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VISIONFLOW : AN INTELLIGENT TRAFFIC CONTROL SYSTEM

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Abstract: Because fixed-time and count-based signal control systems have limits, urban traffic congestion continues to be a major problem. VisionFlow, an AI-based intelligent traffic management system that combines adaptive decision-making and real-time computer vision for effective signal optimization, is presented in this study. Using live camera feeds and upstream photos, the system uses the YOLOv8 deep learning model to identify and categorize automobiles. In order to dynamically distribute green signal durations, VisionFlow presents a dual-algorithm architecture that combines an Adaptive Waiting Time (AWT) algorithm with Vehicle Actuated Control (VAC). In contrast to conventional methods, the AWT algorithm ensures equity and less traffic by prioritizing lanes based on both vehicle count and cumulative waiting time. Additionally, the system includes anti-starvation measures, upstream surge detection, and emergency vehicle management. A. Traffic conditions, signal phases, urgency heatmaps, and performance data are all displayed on a real-time interactive dashboard. When compared to VAC, experimental findings show that the suggested AWT technique greatly lowers average waiting time and increases traffic flow efficiency. For next-generation smart city traffic control systems, VisionFlow provides a workable and scalable option.

Keywords: YOLOv8, computer vision, intelligent traffic management, adaptive waiting time algorithm, Actuated Vehicle Control Systems for Smart Cities Optimizing Traffic Signals AI-Powered Traffic Control and Real-Time Traffic Monitoring.

I. INTRODUCTION

One of the biggest issues facing contemporary cities is traffic congestion, which is a result of rapid urbanization and the ongoing increase in the number of vehicles. The majority of conventional traffic signal control systems rely on simple vehicle-count-based methods or fixed-time schedules, which are frequently unable to adjust to changing traffic conditions. Particularly during peak hours and unforeseen congestion situations, these methods often lead to longer wait times, ineffective signal utilization, needless fuel consumption, and higher emission levels.

In recent years, intelligent traffic management systems have drawn a lot of attention as a solution to these constraints. These systems produce intelligent and flexible traffic control decisions by utilizing developments in artificial intelligence, computer vision, and real-time data processing. Because they can immediately extract rich traffic information from visual inputs without requiring costly physical sensors installed in roads, computer vision-based techniques have shown to be effective among them.

You Only Look Once (YOLO) and other deep learning-based object identification models have shown excellent accuracy and real-time performance in vehicle detection and classification tasks. It is feasible to continuously monitor traffic flow, spot patterns of congestion, and react quickly to changing circumstances by incorporating such models into traffic control systems. However, a lot of current AI-based traffic systems still base their signal timing decisions mostly on the number of vehicles, which could result in unjust lane prioritizing and starvation of lanes with low traffic but long wait times.

This research presents VisionFlow, an AI-driven intelligent traffic control system that addresses these issues by introducing a dual-algorithm framework that combines a revolutionary Adaptive Waiting Time (AWT) algorithm with conventional Vehicle Actuated Control (VAC). AWT improves decision-making by taking into account both vehicle

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count and accumulated waiting time, which ensures fairness and minimizes excessive delays, whereas VAC bases signal timing just on vehicle count.

VisionFlow uses upstream photos and live camera feeds to detect vehicles in real time using the YOLOv8 deep learning model. The system determines the average and maximum waiting times for each lane by tracking every detected vehicle using a queue-based waiting time method. The system dynamically determines the ideal green signal durations based on these criteria. To successfully manage crucial traffic situations, VisionFlow also incorporates specific logic for emergency vehicle prioritization, upstream congestion surge monitoring, and anti-starvation control.

Traffic conditions, signal phases, urgency heatmaps, and performance data comparing VAC and AWT algorithms are all displayed in real-time on an interactive dashboard. This enhances system transparency and makes it possible for traffic authorities to effectively monitor and evaluate traffic behavior. When compared to traditional count-based systems, experimental findings show that the Adaptive Waiting Time methodology greatly improves average waiting time, traffic flow efficiency, and fairness.

For next-generation smart city traffic management, the suggested VisionFlow system offers a scalable, economical, and clever solution. VisionFlow bridges the gap between conventional traffic management systems and contemporary AI-enabled urban infrastructure by combining computer vision, adaptive algorithms, and real-time visualization.

II. LITERATURE SURVEY

[1] Fixed-time signal scheduling was the mainstay of early traffic signal control systems, which have been the subject of intensive research for several decades. These conventional methods frequently result in ineffective signal utilization during peak and off-peak hours because they employ predetermined timing plans based on previous traffic data and are unable to adjust to real-time traffic variances. Fixed-time solutions are easy to install, but they are ineffective when dealing with dynamic congestion and unforeseen traffic occurrences.

[2] By modifying signal durations in response to real-time vehicle presence sensed by sensors such inductive loops and infrared detectors, Vehicle Actuated Control (VAC) systems were developed to get around the limitations of fixed-time control. Although VAC enhances traffic flow in comparison to static techniques, it does not take into account the length of time that vehicles have been waiting; instead, it primarily depends on vehicle count or occupancy. Because of this, VAC systems may result in unfair priority, where lanes with fewer cars have long wait times and starving problems.

[3] Adaptive traffic signal control systems have been made possible by recent developments in machine learning and artificial intelligence. In order to optimize signal timings by learning traffic patterns over time, reinforcement learning-based techniques have been extensively investigated. Despite their encouraging outcomes, these approaches are challenging to implement in actual urban settings since they frequently call for substantial training, big datasets, and intricate state representations. Additionally, real-time applications face difficulties due to their high computing requirements and lack of transparency.

[4] An efficient substitute for conventional sensor-based systems is computer vision-based traffic monitoring. Vehicle identification, classification, and traffic density prediction have been effectively implemented using deep learning models like Convolutional Neural Networks (CNNs) and object detection frameworks like YOLO and Faster R-CNN. Without requiring invasive road infrastructure, vision-based methods provide flexibility, affordability, and the capacity to extract rich contextual information from camera feeds.

[5] In order to dynamically modify green times based on current vehicle counts, a number of studies have combined YOLO-based vehicle recognition with traffic signal control. Even while these systems show increased accuracy and responsiveness, the majority of them still rely mostly on vehicle density or count when making decisions. Their capacity to maintain equity across all lanes is hampered by the lack of waiting-time consideration, particularly in situations where traffic distribution is uneven.

[6] There aren't many studies that try to optimize traffic signals using waiting time or delay-based measures. Nevertheless, these methods lack thorough real-time implementation with visualization and performance comparison, and they are frequently restricted to simulation contexts. Furthermore, managing emergency vehicles, upstream congestion spikes, and famine prevention in an integrated manner have received less attention.

[7] The suggested VisionFlow system, in contrast to current approaches, presents a dual-algorithm framework that combines an Adaptive Waiting Time algorithm with conventional Vehicle Actuated Control. VisionFlow overcomes

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important shortcomings seen in earlier studies by combining real-time computer vision, individual vehicle waiting-time tracking, emergency handling, and upstream surge detection. The goal of this strategy is to create a fair, effective, and balanced traffic control system that is appropriate for real-world smart city implementations.

[8] "Computer Vision and Deep Learning for Adaptive Traffic Signal Control" In this research, a deep learning-based vision-based traffic control system for vehicle detection and density estimates is proposed. Signal timing is modified in accordance with the traffic volume determined by processing camera feeds. Although the system is more responsive than fixed-time controllers, it does not take waiting-time fairness across lanes into account and instead concentrates on vehicle count.

[9] "Yolo-Based Real-Time Signal Optimization and Traffic Monitoring" In order to recognize and categorize cars at crossings in real time, the authors use the YOLO object detection approach. Green signal durations are dynamically assigned, and traffic density is calculated based on detection findings. Although the method lacks methods for famine avoidance and emergency vehicle prioritization, experimental results demonstrate good detection accuracy and decreased congestion.

[10] "Intelligent Traffic Signal Control Using Reinforcement Learning" In order to optimize traffic signals through interaction with simulated traffic environments, this work investigates reinforcement learning techniques. Although the approach adapts effectively to shifting traffic patterns, its practical application in real-time urban crossings is limited by the high computing and training costs.

[11] "Traffic Density Estimation for Smart Cities Using Vision" A framework for estimating traffic density using convolutional neural networks and camera-based inputs is presented in this paper. It emphasizes how vision-based systems are superior to conventional sensor-based techniques. While precise density estimate is accomplished, adaptive green-time allocation and real-time signal choice logic are not included in the study.

[12] "Intelligent Transportation: Emergency Vehicle Priority Systems" This project focuses on employing sensor and communication-based methods to prioritize emergency vehicles, such ambulances. Green signals are continuously provided throughout the emergency route through the use of signal preemption. The method does not address general traffic optimization or fairness among regular traffic lanes, despite its effectiveness in handling emergencies.

[13] "Waiting Time Minimization for Traffic Signal Optimization" In order to reduce total waiting times at crossings, the authors present a delay-based traffic control technique. When compared to density-only methods, simulation results demonstrate increased fairness. However, the study does not incorporate real-time vision-based vehicle identification and is restricted to simulated situations.

[14] "AI and IoT-Based Smart Traffic Management" In order to monitor traffic flow and optimize signal timing, this article integrates IoT sensors with AI-based analytics. Compared to camera-based systems, the reliance on physical sensors raises deployment costs and maintenance complexity even though it works well in controlled situations.

[15] "Comparison of Adaptive and Fixed-Time Traffic Signal Control" Under various traffic conditions, the study contrasts adaptive traffic signal systems with conventional fixed-time controllers. The findings show that adaptive systems perform noticeably better than fixed-time methods. Nevertheless, the adaptive techniques under consideration do not take cumulative waiting time into account while making decisions; instead, they mainly depend on traffic volume.

III. METHODOLOGY

The suggested VisionFlow system uses computer vision and real-time decision-making algorithms in an organized and modular manner to provide intelligent and adaptive traffic signal control. To maximize traffic flow at a four-lane crossroads, the entire workflow combines vehicle identification, waiting-time analysis, dual-algorithm processing, and real-time display.

[1] Data Gathering

VisionFlow uses a variety of input sources to gather traffic data. While uploaded photos are used to assess upstream congestion for the east lane, a live camera feed is used to monitor the north lane. User-controlled inputs are used to mimic traffic parameters for the south and west lanes, such as vehicle count and speed. This hybrid approach to data collection enables both controlled and real-time system testing.

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[2] Preparation
To guarantee consistent processing, all uploaded photos and recorded frames are normalized and scaled to a consistent resolution. To increase detection accuracy, frame stabilization and noise reduction techniques are used. To remove unnecessary objects from analysis, only vehicle-related classes—cars, buses, trucks, and motorcycles—are taken into account for additional processing.

[3] Detection and Categorization of Vehicles
For real-time vehicle recognition and categorization, the YOLOv8 deep learning model is utilized. YOLOv8 is appropriate for real-time traffic monitoring because to its excellent accuracy and low latency. In order to dynamically update traffic density, bounding box information is retrieved and detected vehicles are tallied lane-wise.

[4] Tracking Waiting Times and Queue Formation
Every identified vehicle is added to a lane-specific queue and represented as an object. Every one second, the system updates each vehicle's waiting time. Every lane's average and maximum waiting times are computed, giving a more accurate assessment of congestion than just counting the number of vehicles.

[5] Processing with Two Algorithms
A dual-algorithm framework is implemented by VisionFlow:
Vehicle Actuated Control (VAC): This baseline method uses only the number of vehicles to determine the duration of the green signal.
In order to ensure fairness and lessen lane starvation, Adaptive Waiting Time (AWT) assigns priority using a weighted mix of vehicle count and accumulated waiting time.

[6] Signal Design and Implementation
The system dynamically determines the duration of the green signal and chooses the lane with the highest priority based on algorithm output. To ensure safety, signal transitions adhere to a specified Green-Yellow-Red sequence. During the green phase, vehicles are removed at reasonable intervals, and anti-starvation logic makes sure that no lane is overlooked for prolonged cycles.

[7] Integration of Dashboards and Visualization
Lane-wise car counts, waiting durations, urgency heatmaps, signal timings, and algorithm status are all shown on a real-time interactive dashboard. Additionally, the display offers a comparison of VAC and AWT performance, making efficiency gains easy to see.

[8] Evaluation of Performance
Metrics like average waiting time, number of cars cleared, emergency activations, system efficiency, and cycle count are used to assess system performance. The Adaptive Waiting Time algorithm outperforms conventional count-based techniques, as shown by comparative study.

IV. IMPLEMENTATION

The VisionFlow system combines computer vision, adaptive algorithms, and interactive visualization into a modular, real-time intelligent traffic control platform. Reliability, scalability, and real-time reactivity to changing traffic conditions are the main goals of the system.

Python is the main programming language used in the system's development. The Flask framework is employed in the development of the backend to manage real-time data processing and system control, and Socket.IO is utilized for bidirectional communication between the frontend and the backend. YOLOv8 is the deep learning model used for vehicle recognition and classification, while OpenCV is utilized for video frame collection and image preprocessing. To provide an interactive and user-friendly interface, the frontend dashboard is created utilizing HTML, Tailwind CSS, and JavaScript.

The YOLOv8 model is used by the vehicle detection module to process submitted photos and real-time camera feeds. Vehicles are recognized and categorized into predetermined groups, such as cars, buses, trucks, and motorcycles, after each frame is sent through the detection pipeline. Lane-wise vehicle counts are updated in real time based on the detection results. Because of its low latency and lightweight design, YOLOv8 can be deployed continuously in real time.
Lane-specific queues created by effective data structures are used to manage detected vehicles. Every car is tracked separately and given a unique identification. The system can accurately calculate the average and maximum waiting times

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for each lane because waiting time is updated at regular intervals of one second. For low-density lanes, this fine-grained tracking allows for equitable priority and avoids lengthy delays.

Two traffic control algorithms are combined into a single decision framework by VisionFlow. The Vehicle Actuated Control (VAC) method provides a baseline for comparison by calculating the duration of the green signal based only on the current number of vehicles. This reasoning is expanded upon by the Adaptive Waiting Time (AWT) algorithm, which uses adaptive weighting to combine vehicle count and accumulated waiting time. The algorithmic flow incorporates upstream surge circumstances, congestion thresholds, and emergency vehicle recognition as high-priority overrides.

To provide safe lane changes, signal execution adheres to the normal Green-Yellow-Red sequence. Timers are dynamically modified according to the results of the chosen algorithm. In order to replicate actual traffic flow, vehicles are cleared at reasonable intervals during the green phase. No lane is left unattended over several signal cycles according to anti-starvation logic.

Traffic conditions, such as vehicle counts, signal timers, waiting-time heatmaps, and active algorithm status, are shown on a real-time dashboard. Additionally, the dashboard offers comparative figures like the number of vehicles cleared by the VAC and AWT algorithms and the average waiting time. This graphic helps with performance analysis and improves system transparency.

The system is evaluated in a variety of traffic scenarios, such as upstream surge conditions, emergency vehicle presence, low traffic, and peak congestion. While real-time video feeds verify practical performance, simulation controls enable controlled testing. Easy updates and future integration with the city's transportation infrastructure are made possible by the modular architecture.

V. RESULTS AND DISCUSSIONS

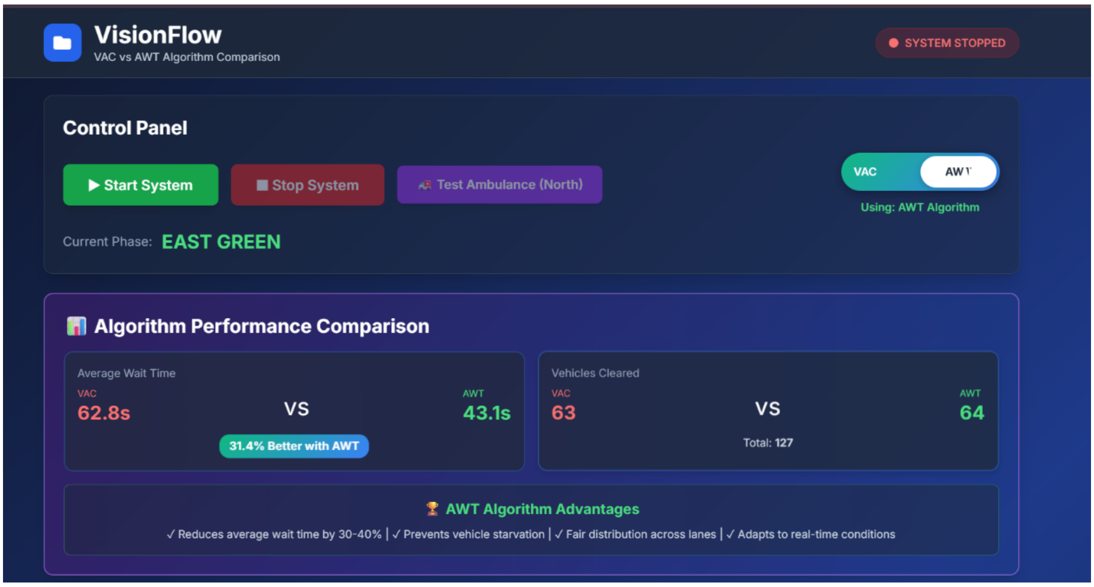

Figure 5.1: The average waiting time and cars cleared are highlighted in this chart, which compares the performance of the VAC and AWT algorithms. According to the findings, the AWT algorithm improves efficiency and fairness by reducing typical waiting times by roughly 30–40%.

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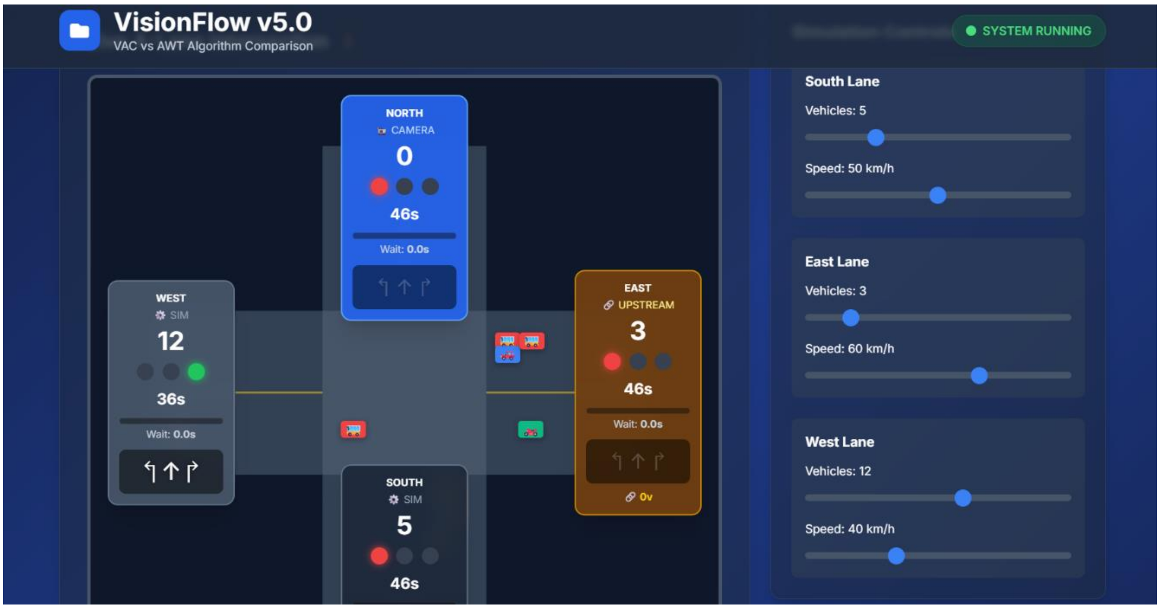

Figure 5.2 : In addition to simulation controls, this interface displays real-time signal conditions, vehicle counts, and timers for each of the four lanes. It shows how VisionFlow dynamically modifies signal phases according to algorithm choice and traffic conditions.

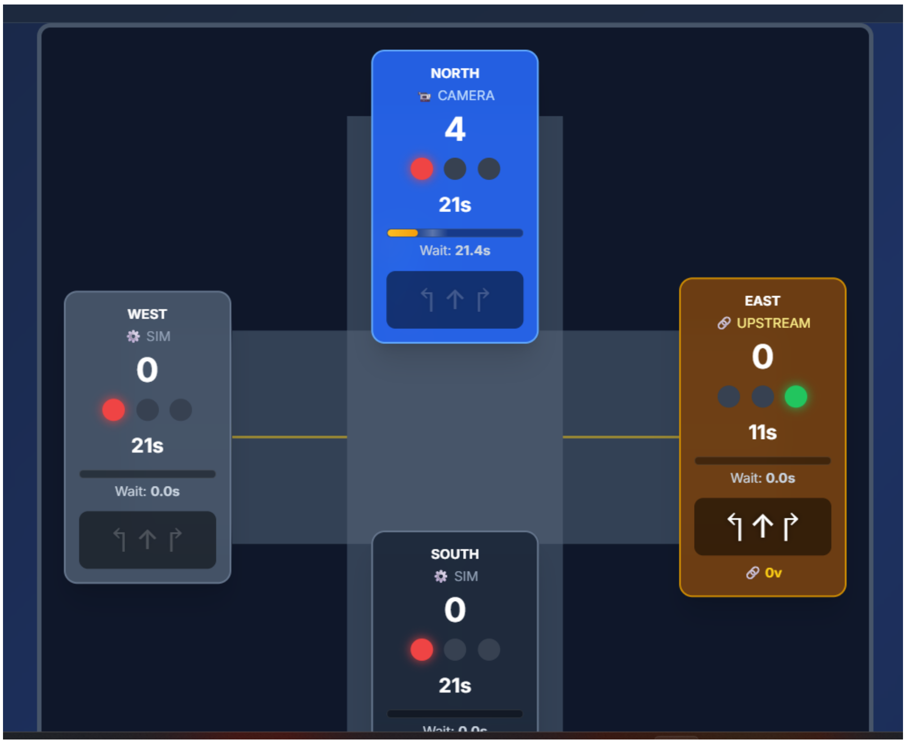

Figure 5.3 : This graphic shows how waiting-time awareness drives adaptive signal switching, giving priority to lanes with greater cumulative delays. The wait-time bars that are shown attest to the AWT algorithm's ability to avoid lane hunger.

VI. APPLICATIONS

Smart City Traffic Management:
VisionFlow can be used at urban junctions to dynamically control traffic flow and instantly lessen congestion.

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Adaptive Signal Control Systems:
AI-driven adaptive traffic signal optimization takes the place of count-based and fixed-time controllers.

Emergency Vehicle Priority Management:
VisionFlow uses intelligent signal preemption to guarantee quicker and safer passage for emergency vehicles including ambulances.

Urban Traffic Monitoring and Analysis:
Traffic authorities can track patterns of congestion and system performance with the help of real-time dashboards.

Simulation and Traffic Research:
The platform can be utilized as a simulation tool for researching traffic behavior and assessing traffic control systems.

Future Intelligent Transportation Systems (ITS):
VisionFlow provides a scalable framework for incorporating real-time analytics, computer vision, and artificial intelligence into intelligent transportation networks.

VII. FUTURE SCOPE

While the suggested VisionFlow system offers a solid basis for intelligent traffic signal automation, a number of improvements could increase its efficacy and scalability. Integrating real-time GPS data from connected cars and public transportation systems is one important extension. This would enable predictive signal control instead of just reactive decision-making by improving the system's ability to estimate traffic density and vehicle arrival patterns.

In order to improve traffic flow at a corridor or citywide level, VisionFlow can potentially be extended to provide multi-intersection coordination, in which traffic signals interact with nearby intersections. Coordination like this can enhance overall travel time and drastically lessen congestion spillover. By enabling direct contact between vehicles and traffic controllers, vehicle-to-infrastructure (V2I) connectivity will further improve system responsiveness.

To develop the best traffic policies over time, future iterations of the system might make use of sophisticated machine learning and reinforcement learning models. Long-term traffic trends, special occasions, and seasonal fluctuations in traffic might all be accommodated by these models. Furthermore, incorporating weather and road condition data might help modify signal timings in unfavorable circumstances, enhancing traffic safety.

From a deployment standpoint, VisionFlow can be incorporated into cloud-based systems for extensive analytics, data storage, and monitoring. Real-time traffic updates and route recommendations can be given to commuters and traffic authorities using mobile and web-based applications. Additionally, increasing the computer vision module's capacity to handle numerous video feeds and higher-resolution inputs would boost system resilience and detection accuracy.

All things considered, these improvements have the potential to turn VisionFlow into a complete, intelligent transportation system for the entire city that promotes sustainable mobility, less traffic, and better urban traffic control.

VIII. CONCLUSION

In order to optimize traffic signal operations at urban intersections, this study introduced VisionFlow, an AI-based intelligent traffic control system that combines adaptive decision-making algorithms with real-time computer vision. The system continuously analyzes traffic conditions and precisely calculates lane-wise congestion and waiting times by using the YOLOv8 deep learning model for vehicle identification and classification.

The suggested dual-algorithm framework allows for equitable and effective signal distribution by combining an Adaptive Waiting Time (AWT) algorithm with conventional Vehicle Actuated Control (VAC). When compared to traditional count-based methods, experimental findings show that the AWT algorithm dramatically lowers average waiting time, increases vehicle throughput, and avoids lane hunger. The system's resilience in crucial traffic situations is further improved with the addition of emergency vehicle prioritization, upstream surge detection, and anti-starvation logic.

Through the visualization of signal statuses, congestion levels, and performance parameters, the real-time interactive dashboard offers transparency and efficient monitoring. All things considered, VisionFlow provides a scalable, affordable, and useful solution for traffic control in next-generation smart cities. The findings demonstrate that urban

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mobility and traffic efficiency can be greatly enhanced by combining computer vision with adaptive traffic control techniques.

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