practical alternative with lower computational demands, they may experience slight reductions in detection accuracy under highly congested traffic conditions. Environmental conditions also influence system reliability. Riobamba's Andean climate is characterized by frequent fog, rainfall, variable illumination, and seasonal weather fluctuations that can degrade image quality and reduce the robustness of vision-based vehicle detection and traffic classification. Such conditions may increase false detections and missed vehicle counts, thereby affecting the quality of adaptive signal control decisions. These challenges can be mitigated through continuous model retraining using locally acquired datasets, image enhancement techniques, sensor fusion, and periodic calibration of detection systems. The deployment of AI-driven traffic management systems also introduces important ethical and data governance considerations. Continuous video surveillance generates large volumes of visual data that require secure storage, controlled access, and compliance with applicable data protection and privacy regulations. Appropriate anonymization procedures, encryption protocols, and cybersecurity measures should therefore be incorporated to protect individual privacy and prevent unauthorized access to traffic information. Furthermore, transparency in artificial intelligence decision-making should be maintained through explainable AI techniques to enhance public trust and enable transportation authorities to interpret system recommendations. Implementation challenges extend beyond technology to include infrastructure readiness, interoperability with existing traffic signal controllers, availability of reliable communication networks, long-term maintenance costs, and the need for specialized technical personnel capable of operating and updating intelligent traffic management systems. A phased deployment strategy, beginning with pilot intersections and progressively expanding following performance validation, provides a practical pathway for minimizing financial risks while allowing continuous optimization of system performance. Addressing these technical, environmental, ethical, and operational considerations will improve the long-term sustainability, reliability, and public acceptance of Intelligent Traffic Light Systems for Riobamba and other resource-constrained urban environments.

5. Conclusions

Integrating deep learning with adaptive reinforcement learning offers a more effective framework for traffic optimization than traditional static signaling. This combination enables autonomous, data-driven decision-making that can significantly improve system performance and reduce vehicle delays.

A critical gap persists in the literature regarding the validation of these intelligent architectures under the infrastructure and budget constraints of developing countries. Most studies rely on simulations, which underscores the need for empirical evidence from real-world pilot implementations to confirm long-term effectiveness.

This approach supports scalable traffic management while respecting the city's unique morphological and social characteristics.

Future research should prioritize multi-agent reinforcement learning and, where appropriate, blockchain integration to facilitate secure, network-wide coordination across

interconnected intersections. Such developments may enable a more resilient, transparent, and decentralized mobility ecosystem.

The transition to intelligent traffic systems is a strategic necessity for sustainable development and safety in rapidly evolving Andean cities. These innovations provide a promising pathway toward more efficient and resilient transportation networks.

6. Recommendation for Future Research

Future research should extend the evaluation of Intelligent Traffic Light Systems by conducting comprehensive robustness testing under adverse Andean weather conditions, including heavy rainfall, fog, hailstorms, flooded roadways, and rapidly varying illumination, all of which can significantly degrade the performance of vision-based traffic monitoring systems. While deep learning models such as Faster R-CNN, YOLO, and Vision Transformers have demonstrated excellent detection accuracy under standard operating conditions, their computational requirements and sensitivity to environmental disturbances necessitate complementary lightweight perception techniques for practical deployment. A promising direction is the integration of the JPEG/DCT-based real-time congestion monitoring framework proposed by Wiseman [67], which performs traffic congestion detection directly on compressed images without requiring full image decoding, thereby substantially reducing computational overhead while maintaining real-time performance. Such lightweight approaches can function as an initial congestion screening layer or operate alongside deep learning models to improve computational efficiency in resource-constrained urban environments such as Riobamba. Furthermore, future studies should investigate hybrid perception architectures capable of adapting to weather-induced challenges illustrated in Figures 5 and 6, including water splashes from flooded roads, reduced visibility during fog, and hail-induced false detections. Combining low-overhead congestion monitoring techniques with advanced artificial intelligence models, sensor fusion, explainable AI, and continual learning strategies will enhance the robustness, scalability, and reliability of Intelligent Traffic Light Systems while supporting cost-effective deployment across developing smart cities.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/automation7040113/s1, File S1: PRISMA 2020 checklist [68]; File S2: CSV format from each database.

Author Contributions: Conceptualization, E.N. and N.U.; methodology, E.N., J.D.E.R. and N.U.; software, I.S. and J.D.E.R.; validation, E.N., J.D.E.R. and I.S.; formal analysis, E.N. and J.D.E.R.; investigation, E.N., J.D.E.R., I.S. and N.U.; data curation, E.N., J.D.E.R. and I.S.; writing—original draft preparation, E.N., J.D.E.R., I.S. and N.U.; writing—review and editing, E.N., J.D.E.R., I.S. and N.U.; visualization, E.N., J.D.E.R. and I.S.; supervision, E.N., J.D.E.R., I.S. and N.U. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Acknowledgments: The authors would like to acknowledge the use of ChatGPT-5.5 (OpenAI, San Francisco, CA, USA) for linguistic support, including English language refinement, grammar checking, and improvement of manuscript readability. The authors reviewed, edited, and take full responsibility for the final content of the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

ITLS	Intelligent Traffic Light Systems
DRL	Deep Reinforcement Learning
DQN	Deep Q-Network
RPN	Region Proposal Network
CNN	Convolutional Neural Network
mAP	Mean Average Precision
FPS	Frames Per Second
IoT	Internet of Things

References

1. Abbas, B.; Alyas, T.; Abbas, Q.; Alqahtany, S.S.; Alghamdi, T.; Aljohani, N.; Tabassum, N.; Ibrahim, A.M. A hybrid support vector machine and neural network model with fuzzy logic fusion for smart city traffic prediction. *Sci. Rep.* **2025**, *15*, 34758. [CrossRef] [PubMed]
2. Rinchi, O.; Alsharoa, A.; Shatnawi, I.; Arora, A. The Role of Intelligent Transportation Systems and Artificial Intelligence in Energy Efficiency and Emission Reduction. *arXiv* **2024**, arXiv:2401.14560. [CrossRef]
3. Pajkovski, D.; Kondoska, M.A.; Popovska, H.D. A smart city model for an intelligent traffic light decision system. *Int. J. Inf. Sci. Technol.* **2025**, *15*, 11–18. [CrossRef]
4. Reza, S.; Oliveira, H.S.; Machado, J.J.M.; Tavares, J.M.R.S. Urban Safety: An Image-Processing and Deep-Learning-Based Intelligent Traffic Management and Control System. *Sensors* **2021**, *21*, 7705. [CrossRef] [PubMed]
5. Damadam, S.; Zourbakhsh, M.; Javidan, R.; Faroughi, A. An Intelligent IoT Based Traffic Light Management System: Deep Reinforcement Learning. *Smart Cities* **2022**, *5*, 1293–1311. [CrossRef]
6. Liu, J. Enancing Urban Traffic Management: A Comprehensive Study of Adaptive Control Traffic Light Systems. *Highlights Sci. Eng. Technol.* **2024**, *111*, 473–479. [CrossRef]
7. Jaramillo-Alcázar, Á.; Govea, J.; Villegas-Ch, W. Advances in the Optimization of Vehicular Traffic in Smart Cities: Integration of Blockchain and Computer Vision for Sustainable Mobility. *Sustainability* **2023**, *15*, 15736. [CrossRef]
8. Phand, A.; Bagade, S.; Bandgar, N.; Wayal, G. Real-Time Traffic Light Optimization Using AI and IOT. *Int. J. Res. Appl. Sci. Eng. Technol.* **2024**, *12*, 3534–3539. [CrossRef]
9. Chaudhuri, A. Smart traffic management of vehicles using faster R-CNN based deep learning method. *Sci. Rep.* **2024**, *14*, 10357. [CrossRef] [PubMed]
10. Abbas, S.K.; Khan, M.U.G.; Zhu, J.; Sarwar, R.; Aljohani, N.R.; Hameed, I.A.; Hassan, M.U. Vision based intelligent traffic light management system using Faster R-CNN. *CAAI Trans. Intell. Technol.* **2024**, *9*, 932–947. [CrossRef]
11. Saadi, A.; Abghour, N.; Chiba, Z.; Moussaid, K.; Ali, S. A survey of reinforcement and deep reinforcement learning for coordination in intelligent traffic light control. *J. Big Data* **2025**, *12*, 84. [CrossRef]
12. Mansouryar, S.; Colombaroni, C.; Isaenko, N.; Fusco, G. Deep Reinforcement Learning Approach for Traffic Light Control and Transit Priority. *Future Transp.* **2025**, *5*, 137. [CrossRef]
13. Bao, J.; Wu, C.; Lin, Y.; Zhong, L.; Chen, X.; Yin, R. Optimizing Traffic Signal Control: A Scalable Approach with Federated Reinforcement Learning. *Res. Sq.* **2023**. *preprint*. [CrossRef] [PubMed]
14. Li, S.; Wei, C.; Yan, X.; Ma, L.; Chen, D.; Wang, Y. A Deep Adaptive Traffic Signal Controller With Long-Term Planning Horizon and Spatial-Temporal State Definition Under Dynamic Traffic Fluctuations. *IEEE Access* **2020**, *8*, 37087–37104. [CrossRef]
15. Torres, S.H.N.; Clavijo, C.R.B.; Pérez, E.F. Urban Morphogenesis: A construction of senses and imaginaries for social representation of design in structures of tourist and community interaction in Laguna de Colta. *Medwave* **2023**, *23*, eUTA338. [CrossRef]
16. León, E.; Ygnacio, M.A.C. Una revisión sistemática de literatura sobre implementaciones de sistemas de control de tráfico. *Interfases* **2024**, 157–178. [CrossRef]
17. Nautiyal, K.; Gangodkar, D.; Diwakar, M.; Singh, P.; Bijalwan, A. Intelligent traffic light management using predictive and dynamic traffic flow analysis. *Sci. Rep.* **2025**, *15*, 37188. [CrossRef] [PubMed]
18. Ashkanani, M.; Alajmi, A.; Alhayyan, A.; Esmael, Z.; AlBedaiwi, M.; Nadeem, M. A Self-Adaptive Traffic Signal System Integrating Real-Time Vehicle Detection and License Plate Recognition for Enhanced Traffic Management. *Inventions* **2025**, *10*, 14. [CrossRef]
19. Almomany, A.; Eedi, E.; Sütçü, M. Real-time traffic signal optimization for urban mobility: A reinforcement learning-enhanced framework with application to Kuwait City. *Front. Robot. AI* **2025**, *12*, 1669952. [CrossRef] [PubMed]
20. Zahwa, F.; Cheng, C.; Simić, M. Novel Intelligent Traffic Light Controller Design. *Machines* **2024**, *12*, 469. [CrossRef]
21. Adnan, M.F.; Ahmed, N.; Ishraque, I.; Amin, M.S.A.; Hasan, M.S. Traffic Congestion Prediction using Deep Convolutional Neural Networks: A Color-coding Approach. *arXiv* **2022**, arXiv:2209.07943. [CrossRef]

22. Deguerre, B.; Chatelain, C.; Gasso, G. End-to-End Traffic Flow Rate Estimation From Compressed Video Streams. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 8949–8959. [CrossRef]
23. Moreno, R.J.; Baquero, J.E.M.; Umaña, L.A.R. Ambulance detection for smart traffic light applications with fuzzy controller. *Int. J. Power Electron. Drive Syst./Int. J. Electr. Comput. Eng.* **2022**, *12*, 4876–4882. [CrossRef]
24. Al-Kharabsheh, E. Reinforcement Learning in Urban Network Traffic-signal Control. *Jordan J. Civ. Eng.* **2023**, *17*, 709–722. [CrossRef]
25. Chand, D.; Gupta, S.; Kavati, I. Computer Vision based Accident Detection for Autonomous Vehicles. In Proceedings of the 2021 IEEE 18th India Council International Conference (INDICON), New Delhi, India, 10–13 December 2020. [CrossRef]
26. Jartarghar, U.; Sanghvi, D.; Nidgundi, M.; Kumar, K.; Varur, S. Vision Transformer-Based Multi-Phase Accident Detection and False Positive Mitigation. *Res. Sq.* **2024**. *preprint*. [CrossRef] [PubMed]
27. Gowda, P.S.; Shivanand, N. A Novel Approach for Car Accident Detection and Analysis Using AIML Techniques. *Int. J. Res. Appl. Sci. Eng. Technol.* **2023**, *11*, 690–696. [CrossRef]
28. Agafonov, A.; Myasnikov, V. Traffic Signal Control: A Double Q-learning Approach. *Ann. Comput. Sci. Inf. Syst.* **2021**, *25*, 365–369. [CrossRef]
29. Elkin, D.; Vyatkin, V. Distributed Approach to Traffic Management Automation Implemented According to IEC 61499. In *Technological Innovation for Life Improvement*; IFIP Advances in Information and Communication Technology; Springer: Cham, Switzerland, 2020; pp. 159–167. [CrossRef]
30. Armas, R.; Aguirre, H.; Daolio, F.; Tanaka, K. Evolutionary design optimization of traffic signals applied to Quito city. *PLoS ONE* **2017**, *12*, e0188757. [CrossRef] [PubMed]
31. Manguri, K.H.; Mohammed, A.A. Emergency vehicles classification for traffic signal system using optimized transfer DenseNet201 model. *Indones. J. Electr. Eng. Comput. Sci.* **2023**, *32*, 1058–1069. [CrossRef]
32. Pallares, M.M.; Yoo, S.G.; Aguilar, W.G. VARVO: A Novel Method for the Fast Detection of Vehicle Crash Events from Video Only Data. *Rev. Politécnica* **2023**, *52*, 25–34. [CrossRef]
33. Fogue, M.; Garrido, P.; Martínez, F.J.; Cano, J.; Calafate, C.T.; Manzoni, P. A System for Automatic Notification and Severity Estimation of Automotive Accidents. *IEEE Trans. Mob. Comput.* **2013**, *13*, 948–963. [CrossRef]
34. Cavalheiro, E.R.M.; Quaresma, C.C.; Conti, D. O uso da luz de tráfego inteligente na mobilidade urbana sustentável: Uma revisão sistemática da literatura. *Rev. Bras. Gest. Desenvolv. Reg.* **2021**, *17*, 274–289. [CrossRef]
35. Attioui, M.; Lahby, M. A Systematic Literature Review of Traffic Congestion Forecasting: From Machine Learning Techniques to Large Language Models. *Vehicles* **2025**, *7*, 142. [CrossRef]
36. Adewopo, V.; ElSayed, Z.; ElSayed, Z.; Özer, M.; Abdelgawad, A.; Bayoumi, M. A review on action recognition for accident detection in smart city transportation systems. *J. Electr. Syst. Inf. Technol.* **2023**, *10*, 57. [CrossRef]
37. Tsigdinos, S.; Nikitas, A.; Bakogiannis, E. Contextualizing urban road network hierarchy and its role for sustainable transport futures: A systematic literature review using bibliometric analysis and content analysis tools. *Front. Eng. Manag.* **2024**, *12*, 361–393. [CrossRef]
38. Afolabi, A.; Ogunrinde, O.; Zabihollah, A. Digital Twin and AI Models for Infrastructure Resilience: A Systematic Knowledge Mapping. *Appl. Sci.* **2025**, *15*, 13135. [CrossRef]
39. Tavares, R. Comparison of Image Preprocessing Techniques for Vehicle License Plate Recognition Using OCR: Performance and Accuracy Evaluation. *arXiv* **2024**, arXiv:2410.13622. [CrossRef]
40. Noaeen, M.; Naik, A.; Goodman, L.; Crebo, J.; Abrar, T.; Abad, Z.S.H.; Bazzan, A.L.; Far, B. Reinforcement Learning in Urban Network Traffic Signal Control: A Systematic Literature Review. *Expert Syst. Appl.* **2021**, *199*, 116830. [CrossRef]
41. Li, Y.; Huang, Y.; Tao, Q. Improving real-time object detection in Internet-of-Things smart city traffic with YOLOv8-DSAF method. *Sci. Rep.* **2024**, *14*, 17235. [CrossRef] [PubMed]
42. Bagabaldo, A.R.; Hackl, J. Digital Twins for Intelligent Intersections: A Literature Review. *arXiv* **2025**, arXiv:2510.05374. [CrossRef]
43. Suri, S.; Rambhatla, S.; Chellappa, R.; Shrivastava, A. SparseDet: Improving Sparsely Annotated Object Detection with Pseudo-positive Mining. In Proceedings of the 2021 IEEE/CVF International Conference on Computer Vision (ICCV), Paris, France, 1–6 October 2023; pp. 6747–6758. [CrossRef]
44. Shinoda, R.; Shiohara, K. OpenAnimalTracks: A Dataset for Animal Track Recognition. *arXiv* **2024**, arXiv:2406.09647. [CrossRef]
45. Deng, Q.; Huang, X.; Zhong, T. Enhanced Faster R-CNN with Temporal and Context Modules for Power Plant Safety Monitoring. *Informatica* **2025**, *49*, 179–198. [CrossRef]
46. Kumar, A.; Behera, L. High-Speed Detector For Low-Powered Devices In Aerial Grasping. *arXiv* **2024**, arXiv:2402.14591. [CrossRef]
47. Abdullah, S.M.; Periyasamy, M.; Kamaludeen, N.A.; Towfek, S.K.; Marappan, R.; Raju, S.K.; Alharbi, A.H.; Khafaga, D.S. Optimizing Traffic Flow in Smart Cities: Soft GRU-Based Recurrent Neural Networks for Enhanced Congestion Prediction Using Deep Learning. *Sustainability* **2023**, *15*, 5949. [CrossRef]
48. Khan, A.B.F.; Ivan, P. Integrating Machine Learning and Deep Learning in Smart Cities for Enhanced Traffic Congestion Management: An Empirical Review. *J. Urban Dev. Manag.* **2023**, *2*, 211–221. [CrossRef]

49. Olusanya, O.O.; Owosho, Y.; Daniyan, I.; Elegbede, A.W.; Sodipo, Q.B.; Adeodu, A.; Phuluwa, H.S.; Ramasu, T.K.; Katumba, M.G.K.-K. Multi-agent reinforcement learning framework for autonomous traffic signal control in smart cities. *Front. Mech. Eng.* **2025**, *11*, 1650918. [CrossRef]
50. Vivaswath, S.; Blesses Prince, P. A Comprehensive Review on Real-Time Traffic Signal Coordination Using Machine Learning: Optimizing Urban Traffic Flow for Efficiency and Sustainability. *Int. J. Res. Appl. Sci. Eng. Technol.* **2024**, *12*, 1311–1315. [CrossRef]
51. Huang, Z. Reinforcement learning based adaptive control method for traffic lights in intelligent transportation. *Alex. Eng. J.* **2024**, *106*, 381–391. [CrossRef]
52. Shanmugam, A.; Fernandes, C.; Sharma, D.; Upadhyaya, V. Integrated Traffic Management System: A review. In Proceedings of the IC3-2024: 2024 Sixteenth International Conference on Contemporary Computing, Noida, India, 8–10 August 2024; pp. 546–556. [CrossRef]
53. Manguri, K.H.; Mohammed, A.A. Smart optimizer selection technique: A comparative study of modified DensNet201 with other deep learning models. *Inform. Autom. Pomiary W Gospod. I Ochr. Sr.* **2023**, *13*, 39–43. [CrossRef]
54. Khan, A.; Rahman, S.; Ullah, F.; Khattak, M.I.; Bait-Suwailam, M.M.; El-Sayed, H. V2I-VTL: IoT-Enabled adaptive traffic light controller and emission reduction at intersection. *PeerJ Comput. Sci.* **2024**, *10*, e2507. [CrossRef]
55. Vieira, M.A.; Vieira, M.; Louro, P.; Vieira, P.; Fernandes, R. Adaptive Traffic Control Using Cooperative Communication Through Visible Light. *SN Comput. Sci.* **2024**, *5*, 159. [CrossRef]
56. Tomar, I.; Indu, S.; Pandey, N. State-of-Art Review of Traffic Light Synchronization for Intelligent Vehicles: Current Status, Challenges, and Emerging Trends. *Electronics* **2022**, *11*, 465. [CrossRef]
57. Junqi, S.; Chenhao, Z.; Yuxuan, C.; Yucheng, H.; Rui, Z. MoveLight: Enhancing Traffic Signal Control through Movement-Centric Deep Reinforcement Learning. *arXiv* **2024**, arXiv:2407.17303. [CrossRef]
58. Gohar, M.T.; Shahrjerdi, M. An Integrated AI-Driven Framework for Smart Urban Traffic Management: Towards Sustainable, Efficient, and Safe Cities. *Preprints.org* **2025**. [CrossRef]
59. Mahato, S.B. Smart Traffic Signals: Comparing MARL and Fixed-Time Strategies. *arXiv* **2025**, arXiv:2505.14544. [CrossRef]
60. Singh, V.; Sahana, S.K.; Bhattacharjee, V. A novel CNN-GRU-LSTM based deep learning model for accurate traffic prediction. *Discov. Comput.* **2025**, *28*, 38. [CrossRef]
61. Ouyang, C.; Zhan, Z.; Lv, F. A Comparative Study of Traffic Signal Control Based on Reinforcement Learning Algorithms. *World Electr. Veh. J.* **2024**, *15*, 246. [CrossRef]
62. Nigam, N.; Singh, D.P.; Choudhary, J. A Review of Different Components of the Intelligent Traffic Management System (ITMS). *Symmetry* **2023**, *15*, 583. [CrossRef]
63. Ponnusamy, S.; Prasad, M.M.; Swarnalakshmi, G.; Karthikeyan, S.S.; Naik, S.; Moses, E.A. Smart Signal Control Using Reinforcement Learning to Ease Urban Traffic. In Proceedings of the 1st International Conference on Research and Development in Information, Communication, and Computing Technologies, Nagapattinam, India, 4–5 April 2025. [CrossRef]
64. Shen, J. Hierarchical reinforcement learning-based traffic signal control. *Sci. Rep.* **2025**, *15*, 32862. [CrossRef] [PubMed]
65. Kordi, A.O.; Ahmed, K.G. Towards a socially vibrant city: Exploring urban typologies and morphologies of the emerging 'CityWalks' in Dubai. *City Territ. Archit.* **2023**, *10*, 34. [CrossRef]
66. Hansali, Y.E.; Farrag, S.; Yasar, A.-U.-H.; Zavantis, D. Artificial Intelligence-Based Smart Traffic Enforcement and Management System in Urban Areas. 2022. Available online: https://ssrn.com/abstract=4227717 (accessed on 12 March 2026).
67. Wiseman, Y. Real-Time Monitoring of Traffic Congestions. In Proceedings of the IEEE International Conference on Electro Information Technology (EIT 2017), Lincoln, NE, USA, 18–20 May 2017; pp. 501–505.
68. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [CrossRef] [PubMed]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.