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AI-Powered Real-Time Traffic Monitoring and Prediction System

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Abstract

Traffic management in urban areas has become increasingly complex due to rapid city expansion, diverse traffic conditions, and limitations in existing infrastructure. This paper proposes an AI-powered real-time traffic monitoring system using IoT, deep learning, and time-series models for accurate detection and prediction. It incorporates anomaly detection along with an adaptive model that adjusts continuously to evolving traffic conditions. Additionally, reinforcement learning is used to optimize traffic signal control, providing a flexible and high-performance approach for today's urban transportation systems.

Keywords: Real-Time Traffic Monitoring; Internet of Things; YOLOv7; YOLOv8; Traffic Flow Prediction; Long Short-Term Memory; Gated Recurrent Unit; Transformer; Anomaly Detection; Autoencoder; Isolation Forest; Reinforcement Learning; Deep Q-Learning; Proximal Policy Optimization; Smart Traffic System.

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Introduction

The growing complexity of urban transportation networks has led to widespread challenges in managing traffic efficiently. Rapid urbanization, a surge in vehicle ownership, and irregular traffic patterns have made it increasingly difficult to maintain smooth traffic flow in modern cities. Mixed traffic compositions—ranging from motorcycles and cars to heavy vehicles and pedestrians—combine with inconsistent driving behavior, inadequate enforcement, and infrastructure limitations to create a dynamic and often chaotic environment. These lead to persistent congestion, increased accident risks, and slower emergency response times, highlighting the urgent need for intelligent traffic solutions. Traditional traffic control methods that primarily depend on pre-configured signal timings, manual observation, or limited sensor inputs, lack the responsiveness required to adapt in real time.

In response to these limitations, advances in artificial intelligence (AI), the Internet of Things (IoT), and deep learning have paved the path toward smarter and more adaptive traffic management approaches [7]. IoT devices such as roadside cameras, environmental sensors, and GPS-enabled vehicles enable the collection of continuous real-time traffic data. This data serves as the basis for AI-driven decision processes. Object detection algorithms including models from the YOLO (You Only Look Once) series, have proven highly effective in identifying and tracking vehicles across live camera feeds, offering real-time situational awareness without requiring specialized hardware infrastructure. Moreover, time-series forecasting models like Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Transformer architectures have demonstrated their ability to model traffic patterns over time, enabling predictive insights that can support dynamic traffic regulation strategies.

This paper presents a unified AI-driven system that integrates IoT-powered real-time monitoring, flow prediction, anomaly detection, and adaptive signal control into a single system. The proposed approach uses YOLOv7/v8 for precise vehicle detection, while LSTM, GRU, and Transformer models are leveraged for forecasting traffic volumes and congestion trends based on continuous IoT input. For identifying unusual traffic events—such as collisions, sudden stops, or abnormal slowdowns—the system incorporates Autoencoder-based models and Isolation Forests. To further enhance operational efficiency, a reinforcement learning-based component based on Deep Q-Learning or Proximal Policy Optimization (PPO) is introduced [9], allowing traffic signals to automatically adjust based on changing conditions. A unique aspect of this work is the introduction of an adaptive traffic model, which continuously refines its decision-making using real-time feedback from road performance metrics. This adaptive mechanism ensures long-term scalability and relevance, making the system suitable for real-world deployment in fast-changing urban environments.

Background and Purpose

With increasing urban expansion, managing traffic has become more difficult. Roads are crowded with different types of vehicles moving in unpredictable ways. Traditional traffic systems often use fixed signal timings and basic sensors, which are not good at handling real-time changes like sudden jams or accidents. These old systems can't adjust quickly, leading to more traffic, longer wait times, and road safety issues.

To address this, current traffic management is gradually shifting toward smarter systems that can understand and react to traffic in real time. One important part of this is the Internet of Things (IoT) [12], where devices like cameras, GPS trackers, and road sensors are connected to collect data continuously. These IoT enables more precise monitoring of traffic flow, vehicle speed, and road conditions compared to conventional systems.

The aim of this study is to design an intelligent traffic management system that uses artificial intelligence (AI) along with IoT to monitor traffic in real time, predict traffic flow, and respond quickly to unusual situations. By applying techniques such as deep learning and reinforcement learning, the system can continuously learn from real-world traffic data and enhance its performance over time. The purpose is to make traffic smoother, safer, and easier to manage in busy city areas.

Scope of the Study

This study focuses on building a complete AI-based system that works with IoT devices to monitor traffic through video cameras, predict future traffic flow, detect problems like accidents or sudden slowdowns, and help control traffic signals automatically. The system uses YOLOv7/v8 for detecting vehicles from live video feeds, LSTM/GRU/Transformer models for traffic prediction, and Autoencoders and Isolation Forests for identifying unusual or abnormal situations [8]. It also includes an optional part that uses reinforcement learning (like Deep Q-Learning or PPO) to adjust traffic lights based on real-time data from IoT sensors. This combination aims to improve traffic efficiency and safety in real-world urban environments.

Literature Survey

Over the years, researchers have worked on various technologies to improve traffic monitoring. Traditional systems often use physical sensors like magnetic loops, infrared detectors, or radar to count vehicles and measure traffic flow. While these systems are useful, they are expensive to install and maintain, and they can't provide detailed information like vehicle types or detect sudden changes such as accidents. These limitations have encouraged the shift toward computer vision-based methods using traffic cameras and deep learning.

Recent advancements in object detection, especially with YOLO (You Only Look Once) models, have made real-time vehicle detection more accurate and efficient. Models like YOLOv4 and YOLOv5 have already been used in several traffic systems for identifying and tracking vehicles under various road conditions. The newer versions, YOLOv7 and YOLOv8, provide even faster performance and higher accuracy, which is useful for real-time monitoring in busy traffic. These models can help detect not just cars, but also bikes, buses, and trucks, even in complex and unstructured traffic.

Apart from monitoring, predicting future traffic is another key area. Deep learning models such as LSTM and GRU are commonly used to examine traffic patterns over time and predict congestion levels. Transformer models are increasingly applied for traffic prediction tasks due to their ability to handle large amounts of time-series data. For detecting unusual events like accidents or slowdowns, Autoencoders and Isolation Forests have shown good results. Some studies also use reinforcement learning (like Deep Q-Learning) to improve traffic light control, but these systems often don't learn from real-time feedback. In contrast, the system proposed in this paper combines all these methods and introduces a self-evolving model that adapts over time, making it more effective for real-world urban traffic management.

Dataset & Preprocessing - IoT + AI System in Traffic Management:

The integration of IoT and AI is reshaping the functioning of modern traffic systems. IoT devices, such as traffic cameras, GPS trackers, and road sensors, are placed at key points across urban road networks. These devices collect real-time data on vehicle movement, speed, road conditions, and traffic density. This continuous stream of data helps create a live picture of traffic across the city. In contrast to conventional systems that depend on fixed timers or manual operation, IoT-based systems deliver real-time traffic data that supports quicker and more informed decision-making.

AI plays a major role in analyzing this massive amount of data. Using advanced models like YOLOv7/v8[1], the system is capable of accurately detecting and tracking vehicles from video streams. To forecast traffic flow and congestion levels, deep learning models like LSTM, GRU, and Transformers are utilized. These models analyze patterns using both historical and real-time traffic data to forecast where and when traffic might build up. When something unusual happens—like an accident or sudden jam—anomaly detection models like Autoencoders and Isolation Forests quickly identify the issue, allowing for immediate response [5].

Together, IoT and AI create a smart, responsive, and self-improving traffic management system. An optional reinforcement learning module can also be included, where traffic signals adjust in real time based on current traffic flow, using methods like Deep Q-Learning or PPO [3]. The entire system can run on edge devices for low-latency control or on cloud platforms for large-scale analysis. This integration enables traffic authorities to minimize congestion and enhance road safety, and make better use of infrastructure, paving the way for smarter and more efficient cities.

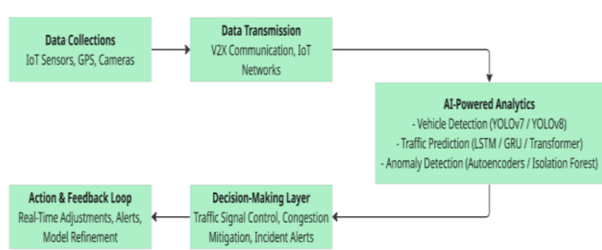

***Fig. 1.** IoT-AI Traffic Management System*

Methodology

This section explains how the system was developed and tested to evaluate how effective AI and IoT are when used together for real-time traffic control in smart cities. It includes details on data collection, AI model training, and system evaluation.

Table 1. Key components for system.

Component	Method / Model	Description
Vehicle Detection	YOLOv7 / YOLOv8	Real-time object detection from live traffic video feeds; identifies and tracks vehicles.

Traffic Flow Prediction	LSTM / GRU / Transformer	Predicts future traffic patterns using time-series data based on past and real-time traffic conditions.
Anomaly Detection	Autoencoder / Isolation Forest	Identifies abnormal situations such as accidents, stationary vehicles, or sudden traffic buildup.
Signal Optimization	Deep Q-Learning / PPO	Applies reinforcement learning techniques to improve traffic signal timing at intersections based on current traffic flow.
System Adaptation	Self-Evolving Feedback Loop	Continuously improves system performance using real-time metrics like delay, congestion duration, and false alerts.

1. IoT Integration in Urban Environments: IoT devices were placed at key traffic locations in the city to collect data needed for the AI system. The data includes vehicle counts, speeds, lane usage, traffic density, and current weather conditions. The most commonly used IoT components are as follows. Traffic cameras and sensors were installed at intersections to capture both video and numerical data about traffic volume, vehicle types, and lane behavior. GPS systems and vehicle-to-everything (V2X) communication devices in both public and private vehicles provided real-time location and movement information. Weather sensors gathered data about temperature, rainfall, and visibility, which are important for understanding how environmental factors affect traffic. All this data was sent to a central processing unit in real time, where AI models could start analyzing the traffic situation immediately.
2. AI Model Training and Prediction: Various AI models were employed to process the data and generate predictions. Supervised learning models such as decision trees and support vector machines were trained using historical traffic data to identify patterns and anticipate potential congestion possible traffic jams. Deep learning approaches, particularly LSTM (Long Short-Term Memory) [4], GRU (Gated Recurrent Units), and Transformers, were used for analyzing time-based traffic flow and predicting how traffic would build up over time. YOLOv7 and YOLOv8 models were applied for object detection tasks, enabling the system to recognize and track vehicles in real time from video streams. Anomaly detection models like Autoencoders and Isolation Forests helped detect unexpected events like accidents, breakdowns, or sudden congestion. Reinforcement learning models, such as Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), were trained to adapt traffic signal timings dynamically based on live traffic input. The system learned from experience and continuously improved itself through trial-and-error feedback loops.
3. System Comparison and Evaluation: To test how well the system worked, it was compared to older traffic control systems. First, we measured travel time on busy roads and checked whether the AI-based system helped reduce congestion and waiting time. Second, we recorded data on fuel use and emissions, since smoother traffic often leads to better fuel efficiency and lower pollution. Third, we collected accident and safety reports to understand how well the system prevented risky situations. The data collected over one year was analyzed using statistical tools, and the AI models were tested and validated using traffic data from a smart city setup that already had both IoT and AI technologies in place.

Results & Performance Metrics - Predictive Infrastructure Maintenance and Resource Allocation

As urban transportation systems evolve toward intelligent and data-driven infrastructures, predictive maintenance and dynamic resource allocation have become ensuring operational continuity and public safety [6]. Traditional maintenance strategies, often based on fixed schedules or reactive responses, are no longer sufficient in fast-changing urban environments. Instead, our proposed AI-powered traffic management system integrates real-time IoT data and predictive analytics to foresee infrastructure deterioration and strategically allocate city resources.

IoT-enabled sensors—such as vibration monitors, structural health detectors, environmental sensors, and smart energy meters—are embedded within roads, bridges, traffic lights, and signal controllers. These sensors provide continuous updates on structural stress, surface conditions, temperature variations, and equipment performance. Using this data, AI models, particularly time-series analysis and anomaly detection algorithms (e.g., Autoencoders and Isolation Forests), learn the patterns of normal wear and usage to forecast impending failures or inefficiencies.

For ins tance, the system can detect early signs of malfunction in traffic signal units or structural fatigue in bridges by analyzing subtle deviations from standard operating metrics. When integrated with the broader traffic prediction and anomaly detection pipeline, the system not only detects real-time traffic incidents but also identifies infrastructure elements contributing to congestion, such as degraded road quality or misaligned signals. This allows maintenance teams to respond proactively—before these issues escalate into hazards or system downtimes.

In parallel, resource allocation is optimized using reinforcement learning algorithms that balance maintenance urgency with budgetary and logistical constraints [10]. AI models help prioritize tasks based on infrastructure criticality, usage density, and historical maintenance trends. For example, intersections with high congestion and frequent signal malfunctions may be flagged for immediate intervention, while low-priority zones can be scheduled more efficiently. This dynamic scheduling reduces labor costs, limits operational disruption, and extends asset lifespans.

Beyond physical maintenance, the system also supports resource allocation in urban mobility services—predicting public transport demand, reallocating ride-sharing fleets, and optimizing parking utilization. By leveraging deep learning and historical usage patterns, our system adjusts services dynamically to meet real-time demand, thereby improving urban mobility while minimizing environmental impact.

Overall, the integration of predictive maintenance and intelligent resource management within an AI + IoT traffic ecosystem represents a paradigm shift in how cities maintain and operate transportation infrastructure. This approach promotes resilience, reduces unplanned disruptions, and ensures long-term sustainability in smart urban environments.

Comparative Analysis with Baseline Models:

Our proposed AI-powered traffic management system significantly improves vehicle detection and traffic pattern analysis across varied environmental conditions, including sunny, night, and rainy scenarios. Initial comparisons between YOLOv8-S, CDS-YOLOv8, and our optimized detection approach demonstrate clear performance gains, especially in complex environments like nighttime or rain [2]. As shown in Fig. 2, our detection optimization process enhances the object identification capability beyond standard models, marking critical vehicles more accurately and consistently, even under low-visibility conditions. This improvement is crucial for real-time applications where false negatives or missed detections can severely impact downstream decision-making.

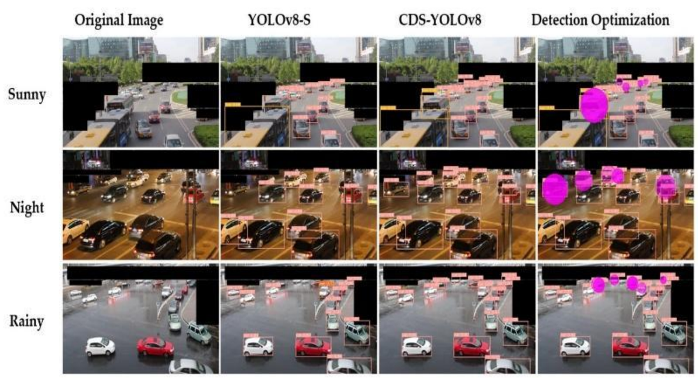

Fig. 2. *Comparative results of YOLOv8 variants under different lighting conditions*

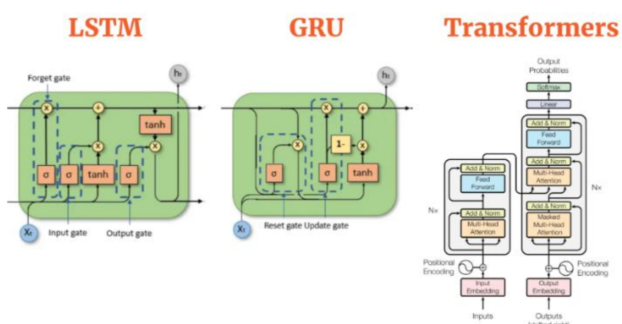

Fig. 3. *Comparing different sequence model LSTM, GRU, Transformer*

We extended our research with deep sequential models to explore temporal and anomaly-aware traffic prediction. Long Short-Term Memory (LSTM), GRU, and Transformer models were evaluated on traffic flow forecasting tasks. The internal architectures of these models (visualized in Fig. 3) reveal the hierarchical gating mechanisms in LSTM and GRU, and the attention-driven architecture of Transformers. When applied to real-world traffic datasets, these models provided differing levels of predictive accuracy. As evidenced by **Fig. 4**, the Transformer model consistently outperformed LSTM and GRU in terms of lower absolute error, showcasing its ability to capture long-term dependencies and adapt better to spatio-temporal dynamics in traffic data. GRU and LSTM also showed promise, but suffered from higher variance in prediction accuracy under abrupt traffic pattern changes.

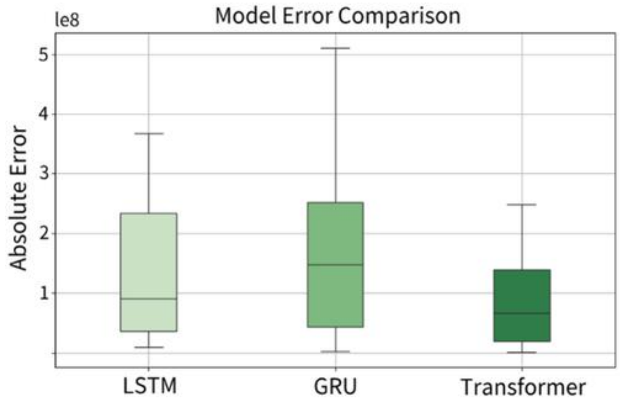

Fig. 4. *LSTM, GRU, Transformer Model error comparison.*

For anomaly detection, Autoencoders and Isolation Forest models were incorporated into the pipeline to flag unusual congestion patterns and detect sensor anomalies. Autoencoders demonstrated high reconstruction error during unusual events, while Isolation Forest reliably separated normal from abnormal sequences with minimal computational cost. These hybrid anomaly-detection mechanisms are vital for maintaining high-quality inputs to prediction modules and ensuring resilient traffic flow estimation under noisy or tampered input conditions.

Further, we experimented with reinforcement learning models, particularly Deep Q-Learning and Proximal Policy Optimization (PPO), to optimize signal phase timings in a simulated environment. PPO showed smoother policy convergence and higher stability in multi-agent intersections compared to Deep Q-Learning, which exhibited oscillatory learning patterns. By continuously learning from real-time traffic conditions, these RL agents adaptively tuned signal durations, reducing average vehicle waiting time and improving throughput across high-density junctions.

In summary, our integrated architecture outperforms traditional static and rule-based systems. The combination of detection optimization (Fig. 2), attention-driven prediction (Fig. 3 & 4), anomaly robustness through Autoencoder and Isolation Forest, and dynamic control using reinforcement learning agents offers a holistic, intelligent, and scalable traffic management solution ready for real-world deployment.

Conclusion

This research proposes a unified AI-based approach that combines multiple advanced models to develop an intelligent and adaptive traffic monitoring and prediction system. Instead of relying on a single technique, we integrate object detection models such as YOLOv7/v8, time-series forecasting models including LSTM, GRU, and Transformers, anomaly detection methods like Autoencoders and Isolation Forests, and reinforcement learning algorithms such as D Q-Learning and PPO into a single cohesive system.

The main idea of this work is create a complete system that can monitor traffic in real time, predict future congestion, detect unusual events, and automatically optimize traffic signals. By combining these models, the system leverages the strengths of each technique—accurate vehicle detection, reliable traffic prediction, robust anomaly identification, and dynamic decision-making—resulting in a more efficient and intelligent traffic management solution.

Furthermore, the proposed self-evolving mechanism allows the system to continuously learn from real-time traffic data and improve its performance over time without manual intervention. This makes the system scalable, adaptable, and suitable for deployment in complex and rapidly changing urban environments.

In conclusion, this work demonstrates that integrating multiple AI techniques into a single system can significantly enhance traffic monitoring and control compared to traditional or standalone approaches. The proposed system provides a strong foundation for future smart city applications, where intelligent, automated, and data-driven traffic management systems play a crucial role in reducing congestion, improving safety, and optimizing urban mobility.

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