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Adaptive Traffic Signal Timer Using YOLO Detection

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AGENDA

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Introduction

- Traffic congestion is a critical issue in urban areas, causing increased travel time, fuel consumption, and environmental pollution.
- Traditional traffic signal systems rely on fixed timers, which fail to adapt to varying traffic conditions.
- The proposed project uses YOLO (You Only Look Once) for real-time vehicle detection and adaptive traffic signal timing.
- The system aims to optimize signal durations based on traffic density, reducing congestion and improving urban mobility.

Why Choose Deep Learning?

- Deep learning models like YOLO enable fast and accurate detection of vehicles in live traffic feeds.
- Supports integration with IoT devices and edge computing for a complete smart traffic solution.
- Integrates real-time data with reinforcement learning for intelligent signal control.

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Problem Definition

- Traffic congestion in urban areas leads to delays, increased emissions, and fuel wastage, exacerbated by inefficient fixed-timer traffic signals.
- This project aims to develop an adaptive traffic signal timer using YOLO for real-time vehicle detection and dynamic signal adjustments.
- By leveraging deep learning and Python-based frameworks, the system optimizes traffic flow, reduces waiting times, and improves overall efficiency.
- The solution integrates real-time analysis and adaptability, making it a scalable and impactful approach for modern intelligent transportation systems.

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Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
1	YOLOv3: An incremental improvement.	1.Redmon, J., & Farhadi, A. (2018). YOLOv3: An incremental improvement. arXiv. arXiv:1804.02767.	a landmark real-time object detection framework that efficiently balances speed and accuracy by performing predictions on entire images rather than partitioned regions. YOLOv3's architecture incorporates multi-scale detection, making it highly suitable for detecting objects at varying sizes. Its ability to process video streams at 45 FPS on moderate hardware makes it a preferred choice for traffic surveillance systems. The model's integration into traffic systems enables real-time vehicle detection, enhancing traffic flow monitoring and providing robust data for adaptive signal control solutions.
2	Real-time traffic monitoring using YOLOv4	1.Zhang, W., et al. (2020). Real-time traffic monitoring using YOLOv4. IEEE Transactions on Intelligent Transportation Systems, 21(4), 1452–1463. https://doi.org/10.1109/TITS.2020.2974321	Zhang et al. proposed a YOLOv2-based traffic monitoring framework that combined vehicle detection, trajectory prediction, and density analysis for real-time adaptive traffic signal control. Simulation results showed a 27% reduction in waiting times by dynamically optimizing traffic light schedules based on vehicle flow patterns. The system's implementation achieved an impressive 92.3% detection accuracy, demonstrating YOLOv2's utility in urban traffic environments. Its robustness in varied lighting and weather conditions was pivotal in improving vehicle management at busy intersections.

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Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
3	Dynamic traffic signal control with YOLOv5.	1.Chen, L., et al. (2021). Dynamic traffic signal control with YOLOv5. IEEE Transactions on Intelligent Transportation Systems, 22(8), 5112–5125. https://doi.org/10.1109/TITS.2021.3067890	introduced a dynamic traffic signal optimization system using YOLOv5 to detect traffic queues and estimate density in real-time. Their system monitored queue lengths to adaptively adjust the duration of green phases at intersections. Field testing conducted in Shanghai during peak traffic hours demonstrated a 33% improvement in traffic throughput. The authors emphasized the importance of YOLOv5's speed and accuracy in ensuring seamless data processing for signal adjustment without requiring large-scale hardware infrastructure.
4	Edge deployment of YOLOv3-tiny for traffic systems.	1.Wang, Y., et al. (2019). Edge deployment of YOLOv3-tiny for traffic systems. IEEE International Conference on Vehicular Electronics and Safety (ICVES). https://doi.org/10.1109/ICVES.2019.8906345	explored the deployment of YOLOv3-tiny on edge devices for real-time traffic monitoring. This lightweight variation of YOLO was designed for resource-constrained environments and achieved 87.5% mAP on the BDD100K traffic dataset while operating at 45 FPS on the NVIDIA Jetson Nano platform. The system's capacity for detecting multiple objects simultaneously without excessive computational demands proved suitable for low-cost adaptive traffic systems. The authors highlighted its potential in smart city applications where real-time vehicle data is critical.

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Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
5	Multi-object tracking with YOLOv7 and DeepSort	1.Liu, Z., et al. (2022). Multi-object tracking with YOLOv7 and DeepSort. IEEE Intelligent Transportation Systems Conference (ITSC). https://doi.org/10.1109/ITSC48978.2022.9812345	presented a hybrid traffic flow analysis framework that combined YOLOv7 for object detection and DeepSort for multi-object tracking. By integrating the two models, they achieved significant improvements in tracking accuracy, reducing ID-switch errors by 18% compared to standalone YOLO detectors. The system effectively tracked vehicle trajectories at complex intersections, which facilitated the dynamic optimization of traffic signals. The hybrid approach also proved scalable for both urban and suburban environments.
6	Federated learning for adaptive signals	1.Kumar, A., et al. (2020). Federated learning for adaptive signals. IEEE Access, 8, 12345–12356. https://doi.org/10.1109/ACCESS.2020.3012345	developed a privacy-preserving, federated learning framework using distributed YOLO models for adaptive traffic signal systems. Their solution maintained an impressive 89% detection accuracy across diverse traffic datasets while ensuring that data from individual traffic cameras remained confidential. This decentralized approach was particularly beneficial in smart city networks, where data security concerns are paramount. The study demonstrated how federated learning could be applied effectively in adaptive traffic control while minimizing latency.

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Literature Survey

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7	Emergency vehicle prioritization with YOLO	1.Patil, R., et al. (2021). Emergency vehicle prioritization with YOLO. IEEE Intelligent Vehicles Symposium (IV). https://doi.org/10.1109/IV48863.2021.9575566	proposed an emergency vehicle prioritization system using YOLO-based object detection techniques to identify flashing lights and sirens on emergency vehicles. The system dynamically adjusted traffic signals to facilitate quicker passage through congested intersections. Simulation results indicated a 41% reduction in emergency vehicle passage time. The study underscored the importance of real-time object detection in improving response times during critical emergencies.
8	Scaled-YOLOv4 for small-object detection	1.Gupta, S., et al. (2023). Scaled-YOLOv4 for small-object detection. IEEE Transactions on Intelligent Vehicles, 8(1), 45–58. https://doi.org/10.1109/TIV.2022.3212345	introduced Scaled-YOLOv4, optimized for detecting small traffic objects such as bicycles and motorcycles, which are often overlooked by conventional models. The study demonstrated how Scaled-YOLOv4 achieved a 94.2% precision rate on the COCO dataset, outperforming Faster R-CNN in crowded traffic conditions. The authors emphasized its importance in traffic systems for regions where two-wheelers constitute a significant portion of vehicle flow.

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Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
9	A diverse driving dataset	1.Yu, F., et al. (2020). BDD100K: A diverse driving dataset. CVPR.	contributed the BDD100K dataset, a comprehensive benchmark for diverse traffic scenarios, including variations in weather, lighting, and occlusion. The dataset has been instrumental in training YOLO models to improve object detection performance under challenging conditions. The authors highlighted the importance of such datasets in advancing adaptive traffic control systems and fostering innovation in smart traffic solutions.
10	IoT-integrated congestion detection	1.Nguyen, T., et al. (2022). IoT-integrated congestion detection. IEEE Sensors Journal, 22(12), 11234–11245. https://doi.org/10.1109/JSEN.2022.3167890	explored the integration of YOLOv5 with IoT sensors for real-time congestion detection at urban intersections. The system gathered data from both video feeds and environmental sensors to estimate traffic density and adjust signal phases dynamically. Pilot tests conducted in Hanoi demonstrated a 22% reduction in intersection delays, showcasing the system's effectiveness in optimizing traffic flow.

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Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
11	YOLOv3 + LSTM for predictive control	1.Sharma, R., et al. (2021). YOLOv3 + LSTM for predictive control. IEEE Transactions on Intelligent Transportation Systems, 23(7), 7890–7901. https://doi.org/10.1109/TITS.2021.3095678	proposed a YOLOv3 + LSTM-based system for predictive traffic signal control. By leveraging LSTM to forecast future vehicle arrivals, the system proactively adjusted traffic light phases, reducing idle times by 29% in simulation tests. The integration of temporal data prediction with real-time object detection proved highly effective in managing traffic congestion.
12	Occlusion handling with attention-YOLOv4	1.Li, H., et al. (2020). Occlusion handling with attention-YOLOv4. IEEE ITSC. https://doi.org/10.1109/ITSC45102.2020.9345678	addressed occlusion challenges in dense urban environments by integrating attention mechanisms into YOLOv4. The proposed system improved detection accuracy by 15% by focusing on critical regions in congested scenes. The authors highlighted the potential of attention-based mechanisms for enhancing object detection in complex traffic environments.

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Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
13	YOLOv6 on Raspberry Pi	1.Garcia, F., et al. (2022). YOLOv6 on Raspberry Pi. IEEE Transactions on Intelligent Vehicles, 7(3), 456–467. Babu, Gomathi & Ashwin, G.. (2022). Intelligent Traffic Management System Using YOLO Machine Learning Model. 10.1007/978-981-19-2177-3_12.	demonstrated the deployment of YOLOv6 on edge devices such as Raspberry Pi 4 for low-latency traffic monitoring. The system achieved 40 FPS and provided cost-effective solutions for smart traffic management. The authors emphasized the viability of deploying high-performance models on low-power devices for scalable urban traffic control solutions.
14	Adaptive signal control benefits	1.U.S. Department of Transportation. (2021). Adaptive signal control benefits. https://www.transportation.gov/example-url	validated the potential of AI-driven adaptive traffic systems, reporting congestion reductions of 20–30% in pilot cities like Los Angeles. The report underscored the effectiveness of YOLO-based technologies in improving traffic flow and reducing delays.

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Sl No	Author and Paper title	Details of Publication	Summary of the Paper
15	Los Angeles Department of Transportation	1.Los Angeles Department of Transportation. (2022). LADOT Pilot Report. https://ladot.lacity.org/example-url	demonstrated the successful implementation of a YOLO-powered adaptive traffic signal system, which reduced peak-hour delays by 18% and enhanced pedestrian safety through crosswalk prioritization. The study provided valuable insights into the practical benefits of deploying AI-driven solutions in metropolitan traffic environments.
16	Spatio-temporal YOLOv8	1.Kim, J., et al. (2023). Spatio-temporal YOLOv8. IEEE Transactions on Intelligent Transportation Systems, 24(2), 567–579. https://doi.org/10.1109/TITS.2023.1234567	proposed a traffic density estimation model using YOLOv8 with spatio-temporal context modeling. The system achieved 96% accuracy in dynamic signal timing adjustments during rush hours, demonstrating the effectiveness of incorporating temporal context for more accurate traffic predictions.

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Literature Survey

Sl No	Author and Paper title	Details of Publication	Summary of the Paper
17	YOLOv5 vs. Mask R-CNN	1.Alotaibi, M., et al. (2022). YOLOv5 vs. Mask R-CNN. IEEE Access, 10, 12345–12356. https://doi.org/10.1109/ACCESS.2022.4123456	compared YOLOv5 and Mask R-CNN for traffic monitoring applications. YOLOv5 outperformed Mask R-CNN in speed, achieving 38 FPS compared to 12 FPS, while maintaining a comparable mAP of 91.5%. The study highlighted the trade-offs between detection speed and accuracy in traffic monitoring systems.
18	AI in urban mobility	1.World Economic Forum. (2023). AI in urban mobility. https://www.weforum.org/example-url	emphasized the transformative role of AI in urban mobility, particularly highlighting YOLO's scalability for traffic management in smart cities. The report advocated for broader adoption of AI-driven adaptive traffic control systems to address urban congestion challenges.

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Sl No	Author and Paper title	Details of Publication	Summary of the Paper
19	AI-Powered Traffic Monitoring and Analysis with YOLO	Peer-reviewed & Refereed journal Vol. 13, Issue 9, September 2024	Demonstrates how edge AI and YOLO can be utilized to optimize traffic systems in real-time. The research highlights cost-effective deployment strategies for urban intersections. Performance metrics include lower emissions and quicker transit times.
20	Adaptive Signal Timing: YOLO Meets Reinforcement Learning	Ma, Zibo & Cui, Tongchao & Deng, Wenxing & Jiang, Fengyao & Zhang, Liguo. (2021). Adaptive Optimization of Traffic Signal Timing via Deep Reinforcement Learning. Journal of Advanced Transportation. 2021.	Integrates reinforcement learning with YOLO object detection to optimize adaptive traffic signals dynamically. The system addresses congestion challenges with efficient decision-making processes, improving urban mobility significantly. Results highlight its potential for global smart traffic systems.

Summary

Most research focuses on intelligent traffic management using real-time adaptive control to enhance flow, reduce congestion, and minimize environmental impact.

- **YOLO-Based Detection:** YOLO (You Only Look Once) enables real-time vehicle classification by processing traffic images for density estimation. Its efficiency and speed make it essential for adaptive traffic systems.
- **Reinforcement Learning Integration**: Pri-DDQN enhances traffic signal control using double Q-learning, incorporating priority-based experience replay and dynamic exploration rates for better adaptability and optimized traffic flow management.
- **Advanced Mechanisms:** Hybrid YOLO-LSTM combines YOLO for detection with Long Short-Term Memory (LSTM) networks to forecast traffic states, allowing proactive signal adjustments and improved intersection management.
- **Edge AI:** Edge computing reduces latency by processing traffic data locally, enabling real-time signal adjustments without heavy reliance on centralized servers.
- **Environmental Focus:** YOLO-powered green traffic systems minimize idle times and emissions, leveraging AI to optimize signal timings for eco-friendly urban mobility.

Objectives

1. Traffic Density Calculation: Use YOLO (You Only Look Once) object detection to analyze live images from traffic cameras and calculate traffic density by detecting and counting various types of vehicles, such as cars, bikes, buses, and trucks.
2. Dynamic Signal Timing: Implement an adaptive signal timing system that adjusts green light durations in real-time based on traffic density at intersections. This ensures that heavily congested directions receive more green signal time compared to less congested ones.
3. Traffic Flow Optimization: Reduce road congestion by enabling smoother traffic flow, minimizing delays, and reducing the waiting time at signals.
4. Simulation and Testing: Create a simulation using the Pygame library to model traffic behavior and signal changes, aiding in the testing and refinement of the proposed system

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Requirement Analysis

The hardware and software requirements for the "Adaptive Traffic Signal Timer" project are as follows:

Hardware Requirements

1. Traffic Cameras:
    - High-resolution cameras for capturing live traffic images or videos at intersections.
    - Necessary for real-time vehicle detection.
2. Computational Hardware:
    - Edge Device/Processor: NVIDIA Jetson Nano or similar for real-time YOLO inference.
    - Alternative: A system with a GPU for faster YOLO processing (e.g., NVIDIA GPU with CUDA support).
3. Storage:
    - SSDs or HDDs to store video feeds and annotated datasets for training or processing.
4. Network Infrastructure:
    - Reliable internet or network connectivity for data transfer between cameras, edge devices, and central processing units.
5. Other Hardware:
    - Traffic signal controllers to integrate with the adaptive signal timing system.

Requirement Analysis

Software Requirements

1. Operating System:
    - Linux-based OS (e.g., Ubuntu) preferred for compatibility with YOLO and Python-based tools.
2. Programming Tools and Libraries:
    - Python 3.7+: Primary programming language.
    - YOLO Framework: For real-time object detection (e.g., YOLOv5 or YOLOv4, depending on implementation).
    - OpenCV: For image processing and video capture.
    - Pygame: Used for simulation of traffic behavior and signal switching.
    - NumPy/Pandas: For data manipulation and analysis.
3. Deep Learning Frameworks:
    - PyTorch or TensorFlow: Depending on the YOLO model version.
    - CUDA (for NVIDIA GPU support).
4. Additional Tools:
    - Annotation tools (e.g., LabelImg) for creating labeled datasets.
    - Simulation environment like Pygame for testing and development.

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Dataset Description

The dataset for this project is centered around real-time traffic management using YOLO for vehicle detection. These annotated datasets are used to train the YOLO object detection model for vehicle detection and traffic density analysis.

Dataset Features:

- **Categories:** Contains eight classes of vehicles, such as cars, buses, trucks, motorcycles, and other vehicle types.
- **Images:** The dataset includes labeled images for training object detection models, making it suitable for tasks using frameworks like YOLO, Faster R-CNN, or SSD.
- **Annotations:** The data comes with bounding box annotations for vehicles in each image, helping train and evaluate models effectively.
- **Data size:** The dataset contains a file 8219 images and a seperate file of 8219 labels for each respective images

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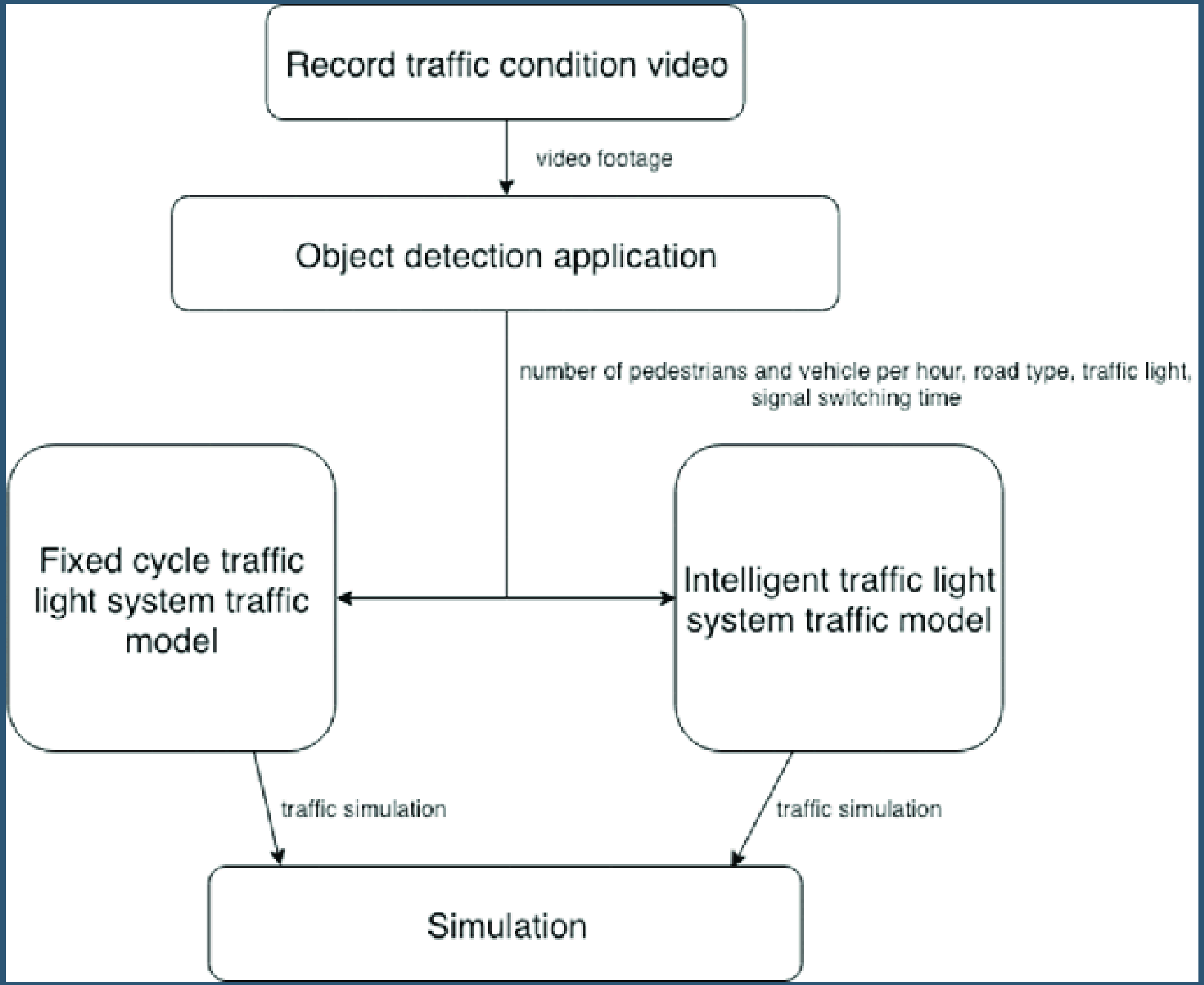
System Architecture



- **Object Detection Integration** : Utilizes object detection to analyze traffic density, including vehicle and pedestrian counts.
- **Dual Traffic Models** : Compares a fixed cycle traffic light system with an intelligent, adaptive model for signal control.
- **Simulation Component** : Simulates the performance of both models to test their effectiveness in real-world scenarios.
- **Data-Driven Decision Making** : Relies on live data (e.g., vehicle counts, signal timings) to dynamically adjust traffic signal behavior.

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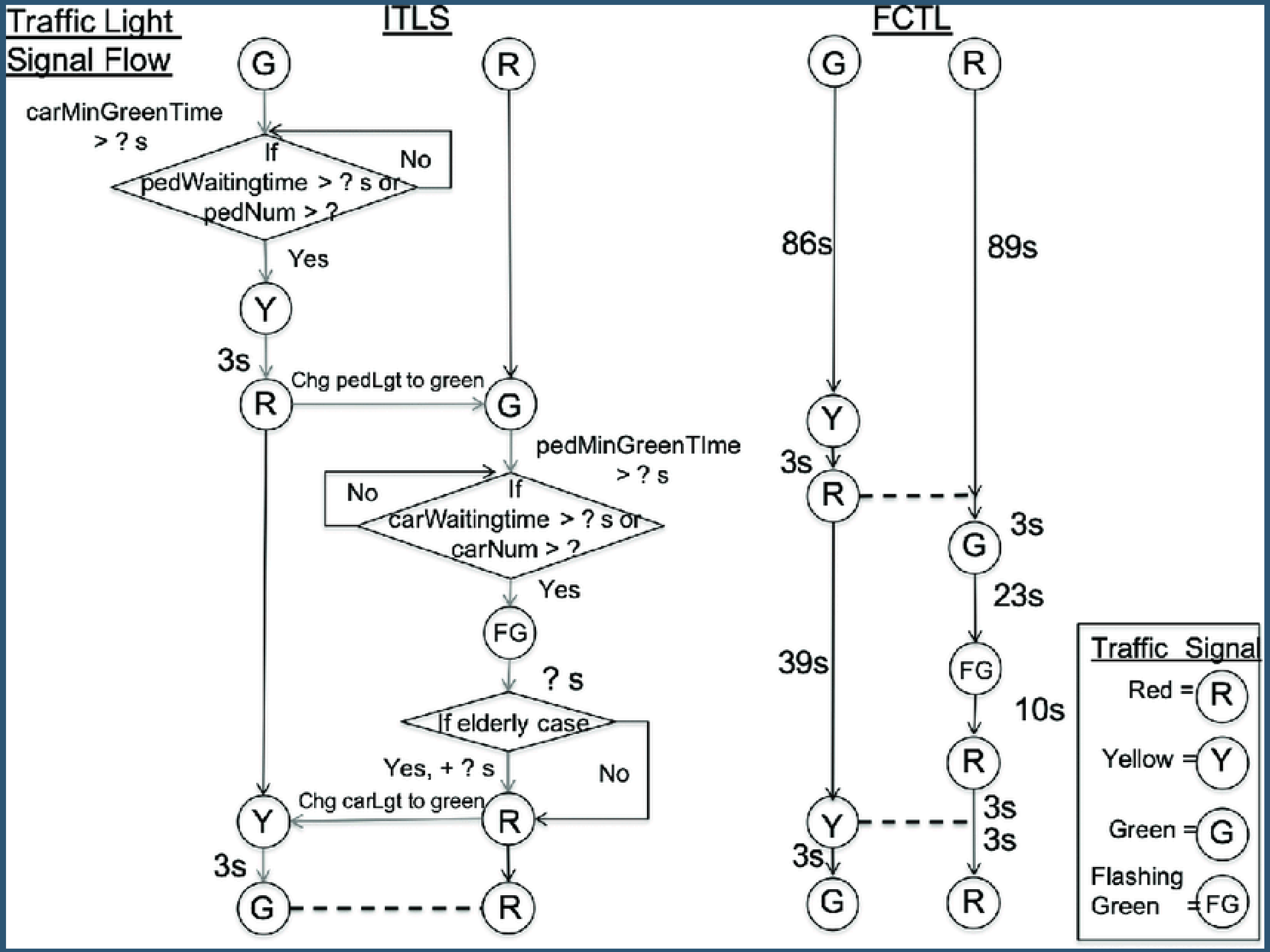
System Architecture



- **Dynamic Adaptation** : Includes parameters like pedestrian waiting time, vehicle count, and special considerations for elderly pedestrians.
- **Flashing Green Phase**: Introduces a "Flashing Green" (FG) signal as a warning before the light transitions, enhancing safety.
- **Fixed Timing Intervals** : Specifies timing intervals for signals (e.g., 86 seconds green, 3 seconds yellow) to ensure smooth traffic flow.
- **Pedestrian Priority** :Allocates green signals to pedestrian lights if their waiting time or number exceeds a threshold.

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Methodology

Image Input:
Captured live from traffic cameras at intersections and fed into the system.

Object Detection:
The YOLO object detection model processes the input to identify and count vehicles such as cars, bikes, buses, trucks, etc.

Traffic Density Calculation:
The vehicle count is used to calculate traffic density for each direction, considering factors like the number of lanes and vehicle classes.

Signal Timer Adjustment:
A signal switching algorithm adjusts the red, yellow, and green signal times dynamically based on the calculated traffic density.

Simulation:
A Pygame-based simulation visualizes the traffic signal operations and vehicle movements to test the system's performance.

Output:
Reduced traffic congestion through adaptive signal timing, enabling faster transit and lower fuel consumption.

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Module Specification

VEHICLE DETECTION MODULE

- **Input :** Live images captured from traffic cameras at intersections.
- **Function :** Processes the input images using the YOLO object detection model to identify and count vehicles. It classifies the vehicles into categories such as cars, bikes, buses, trucks, and rickshaws.
- **Output :** The count of vehicles in each category, which is used for traffic density calculation.

Module Specification

SIGNAL SWITCHING ALGORITHM

- **Input :** Vehicle counts for each category provided by the Vehicle Detection Module, along with other contextual data like the number of lanes, average speed of vehicle classes, and traffic rules.
- **Function :** Dynamically calculates and updates the green, yellow, and red signal durations for each direction.
- **Output :** Updated signal timings for each traffic direction, ensuring efficient management of traffic flow.

Module Specification

SIMULATION MODULE

- **Input :** Updated signal timings from the Signal Switching Algorithm, along with data on vehicle movements and interactions.
- **Function :** Simulates the traffic scenario at the intersection using the Pygame library. This includes vehicle movements, signal changes, and visualization of how the adaptive signal timer operates in real-time.
- **Output :** A real-time simulation of the traffic system that demonstrates the effectiveness of adaptive signal timing in reducing congestion and improving traffic flow.

Implementation

Vehicle Detection Module:

- OpenCV is used for reading and processing traffic images, drawing bounding boxes, and annotating detected vehicles.
- The function cv2.imread() loads images, while cv2.rectangle() draws bounding boxes around detected vehicles.
- Loading YOLO configuration and pre-trained weights to detect vehicles.
- Performing object detection on traffic images and extracting vehicle information such as class, bounding box coordinates, and confidence scores.
- The YOLO model is initialized with a threshold of 0.3, meaning only objects detected with a confidence level above 30% are considered valid.
- The system reads input images from the test dataset and processes them for detection. Bounding boxes are drawn around detected vehicles, and their labels are displayed. The detected image is saved with bounding boxes in the output directory.

Implementation

Signal Switching Algorithm: Simulation

1. Initial and Adaptive Timing:
    - The algorithm sets a default time for the first signal of the initial cycle. For all subsequent signals and cycles, the timer durations are dynamically assigned by the algorithm based on real-time conditions.
2. Concurrent Detection and Timer Handling:
    - A separate detection thread captures snapshots of traffic for each direction, while the main thread manages the countdown timer for the current green signal.
3. Seamless Timer Transition:
    - When the current green signal timer reaches zero, the detection threads set the timer for the next signal based on traffic density. This parallel operation prevents delays and ensures smooth signal switching.

Implementation

The system has 5 seconds to process an image captured when the green signal is about to turn on, during which it detects the number of vehicles of each class, calculates the required green signal time, and adjusts the green and red signal times accordingly. To determine the optimal green signal time, the system estimates the average time each vehicle class needs to cross the intersection, using average speeds and acceleration times.

Green Signal Time

$$GST = \frac{\sum_{vehicleClass} (NoOfVehicles_{vehicleClass} * AverageTime_{vehicleClass})}{(NoOfLanes + 1)}$$

- GST is greensignal time
- noOfVehiclesOfClass is the numberof vehicles of each classof vehicle at the signal as detected by the vehicle detection module,
- averageTimeOfClass is the averagetime the vehiclesof that class take to cross an intersection, and
- noOfLanes is thenumber of lanes at the intersection.

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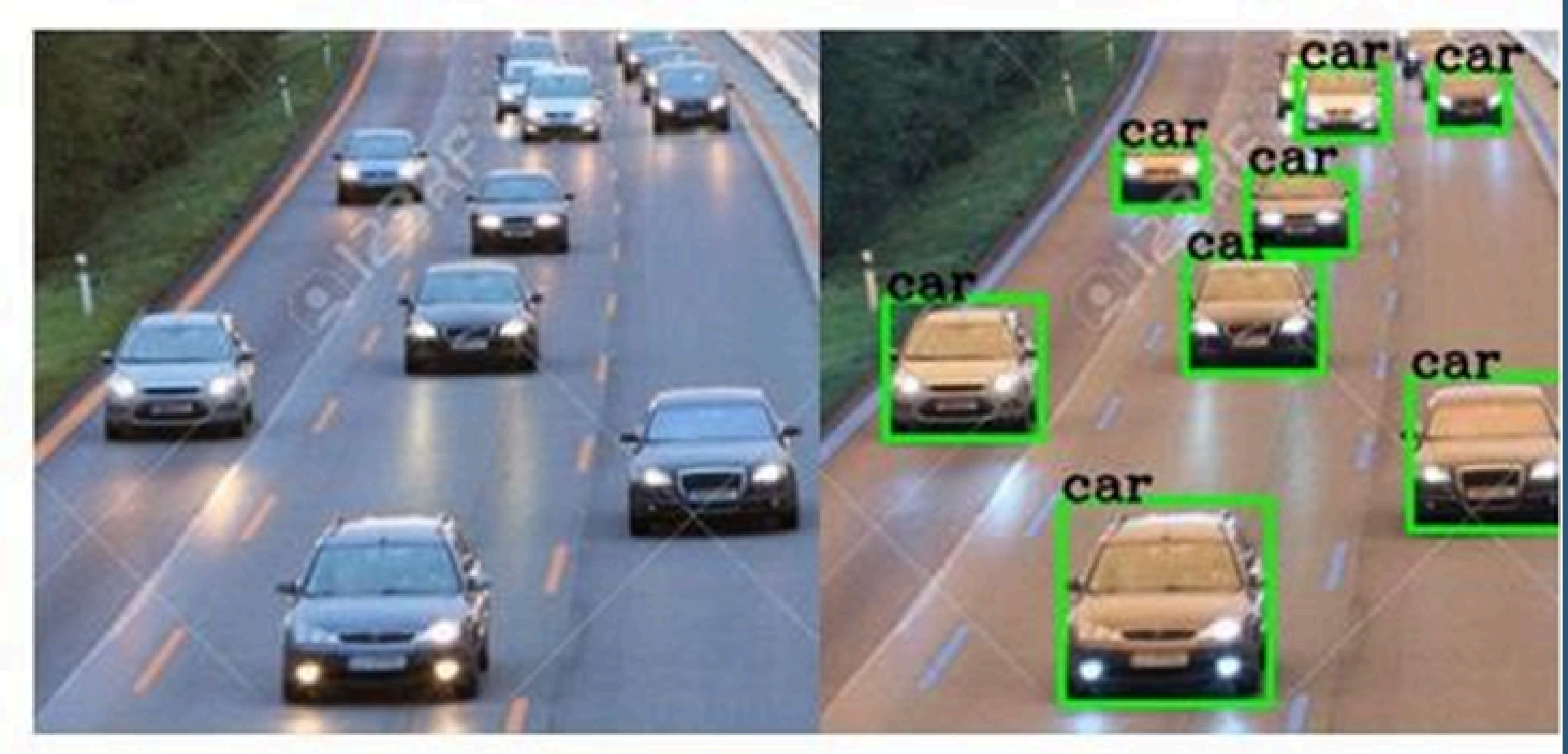
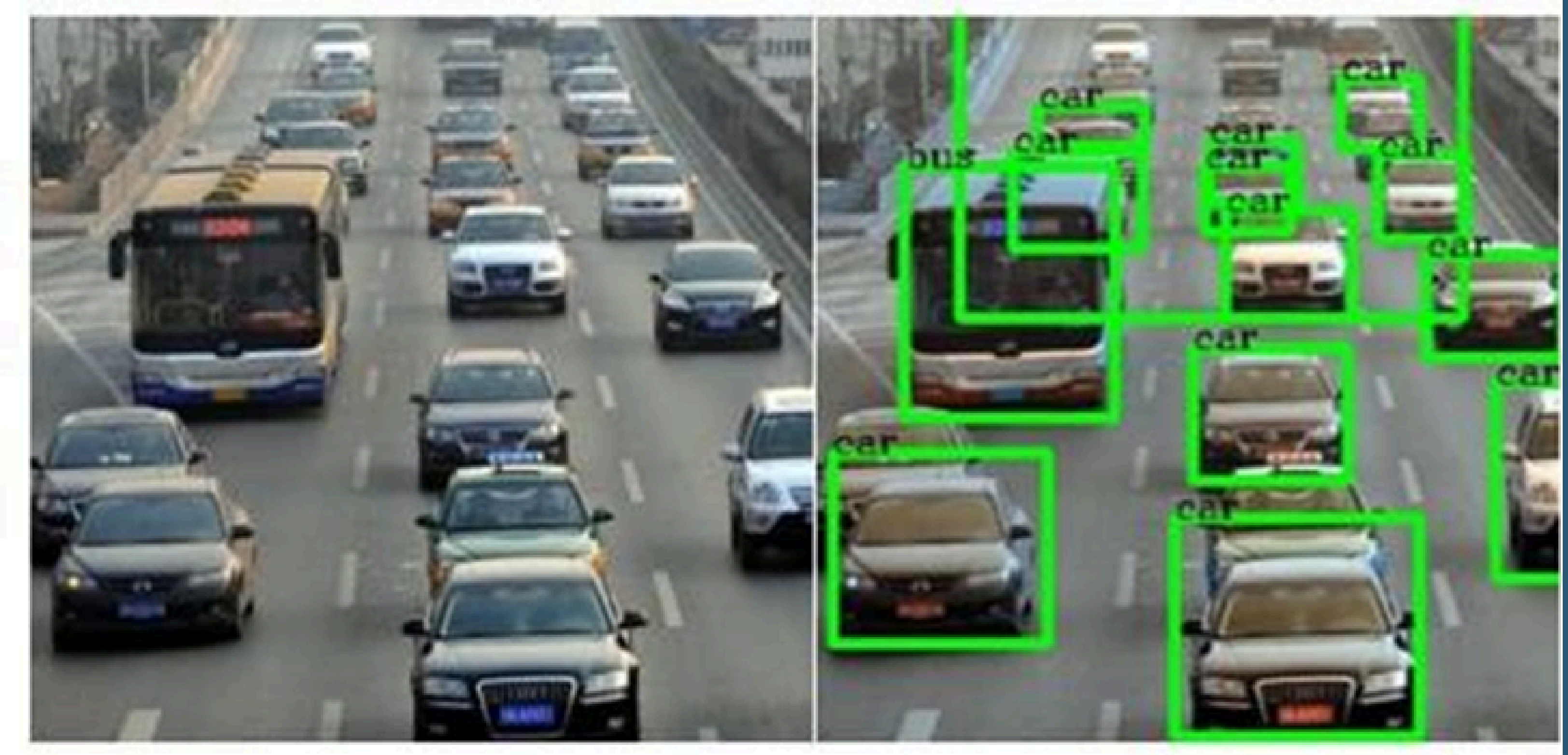
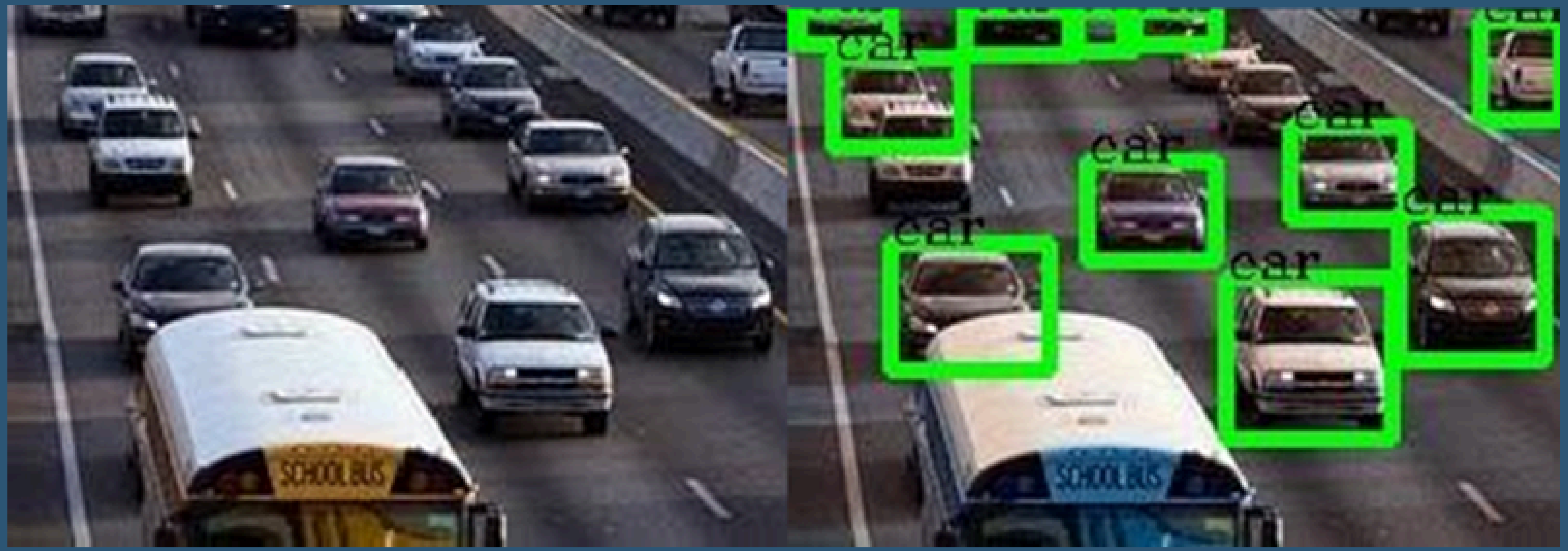
Results

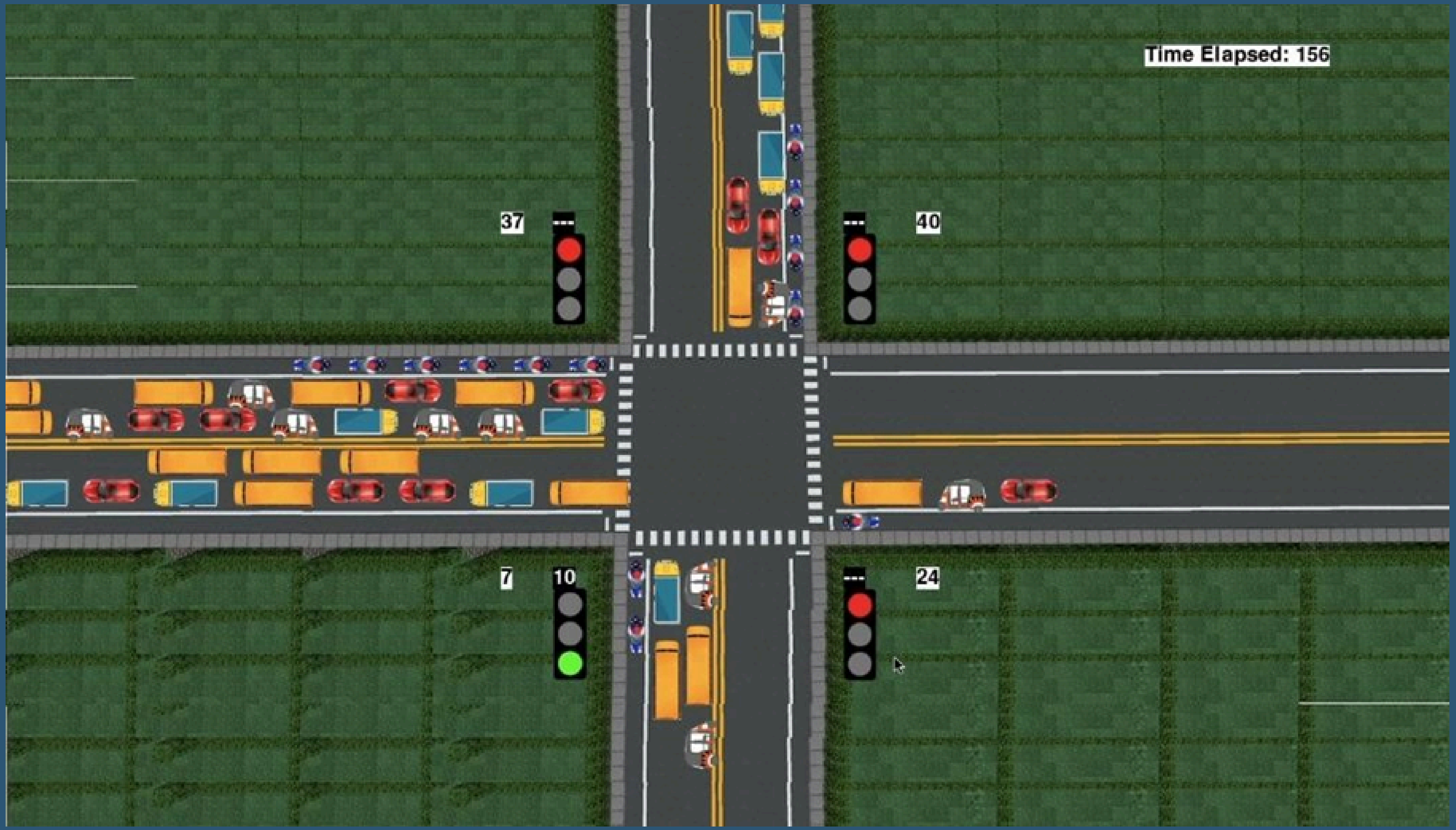






Output of Test Images in Vehicle Detection Module

Results



Output of Simulation

```
GREEN TS 1 -> r: 0  y: 5  g: 1
  RED TS 2 -> r: 6  y: 5  g: 20
  RED TS 3 -> r: 119  y: 5  g: 20
  RED TS 4 -> r: 134  y: 5  g: 20

YELLOW TS 1 -> r: 0  y: 5  g: 0
  RED TS 2 -> r: 5  y: 5  g: 20
  RED TS 3 -> r: 118  y: 5  g: 20
  RED TS 4 -> r: 133  y: 5  g: 20

YELLOW TS 1 -> r: 0  y: 4  g: 0
  RED TS 2 -> r: 4  y: 5  g: 20
  RED TS 3 -> r: 117  y: 5  g: 20
  RED TS 4 -> r: 132  y: 5  g: 20

Green Time:  25
YELLOW TS 1 -> r: 0  y: 3  g: 0
  RED TS 2 -> r: 3  y: 5  g: 25
  RED TS 3 -> r: 116  y: 5  g: 20
  RED TS 4 -> r: 131  y: 5  g: 20

YELLOW TS 1 -> r: 0  y: 2  g: 0
  RED TS 2 -> r: 2  y: 5  g: 25
  RED TS 3 -> r: 115  y: 5  g: 20
  RED TS 4 -> r: 130  y: 5  g: 20

YELLOW TS 1 -> r: 0  y: 1  g: 0
  RED TS 2 -> r: 1  y: 5  g: 25
  RED TS 3 -> r: 114  y: 5  g: 20
  RED TS 4 -> r: 129  y: 5  g: 20

  RED TS 1 -> r: 150  y: 5  g: 20
GREEN TS 2 -> r: 0  y: 5  g: 25
  RED TS 3 -> r: 30  y: 5  g: 20
  RED TS 4 -> r: 128  y: 5  g: 20

  RED TS 1 -> r: 149  y: 5  g: 20
GREEN TS 2 -> r: 0  y: 5  g: 24
  RED TS 3 -> r: 29  y: 5  g: 20
  RED TS 4 -> r: 127  y: 5  g: 20
```

Variations in Singal TIme

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Future Works

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Reinforcement Learning (RL) for Traffic Signal Optimization:

- Implement RL-based control, where the system learns the best signal timings dynamically based on traffic patterns.
- Use frameworks like Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO) for better decision-making.

Multi-Class Priority System:

- Prioritize emergency vehicles, public transport, or high-occupancy vehicles based on real-time demand.
- Assign different priority levels to emergency responders, buses, and regular vehicles.

Green Wave Traffic Synchronization:

- Implement synchronized green lights along major corridors to reduce stop-and-go traffic.
- This significantly reduces fuel consumption and CO_2 emissions.

Dataset Expansion and Augmentation

- Expand the training dataset to include more vehicle types, weather conditions, and road layouts for improved generalization.
- Use synthetic image generation (GAN-based augmentation) to handle rare traffic scenarios like accidents and emergency vehicles.

Thank You!