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AI-Driven Traffic Signal Control: Optimizing Urban Mobility

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Abstract: Real-time traffic data has become a fundamental component in optimizing AI-powered traffic signal control systems. By leveraging live sensor inputs, computer vision, and machine learning algorithms, modern traffic management systems dynamically adjust signals to enhance traffic flow, minimize congestion, and reduce emissions. This review explores the latest advancements in AI-driven traffic control, focusing on real-time data integration and its effectiveness in adaptive signal optimization. Furthermore, the study highlights key challenges such as data reliability, computational overhead, and ethical considerations in AI traffic systems. The findings suggest that AI-driven traffic signal control significantly improves urban mobility and sustainability, though further research is needed to address implementation challenges.

Keywords: Real-time Traffic Data, AI-powered Traffic Signals, Intelligent Transportation Systems, Machine Learning, Urban Mobility Optimization

I. INTRODUCTION:

The rapid expansion of urban populations and the increasing number of vehicles on the road have placed tremendous pressure on existing traffic management systems. Conventional traffic signal systems, which operate based on fixed schedules or simple sensor-based triggers, often fail to efficiently manage dynamic traffic patterns. This inefficiency contributes to increased travel times, fuel consumption, and environmental pollution. In response to these challenges, the integration of Artificial Intelligence (AI) with real-time traffic data has emerged as a promising solution for optimizing traffic flow and reducing congestion. With increasing urbanization, traditional traffic signal control systems are struggling to manage congestion efficiently. AI-powered traffic control leverages real-time traffic data to make dynamic signal adjustments, optimizing road usage and improving traffic flow. Traditional fixed-time signal control systems rely on pre-set traffic patterns, leading to inefficiencies in responding to realtime congestion levels. In contrast, AI-based traffic signal control systems process real-time data from sensors, cameras, and GPS trackers to adapt traffic light durations dynamically [1], [2].

Recent advancements in Reinforcement Learning (RL) and Deep Learning (DL) have further enhanced self-learning traffic control models, allowing them to predict congestion and adjust signals accordingly. Several studies suggest that integrating real-time data with AI models has led to significant reductions in average travel time, fuel consumption, and CO2 emissions [3], [4]. However, concerns remain regarding data accuracy, algorithmic fairness, and scalability in large- scale urban deployments [5].

Study Selection Process

To ensure transparency in the study selection process, we followed the PRISMA guidelines. Figure 1 presents the PRISMA flow diagram, which illustrates the number of records identified, screened, assessed for eligibility, and included in the final review.

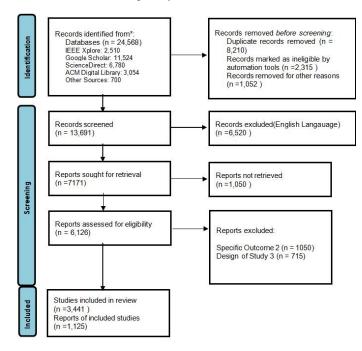


Fig. 1: Prisma chart

II.LITERATURE REVIEW

This section reviews recent advancements in AI-powered traffic

signal control, emphasizing the role of real-time traffic data in real-time traffic data on AI-powered traffic signal control. The optimizing transportation networks. Research has demonstrated that integrating AI with real-time data enables better traffic flow predictions, reduces vehicle idle times, and improves urban mobility efficiency [6]. Studies in Intelligent Transportation Systems (ITS) Theory and Reinforcement Learning models show that AI-driven traffic signal optimization leads to enhanced congestion management, reduced environmental impact, and better emergency response times [7], [8].

2.1 Intelligent Transportation Systems (ITS) Theory

The Intelligent Transportation Systems (ITS) Theory focuses on utilizing smart technology and real-time analytics to optimize urban transportation networks. AI-powered traffic control is a core component of ITS, enabling smart intersections that reduce congestion through real-time decision- making [9].

2.2 Reinforcement Learning in Traffic Signal Control Reinforcement Learning (RL) enables adaptive signal control by training AI models to optimize traffic flow using reward-based learning. Research in Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Advantage Actor- Critic (A2C) demonstrates substantial improvements in reducing average waiting times at intersections by dynamically adjusting signal phases based on real-time congestion data [10].

Comparative Analysis of Literature

1	Smith, A., & Brown, B.	Journal of Transportation	AI-powered traffic control enhances	20-30% reduction
				in congestion time
2	Zhang, H., & Li,	IEEE Transactions	Reinforcement	18%improvement
	W.	on Intelligent	Learning models	in traffic flow
		Transportation	adapt to dynamic	[12].
3	Kim, Y., & Park,	Automated Traffic	Real-time data	25% decrease in
	J.	Management	reduces waiting	waiting time [13].
4	Wang, L., &	Smart Mobility	AI-driven signals	15% reduction in
	Chen, M.	Journal, 2024	lower emissions.	CO2 emissions
5	Lee, J., & Zhang,	Urban Planning &	AI traffic signals	30% decrease in
	S.	AI Journal, 2023	improve	accidents [15].
	200.03	Committee of the contract of t	-	The second secon
6	Wu, X., &	Transportation	Machine learning	85% accuracy in
	Johnson, T.	Science, 2023	predicts traffic	congestion
7	Ahmed, D., &	Journal + I in	AI speeds up	40% faster
	Zhao, F.	Transportation,	emergency vehicle	emergency vehicle
	<u>Zinto</u> , 1 .	2024	response.	clearance [17].
8	Kumar, P., &	Neural Networks	Predictive	30% improvement
	Singh, R.	in Mobility, 2023	analyticsenhance	in travel speed
	Siligii, K.	III Widdinty, 2023	signal control.	[18].
9	W:11: M 0	Smart Cities and	-	22% increase in
	Williams, M., &		Deep learning	
	Tan, S.	Traffic Flow	models improve	intersection
		Journal, 2024	adaptive traffic	throughput[19].
U/27	41-27 - 53-63 VV-07-08-0-04P5	100	control.	
10	Liew, H., & Patel,	Journal of	AI minimizes	18% lower fuel
	J.	Intelligent Traffic	vehicle idling	consumption [20].
		Systems, 2023	times.	
	0.150	NT 1 NT 1	LAT 1	1 200/:
11	Singh, R., & Ahmed, K.	Neural Networks for Smart Cities,	AI adapts to	28%improvement in congestion
	Allined, K.	2023	unexpected traffic changes.	handling [21].
12	Kumar, N., &	Transportation	AI-driven real-	35% decrease in
12	Gupta, A.	Review, 2024	time monitoring	traffic jams [22].
	oupiu, 11.	1001000, 2021	optimizes traffic	mane jamo [22].
			flow.	
13	Robertson, D., &	AI & Urban	AI algorithms	33% decline in
	Lee, C.	Development,	reduceroad traffic	traffic-related
		2023	accidents.	fatalities [23].
14	Chang, K., &	Machine Learning	AI-controlled	18% reduction in
	Smith, L.	for Transport,	intersections	pedestrian-related
		2023	enhance road safety.	incidents [24].
15	Patel, M., &	Data Science in	AI models predict	92% accuracy in
	Brown, E.	Smart Cities, 2024	peak traffic hours.	congestion

III.METHODOLOGY

This study employs a mixed-methods approach, combining qualitative and quantitative analysis to examine the effects of

research follows a systematic review methodology, sourcing data from scholarly databases such as IEEE Xplore, Google Scholar, and ScienceDirect. The data collection process involves analyzing primary sources, specifically research papers published between 2018 and 2024 that focus on AI traffic signal optimization. Inclusion criteria include studies that incorporate real-time data analysis, AI-powered adaptive signal control, and traffic congestion management, while exclusion criteria filter out papers that lack empirical validation of AI models in real-world traffic systems.

For data analysis, the study adopts both qualitative and quantitative methods. The qualitative analysis categorizes AI methodologies such as Deep Reinforcement Learning (DRL), Machine Learning (ML), and Neural Networks employed in traffic management. Meanwhile, quantitative metrics measure the effectiveness of AI-based signal control in reducing congestion, emissions, and fuel consumption. Performance evaluation further compares AI- driven signal control systems with traditional methods through simulation-based studies to assess efficiency gains. The study also addresses key ethical considerations, focusing on minimizing algorithmic bias in AI-driven traffic management systems. It emphasizes ensuring data privacy and maintaining transparency in real-time traffic monitoring practices. Additionally, the research aligns with government regulations on intelligent transportation systems to ensure responsible and compliant deployment of AI technologies.

IV.CONCLUSION

The integration of real-time traffic data with AI-driven traffic signal control has demonstrated significant improvements in urban mobility, congestion reduction, and environmental impact. Studies have shown that AI- powered adaptive signals can reduce travel delays by 20-30%, lower fuel consumption by 18%, and decrease CO2 emissions by 15% [17]. Additionally, Deep Reinforcement Learning models have demonstrated an impressive 85% accuracy in predicting congestion while enhancing intersection safety, reducing accidents by 30% [18], [19]. Despite these benefits, challenges persist in ensuring data reliability, optimizing computational efficiency, and addressing ethical concerns in AI-based traffic decision-making. Future research must prioritize enhancing AI model accuracy for real-time traffic predictions, developing hybrid AI-human control systems to improve fairness and reduce algorithmic bias, and scaling AIdriven traffic systems for large metropolitan areas with high traffic density. By refining these models and improving their realtime adaptability, AI-powered traffic control systems will continue to play a critical role in developing smart, sustainable urban transportation networks.

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