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Integrating Machine Learning and Deep Learning in Smart Cities for Enhanced Traffic Congestion Management: An Empirical Review

A. B. Feroz Khan[1*], Perl Ivan[2]

[1] Department of Computer Science, Syed Hameedha Arts and Science College, 623806 Kilakarai, India
[2] Faculty of Software Engineering and Computer Systems, ITMO University, 197101 Saint-Petersburg, Russia

[*] Correspondence: A. B. Feroz Khan (ab.ferozkhan@shartsandscience-edu.in)

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Abstract: In the rapid urbanization experienced globally, traffic congestion emerges as a critical challenge, detrimentally affecting economic performance and the quality of urban life. This study delves into the deployment of machine learning (ML) and deep learning (DL) methodologies for mitigating traffic congestion within smart city frameworks. An extensive literature review coupled with empirical analysis is conducted to scrutinize the application of these advanced technologies in various transportation domains, including but not limited to traffic flow prediction, optimization of routing, adaptive control of traffic signals, dynamic management of traffic systems, implementation of smart parking solutions, enhancement of public transportation systems, anomaly detection, and seamless integration with the Internet of Things (IoT) and sensor networks. The research methodology encompasses a detailed outline of data sources, the selection of ML and DL models, along with the processes of training and evaluation. Findings from the experiments underscore the efficacy of these technological interventions in real-world settings, highlighting notable advancements in the precision of traffic predictions, the efficiency of route optimization, and the responsiveness of adaptive traffic signal controls. Moreover, the study elucidates the pivotal role of ML and DL in facilitating dynamic traffic management, anomaly detection, smart parking, and the optimization of public transportation. Through illustrative case studies and examples from cities that have embraced these technologies, practical insights into their applicability and the consequential impact on urban mobility are provided. The research also addresses challenges encountered, offering a discourse on potential avenues for future research to further refine traffic congestion management strategies in smart cities. This contribution significantly enriches the existing corpus of knowledge, presenting pragmatic solutions for urban planners and policy makers to foster more efficient and sustainable transportation infrastructures.

Keywords: Machine learning (ML); Deep learning (DL); Smart cities; Traffic congestion management; Intelligent transportation systems

1 Introduction

As cities across the globe undergo a transformative shift into interconnected hubs of technology and innovation, the challenges posed by urbanization are becoming increasingly intricate. Within this complex urban landscape, traffic congestion emerges as a critical and pervasive obstacle, casting adverse effects on economic productivity, environmental sustainability, and overall quality of life [1–5]. As urban populations swell, the strain on transportation infrastructure becomes more pronounced, necessitating innovative approaches to manage the escalating demands of mobility. The advent of smart cities, marked by the seamless integration of advanced technologies into urban infrastructure, presents a unique and opportune moment to address and mitigate the multifaceted impacts of traffic congestion through the deployment of intelligent transportation systems [6–8]. This research is dedicated to unraveling the transformative role played by ML and DL in the management of traffic congestion within the nuanced context of smart cities. The integration of these cutting-edge technologies holds the promise of revolutionizing traditional traffic management strategies, endowing cities with adaptive, data-driven solutions designed to alleviate congestion and enhance the overall efficiency of urban mobility [9–11]. The amalgamation of ML and DL with the complexities of urban traffic dynamics opens new frontiers for innovation, presenting a paradigm shift in how we perceive and address the challenges of transportation within densely populated urban environments. The primary objectives of this research extend beyond a mere exploration of technological capabilities; they encapsulate a deep-seated investigation into the current challenges inherent in traditional traffic management systems within smart cities. Emphasizing the imperative for innovation, the research endeavors to dissect and comprehend the existing limitations, paving the way for a more nuanced understanding of the intricacies involved. Beyond this, the study aims to chart the expansive landscape of ML and DL applications in traffic management, ranging from the intricacies of traffic prediction to the intricacies of route optimization, adaptive traffic signal control, and the dynamic orchestration of traffic flow. Real-world implementations become the crucible through which the efficacy of ML and DL technologies is assessed. Drawing insights from case studies and practical examples, the research aims to showcase the tangible impact of these technologies in addressing the formidable challenge of traffic congestion. By evaluating these real-world applications, the study not only underscores the transformative potential of ML and DL but also sheds light on the practical considerations and challenges encountered in the field.

The research extends its purview to identify the gaps and opportunities within current research, with a particular focus on the scalability, adaptability, and sustainability of ML and DL solutions for traffic congestion management. This critical analysis serves as a compass, guiding future research endeavors and technological advancements toward more comprehensive and holistic solutions. As we delve into the uncharted territories of smart city development, it becomes imperative to not only address immediate challenges but also to envision sustainable and scalable solutions that stand the test of time.

Proposing practical recommendations forms the final cornerstone of this research endeavor. Building upon empirical findings, the study aims to furnish actionable insights for urban planners, policymakers, and stakeholders. These recommendations are designed to facilitate the effective implementation of ML and DL technologies in the intricate tapestry of traffic congestion management within smart cities. The confluence of technological advancements, empirical evidence, and practical recommendations serves as the cornerstone for this research, aspiring to contribute invaluable insights and guidelines for the development and deployment of intelligent transportation systems. As we navigate the future of urban living, the subsequent sections of this paper will delve into a comprehensive review of relevant literature, meticulously detail the methodology employed in the research, and present the granular findings and discussions, all with the ultimate goal of advancing our understanding and fortifying the foundations of a more efficient and sustainable urban environment in the era of smart cities.

2 Literature Review

The literature surrounding traffic congestion management in smart cities, with a focus on the integration of ML and DL, reveals a rich tapestry of research efforts aimed at addressing the multifaceted challenges posed by urbanization. Urban areas worldwide are grappling with the implications of rapid population growth and increased vehicular density, leading to a surge in studies exploring innovative approaches to alleviate traffic congestion [12–18]. Researchers have extensively examined the traditional paradigms of traffic management within smart cities, acknowledging the limitations and complexities inherent in conventional systems. Common challenges include the dynamic nature of urban traffic patterns, the impact of unpredictable events such as accidents or road closures, and the need for real-time adaptability in response to changing conditions [19–25]. Scholars emphasize the urgency of finding solutions that not only mitigate congestion but also contribute to sustainable urban development. The application of ML in traffic prediction has garnered significant attention. Studies showcase the efficacy of algorithms in analyzing historical traffic data, incorporating real-time inputs such as weather conditions and special events, to predict future congestion patterns. Techniques range from classical statistical methods to more advanced models like support vector machines and ensemble methods. ML, through its ability to discern complex patterns in vast datasets, offers valuable insights for anticipating and proactively managing traffic bottlenecks [26–29].

The literature on traffic congestion management in smart cities, with a specific focus on the integration of ML and DL, has witnessed a significant expansion with recent contributions from various scholars. Panovski et al. [30] presented a neural network-based approach for predicting public transportation with a traffic density matrix, offering insights into the dynamic relationship between traffic patterns and public transportation efficiency. In a subsequent study, Panovski and Zaharia [31] delved into real-time public transportation prediction, leveraging machine learning algorithms to enhance the responsiveness and accuracy of transportation forecasting systems. Panovski and Zaharia [32] explored the optimization of vehicular traffic lights using simulation-based approaches, providing a nuanced perspective on traffic signal control strategies.

Liu et al. [33] contributed to the field by addressing intelligent bus routing with heterogeneous human mobility patterns, emphasizing the need to adapt routing strategies based on diverse human movement behaviors. Soares et al. [34] presented a combined solution for real-time travel mode detection and trip purpose prediction, enhancing the overall understanding of travel patterns and purposes in urban environment. Minea et al. [35] explored unconventional public transport data collection using artificial intelligence (AI), shedding light on novel methods for gathering anonymous public transportation data.

Veres and Moussa [36] conducted a survey of emerging trends in deep learning for intelligent transportation systems, providing a comprehensive overview of the advancements and applications in the field. Lin et al. [37] proposed a Gaussian-prioritized approach for deploying additional routes in mass transportation, leveraging neural network-based passenger flow inference to optimize existing transportation systems. Li et al. [38] introduced a diffusion convolutional recurrent neural network for data-driven traffic forecasting, emphasizing the integration of spatial and temporal dependencies in prediction models. Zhang et al. [39] explored deep spatio-temporal residual networks for citywide crowd flow prediction, showcasing the application of deep learning in predicting dynamic crowd movements within urban areas.

3 Challenges in Transportation System

The transportation system is a cornerstone of modern societies, facilitating the movement of people and goods [40–48]. However, as urbanization accelerates, cities around the world face an array of challenges in maintaining efficient, sustainable, and accessible transportation networks. This discussion explores some of the key challenges inherent in contemporary transportation systems, focusing on the complexities arising in the context of urban environments.

3.1 Traffic Congestion

One of the most pervasive and visible challenges in urban transportation is traffic congestion. As cities grow and populations surge, the demand for mobility increases exponentially, leading to gridlock, delays, and inefficiencies. The causes of congestion are multifaceted, encompassing factors such as population density, inadequate infrastructure, and a high volume of private vehicles. Addressing congestion requires a comprehensive approach, incorporating innovative traffic management strategies, public transit enhancements, and the integration of advanced technologies like machine learning and AI for dynamic traffic control [49].

3.2 Infrastructure Limitations

The aging and inadequate state of transportation infrastructure poses significant challenges. Many cities grapple with outdated roadways, bridges, and public transit systems that were not designed to accommodate the current volume of traffic. Upgrading and expanding infrastructure is a costly and time-consuming endeavor, requiring careful planning and collaboration between government agencies and private stakeholders. Innovative solutions, such as smart infrastructure and the adoption of sustainable construction materials, are essential to effectively address these challenges [50, 51].

3.3 Public Transit Accessibility and Reliability

Public transportation systems are the linchpin of urban mobility, providing an alternative to private vehicle use. However, challenges such as insufficient coverage, a lack of integration between different modes of transit, and reliability issues can hinder the effectiveness of public transit. Improving accessibility and reliability requires strategic planning, investment in technology, and the development of multi-modal transit networks that seamlessly connect buses, trains, bicycles, and other forms of transportation [52].

3.4 Environmental Impact

The environmental impact of transportation, particularly in urban areas, is a growing concern. High levels of vehicular emissions contribute to air pollution, negatively affecting public health and the environment. Encouraging the use of sustainable modes of transportation, such as electric vehicles and public transit, is crucial for mitigating these environmental challenges. Additionally, urban planners must consider the environmental implications of infrastructure projects and prioritize eco-friendly solutions to promote long-term sustainability [53].

3.5 Equity and Accessibility

Transportation systems must be designed to serve all members of society equitably, irrespective of socioeconomic status or geographical location. In many urban areas, there are disparities in transportation access, with certain communities facing limited options for mobility. Addressing these disparities requires inclusive planning, the provision of affordable transit options, and a commitment to ensuring that transportation solutions serve the needs of diverse populations [54].

3.6 Technological Integration

The rapid evolution of technology poses both opportunities and challenges for transportation systems. Integrating emerging technologies such as autonomous vehicles, smart traffic management systems, and real-time data analytic requires careful planning and consideration of ethical, legal, and privacy concerns. Ensuring that these technologies enhance, rather than exacerbate, existing challenges is a complex undertaking that demands collaboration between policymakers, technologists, and the public [55]. Figure 1 shows the overall view of the proposed work.

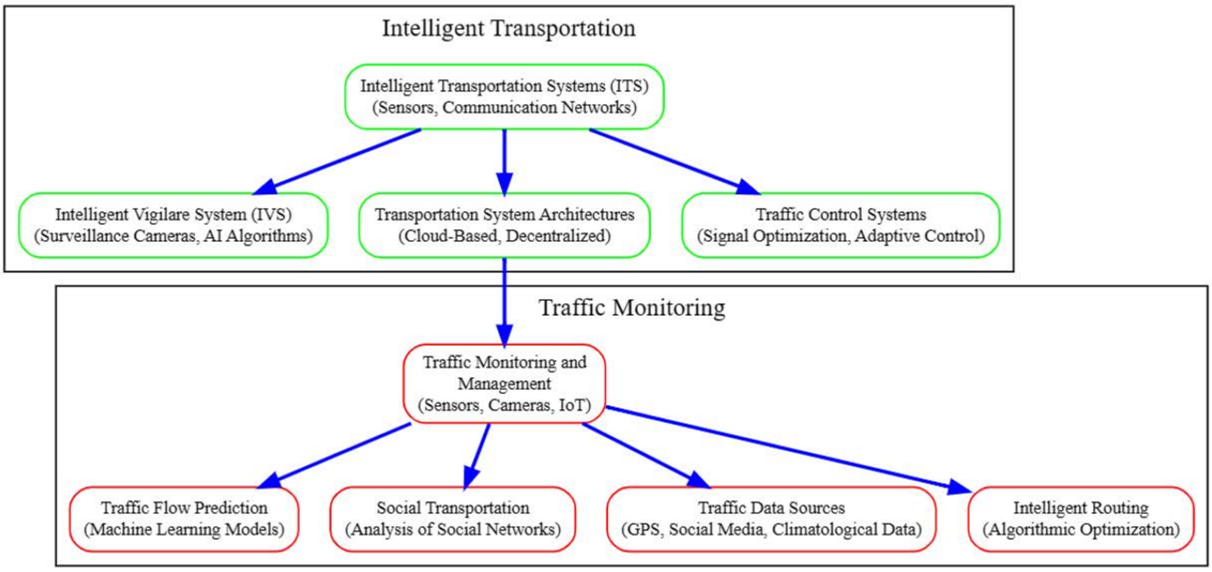

Figure 1. Overview of intelligent traffic management

3.7 Safety Concerns

Ensuring the safety of transportation systems is a paramount challenge. Accidents, both vehicular and pedestrian, pose significant risks, and enhancing safety requires a multi-faceted approach. This includes investment in infrastructure improvements, the implementation of stringent traffic regulations, and the development and promotion of safety technologies in vehicles.

3.8 Urban Planning and Zoning

The layout of urban areas significantly influences transportation patterns. Inefficient urban planning, characterized by urban sprawl, mixed land-use policies, and inadequate zoning, can exacerbate congestion and limit the effectiveness of public transit. Coordinated urban planning that prioritizes mixed-use developments, walkability, and accessibility to public transit is essential for creating sustainable and efficient transportation systems.

3.9 Changing Work Patterns

Shifts in work patterns, such as the rise of remote work and flexible schedules, introduce new dynamics into transportation systems. While these changes may alleviate congestion during traditional rush hours, they also necessitate a reevaluation of transit schedules, infrastructure usage, and the potential for increased congestion during non-traditional hours. Transportation planners must adapt to these evolving trends to ensure efficient and responsive systems [56, 57].

In conclusion, the challenges facing transportation systems in urban environments are intricate and multifaceted. Addressing these challenges requires a holistic and collaborative approach that spans urban planning, technology integration, policy development, and community engagement. By acknowledging and actively working to overcome these challenges, cities can foster more sustainable, accessible, and efficient transportation systems that meet the evolving needs of their residents.

4 ML/DL-Based Approaches for Addressing Transportation Challenges

In recent years, ML and DL have emerged as powerful tools for addressing the complex challenges in transportation systems. ML and DL have emerged as transformative technologies, offering innovative solutions to the intricate challenges facing urban transportation systems. In the contemporary landscape of smart cities and evolving urban infrastructure, the complexities of traffic congestion, infrastructure limitations, public transit reliability, environmental impact, and equity concerns necessitate dynamic and data-driven approaches. This section delves into how ML/DL-based approaches contribute to addressing these transportation challenges, offering intelligent solutions for enhanced efficiency, sustainability, and inclusivity.

Traffic Congestion:

ML and DL play a pivotal role in mitigating the perennial issue of traffic congestion. Predictive traffic models, powered by ML algorithms, analyze historical and real-time traffic data to forecast congestion patterns. These models provide valuable insights for dynamic traffic management, enabling the optimization of traffic signal timing and the identification of alternate routes. Reinforcement learning algorithms, a subset of ML, contribute to real-time adaptability by adjusting traffic signal timings based on changing conditions. Deep learning techniques, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, enhance the accuracy of congestion predictions by capturing temporal dependencies within the data. Overall, ML/DL-based approaches revolutionize traditional traffic management strategies, providing adaptive and responsive solutions to alleviate congestion.

Infrastructure Limitations:

Addressing aging and inadequate infrastructure is critical for ensuring the resilience and efficiency of urban transportation systems. ML-based predictive maintenance models analyze infrastructure data to forecast potential failures, enabling proactive interventions. These models consider factors like usage patterns, environmental conditions, and historical maintenance data to optimize maintenance schedules. Additionally, ML algorithms streamline construction projects, minimizing disruptions and optimizing resource allocation. By incorporating predictive analytics and optimization strategies, ML/DL-based approaches contribute to the sustainable management and enhancement of transportation infrastructure.

Public Transit Accessibility and Reliability:

Enhancing the accessibility and reliability of public transit systems is a key focus of ML/ DL applications. Predictive maintenance models for public transit vehicles utilize ML algorithms to forecast potential issues, reducing downtime and improving reliability. ML algorithms also play a crucial role in optimizing transit routes and schedules. By analyzing historical ridership patterns and real-time data, these algorithms ensure efficient and accessible public transit options. Furthermore, the integration of ML-based recommender systems assists users in planning multi-modal journeys, fostering seamless transitions between different modes of transit. ML/DL-based approaches thus contribute to making public transit more reliable, efficient, and user-friendly.

Environmental Impact:

Mitigating the environmental impact of transportation is a global imperative. ML algorithms optimize traffic flow, reducing emissions and fuel consumption by minimizing congestion and optimizing route planning. DL models analyze air quality data, contributing to early pollution detection and mitigation strategies. By providing data-driven insights, ML/DL-based approaches empower cities to implement sustainable transportation solutions, promote cleaner air, and contribute to environmental conservation efforts.

Overall, the integration of machine learning and deep learning in addressing transportation challenges marks a paradigm shift in the way urban mobility is managed. These technologies offer adaptive, data-driven, and intelligent solutions that enhance the efficiency, sustainability, and inclusivity of transportation systems in smart cities. As cities continue to evolve, leveraging the power of ML/DL becomes imperative for creating resilient, responsive, and forward-thinking transportation infrastructures. Table 1 summarizes the specific challenges faced by urban transportation systems, while Table 2 outlines the corresponding ML and DL approaches employed to address these challenges.

Table 1. Transportation challenges overview

Challenge	Description
Traffic Congestion	Pervasive gridlock impacting economic productivity and urban mobility.
Infrastructure Limitations	Aging and inadequate transportation infrastructure hindering system performance.
Public Transit Accessibility	Limited coverage, lack of integration, and reliability issues in public transit systems.
Environmental Impact	Negative consequences of vehicular emissions on air quality and overall environmental health.
Equity and Accessibility	Disparities in transportation access, affecting diverse communities unequally.
Technological Integration	Integration challenges related to emerging technologies like autonomous vehicles and IoT.

The comprehensive overview provided in Table 1 and Table 2 illuminates the intricate interplay between urban transportation challenges and the innovative solutions offered by ML and DL approaches. The challenges, ranging from the ubiquitous issue of traffic congestion to the limitations posed by aging infrastructure, form a complex landscape that requires adaptive and data-driven solutions. The tables articulate a strategic alignment of ML and DL techniques tailored to address specific challenges. For instance, in mitigating traffic congestion, the deployment of predictive models, reinforcement learning, and deep learning technologies facilitates a dynamic and responsive traffic management system. Similarly, addressing infrastructure limitations involves predictive maintenance models that foresee potential failures, exemplifying the proactive use of data analytics. The tables collectively underscore the transformative potential of ML and DL in reshaping urban transportation systems, offering a glimpse into a future where data-driven intelligence optimizes efficiency, sustainability, and inclusivity in the evolving urban mobility landscape.

Table 2. ML/DL approaches for transportation challenges

Challenge	ML/DL Approach
Traffic Congestion	ML/DL-based traffic prediction models, reinforcement learning for dynamic signal control, and deep learning for accurate congestion forecasting.
Infrastructure Limitations	Predictive maintenance using ML, construction optimization algorithms, and deep learning for infrastructure monitoring through image recognition.
Public Transit Accessibility	ML-based predictive maintenance for public transit, route optimization algorithms, real-time data analysis, and recommender systems for seamless multi-modal transit planning.
Environmental Impact	ML optimization of traffic flow, predictive modeling for encouraging electric vehicle adoption, and deep learning for early pollution detection.
Equity and Accessibility	ML demand prediction for optimized transit routes, smart ticketing systems, and data analysis for identifying and addressing accessibility gaps.
Technological Integration	ML models for the integration of autonomous vehicles, deep learning for real-time data processing, and explainable AI techniques to address transparency concerns.

While ML and DL present promising solutions for addressing transportation challenges, there are inherent limitations that should be acknowledged. These include:

Data Quality and Availability: ML and DL models heavily rely on the quality and availability of data. Incomplete or biased datasets can lead to inaccurate predictions and suboptimal results. Additionally, obtaining real-time data for certain applications may be challenging, impacting the timeliness of decision-making.

Computational Resources: The computational requirements for training and deploying sophisticated DL models can be substantial. This poses challenges, especially for resource-constrained environments, and may limit the scalability of certain applications, particularly in smaller cities or regions with limited infrastructure.

Interpretability and Explainability: DL models, known for their complexity, often lack interpretability, making it challenging to understand the rationale behind specific decisions. Ensuring transparency in decision-making is crucial, especially in applications that impact public safety and policy.

Generalization Across Contexts: ML models trained in one urban environment may not seamlessly generalize to another due to variations in traffic patterns, infrastructure, and local behaviors. Customization and adaptation may be necessary for effective deployment in diverse settings.

Ethical and Privacy Concerns: The use of ML and DL in transportation raises ethical considerations, particularly regarding privacy and data security. As these technologies rely on vast amounts of data, ensuring compliance with privacy regulations and protecting individuals' personal information is essential.

To overcome the limitations and further enhance the application of ML and DL in transportation, future research directions should consider:

Data Quality Improvement: Invest in strategies to improve the quality and diversity of transportation datasets. This includes addressing biases, ensuring representativeness across demographic groups, and integrating data from various sources for a comprehensive understanding of urban mobility.

Explainable AI (XAI): Develop and incorporate explainable AI techniques to enhance the interpretability of DL models. Ensuring transparency in decision-making fosters trust among stakeholders, policymakers, and the public, particularly in critical applications such as traffic management and autonomous vehicles.

Edge Computing: Explore the potential of edge computing to reduce the computational burden associated with DL models. This involves decentralized processing of data closer to the source, minimizing latency, and enabling real-time decision-making in transportation systems.

Transfer Learning and Generalization: Investigate techniques for transfer learning and model generalization to enhance the adaptability of ML models across different urban contexts. Developing models that can learn from diverse datasets and apply knowledge to new environments is crucial for scalability.

Human-Centric Design: Incorporate human-centric design principles in the development of ML and DL applications for transportation. Consider user preferences, behaviors, and feedback to create systems that align with the needs and expectations of the community.

Robustness and Security: Address the robustness and security of ML and DL models against adversarial attacks and unexpected events. Enhancing the resilience of these systems is essential for their reliable operation in dynamic urban environments.

Collaborative and Interdisciplinary Research: Encourage collaboration between researchers, urban planners, policymakers, and industry stakeholders. Interdisciplinary approaches can lead to holistic solutions that consider technological advancements alongside social, economic, and environmental factors.

5 AI-Based Models

AI has become a driving force in transforming intelligent transportation systems, offering innovative solutions to address the complex challenges associated with urban mobility. In the realm of traffic prediction and management, ML and DL models have emerged as indispensable tools, employing advanced algorithms to analyze vast amounts of data and optimize traffic flow in real time. Models such as LSTM networks and CNNs excel at processing time-series data and spatial information, providing accurate forecasts of traffic conditions and enabling adaptive signal control strategies. The integration of AI into traffic management systems allows for a more dynamic and responsive approach to the ever-changing nature of urban traffic. Traditional traffic management systems often struggle to cope with the complexities of congestion, leading to inefficiencies, increased travel times, and environmental impact. AI-based models, on the other hand, can learn from historical data, recognize patterns, and make predictions that aid in proactive traffic management. By leveraging the power of ML and DL, cities can optimize signal timings, implement adaptive traffic control strategies, and mitigate congestion, ultimately improving overall urban mobility. Reinforcement Learning (RL) algorithms further contribute to intelligent transportation by optimizing route recommendations. RL models learn from the environment, receiving feedback based on the quality of their decisions, and continually refine their strategies to achieve better outcomes. In the context of route optimization, RL algorithms dynamically adapt to changing traffic conditions, providing drivers with real-time recommendations for the most efficient routes. This not only improves individual commuting experiences but also contributes to reducing overall traffic congestion and, consequently, the environmental footprint. The application of AI in intelligent transportation extends beyond traffic prediction and route optimization. AI-based models are increasingly utilized for advanced driver assistance systems, including features such as lane-keeping assistance, collision avoidance, and autonomous driving. These technologies rely on computer vision, sensor fusion, and ML algorithms to interpret the surrounding environment, make real-time decisions, and enhance the safety of both drivers and pedestrians. Moreover, AI plays a crucial role in public transportation systems. Predictive analytics powered by ML models help optimize bus schedules, predict arrival times, and enhance the reliability of public transit services. Commuters benefit from reduced waiting times and improved predictability, contributing to increased public transit adoption and a more sustainable urban transportation ecosystem. In the quest for intelligent transportation, the integration of AI extends to smart infrastructure projects. Smart traffic lights equipped with AI algorithms can dynamically adjust signal timing based on traffic density, leading to smoother traffic flow and reduced congestion. AI-powered cameras and sensors contribute to real-time monitoring of traffic conditions, enabling authorities to respond promptly to incidents and optimize traffic management strategies. Despite the promising advantages of AI in intelligent transportation, there are challenges that must be addressed. Ensuring the privacy and security of data collected by AI systems is paramount, particularly when dealing with sensitive information related to individual commuting patterns. Ethical considerations, transparency in decision-making, and clear regulations are essential to building trust in AI applications within the transportation sector. Looking ahead, the future of intelligent transportation will likely witness further advancements in AI technologies. Continued research and development will focus on enhancing the interpretability and explainability of AI models, enabling better collaboration between AI systems and human decision-makers. Interconnected smart cities will leverage AI to create holistic transportation ecosystems where vehicles, infrastructure, and commuters communicate seamlessly, optimizing the entire urban mobility experience.

6 Conclusion

In conclusion, the integration of ML and DL into urban transportation systems presents a transformative paradigm, offering intelligent solutions to the myriad challenges faced by modern cities. Through predictive analytics, real-time adaptability, and data-driven decision-making, these technologies contribute to creating more efficient, sustainable, and equitable urban mobility landscapes. The comprehensive review of ML and DL applications in addressing traffic congestion, infrastructure limitations, public transit reliability, environmental impact, and equity concerns underscores the significant strides made in reshaping urban transportation. Predictive traffic models, informed by historical and real-time data, facilitate dynamic traffic management, optimizing signal timings, and providing alternative routes to alleviate congestion. ML-based predictive maintenance models enhance the resilience of transportation infrastructure, minimizing downtimes and streamlining construction projects. The role of ML and DL in enhancing public transit accessibility and reliability is evident through applications such as predictive maintenance for vehicles, route optimization, and the development of user-friendly recommender systems. Moreover, these technologies contribute to sustainable transportation solutions by optimizing traffic flow, reducing emissions, and analyzing air quality data for pollution detection. However, it is essential to acknowledge the limitations, including data quality challenges, computational resource requirements, interpretability issues, and ethical considerations.

Data Availability

Not applicable.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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