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Research Article

Leveraging Machine Learning Analytics for Intelligent Transport System Optimization in Smart Cities

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Abstract: Urbanization has intensified transportation challenges such as congestion, inefficiency, and safety risks. Traditional traffic management approaches often fail to adapt to dynamic urban conditions, leading to delays and environmental burdens. This paper explores how Machine Learning (ML)-driven Intelligent Transportation Systems (ITS) can optimize urban mobility by integrating predictive, adaptive, and data-driven solutions. Using models such as Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and reinforcement learning, ITS applications are analyzed in traffic flow prediction, adaptive signal control, smart parking, and AI-powered public transport scheduling. Real-world implementations in cities including Los Angeles, Barcelona, Singapore, and Dubai demonstrate the potential of ML-enabled ITS to reduce congestion, improve safety, and enhance sustainability. The paper also addresses critical challenges such as data privacy, infrastructure costs, and algorithmic fairness, while highlighting future research directions in federated learning, vehicle-to-everything (V2X) communication, and integration with autonomous vehicles. Findings underscore that ML-driven ITS is not only key to improving transportation efficiency but also a foundation for building sustainable smart cities.

1. Introduction

The rapid rise of urban populations has increased demand for efficient transportation. Traditional traffic management methods rely on static rules and historical patterns, making them ineffective in real-time congestion handling. The integration of AI and ML in transport systems enhances efficiency by providing dynamic, data-driven solutions. Machine learning models, such as 2Long Short-Term Memory (LSTM) networks,have shown a 30% improvement in traffic congestion prediction accuracy, allowing cities to better manage peak-hour demands.
ITS utilizes state-of-the-art information and communication technology to enhance several areas of transportation, including traffic management, vehicle operation, and public transit systems. ITS seeks to alleviate traffic congestion, decrease journey durations, improve safety, and limit environmental effects using real-time data, sensor networks, and intelligent algorithms.ITS has a broad scope that includes multiple areas of transportation a wide range of applications, including intelligent traffic signal systems, autonomous vehicle technology, dynamic route planning, electronic toll collection, and real-time public transittracking.

These advancements not only enhance everyday transportation for individuals but also contribute to wider social objectives such as energy conservation, less emissions, and improved urban planning. With the ongoing acceleration of urbanization and increasing demand for efficient transportation, ITS plays a crucial role in determining the future of mobility. Global governments, corporations, and researchers are allocating resources toward implementing ITS technologies to establish more intelligent, interconnected, and environmentally friendly transportation ecosystems.With the rapid urbanization and expansion of smart cities, the complexity and volume of urban traffic have grown exponentially, necessitating innovative approaches for efficient transport management. Traditional traffic control mechanisms, based on fixed schedules and historical data, often fail to respond to real-time changes in traffic flow, leading to increased congestion, longer travel times, and elevated environmental impacts. Intelligent Transport Systems (ITS) integrated with Machine Learning (ML) analytics offer a promising solution by enabling adaptive, predictive, and data-driven management of urban mobility. Machine Learning techniques provide the capability to analyze vast and heterogeneous traffic datasets from sensor networks, GPS data, to social media feeds, extracting meaningful patterns and delivering precise predictions about traffic congestion, travel times, and transit demand.These insights empower ITS to dynamically optimize traffic signals, route planning, and public transit operations, thus enhancing system efficiency and commuter experience. Moreover, the incorporation of advanced ML models like Long Short-Term Memory (LSTM) and reinforcement learning has demonstrated significant improvements in traffic forecasting accuracy and adaptive signal control.The convergence of ML analytics with ITS not only supports real-time traffic management but also contributes to sustainability goals by reducing fuel consumption and emissions, improving road safety, and promoting smarter urban planning. This research investigates how leveraging ML-driven analytics can optimize ITS performance, highlighting case studies, methodologies, and emerging technologies pivotal for the future of intelligent urban mobility.

2. Literature Review

Research in the field of AI-based AI for transportation/ITS has emphasized the role of traffic prediction approaches, adaptive signal control, and intelligent signage. Evidence from studies indicates that reinforcement learning methods like MARLIN-AI-SC can decrease intersection waiting times by around 20%, thereby enhancing overall traffic performance. In addition, AI-supported scheduling for public transport has improved demand-based routing, helping reduce delays and increase fuel efficiency. A considerable amount of work has also examined deep learning techniques—particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models—for forecasting traffic patterns and congestion levels.

3. AI Applications in Intelligent Transportation Systems (ITS)

Recent advancements in Artificial Intelligence (AI) have significantly enhanced the performance and capabilities of Intelligent Transportation Systems (ITS). In 2017, Long Short-Term Memory (LSTM) networks were applied to traffic volume forecasting, yielding more than a 30% improvement in accuracy compared to traditional models such as ARIMA. Building on this, in 2018, Li et al. introduced a spatio-temporal graph convolutional network designed to better capture both spatial and temporal dependencies in traffic data. These approaches have proven instrumental in enabling more effective real-time traffic management and decision-making.A critical application of AI in ITS is adaptive traffic signal control. For instance, MARLIN-ATSC, based on multi-agent reinforcement learning, has been developed to optimize traffic light phases dynamically. Similarly, a deep reinforcement learning framework introduced in 2019 demonstrated the ability to adjust signal timings in response to real-time traffic conditions, effectively reducing both delays and vehicle emissions.AI is also improving public transportation systems, making them more efficient and user-friendly. In 2020, machine learning models were utilized to optimize bus scheduling by analyzing real-time passenger data, leading to reduced fuel consumption and shorter wait times. In several European and Asian cities, demand-responsive transport (DRT) systems powered by AI are being used to dynamically adjust routes based on passenger demand. Notable examples include ViaVan in London and Kutsuplus. Additionally, reinforcement learning algorithms have been employed to develop real-time route optimization systems using GPS data, resulting in an average travel time reduction of around 15%. Popular navigation platforms like Google Maps and Waze also leverage AI to anticipate traffic conditions and suggest optimal routes based on live updates.

4. Incident Detection and Traffic Management:

AI, particularly through computer vision, plays a vital role in automatic incident detection. Techniques such as Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), and YOLO (You Only Look Once) are employed to analyze CCTV footage and identify events such as accidents, stalled vehicles, or wrong-way driving in real time. This capability enables quicker emergency response and helps prevent secondary accidents.Furthermore, AI contributes to more efficient traffic signal control, reducing vehicle idle time, minimizing fuel consumption, and decreasing air pollution. Overall, the integration of AI technologies into ITS supports broader sustainability and mobility goals by enhancing system efficiency, safety, and environmental performance.

Modern Intelligent Transportation Systems (ITS) integrate Machine Learning with Internet of Things (IoT) technologies and edge computing devices to enhance operational efficiency. Edge AI enables real-time decision-making at traffic signals and within autonomous vehicles, facilitating rapid responses to dynamic traffic conditions. The integration of smart sensors, RFID, and connected vehicles forms a feedback loop that supports accurate traffic predictions and real-time management.

Case Studies in Smart Cities

- **Barcelona** has adopted AI-driven transportation planning that leverages real-time data to manage road traffic, public transportation networks, and bike-sharing systems.
- **Singapore's ITS Master Plan** incorporates AI and Machine Learning to alleviate traffic congestion and implement dynamic toll pricing.
- **Los Angeles** employs an AI-based traffic control system that regulates over 4,500 traffic signals citywide to optimize flow and reduce congestion.

Limitations and Challenges

Despite these advancements, several challenges persist. Data privacy concerns, effective data governance, and interoperability among heterogeneous systems remain critical issues. Additionally, certain machine learning models may exhibit algorithmic bias, leading to unfair outcomes. For sustainable development and public acceptance, it is essential to ensure the accuracy of real-time data, optimize resource utilization, and foster trust through transparency and accountability.

5. Machine Learning Applications in ITS

Traffic Flow Prediction Models.1

Traffic flow prediction models utilize machine learning techniques such as LSTM, XGBoost, and Convolutional Neural Networks (CNNs) to analyze real-time traffic data. These models are designed to forecast traffic congestion and recommend optimal routes. The primary objective is to estimate the number of vehicles on a specific road or network during a given time period. Accurate predictions can help alleviate congestion, enhance road safety, and support more informed decision-making within smart transportation systems.

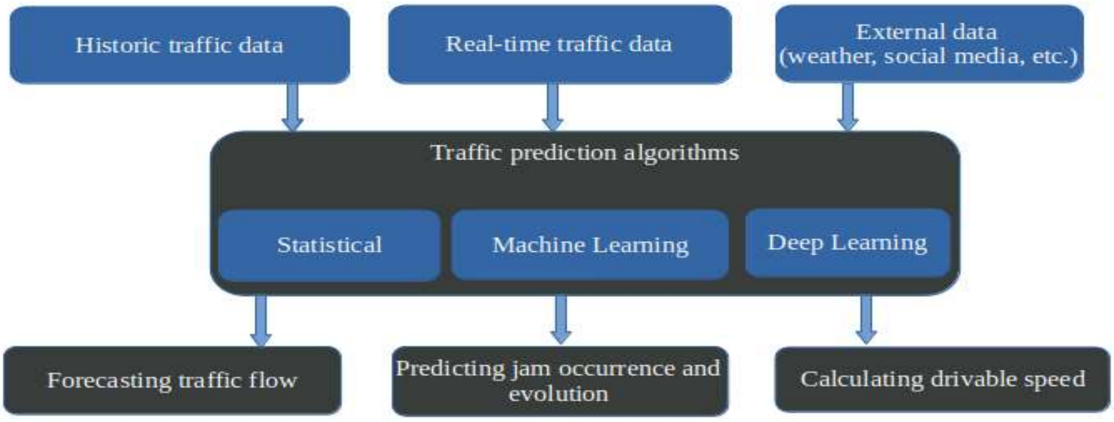

Figure 1: *Approaches to Traffic Prediction using Data-Driven Algorithms*

Traffic flow prediction plays an important role in Intelligent Transport Systems (ITS).It helps manage traffic proactively by guessing how busy roads, intersections, or highways will be in the future. The main goal is to estimate how many cars will pass through a certain road or network during a specific time period, which can be as short as a Getting accurate predictions is important for reducing traffic jams, making travel times more reliable, and helping both drivers and traffic control centers plan better routes.

Adaptive Traffic Signal Control

Signals that use reinforcement learning adjust their timing on their own to help ease traffic congestion and improve travel efficiency.Adaptive Traffic Signal Control (ATSC) systems change the timing of traffic lights in real time depending on how busy the roads are, instead of using a set schedule.This helps cut down on traffic, the time people spend waiting, fuel use, and harmful gas emissions.

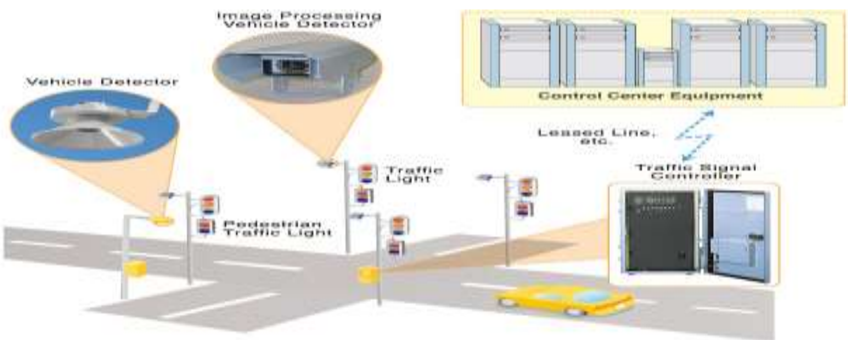

Figure 2: *Smart Traffic Signal Control System Architecture*

Adaptive Traffic Signal Control (ATSC) systems utilize real-time traffic data from various sources, including sensors, cameras, and GPS, to dynamically adjust traffic signal timings. These systems employ

Reinforcement Learning to determine the most effective light configurations. Unlike traditional fixed-timing schedules, ATSC systems learn to adapt signal timings based on changing traffic conditions. This approach helps reduce congestion, minimize waiting times, and improve fuel efficiency.

Smart Parking Systems

AI-based parking optimization uses sensor data to find available parking spots, which helps reduce traffic in cities.Smart parking systems use real-time information, sensors, and machine learning to manage and improve how parking spaces are used in urban areas.These systems help drivers find parking faster, lower traffic, and make transportation more efficient overall.

Figure 3: *Smart Intersection with License Plate Recognition and Smart Parking*

Smart Parking Systems, when integrated with License Plate Recognition (LPR) at smart intersections, represent a significant advancement in urban transportation management. These systems combine IoT sensors, CCTV cameras, and AI technologies to optimize parking and help reduce urban traffic congestion. When a vehicle approaches a smart intersection, LPR cameras capture and identify its license plate. This process enables accurate logging of arrival times, verification of parking permissions, and efficient allocation of available parking spaces.

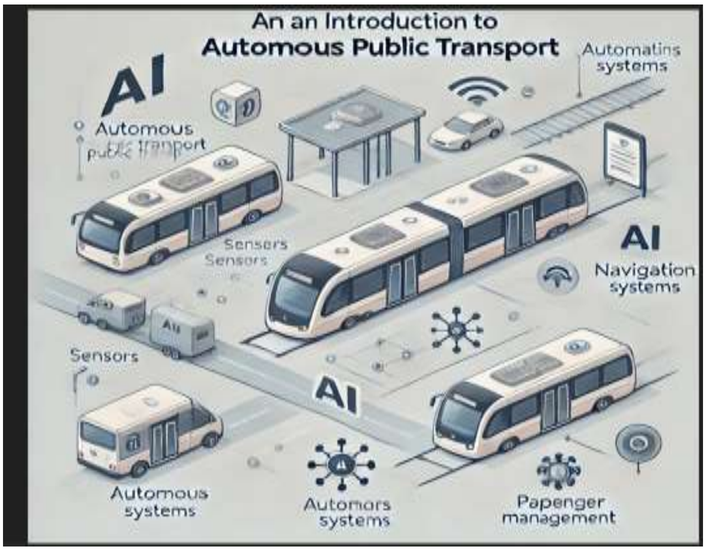

Figure 4 : *AI-Driven Autonomous Public Transport Ecosystem*

Integration AI-Powered Public Transport Optimization

Machine learning helps make bus and train schedules better, which makes traveling faster and fewer delays happen. This system uses artificial intelligence and machine learning to study how people use public transportation. It then changes things like routes, schedules, and how full vehicles get to match what people need at any given time.The key goal is to provide people with faster, more reliable, and more efficient public transportation in smart cities.

AI-powered public transport optimization is a major development in smart cities. It makes use of machine learning, artificial intelligence, and big data to improve how transportation systems such as buses, metros, and light rail operate.Old systems follow fixed schedules and set routes, which don't adjust to changing needs.This can cause packed buses, extended waiting times, and poor use of vehicles.AI-based systems, on the other hand, look at real-time and past data, including ticket sales, GPS info, how many people are on board, road conditions, events, and weather.This allows for adjustments to the schedule, the frequency of service runs, the routes that are used, and the number of vehicles that are deployed.

AI-Driven Road Safety Enhancements

Computer vision models and AI-driven holographic stop signs help make roads safer for both people and vehicles.This system uses machine learning, artificial intelligence, and data analysis to spot dangerous situations, predict possible accidents, and suggest or carry out safety actions.The goal is to make driving safer by preventing accidents from happening in the first place, rather than just handling them once they've already occurred.

Figure 5: *Intelligent Crosswalk Monitoring for Pedestrian Safety in Smart Cities*

AI-powered road safety improvements are transforming how cities manage transportation by shifting focuz from fixing issues after they happen to preventing accidents before they occur. This approach combines machine learning, computer vision, and real-time data analysis to monitor traffic, identify dangerous situations, and respond as needed. Key features of this system include smart crosswalks, holographic stop signs, AI-equipped cameras, and vehicles that communicate with each other through V2X technology.One of the biggest advances is the use of computer vision for crosswalk monitoring.

These systems use smart cameras and sensors at intersections to monitor pedestrians, cyclists, and vehicles as they move. They rely on deep learning models such as YOLO or RCNN to detect when people are crossing the street, figure out if they're waiting or stepping into the road, and then alert drivers accordingly.This helps prevent accidents, especially in places where many people walk, like near schools, busy streets, and city centers.

6. Methodology

The methodology adopted in this study is designed to analyze how Machine Learning (ML) techniques can be effectively integrated into Intelligent Transportation Systems (ITS) for optimizing mobility in smart cities. The process is structured into four key stages: data acquisition, preprocessing, model selection, and evaluation.

6.1. Data Acquisition

Urban transportation data is collected from heterogeneous sources such as GPS devices, roadside sensors, traffic cameras, loop detectors, connected vehicles, and Internet of Things (IoT) infrastructure. Supplementary data from public transport schedules, ride-sharing platforms, and environmental monitoring systems is also utilized to capture a holistic view of traffic dynamics.

6.2. Data Preprocessing

Raw data often contains noise, inconsistencies, and missing values. Preprocessing steps include data cleaning, normalization, and temporal alignment. For instance, vehicle trajectory data requires spatial-temporal synchronization, while traffic camera images undergo noise reduction and feature extraction to ensure compatibility with machine learning models.

6.3. Model Selection and Implementation

Different ML approaches are applied to address distinct ITS challenges:

- **Traffic Flow Prediction**: Long Short-Term Memory (LSTM) networks are used for time-series traffic forecasting, capturing temporal dependencies in congestion patterns.
- **Image-based Analysis**: Convolutional Neural Networks (CNNs) are employed for license plate recognition, pedestrian detection, and incident classification from surveillance footage.
- **Adaptive Signal Control**: Reinforcement Learning (RL) agents are implemented to optimize traffic light cycles based on real-time conditions, minimizing waiting time and maximizing throughput.
- **Anomaly Detection**: Gradient boosting methods (e.g., XGBoost) are applied to identify unusual traffic behaviors, accidents, or system failures.

6.4. Evaluation Metrics

The performance of ML models is evaluated using statistical and operational indicators, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), accuracy, and F1-score for classification tasks. From an ITS perspective, system-level improvements such as reduction in average travel time, intersection waiting time, fuel consumption, and carbon emissions are also measured.

This methodological framework ensures that both technical accuracy and real-world transport efficiency are considered in assessing the role of ML in ITS optimization.

The impact of ITS implementation on the environment and sustainability

Currently, governments worldwide are facing several issues, such as high energy consumption, pollute d air, busy roads, frequent car accidents, and poor driving conditions.drivers sitting idling for too long, and more fuel being used.This is happening because more people are moving from country areas to cities looking for better jobs and a better way of life.Because of this, cities are getting much more crowded.To make cities smarter and more eco-friendly, it's important to use technologies like Intelligent Transportation Systems, Smart Buildings, and Smart Manufacturing.When Building a Sustainable Smart City starts with focusing on transportation, transforming it into an Intelligent Transportation System. This change improves road safety, lowers fuel consumption, reduce s traffic congestion and accidents,
and also benefits the environment by using less energy and decreasing emissions.

ITS impact on sustainable smart cities

Los
Angeles uses special computer programs to predict how traffic moves and helps plan better ways to co ntrol it. Because of this, people spend less time driving and there is less harmful gas released into the air. Transportation is a major cause of harmful gases, and in the United States, it is responsible for 29% of all these gases. The amount of harmful gases increased a lot in 2021. From 1990 to 2021, the transportation industry produced more harmful gases than any other area.In 2023, Los Angeles started using smart traffic lights that made travel time shorter by 16% and reduced the number of times cars had to stop at intersections by
12%.In 2019, there was a study done on Montreal, a big city in Canada with about 4 million people. Montreal has problems with pollution, too much traffic, and not enough safety.To help reduce fuel use and carbon dioxide emissions, the city became a Sustainable Smart City.

Figure 6: *Smart sustainable cities' framework*

Smart Sustainable Cities (SSC) bring together digital technology and sustainability to make cities better places to live.This method allows cities to handle issues that involve the environment, society, and the economy.The diagram shows a model that looks at three main areas of sustainability—environment, society, and economy—and connects them with six important areas that guide how a smart city works.At the heart of this model is the idea that everyone should be involved and feel included, because smart

city projects should focus on people's needs and well-being.The six Linked areas include Smart People, which focuses on education, creativity,
and engaging communities to ensure citizens are informed and able to generate new ideas. Smart Government is about being.
open and honest, letting people take part in decisions, and using digital tools to help provide services more efficiently.Smart Economy focuses on encouraging new ideas, supporting business growth, and making sure the city stays economically strong in the long run.Smart Living is aimed atimproving people's lives
By improving healthcare, making housing safer and more comfortable,and building a sense of belonging through culture and community, Smart Mobility helps by using smart transportation and ecofriendly travel options to reduce costs.Finally, Smart Environment looks after energy use, pollution, and protecting the natural world to keep the environment healthy and balanced.

Figure 7: *Sustainable smart city Neom, Saudi Arabia*

NEOM is a big, futuristic smart city project being built in the northwest part of Saudi Arabia, along the Red Sea, close to Egypt and Jordan.It was announced in 2017 as part of Saudi Arabia's Vision 2030 plan.The aim is to build a model that shows how people can live in a sustainable way all over the world, by using modern technology and energy from renewable sources.The city will cover over 26,500 square kilometers.It will have smart buildings, tech centers, green spaces, and services that use AI to make life better and help protect the environment.NEOM has different areas.One of them is The Line, a long city that is 170 kilometers in size, designed without cars or roads, so it has zero carbon emissions and is walkable.Other areas are Oxagon, which is a floating industrial city; Trojena, a mountain area with a ski resort that works all year; and Sindalah, a luxury island.The city uses modern

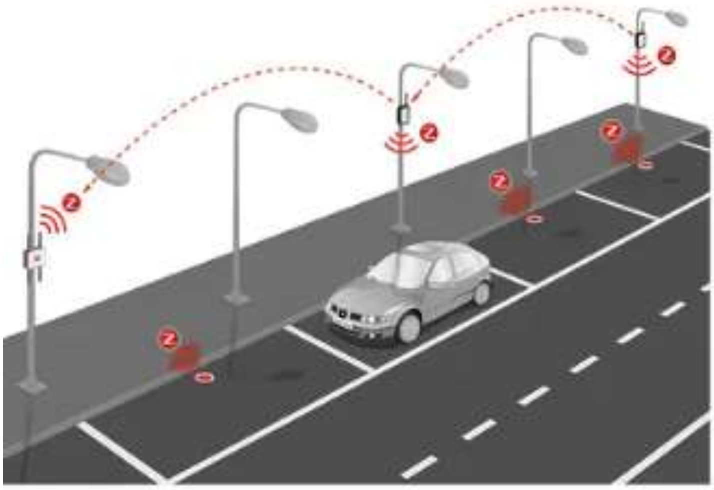

Figure 8: *Smart parking in Barcelona, Spain*

tech like self-driving cars, smart traffic systems, energy grids, and AI to help run the city.NEOM also wants to protect the environment by using water from the sea, green hydrogen, and data to manage resources well.NEOM is about changing the desert into a smart,connected, and green city.It wants to bring in smart people from all over the world, encourage new ideas, and test new ways of building cities.It is one of the most forward-thinking smart city projects in the World Barcelona, Spain, is setting an example by implementing smart parking systems as part of its smart city initiatives. The diagram shows a real-time smart parking setup where sensors are either placed in parking spots or attached to streetlights.These sensors sense when a car is present and send wireless signals to a central city platform.This lets the system track how full parking areas are and share live information about available spots with drivers through their phones or digital signs.This helps drivers find parking faster, which reduces traffic jams, lowers car emissions, and saves fuel.Barcelona’s smart parking system works with IoT (Internet of Things) and data analysis tools.This Let city officials observe how parking is used, figure out when it gets most crowded, and create better plans for how people get around the city. The city also uses changing prices and digital payments to make parking spots available faster and easier to use.The sensors and connected systems also help city workers spot and deal with people who park illegally or stay too long, making traffic control more effective.By using parking spaces Barcelona's smart parking system is a great example of how cities can reduce traffic and its environmental impact. It shows the power of using digital tools, along with AI, to make urban transportation more sustainable. smart policies, can improve daily city life to make it smarter, cleaner, and more pleasant for everyone.

7. Challenges and Future Research Directions

Ethical & Privacy Concerns

AI-based intelligent transportation systems need strong privacy rules to keep user data safe.Using AI for watching people raises ethical questions.Safety is very important, and vehicle-to-vehicle networks will help with safety features like avoiding crashes, detecting blind spots, and helping at intersections.When cars share real-time data about their speed, location, and plans, they can predict possible accidents and act early, which lowers the chance of accidents and makes driving safer.

Infrastructure & Cost Barriers

High deployment costs and the need for 5G & Edge Computing integration pose scalability challenges.

Future Innovations

Federated learning helps keep traffic data secure while allowing AI to improve vehicle-to-everything (V2X) communication, making city transportation better.Future Intelligent Transportation Systems (ITS) will use new technologies like artificial intelligence, machine learning, the Internet of Things, and 5G networks.These tools will help gather, examine, and apply real-time data to manage traffic more smoothly, direct vehicles through better routes, and keep roads and transportation systems in better condition. More andmore, people are starting to use Autonomous Vehicles (AVs), which could change how cities move.As AVs become common, transportation systems will need to change by adding smart traffic lights, special lanes for AVs, and systems that let vehicles talk to each other and to the road infrastructure. AVs can make driving safer, reduce traffic jams, and help save energ.

8. Conclusion

This study highlights the transformative potential of Machine Learning in advancing Intelligent Transportation Systems for smart cities. By leveraging predictive analytics, adaptive traffic signal

Table 1. *Algorithm and contribution related to application*

Year	Algorithm(s)	Contributions	Application
	GCN, LSTM	A hybrid model with GCN and LSTM using attention mechanisms for accurate traffic flow prediction by capturing spatial and temporal patterns.	Traffic Flow Prediction
2019	CNN	STFSA-CNN model: STFSA extracts spatio-temporal features; CNN performs short-term traffic flow prediction.	Traffic Flow Prediction
2020	LSTM, SAE	Achieved 97.7% average accuracy in traffic flow prediction using combined LSTM and Stacked Autoencoder.	Traffic Flow Prediction
2021	LSTM	Used EEMD for data denoising before applying LSTM, achieving the highest accuracy on three traffic datasets.	Traffic Flow Prediction
2019	Autoencoder	AE-based DCPN model trained on SATCS dataset demonstrated better performance than baseline models.	Traffic Congestion Prediction
2019	Backpropagation	Developed a time series-based model for predicting congestion points using backpropagation with high performance.	Traffic Congestion Prediction
2020	CNN, LSTM	CNN-LSTM-Transpose CNN hybrid model used image data to exploit spatial and temporal features, outperforming standard DNNs.	Traffic Congestion Prediction
2021	LSTM	LSTM-based model using sensor data predicted congestion propagation within 5 minutes, achieving 84–95% accuracy across various road types.	Traffic Congestion Prediction
2019	Autoencoder, ANN, SVR, Regression Tree, KNN	Autoencoder with deep feature fusion and SVR outperformed multiple models for traffic speed prediction using heterogeneous data.	Traffic Speed Prediction
2019	LSTM	Interpretable LSTM model captured spatial-temporal dependencies and explained latent traffic features for speed prediction	Traffic Speed Prediction
2020	GNN	GNN with sequence-to-sequence learning predicted traffic speed effectively by representing roads as edges and intersections as nodes.	Traffic Speed Prediction
2019	LSTM	Enhanced LSTM for travel time prediction with a tree structure and attention mechanism to incorporate departure time for improved performance.	Travel Time Prediction
2019	GRU	GRU model with trajectory segmentation achieved 0.070% MAPE for travel time, surpassing SAE-based methods.	Travel Time Prediction
2019	Conv-LSTM	Bus travel time model using non-static spatio-temporal correlation, outperforming Google's traffic model at different times.	Travel Time Prediction
2020	Autoencoder, Deep MLP	Multistage deep learning model with extensive feature engineering predicted travel time (MAE: 200s), though it struggled in rare events like snow.	Travel Time Prediction
2019	Q-learning	n-step Q-learning reduced total traffic delay by 40% compared to traditional signal control; minor issues with left-turning vehicles.	Traffic Signal Control
2019	A2C	Scalable MARL approach using A2C overcame centralization issues and outperformed standard Q-learning in adaptive signal control.	Traffic Signal Control
2020	Q-learning	A flexible model for various intersection structures aimed at maximizing vehicle throughput at intersections.	Traffic Signal Control

Table 2. *Automotive manufacturer's adoption of ITS Technology*.

Automobile manufacturers	**ITS Technology**	**Achievements**	**References**
I. BMW	• VANETs (V2V, V2C, V2X, V2P & V2I)	• Forefront of connected automobile technology • Enhancement of traffic flow • Promotion of environmental and safety objectives • Revolutionize the driving experience by lowering levels of stress. • Improves mobility in terms of both safety and efficiency	[4]
II. Mercedes-Benz	• VANETs (V2X, V2V, V2I) • Smart Parking	• Enhances both safety and convenience. • Significant step forward in the development of autonomous driving technology • Improvements to both the flow of traffic and the safety of drivers • Ensure increased comfort and safety	[5]
III. Audi	• 5 G • VANETs: C-V2X, V2P, V2I	• Safer Vehicles • more satisfying driving experience • Road safety • decrease the probability of pedestrian traffic accidents. • improve drivers' awareness of traffic and road conditions.	[6,7]
IV. Toyota	• VANETs: V2V, V2I & V2X • AI	• Improved driver awareness • accident prevention • installed driver aid technologies • Improve safety by combining human and machine control of a vehicle in emergency scenarios. • It helps mitigate the effects of human error	[8,9 ,10]
V. Cadillac	• VANETs: V2V	• giant leap forward in road safety	[8,11]
VI. Ford	• C-V2X, V2I, V2V & V2P • real-time communication	• improve automated driving, traffic flow, and car safety.	[8,12]
VII. Volkswagen	• V2V, V2X • AI	• Better traffic flow, less energy consumption • Increase safety.	[8,13 ,14]

Table 3. *How specific cities got benefit from implementing ITS.*

City	**ITS Technology**	**Achievements**	**References**
I. Los Angeles, USA	• ITL • Traffic prediction • Mobility prediction	• Reduction of travel time by 16% and pauses at intersections by 12 % • Reduction in GHG emission	[15,16,17]
II. Montreal, Canada	• VANETs (V2P & V2I) • ITL • Cameras	• V2P could decrease the accidents rate by 60 %. • Reduction in fuel Consumption and CO_2 emission. • Fast emergency services	[17]

City	ITS Technology	Achievements	References
III. Singapore, Singapore	• Traffic monitoring by real time data from sensors and cameras with the help of 5G	• Regulate traffic flow. • Reduce congestion. • Established a goal of 36 % Carbon emission.	[18,19]
IV. Barcelona, Spain	• ITL • Smart Parking • Real time automated traffic management	• Reduction in traffic congestion • Reduction in air pollution • Less idling time	[20]
V. Copenhagen, Denmark	• Smart parking • Traffic monitoring by real time data • ITL • VANETs (V2P)	• Being carbon neutral by the year 2025 • Regulate traffic flow. • Reduce congestion	[18,20]
VI. Seoul, South Korea	• IoT Sensors • VANETs • Smart Parking • AI Cameras • Traffic Monitoring	• Steady progress toward its goal of becoming a leading smart city. • Improve in local security. • Respond quickly to accidents. • Improvements in the quality of life	[21]
VII. Dubai, UAE	• Smart traffic management system. • Development of IoT & 5 G networks • Smart Parking	• Reaching net-zero emissions by the year 2050. • Reaching 25 % autonomous mobility by the year 2030. • Established many sustainability transportation projects. • Reduction in traffic congestion • Reduction in air pollution • Enhancing safety and transportation efficiency • Improvement in the quality of life	[19,22,23.24,22].
VIII. New Administrative Capital, Egypt	• Traffic Monitoring by real time data • Smart Parking • Intelligent Sensors • AI cameras • real-time cellular networks	• undergoing the process of being transformed into smart city • Eco-friendly environment and technologically sophisticated	[19,25]

control, smart parking management, and AI-powered public transit optimization, ITS can significantly enhance mobility, reduce emissions, and improve commuter safety. Case studies from global cities demonstrate measurable benefits, including reduced travel time, fuel savings, and improved environmental outcomes. However, challenges remain in ensuring data privacy, reducing infrastructure costs, and overcoming interoperability barriers across heterogeneous systems. Future work must focus on developing scalable, transparent, and ethically aligned AI solutions that integrate with emerging technologies such as 5G, edge computing, autonomous vehicles, and federated learning frameworks. The active participation of automobile manufacturers and urban policymakers will be essential for achieving robust, secure, and citizen-centric ITS deployments. Overall, ML-enabled ITS provides a sustainable pathway for urban mobility, aligning technological innovation with societal and environmental goals.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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