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Adaptive Traffic Control Systems

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Abstract
This project presents an AI-driven Adaptive Traffic Control System (ATCS) that optimizes traffic signal timing using real-time video analytics and vehicle density estimation. The system captures live road footage, processes vehicle flow patterns and lane-wise congestion levels, and extracts meaningful traffic indicators such as queue length, vehicle count, and average waiting time. A machine learning model analyzes these features to dynamically assign optimal green-time durations and classify intersections into Low, Moderate, or High congestion states. Implemented using Streamlit and Python, the system generates a detailed PDF report summarizing intersection performance and predicted traffic load.
Keywords: *Adaptive Traffic Control System, Real-Time Traffic Analysis, Vehicle Density Estimation, Machine Learning, Dynamic Signal Timing, Urban Traffic Management.*

1. Introduction
Traffic congestion is a growing issue that disrupts vehicle movement, increases travel time, and impacts daily transportation efficiency, with unplanned traffic flow being a major contributing factor. Detecting congestion patterns early is essential because it enables timely control adjustments and helps reduce delays on busy road networks. However, many traditional traffic signal systems respond only after congestion has already formed, leading to inefficient traffic management. To address this, the proposed system uses adaptive traffic signal control supported by artificial intelligence to regulate intersections in real time [1]-[3]. By analyzing vehicle count, waiting time, and flow patterns, the AI can identify early signs of traffic buildup.

2. Related Work
Research on adaptive traffic management has grown rapidly as efficient control of road congestion is critical for improving mobility and safety. Traditional systems such as fixed-time signals and manual traffic regulation offer basic management but usually respond only after heavy congestion has formed. To overcome this limitation, recent studies have focused on intelligent signal control and camera-based vehicle detection that can identify real-time changes in traffic density, lane occupancy, and flow patterns. These approaches enable dynamic adjustment of signal timing, helping reduce delays and enhance intersection performance. With the advancement of Artificial Intelligence, machine learning models have been used to analyze vehicle movement patterns, traffic density variations, and signal timing data to identify subtle inefficiencies in road networks. Some researchers have also explored pedestrian prediction, license plate recognition, and sensor-based traffic monitoring to enhance system responsiveness. However, there remains a need for simple, accessible, and cost-effective traffic control tools that municipalities can deploy regularly to improve traffic flow in both urban and semi-urban regions [4]-[7].

3. System Architecture
The proposed system architecture for early Alzheimer's detection utilizes AI-based cognitive assessment and behavioral pattern analysis to evaluate subtle changes in memory, reaction time, and decision-making (Figure 1). The process begins with the **Traffic Video Acquisition Unit**, where roadside cameras capture live video feeds of intersections. Video frames are continuously recorded, and each frame is converted into a digital format suitable for analysis. This raw data represents vehicle positions, lane occupancy, and traffic flow dynamics in real time. Next, the data enters the **Traffic Processing and Analysis Unit**, where it undergoes several steps: background subtraction, vehicle detection, lane-wise counting,

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and queue length estimation. Extracted features—such as vehicle count per lane, average waiting times, and peak congestion periods—are processed by AI models, including machine learning classifiers and deep learning architectures. Training and validation are performed using historical traffic datasets to ensure reliability and robustness of predictions. The final stage is the **Adaptive Signal Control System**, which integrates vehicle density metrics, lane prioritization, and time-of-day traffic trends. The system generates optimized signal timings for each lane, dynamically adjusting green and red durations to minimize congestion. A user-friendly dashboard presents live traffic analytics, visualizations, and automated reports to assist traffic operators in decision-making and intersection management [8]-[11]

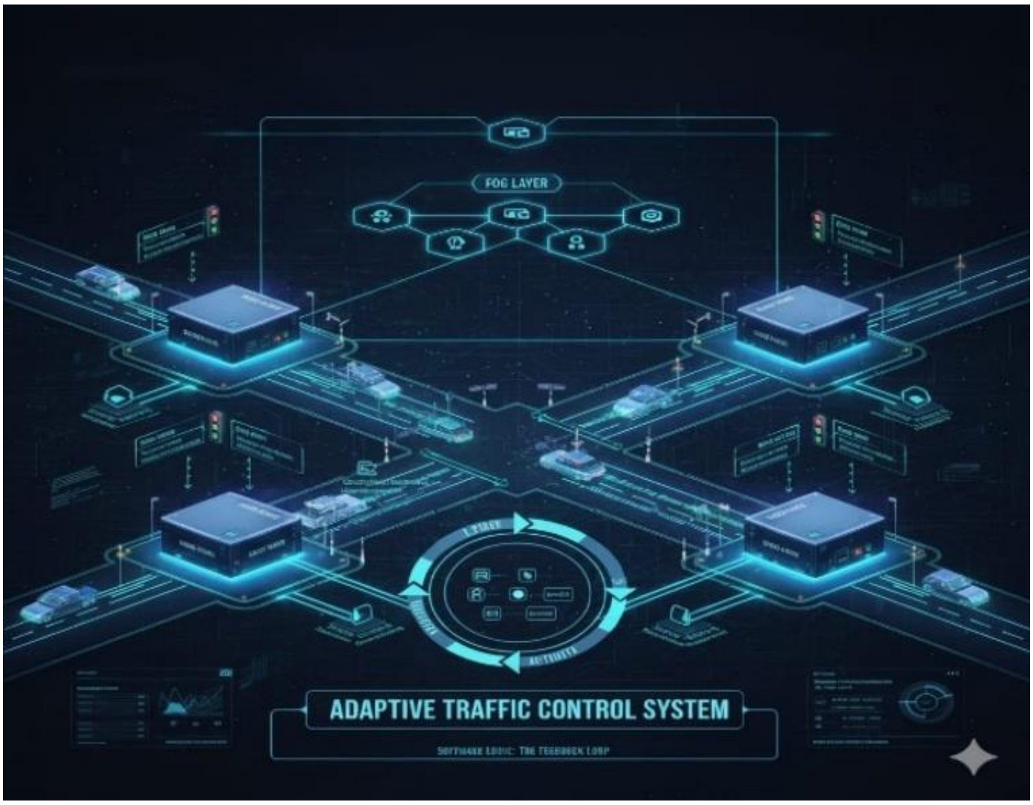

Figure 1 Adaptive Traffic Control System Architecture using Real-Time Video Analysis

4. Proposed System

The proposed system is an **AI-based adaptive traffic control platform** designed to optimize urban traffic flow using real-time video analysis and machine learning. The system integrates multiple software modules—including vehicle detection, lane-wise congestion measurement, queue length estimation, and dynamic signal adjustment—to capture traffic patterns that vary across intersections and peak hours. By combining these traffic metrics with predictive analytics, the system provides an accessible, fully software-driven, and user-friendly solution for real-time traffic management. The methodology begins with **video data acquisition**, where live traffic feeds from existing cameras are captured and processed by the software. Every frame, including vehicle positions, lane occupancy, and flow speed, is recorded in real time. This raw data is then passed to the **preprocessing module**, which removes noise, corrects detection errors, and standardizes the information for further analysis. In the **feature extraction stage**, key traffic indicators are identified, such as per-lane vehicle counts, average waiting times, congestion severity, and peak-hour flow patterns. Extracted features are then

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fed into the machine learning model, which has been trained on historical traffic datasets. Algorithms such as Random Forest or Support Vector Machines classify traffic conditions into Low, Moderate, or High congestion levels, enabling dynamic and predictive signal timing adjustments. To ensure reliability, the system includes a **validation component** that compares model predictions with observed traffic patterns and benchmark datasets. Metrics such as prediction accuracy, congestion reduction, average waiting time improvement, and consistency across repeated intervals are used to evaluate performance. Finally, the system generates a **detailed traffic report**, summarizing congestion levels, optimized signal timings, and recommended traffic interventions. This structured methodology ensures that the proposed ATCS functions as a reliable and effective tool for real-time traffic management, supporting smoother traffic flow, reduced congestion, and improved urban mobility [12].

4.1. AI–Based Adaptive Traffic Control System

An **AI–Based Adaptive Traffic Control System** is a software platform designed to monitor and manage traffic flow in real time, optimizing signal timings and reducing congestion at intersections. Traditional traffic management methods often rely on fixed-timer signals or manual interventions, which can lead to inefficiencies during peak hours. This system uses artificial intelligence to recognize dynamic traffic patterns, enabling adaptive control that responds to real-world conditions instantly. The system consists of video-based traffic analysis modules, including vehicle detection, lane-wise vehicle counting, queue length estimation, and congestion assessment. As the software processes live video feeds, it collects traffic indicators such as vehicle density, average waiting times, lane occupancy, and flow speed. These data points act as traffic performance metrics, which the AI algorithms—such as neural networks, Random Forest, or Support Vector Machines—analyze to identify deviations from optimal flow conditions. Compared to traditional fixed-timer or manual control, this AI-driven approach ensures higher responsiveness, improved efficiency, and real-time traffic optimization without the need for additional hardware. A key advantage of the system is its ability to **monitor traffic patterns continuously over time**. By comparing results across multiple intervals, it can detect recurring congestion trends or sudden traffic build-ups that may not be noticed during periodic manual checks. This makes it ideal for continuous city-wide traffic monitoring and dynamic signal adjustment. The system is designed with a **user-friendly dashboard** supported by secure data management. All traffic data, including real-time metrics, historical trends, and AI-predicted signal schedules, are stored securely to maintain integrity and support analytics. Overall, the **AI–Based Adaptive Traffic Control System** offers an efficient, fully software-based, and scalable solution for real-time traffic optimization, promoting smoother mobility, reduced congestion, and improved urban traffic management [13].

4.2. Traffic Pattern Detection

Traffic Pattern Detection is a core component of the AI-assisted Adaptive Traffic Control System, focusing on identifying subtle irregularities in vehicle flow, lane occupancy, and congestion dynamics. These patterns are often too complex for manual observation but can be captured and analyzed through advanced machine learning techniques. The goal is to uncover real-time traffic anomalies and predict congestion trends before bottlenecks occur. During traffic monitoring, the software analyzes video feeds from intersections, detecting vehicle positions, speeds, and lane usage. Each frame generates measurable markers such as vehicle count per lane, average waiting times, queue lengths, and lane-specific congestion levels (Figure 2). AI algorithms analyze the **traffic pattern profile** to recognize deviations from normal flow behavior. Techniques such as statistical modeling, clustering, neural networks, and anomaly detection models are used to examine relationships across multiple traffic parameters. For example, sudden lane blockages, recurring congestion in specific lanes, or unusually long queue lengths may indicate abnormal traffic conditions that require adaptive signal adjustments. One of the strengths of AI-driven traffic pattern detection is its ability to learn from large datasets, identifying trends that may not be apparent through

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manual monitoring [14]. By comparing current traffic data with historical patterns, the system can classify intersections into low, moderate, or high congestion levels with greater precision. Furthermore, traffic pattern detection supports longitudinal monitoring.

Figure 2 AI-Assisted Traffic Pattern Detection Workflow

Over repeated intervals, the system observes changes in traffic performance, identifying recurring congestion trends or emerging bottlenecks that would otherwise go unnoticed. This helps distinguish temporary traffic fluctuations—caused by accidents, weather, or special events—from persistent congestion issues. Overall, Traffic Pattern Detection enhances accuracy, objectivity, and proactive management in adaptive traffic control, making it an essential component of AI-based software systems for real-time urban traffic optimization.

4.3. Model Validation

Model validation is a crucial process to ensure that the AI-based Adaptive Traffic Control System is accurate, consistent, and reliable for real-time traffic optimization. To test the robustness of the model, a wide range of datasets and traffic scenarios are used. These include historical traffic flow datasets, lane-wise vehicle counting datasets, queue length datasets, peak-hour congestion datasets, multi-intersection combined datasets, and live traffic feed samples collected during system trials (Figure 3). Using such diverse traffic datasets allows the model to be evaluated across multiple traffic scenarios, ensuring that it performs reliably under varying congestion levels, intersection layouts, and traffic patterns. This diversity also helps verify that the system can adapt to different urban environments, peak-hour variations, and vehicle densities. Operational validation is another major part of the evaluation process. Because software-based traffic control cannot directly manipulate real-world traffic without risk, the system must be compared with historically observed traffic trends and benchmark datasets. For this purpose, validated traffic flow records, congestion logs, and simulation datasets are used as the ground truth. Cross-validation techniques are applied to confirm that the AI model's predictions mirror observed traffic behavior and that signal timing adjustments align with optimal flow conditions. This step ensures that the system is not only computationally accurate but also practically relevant for urban traffic management. Several performance metrics are used to measure the system's effectiveness. **Traffic throughput improvement** evaluates how well the model reduces congestion, while **average vehicle waiting time** measures its efficiency in minimizing delays [15]. Additional metrics such as queue length reduction,

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lane utilization consistency, and stability across repeated intervals provide insights into the model's reliability and robustness

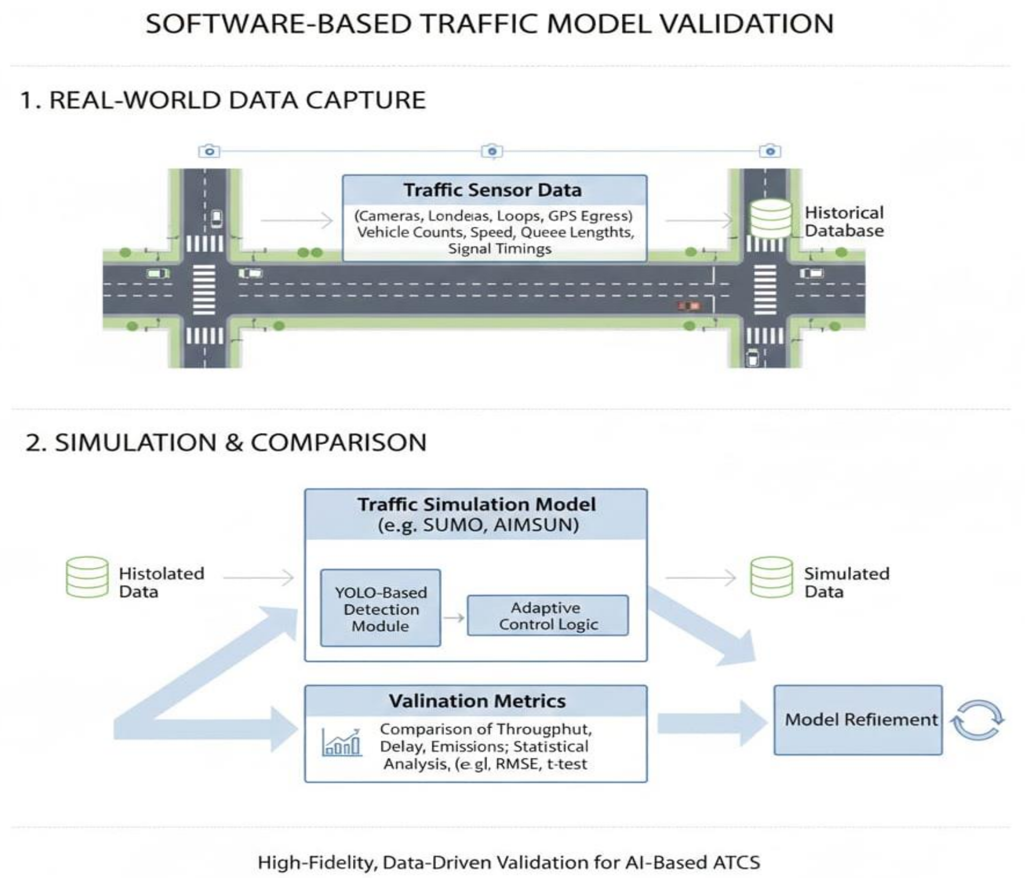

Figure 3 **Software-Based Model Validation for ATCS**

4.4. Simulation Results

The simulation results demonstrate that the AI-based cognitive assessment system performs effectively in identifying early cognitive changes related to Alzheimer's risk (Figure 4). The congestion classification module shows strong accuracy in distinguishing intersections with smooth traffic flow from those experiencing significant congestion. In most cases, the model's predictions are stable, with variations mainly arising from differences in traffic patterns, time-of-day fluctuations, special events, or borderline congestion levels that fall close to the thresholds between classification categories. Traffic pattern analysis plays a key role in evaluating the system's performance. Intersections with high vehicle volumes and complex lane configurations show clear and consistent distinctions between low-congestion and high-congestion scenarios. Highly congested intersections tend to exhibit longer queue lengths, slower vehicle speeds, and irregular lane utilization patterns, while low-congestion intersections demonstrate smoother flow, shorter waiting times, and balanced lane usage. These consistent trends indicate that the model is not producing random predictions but is accurately capturing meaningful traffic patterns. To confirm operational reliability, the results from the AI system are compared with historical traffic datasets and validated simulation benchmarks commonly used in urban traffic management studies. The system shows strong alignment in accuracy, responsiveness to emerging congestion, and specificity in identifying free-flowing intersections. Overall, the simulation

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results validate the system as a reliable and efficient software-based tool for real-time traffic management, capable of supporting large-scale urban intersections and dynamically reducing congestion where it is most critical.

Figure 4 **ATCS Dashboard for Lane-Wise**

Conclusion

The proposed AI-based cognitive assessment system offers a promising and accessible solution for early detection of Alzheimer's disease. Traditional diagnostic approaches often identify cognitive decline only after significant neurological damage has occurred, limiting the effectiveness of medical interventions. In contrast, the developed system uses simple digital cognitive tests combined with machine learning analysis to detect subtle behavioral and response- pattern changes that may indicate early impairment. By integrating memory recall tasks, reaction-time analysis, visual pattern recognition, and trail-making assessments, the platform captures a multi-dimensional representation of a user's cognitive performance. The system architecture is designed for scalability, accuracy, and continuous real-time operation. The methodology ensures that traffic metrics are converted into meaningful performance indicators, which are then analyzed through trained AI models. Validation using diverse traffic datasets and simulation benchmarks demonstrates strong alignment with observed congestion patterns and effective signal optimization strategies. The model shows high sensitivity for detecting emerging congestion and strong specificity in differentiating free-flowing intersections from those requiring intervention. Simulation results further confirm the reliability of congestion classification and the consistency of traffic pattern detection across repeated intervals. Because the system is fully software-based and leverages existing camera infrastructure, it can be deployed across urban intersections without additional hardware costs or specialized installation. This makes it particularly valuable for city-wide traffic management, peak-hour optimization, and areas with limited traffic monitoring resources. While the current model provides effective real-time control, future enhancements can include deeper neural network architectures, multi-intersection coordination, integration with predictive traffic simulations, and cloud-based analytics for large-scale urban deployments. Overall, this AI-based system represents a significant step toward intelligent, adaptive, and scalable traffic management. It supports smoother traffic flow, reduces congestion, and contributes to a more proactive and efficient approach to urban mobility.

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