ENHANCING URBAN TRAFFIC FLOW USING INTELLIGENT TRANSPORTATION SYSTEMS: A MACHINE LEARNING APPROACH

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Abstract: Urban centers worldwide face growing traffic congestion, resulting in increased travel times, fuel consumption, and carbon emissions. Intelligent Transportation Systems (ITS) combined with machine learning offer promising solutions for optimizing urban traffic management. This paper investigates the implementation of machine learning models in ITS to predict traffic patterns, control signal timings, and manage dynamic traffic flows. Results show that machine learning significantly improves traffic efficiency, reduces congestion, and supports sustainable urban mobility.

Keywords: Intelligent Transportation Systems, machine learning, urban traffic management, congestion reduction, signal control

Introduction:

Rapid urbanization and the rise in private vehicle ownership have created significant challenges for city traffic networks. Traffic congestion not only reduces the quality of urban life but also contributes to environmental pollution and economic inefficiencies. Traditional traffic control systems rely on pre-set timing plans and static rules that cannot adapt quickly to fluctuating traffic conditions.

Intelligent Transportation Systems (ITS) integrate advanced communication, sensing, and computing technologies to monitor and manage traffic in real-time. By leveraging machine learning algorithms, ITS can analyze massive amounts of traffic data, detect patterns, and autonomously adjust traffic controls to optimize flow and minimize congestion.

This study examines how machine learning enhances ITS capabilities, focusing on real-time traffic prediction, adaptive traffic signal control, and dynamic route guidance within urban environments.

Materials and Methods:

This research combined a review of existing ITS implementations with a simulation-based experiment. Historical traffic flow data was obtained from a major metropolitan area, including vehicle counts, average speeds, and congestion levels at key intersections.

For traffic prediction, a deep learning model based on Long Short-Term Memory (LSTM) networks was trained to forecast vehicle volumes and congestion hotspots up to 30 minutes ahead. To control signal timings adaptively, a reinforcement learning (RL) agent was developed to adjust green light intervals in real-time based on traffic density and waiting times.

A simulation environment was built using the SUMO (Simulation of Urban Mobility) software to model the city's road network and test the impact of the machine learning-enhanced ITS under various traffic scenarios. Key performance indicators included average travel time, intersection queue length, and total fuel consumption.

Results:

The LSTM model demonstrated strong predictive capability, achieving a mean absolute error of under 7% in forecasting short-term traffic flows. This allowed the system to anticipate congestion and proactively adjust signal plans.The reinforcement learning traffic signal controller significantly outperformed traditional fixed-timing schemes. In peak traffic scenarios, average intersection wait times decreased by 25%, and overall travel times were reduced by 18%. Additionally, optimized traffic flow contributed to smoother vehicle acceleration and deceleration, leading to a 12% reduction in estimated fuel consumption.

Simulations showed that dynamic route guidance based on real-time predictions further alleviated congestion on major arteries by redistributing traffic loads across alternative routes.

Discussion:

The results indicate that integrating machine learning into ITS can dramatically improve urban traffic management. Accurate short-term traffic prediction enables proactive measures, while reinforcement learning provides a flexible approach to signal control that adapts continuously to real-world conditions.Benefits extend beyond reduced congestion, including lower fuel consumption, fewer emissions, and enhanced commuter satisfaction. However, several challenges remain, such as the need for large, high-quality datasets and the integration of heterogeneous traffic data from multiple sources like GPS, road sensors, and connected vehicles.

Cybersecurity, privacy, and interoperability must also be addressed to ensure the reliable deployment of AI-driven ITS. Future research should explore the use of federated learning and edge AI to process traffic data locally while maintaining data security.

Conclusion:

Machine learning-powered Intelligent Transportation Systems offer a promising solution to the persistent problem of urban traffic congestion. By enabling real-time, adaptive traffic control and accurate forecasting, these systems improve urban mobility, reduce environmental impacts, and support sustainable city development. Continued advancements in AI algorithms, data infrastructure, and cross-agency collaboration will be essential for scaling smart traffic management solutions to cities worldwide.

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