AI-Powered Traffic Signal Control

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Abstract - *Traffic jams are a big problem in many cities because there are so many cars on the road and traditional traffic signal systems can't keep up. Most regular traffic lights don't care how many cars are on the road; they just work at certain times. People often have to wait longer than they need to, waste gas, and deal with traffic badly because of these issues. This research suggests an intelligent system for controlling traffic signals that employs computer vision and deep learning to tackle these issues.*

The proposed system employs OpenCV and the YOLOv8 object detection model to identify, track, and tally vehicles in real time from video feeds. To better control traffic, the system changes the length of the green light based on how many cars it sees. A virtual traffic signal interface was also made to show the signal's status, the number of cars, the level of traffic, and the timer. The experiment's results show that the system can adjust to changes in traffic and make traffic flow better overall. The proposed method is cost-effective, scalable, and suitable for smart city applications.

Keywords: *Smart Traffic Signal, Intelligent Transportation System, Vehicle Detection, YOLOv8, Computer Vision, Traffic Density Estimation, Adaptive Signal Control, OpenCV, Deep Learning, Smart Cities*

1. Introduction

As cities around the world grow quickly and more people drive, traffic jams are becoming a common problem. Most current traffic signal systems work on a set schedule, no matter how busy the road is at the time. So, cars often have to wait at empty intersections when other lanes are still too full. This makes travel take longer, wastes gas, and hurts the environment.

To solve these problems, smart traffic management systems that use computer vision and artificial intelligence are becoming more popular. The project focuses on developing an intelligent traffic signal control system that adjusts signal timing based on real-time vehicle density. Instead of using fixed signal durations, the system analyses traffic from video input and dynamically controls the green signal duration to improve traffic flow. For example, recent implementations that process live videos from cameras to count vehicles and change signal timings on the fly to improve flow in heavy traffic (1. 2.) These systems keep an eye on traffic in real time and make decisions on their own, which is better than traditional fixed or manual methods that don't work well when there is a lot of traffic. (2.) In this study, we suggest a smart traffic signal system that uses the YOLO deep learning model to accurately detect and count vehicles in real time, even in crowded situations, and changes the timing of the signals based on traffic density. There is also a virtual traffic signal interface in the system that lets you see things in real time.

The primary objective of this research is to enhance traffic efficiency through a cost-effective, scalable software-based solution that not only reduces human error in manual signal control but also produces historical data to assist authorities in analysing peak traffic patterns and long-term urban congestion trends. The goal of combining these technologies is also to help the environment by cutting down on idle times at intersections, which lowers fuel use and carbon emissions directly 1, 3. This helps make cities more environmentally friendly by reducing the environmental impact of citywide transportation networks (4).

2. Problem Statement

Regular traffic lights follow set schedules that don't consider how traffic is moving at the time. As a result, roads with fewer cars may get green lights that last too long, while roads with a lot of cars may have to wait a long time. For big, busy cities, manual traffic control is also not practical. So, there is a big need for an intelligent and automated traffic signal system that can keep an eye on how many cars are on the road and change the timing of the signals.

To make traffic flow better and cut down on traffic jams. "Static switching" is a problem with the current traffic infrastructure. This means that signal intervals are set based on historical averages instead of real-time demand. Because it can't change, this leads to a lot of traffic jams during non-peak hours when there are sudden traffic surges and people sitting around when traffic is light. Traffic personnel's manual intervention is not scalable and is likely to make mistakes. Because of this, we need an AI-driven, automated system that can monitor, analyse, and improve intersection flow on its own to reduce traffic jams and environmental damage (4).

3. Literature Review

Many researchers have studied smart traffic management systems that use computer vision methods. Previous methods primarily utilized standard image processing algorithms, such as background subtraction and Haar cascade classifiers for vehicle detection. However, these methods often don't work well in complicated situations where the lighting changes, there are shadows, things are blocking the view, or the weather is bad. This is because traditional methods don't work well when there is a lot of traffic or when the flow is uneven across lanes(1, 2). Recent improvements have fixed these problems by combining the SORT algorithm with YOLO to keep track of detected objects across multiple video frames. This makes the count for signal switching more accurate (5).

As deep learning has progressed, contemporary object detection models like YOLO (1, 5;2), SSD, and Faster R-CNN have exhibited enhanced accuracy and real-time performance relative to traditional techniques, especially in high-traffic and challenging conditions (1, 2). A few recent systems have used these models to find vehicles (4; 3; 5), but most of them can only count vehicles and don't fully integrate adaptive traffic signal control (1, 2). Some of them also need expensive hardware setups that go beyond what is already in place (4). Our method, on the other hand, uses YOLO V7 to give a more detailed look at how intersections work by putting vehicles into groups like cars, bikes, and buses and figuring out the best green signal times for each type of vehicle based on how they flow (3), (5).while also using optical character recognition to get environmental metadata from video feeds for automatic signal calibration based on the weather (11).

The system suggested in this study uniquely combines YOLOv7 for accurate deep learning-based vehicle detection and classification (e.g., cars, bikes, buses) even in heavy traffic (3; 5) and SORT for strong unique vehicle tracking across frames(5), and an adaptive smart signal timing algorithm that dynamically adjusts green durations based on real-time density, vehicle types, and even weather metadata via OCR(11; 3)—all within a simple, purely software-based framework that leverages existing CCTV infrastructure without costly hardware(4), outperforming prior systems limited to basic counting or static setups(1, 2) and making it highly scalable and suitable for practical smart city deployments. Unlike R-CNN, which needs a lot of processing power, YOLOv3 and its successors strike a good balance between speed and accuracy, making it possible to analyze intersection occupancy in real time with an average processing time of about 100 ms per frame (6,3).

4. Dataset

Roboflow Universe [2] has the UA-DETRAC-DATASET-10K, which was the main dataset. This dataset is based on the well-known UA-DETRAC benchmark and was made just for finding vehicles in real traffic situations. The system uses the UA-DETRAC dataset, which contains real-world traffic images with labelled vehicles. It includes different traffic conditions such as low, medium, and heavy traffic, along with variations in lighting and environment. The dataset has about 10,000 pictures taken from real traffic surveillance videos. These pictures show different kinds of traffic situations that happen in real life, such as low, medium, and heavy traffic. The data also included different perspectives, road types, and environmental settings, like how the lighting changed during the day and how the weather changed slightly. Because of this variety, the dataset gives a realistic picture of city traffic, which is important for making a traffic management system that works and is reliable.

We carefully added bounding boxes around the vehicles to each picture in the dataset. There are many types of vehicles in the dataset, like cars,

buses, trucks, and vans. These notes make it easier to use modern object detection models like YOLO because the data is already in a format that can be used. This made it much easier to label things by hand and sped up the system's development.

The dataset was mostly used in this project to help with vehicle detection and analysis. A pretrained YOLOv8 model was used to find cars, but the dataset helped us understand how cars look in different traffic situations and made sure that the system worked well in real-life situations. The system can find and identify vehicles more accurately when there are accurate annotations. This directly makes counting vehicles and estimating traffic density more accurate.
This dataset is also very useful because it closely matches how traffic behaves in the real world. This makes it a great choice for testing and confirming the suggested traffic signal controller that uses AI. With this kind of dataset, the system can better adjust to real-world situations and give more accurate results.

Overall, the UA-DETRAC-DATASET-10K is a good base for this study because it is relevant to the real world, has good annotation quality, and works with deep learning models. This makes it the best choice for creating and testing smart traffic management systems.

***Fig.1**: Sample data from UA-DETRAC dataset*

5. Methodology

The proposed smart traffic signal system was built in four main parts, using a modular approach. The video input module reads the traffic video and does some basic preprocessing, like resizing and noise reduction, in the first stage. The YOLOv8 model was used to find cars in each frame during the second stage. A tracking system gave each car a unique ID so that the same car wouldn't be counted more than once. The StrongSORT algorithm improves this tracking process even more by using deep learning features to keep track of an object's identity across multiple frames. This makes it easier to figure out how fast a vehicle is going and to find behavioural patterns that are important for predictive traffic modelling (7), (5). The system also gives priority to emergency vehicles by recognizing certain visual features of ambulances and fire trucks to instantly start pre-emptive green light extensions (11),(8).

Technologies used are: -

- Programming Language: Python
- Libraries: OpenCV, NumPy, Pandas
- Deep Learning Model: YOLOv8
- Tracking Algorithm: SORT (for avoiding duplicate counts)
- Interface: GUI using OpenCV / Tkinter
- Dataset: UA-DETRAC (vehicle detection dataset)

***Fig.2**: Multi-image vehicle detection and traffic density analysis*

In the third stage, the system looked at the total number of vehicles and put the traffic density into three groups: low, medium, and heavy.

Signal time is calculated based on number of vehicles:

$T = T_{min} + k \cdot N$T=Tmin +k·N Where:

T = Green signal time

T_{min}= Minimum base time N = Number of vehicles

k = constant factor

***Fig.2**: Multi-image vehicle detection and traffic density analysis*

The smart timing algorithm changed the length of the green signal based on this classification. In the last step, a virtual traffic signal graphical user interface (GUI) shows the current signal light, number of cars, level of traffic, and timer in real time. This modular design makes the system easy to keep up with, easy to grow, and good for use in real time. Webster's formula can be used to find the exact timing of the green signal based on the number of vehicles and the average class speed (9), (10). This will help improve signal switching logic.

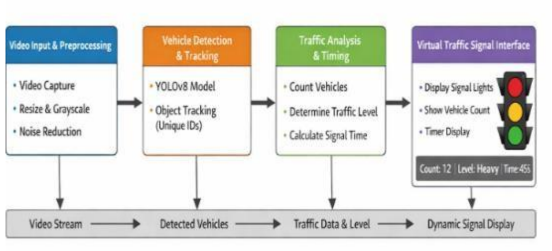

Fig. 3: *Proposed system architecture flowchart*

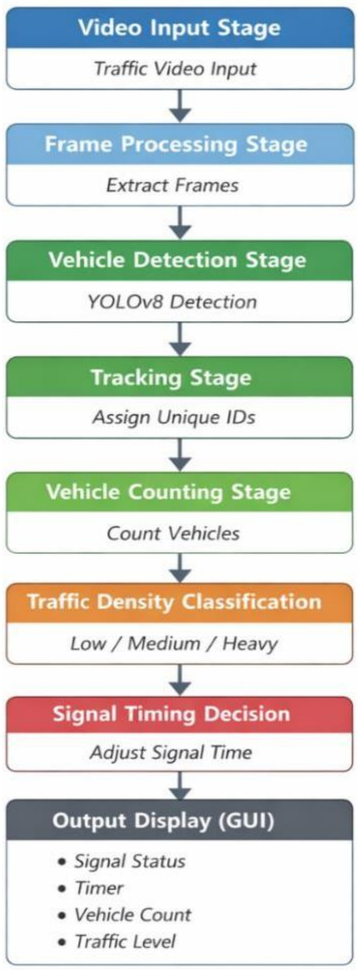

Fig. 4*: End-to-end pipeline for traffic video processing, vehicle detection, counting, and adaptive signal control.*

Intelligent traffic management system operates through a sequence of well-defined stages, transforming raw traffic video into actionable signal control decisions. Each stage plays a crucial role in ensuring accurate vehicle detection, efficient tracking, and adaptive traffic signal timing.

5.1. Video Input Stage

The system begins by acquiring traffic video data, which can be sourced either from real-time surveillance cameras or pre-recorded video datasets. This flexibility allows the model to be tested in both simulated and real-world traffic environments. The input video serves as the primary data source for further analysis.

5.2. Frame Processing Stage

To enable efficient computation, the continuous video stream is divided into individual frames. These frames act as static images that can be processed sequentially. Frame extraction ensures that each moment in the traffic flow is analyzed in detail, forming the basis for accurate vehicle detection.

5.3. Vehicle Detection Stage

In this stage, the system utilizes the advanced deep learning model **YOLOv8** (You Only Look Once version 8) to identify vehicles within each frame. The model is capable of detecting multiple vehicle categories, including cars, motorcycles, buses, and trucks, with high accuracy and real-time performance. Bounding boxes are drawn around detected vehicles to localize them within the frame.

5.4. Tracking Stage

To avoid duplicate counting and ensure continuity, each detected vehicle is assigned a unique identification number. Object tracking algorithms maintain the identity of vehicles across consecutive frames, even as they move through the scene. This step is critical for distinguishing between new and previously detected vehicles.

5.5. Vehicle Counting Stage

Based on the detection and tracking outputs, the system counts the number of vehicles passing through a predefined region of interest. Since each vehicle has a unique ID, the system ensures that no vehicle is counted more than once, improving overall accuracy.

5.6. Traffic Density Classification

The system categorizes traffic conditions into three levels based on the total vehicle count:

- **Low Traffic:** Minimal vehicle presence, indicating free-flow conditions
- **Medium Traffic:** Moderate congestion with manageable flow
- **Heavy Traffic:** High vehicle density, indicating congestion or peak hours

This classification helps in simplifying decision-making for signal control.

5.7. Signal Timing Decision

Using the classified traffic density, the system dynamically adjusts traffic signal timings. Heavier traffic conditions are allocated longer green signal durations, while lighter traffic receives shorter durations. This adaptive mechanism improves traffic flow efficiency and reduces unnecessary waiting time.

5.8. Output Display (GUI)

Finally, the system presents the results through a user-friendly graphical interface. The GUI displays:

- Current traffic signal status (Red/Green)
- Countdown timer for signal changes
- Total vehicle count
- Traffic density level (Low/Medium/Heavy)

6. Results and Discussions

We used a recorded traffic video to test the proposed smart traffic signal system to see how well it could detect vehicles, count them accurately, and change the timing of the signals. The YOLOv8 model was able to find cars, buses, trucks, motorcycles, and other types of vehicles in real time. The object tracking system gave each vehicle a unique ID, which stopped counting duplicates and made the overall accuracy better. The system changed the length of the green signal based on how busy the traffic was during testing. When there weren't many cars on the road, the green time was cut short. When there was a lot of traffic, the green time was automatically lengthened. The virtual traffic signal interface showed the signal state, vehicle count, traffic level, and timer correctly, with no noticeable delay.

The system was tested under different traffic conditions:

- Correct vehicle detection in most cases
- Accurate counting using tracking
- Adaptive signal timing based on traffic density
- Minor errors in low light or occlusion conditions

The experimental results show that the suggested system can adapt to changing traffic conditions and control signal timing better than traffic lights that are set to a certain time. But there were small changes in detection in cases of heavy occlusion and poor lighting. In general, the system shows a lot of promise for smart city environments where traffic can be managed intelligently in real time.

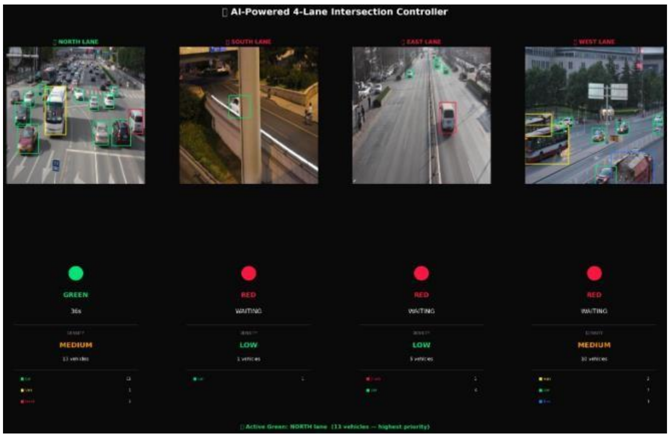

Fig. 5: *AI-powered 4-lane intersection controller showing real-time vehicle detection, lane-wise density classification, and adaptive traffic signal status.*

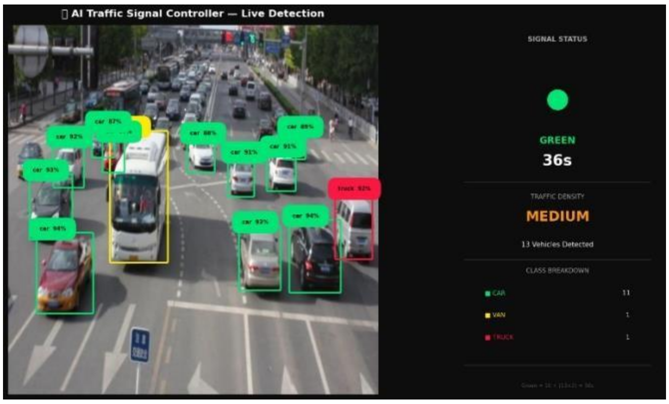

Fig. 6: *Real-time AI-based traffic signal controller displaying vehicle detection, classification, traffic density, and signal status.*

Table 1. Sample Result Table

Lane	Vehicles	Density	Green Time	Signal	Active
NORTH	13	MEDIUM	36	GREEN	YES
SOUTH	1	LOW	12	RED	NO
EAST	5	LOW	20	RED	NO
WEST	10	MEDIUM	30	RED	NO

7. Conclusion

This study introduces an intelligent traffic signal control system that employs computer vision and deep learning to optimize traffic management. The proposed system gets around the problems with traditional fixed-time traffic signals by combining YOLO-based vehicle detection, tracking, and adaptive signal timing. The virtual signal interface shows the system's behaviour in real time in a clear way.

The experimental results show that the system can cut down on unnecessary wait times and make traffic flow better. The suggested solution is affordable, can be used in smart cities, and can be expanded. In the future, the system could be made even better by adding real-world hardware deployments, multi-lane analysis, and giving priority to emergency vehicles.

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