

Signal Master using YOLO

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Abstract: *As urban populations and automobile numbers continue to swell, traffic congestion emerges as a pressing concern, inflicting delays, stress, heightened fuel consumption, and increased air pollution. Megacities, in particular, bear the brunt of this escalating issue. Real-time assessment of road traffic density becomes imperative for efficient signal control and traffic management. Among the pivotal factors influencing traffic flow, the traffic controller stands paramount, necessitating optimization to meet the surging demand. Our proposed system capitalizes on live camera feeds from traffic junctions to conduct traffic density calculations through image processing techniques and artificial intelligence (AI). By harnessing these technologies, the system aims to offer a dynamic solution to the persistent challenge of congestion. The core focus lies in devising an algorithm that dynamically adjusts traffic light signals based on the detected vehicle density, thereby mitigating congestion and fostering smoother transit experiences for commuters. This innovative approach not only promises expedited travel times but also holds the potential to curtail pollution levels, contributing to a more sustainable urban environment. By seamlessly integrating image processing and AI-driven traffic control mechanisms, our system endeavors to pave the way towards a more efficient and eco-friendly transportation infrastructure*

Keywords: Traffic congestion, YOLO, image processing, traffic control, signal switching, object detection, machine learning

I. INTRODUCTION

In burgeoning urban landscapes, the effective management of traffic flow stands as a paramount challenge. With the steady increase in vehicular density, traditional traffic control systems often falter in their ability to adapt swiftly to dynamic conditions, leading to congestion, delays, and safety hazards. To address these pressing issues, the integration of cutting-edge technologies such as computer vision, deep learning, and image processing has emerged as a promising avenue for revolutionizing traffic management strategies. Among these technologies, You Only Look Once (YOLO), combined with OpenCV (Open Source Computer Vision Library), presents a compelling framework for the smart control of traffic lights.

The convergence of YOLO, a state-of-the-art object detection algorithm, with image processing techniques facilitated by OpenCV offers a potent solution for real-time traffic analysis and signal optimization. Unlike traditional methods that rely on pre-defined rules or sensors, YOLO enables efficient detection and tracking of vehicles, pedestrians, and other relevant objects directly from input images or video streams. This capability empowers traffic control systems to dynamically adjust signal timings and prioritize lanes based on the observed traffic patterns, thus enhancing overall flow and minimizing congestion.

This research endeavors to explore the potential of leveraging YOLO and OpenCV for the intelligent control of traffic lights. By harnessing the power of computer vision and deep learning, this study aims to develop a smart traffic management system capable of autonomously analyzing real-time traffic conditions, predicting traffic congestion, and optimizing signal timings accordingly. Through a combination of experimental validation and theoretical analysis, the effectiveness, efficiency, and practical implications of the proposed approach will be thoroughly examined.

The relevance of this research extends beyond academic inquiry, with significant implications for urban planning, transportation engineering, and societal well-being. By advancing the state-of-the-art in traffic control technology, this study seeks to contribute to the development of smarter, safer, and more sustainable cities. Moreover, the insights gleaned from this research endeavor hold the potential to inform policy decisions and infrastructure investments aimed at alleviating traffic congestion and enhancing urban mobility.

In the subsequent sections of this paper, the underlying principles of YOLO, image processing, and OpenCV will be elucidated, followed by a detailed methodology for the implementation of a smart traffic control system. The results of experimental evaluations will be presented and discussed, providing valuable insights into the efficacy and performance of the proposed approach. Finally, conclusions drawn from this research will be synthesized, along with recommendations for future investigations in this burgeoning field of study.

II. LITERATURE SURVEY

Reference[1], a method employing video manipulation is presented. Live stream footage undergoes preprocessing before transmission to servers, where a C++ algorithm is employed to produce outcomes. The study contrasts fixed and adaptive coding approaches, with the dynamic method exhibiting a 35% enhancement.

Reference [2] introduces an Arduino-UNO driven mechanism aimed at alleviating traffic congestion and wait times. This setup captures images via a camera, subsequently processing them in MATLAB. Within MATLAB, images undergo transformation into threshold representations by eliminating saturation and hues, facilitating the computation of traffic density. The connectivity between Arduino and MATLAB is established through USB, utilizing preinstalled simulation packages. Based on traffic volume and density, the Arduino regulates the duration of green light allocation for each lane. However, this approach exhibits several shortcomings. Vehicle overlap presents a challenge, hindering accurate vehicle counting. Additionally, various objects pose interference, as they are also rendered in black and white, making it arduous to distinguish between vehicles and regular objects like billboards, poles, and trees.

In reference [3], a fuzzy logic-based traffic signal system adaptable to prevailing traffic conditions is presented. This setup incorporates two fuzzy controllers, each featuring three inputs and one output, catering to primary and secondary driveways. Simulation experiments conducted utilizing VISSIM and MATLAB demonstrated enhanced traffic conditions under low traffic density scenarios.

In reference [4], an intelligent traffic signal system employing Artificial Neural Network (ANN) and fuzzy controller technology is proposed. This system utilizes camera-captured images from traffic locations. Initially, the image undergoes conversion to grayscale and subsequent normalization. Segmentation is then executed employing a sliding window technique to facilitate car counting regardless of size. The segmented image is processed by the ANN, with the output utilized in the fuzzy controller to establish red and green light timings, based on crisp output. Results indicated an average error rate of 2%, achieved within an execution time of 1.5 seconds.

Reference [5] employs a support vector machine (SVM) algorithm in conjunction with image processing methods. Live video streams are segmented into small frames, where the algorithm is then employed. Utilizing OpenCV, image processing is conducted, converting the images to grayscale prior to SVM application. This system not only discerns traffic density but also identifies red light violations.

Reference [6] surveys diverse methodologies employed in traffic signal control systems. This study notes a shared framework among these methods: selection of input data, extraction of traffic metrics from the input, data processing, density assessment, and parameter refinement.

III. PROPOSED SYSTEM

A. Proposed System Overview

Our proposed system operates by harnessing CCTV camera imagery at traffic intersections to perform real-time traffic density analysis via advanced image processing and object detection techniques. Illustrated in Figure 1, the captured image undergoes vehicle detection utilizing the YOLO algorithm. This process identifies the count of vehicles belonging to distinct classes such as cars, motorcycles, buses, and trucks, pivotal for calculating traffic density. Subsequently, the signal switching mechanism utilizes this density, alongside other pertinent factors, to dynamically adjust the green signal timer for each lane, thereby optimizing traffic flow. Updates to red signal durations are synchronized accordingly. To prevent lane starvation, the green signal duration is bounded by maximum and minimum thresholds. Additionally, a simulation framework is developed to showcase the efficacy of our system and contrast it with the conventional static setup.

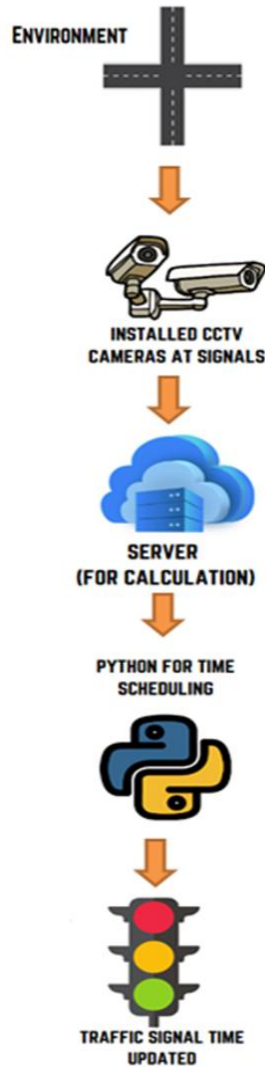


Fig 1: Proposed System Overview

B. Vehicle Detection Module

The YOLO (You Only Look Once) algorithm is a pioneering solution for real-time object detection in images. Unlike traditional methods that involve multiple stages, YOLO approaches object detection as a single regression problem, predicting bounding boxes and class probabilities directly from the entire image in one evaluation. By dividing the image into a grid and applying a convolutional neural network (CNN) to each grid cell, YOLO simultaneously predicts multiple bounding boxes and their corresponding class probabilities. This unified approach not only streamlines the detection process but also eliminates the need for separate models or stages, making YOLO highly efficient and accurate. Moreover, YOLO incorporates non-maximum suppression (NMS) to refine the predictions and ensure that each object is detected only once, further enhancing its performance. Overall, YOLO's speed, accuracy, and simplicity make it a cornerstone in various computer vision applications, particularly those requiring real-time object detection capabilities.

To achieve the desired balance between accuracy and processing time, a tailored YOLO model was developed specifically for vehicle detection. This custom model is adept at recognizing vehicles across various classes including cars, bikes, heavy vehicles such as buses and trucks, and even rickshaws.

The dataset utilized for training the model was curated by gathering images from Google and subsequently labeling them manually via LabelIMG, a graphical image annotation tool. Following this, the model underwent training using pre-existing weights obtained from the YOLO website. Adjustments to the configuration of the .cfg file were made to align with the specifications of our model, notably setting the number of output neurons in the final layer equal to the number of classes to be detected, which in our case were four: Car, Bike, Bus/Truck, and Rickshaw. Additionally, the number of filters was modified using the formula $5 * (5 + \text{number of classes})$, resulting in 45 filters for our setup. Upon configuring these parameters, training ensued until a significant reduction in loss was achieved and further reduction appeared marginal. This signified the completion of training, and subsequently, the weights were updated to meet our requirements. These updated weights were then integrated into the codebase and employed for vehicle detection using OpenCV. A threshold was defined to determine the minimum confidence level required for successful detection. Once the model is loaded and an image is provided, the results are outputted in a JSON format, comprising key-value pairs where labels represent the detected objects, and their respective confidence scores and coordinates. OpenCV was employed once again to overlay bounding boxes onto the images based on the extracted labels and coordinates. Figures below shows test images on which our vehicle detection model was applied. The first image shows the original image and the bottom image is the output after the vehicle detection model is applied on the image, with bounding boxes and corresponding labels.

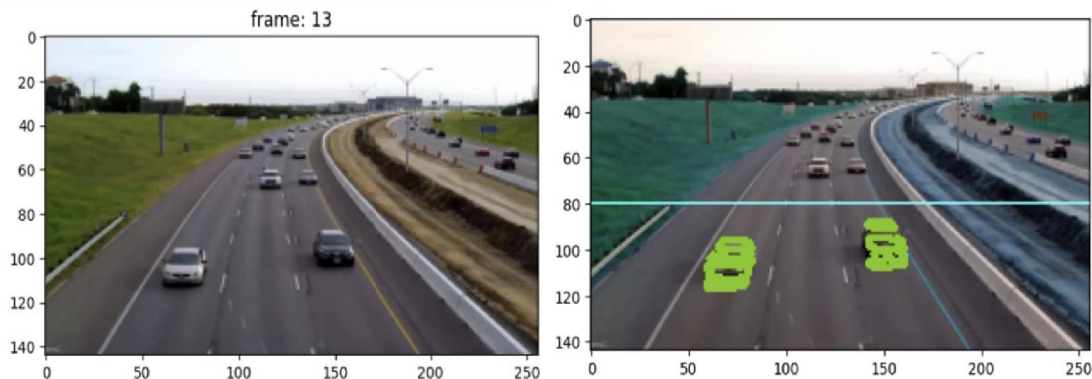


Fig2 . Vehicle Detection Module

C. Signal Switching Algorithm

The Signal Switching Algorithm orchestrates the timing of traffic lights based on the density of vehicles detected by the vehicle detection module, synchronizing green signals and adjusting red signal durations accordingly. It operates in a cyclic manner, smoothly transitioning between signals based on predetermined timers. Input for the algorithm consists of vehicle detection data in JSON format, extracted from the detection module, detailing object labels, confidence levels, and coordinates. This input undergoes parsing to ascertain the total count of vehicles per class. Factors influencing the algorithm's development include processing time, number of lanes, vehicle counts, and traffic density. Additionally, considerations encompass vehicle lag during startup, average speeds for each vehicle class, and minimum-maximum green light durations to prevent lane starvation. The algorithm dynamically sets green light times based on vehicle counts and average crossing times per class, ensuring efficient traffic flow. Implementation involves a separate thread for vehicle detection and main thread for signal timing, enabling seamless timer adjustments. The algorithm optimizes processing by capturing images when the next green signal is imminent, providing time for vehicle detection, green signal calculation, and timer adjustments. The order of signal switching remains consistent with existing systems, ensuring familiarity and avoiding confusion, with provisions for yellow signals accounted for as well. Order of Signals: Red → Green → Yellow → Red

D. Simulation Module

A virtual simulation was meticulously crafted from the ground up utilizing Pygame, aimed at replicating real-world traffic dynamics. This simulation serves as a powerful tool for visualizing and contrasting the proposed dynamic traffic management system with the conventional static approach. Central to the simulation is a 4-way intersection outfitted with four traffic signals, each accompanied by a countdown timer indicating the duration until the signal transitions between green, yellow, and red phases. Additionally, vehicle counts for each signal are prominently displayed. Diverse types of vehicles, including cars, bikes, buses, trucks, and rickshaws, traverse the intersection from various directions, enhancing realism. To further enhance authenticity, vehicles in the rightmost lane are programmed with the possibility of turning, their turning behavior determined randomly upon generation. A comprehensive timer also tracks the elapsed time since the simulation commenced, providing valuable temporal context. This dynamic simulation encapsulates the intricacies of real-life traffic scenarios, offering a compelling platform for analysis and comparison.



Fig3. Simulation Module

Pygame stands out as a versatile collection of Python modules tailored for game development across different platforms. With a focus on computer graphics and sound, Pygame integrates seamlessly with the Python programming language. Building upon the robust SDL library, Pygame enhances functionality, empowering users to craft immersive games and multimedia applications. Its portability ensures compatibility across a wide array of platforms and operating systems, making it a favored choice among developers. Moreover, Pygame is freely available and licensed under LGPL, fostering a vibrant community of creators and innovators.

IV. RESULTS AND ANALYSIS

A. Evaluation of Vehicle Detection Module

The vehicle detection module underwent testing using a diverse set of test images featuring varying numbers of vehicles. The detection accuracy was observed to range between 75-80%. Selected test results are illustrated in Figure 3. While this level of accuracy is satisfactory, it falls short of optimal. The main factor contributing to the lower accuracy is the inadequacy of the dataset. Enhancing the dataset with real-life footage from traffic cameras can substantially improve the model's accuracy. This approach is recommended to elevate the system's performance.

B. Evaluation of the Proposed Adaptive System

To assess the effectiveness of the proposed adaptive system in comparison to the existing static system, we conducted 15 simulations for each system over a 5-minute duration. These simulations featured varying traffic distributions across the four directions. Performance was gauged based on the number of vehicles successfully traversing the intersection per unit of time. Specifically, we focused on the idle time of the signal—when the signal is green but no vehicles pass through the intersection. This metric directly influences vehicle waiting time and queue lengths at other signals. The distribution [a,b,c,d] indicates that the probability of a vehicle being in lane 1, lane 2, lane 3, and lane 4 is respectively

For instance, in simulation 1, the distribution is [300,600,800,1000], implying probabilities of 0.3, 0.3, 0.2, and 0.2. The obtained results were organized into a table detailing the number of vehicles passed lane-wise and the total number of vehicles passed.

Table i. Simulation results of current static system

1	[300,600,800,1000]	70	52	52	65	239
2	[500,700,900,1000]	112	49	48	31	240
3	[250,500,750,1000]	73	53	63	62	251
4	[300,500,800,1000]	74	44	65	71	254
5	[700,800,900,1000]	90	32	25	41	188
6	[500,900,950,1000]	95	71	15	14	195
7	[300,600,900,1000]	73	63	69	24	229
8	[200,700,750,1000]	54	89	10	67	220
9	[940,960,980,1000]	100	10	8	4	122
10	[400,500,900,1000]	81	29	88	37	235
11	[200,400,600,1000]	42	47	54	86	229
12	[250,500,950,1000]	39	52	93	22	206
13	[850,900,950,1000]	74	10	13	17	114
14	[350,500,850,1000]	49	46	69	50	214
15	[350,700,850,1000]	51	64	37	43	195

Table ii. Simulation results of proposed adaptive system

1	[300,600,800,1000]	87	109	41	50	287
2	[500,700,900,1000]	128	55	49	25	257
3	[250,500,750,1000]	94	50	60	58	262
4	[300,500,800,1000]	89	46	69	59	263
5	[700,800,900,1000]	185	25	23	28	261
6	[500,900,950,1000]	94	118	11	16	239
7	[300,600,900,1000]	87	68	70	33	258
8	[200,700,750,1000]	56	108	19	78	261
9	[940,960,980,1000]	193	6	5	7	211

						1
10	[400,500,900,1000]	97	29	100	34	260
11	[200,400,600,1000]	26	52	67	99	244
12	[250,500,950,1000]	52	75	101	7	235
13	[850,900,950,1000]	154	17	12	18	201
14	[350,500,850,1000]	64	53	80	47	244
15	[350,700,850,1000]	66	82	40	48	236

Figure 4, the proposed adaptive system consistently outperforms the current static system, irrespective of the traffic distribution. The extent of performance improvement is directly related to the degree of skewness in the traffic distribution across lanes. The more skewed the traffic distribution, the greater the enhancement in performance.

When the traffic distribution among the four lanes is equal or nearly equal, the proposed system exhibits only a slight improvement over the current system. This scenario is observed in simulations 1, 2, 3, and 4, where the performance enhancement is approximately 9%.

When the traffic distribution is moderately skewed, the proposed system demonstrates a significant improvement over the current system. This scenario is evident in simulations 5, 6, 7, 8, 14, and 15, where the performance enhancement is approximately 22%. Such traffic distributions are commonly observed in real-life scenarios.

When the traffic distribution is sharply skewed, the proposed system exhibits a substantial performance improvement compared to the current system. This situation is exemplified in simulations 9 and 13, where there is a noticeable, steep decline in the red line, resulting in a significant gap between the red and green lines. In such instances, the performance enhancement is approximately 36%.

Comparison of current static system and proposed adaptive system

Under uniform simulation conditions, including traffic distribution, vehicle speeds, probability of turns, inter-vehicle gaps, and others, the simulations were conducted for a total duration of 1 hour and 15 minutes. Each distribution was simulated for 300 seconds (5 minutes). The findings reveal that, on average, the proposed system enhances performance by approximately 23% compared to the current system with fixed timing. This improvement translates to a reduction in idle green signal time and waiting times for vehicles.

Upon comparison with alternative adaptive systems, it was determined that the proposed system surpasses several of them in performance. For instance, [2] reports an accuracy of 70%, whereas the proposed system achieves 80% accuracy. Reference [3] achieves an average performance improvement of 12% compared to static systems, whereas the proposed system achieves a higher improvement of 23%.

V. FUTURE SCOPE

The project can be expanded to incorporate the following features to improve traffic management and reduce congestion:

- 1) Identification of vehicles violating traffic rules: Vehicles that run red lights can be detected in images or video streams by establishing a violation line and capturing the vehicle's license plate if it crosses this line while the signal is red. Similarly, lane changes can also be identified using the same method. These tasks can be accomplished through background subtraction or image processing techniques.
- 2) Accident or breakdown detection: Intersections often witness significant crashes, including angle and left-turn collisions, leading to property damage and injuries. Therefore, promptly and accurately detecting accidents at intersections offers substantial benefits in terms of saving lives and property, as well as reducing congestion and delays.

- 3) This can be accomplished by identifying vehicles that remain stationary in an improper position, such as in the middle of the road for an extended period, while excluding parked vehicles from consideration.
- 4) Synchronization of traffic signals across multiple intersections: Coordinating signals along a street can benefit commuters by allowing vehicles to proceed with minimal stopping once they enter the street.
- 5) Responding to emergency vehicles: Emergency vehicles, such as ambulances, require expedited passage through traffic signals. The model can be trained not only to detect vehicles but also to recognize emergency vehicles. Subsequently, it can adjust timers to prioritize these vehicles, allowing them to cross the signal as quickly as possible.

VI. CONCLUSION

In summary, the proposed system adjusts the duration of green signal times dynamically based on the density of traffic at the signal. It guarantees that the direction with heavier traffic receives a longer green signal duration compared to the direction with lighter traffic. This approach aims to minimize delays and alleviate congestion, leading to decreased waiting times, fuel consumption, and pollution.

Based on simulation results, the system demonstrates approximately a 23% enhancement over the current system in terms of the number of vehicles passing through the intersection, marking a notable advancement. By refining the system through additional calibration using real-life CCTV data for model training, further improvements can be achieved.

Furthermore, the proposed system offers several advantages over existing intelligent traffic control systems like Pressure Mats and Infrared Sensors. Its deployment cost is minimal since it utilizes footage from CCTV cameras already installed at traffic signals, requiring no additional hardware in most cases, particularly at intersections with heavy traffic. Any necessary adjustments typically involve minor alignment. Maintenance costs are also reduced compared to other traffic monitoring systems such as pressure mats, which often endure wear and tear from constant pressure on road surfaces. Hence, integrating the proposed system with existing CCTV cameras in major cities can significantly enhance traffic management

REFERENCES

- [1] Khushi, "Smart Control of Traffic Light System using Image Processing," 2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC), Mysore, 2017, pp. 99-103, doi: 10.1109/CTCEEC.2017.8454966.
- [2] A. Vogel, I. Oremović, R. Šimić and E. Ivanjko, "Improving Traffic Light Control by Means of Fuzzy Logic," 2018 International Symposium ELMAR, Zadar, 2018, pp. 51-56, doi: 10.23919/ELMAR.2018.8534692.
- [3] A. A. Zaid, Y. Suhweil and M. A. Yaman, "Smart controlling for traffic light time," 2017 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT), Aqaba, 2017, pp. 1-5, doi: 10.1109/AEECT.2017.8257768.
- [4] RenjithSoman "Traffic Light Control and Violation Detection Using Image Processing". IOSR Journal of Engineering (IOSRJEN), vol. 08, no. 4, 2018, pp. 23-27
- [5] A. Kanungo, A. Sharma and C. Singla, "Smart traffic lights switching and traffic density calculation using video processing," 2014 Recent Advances in Engineering and Computational Sciences (RAECS), Chandigarh, 2014, pp. 1-6, doi: 10.1109/RAECS.2014.6799542.
- [6] Ms.SailiShinde, Prof. SheetalJagtap, Vishwakarma Institute Of Technology, Intelligent traffic management system:a Review, IJIRST 2016