TRAFFIC LIGHT CONTROL SYSTEM

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Abstract- Ineffective and inflexible traffic signal control at urban intersections can often lead to bottlenecks in traffic flows and cause congestion, delay, and environmental problems. How to manage traffic smartly by intelligent signal control is a significant challenge in urban traffic management. With recent advances in machine learning, especially reinforcement learning (RL), traffic signal control using advanced machine learning techniques represents a promising solution to tackle this problem. In this paper, we take images from the CCTV cameras at traffic junctions as input for real-time traffic density calculation using image processing and object detection. Better accuracy is achieved in the detection of multiple vehicles with the YOLO algorithm. Shorter vehicle waiting times are achieved by intelligent monitoring technology's usage of a signal-switching algorithm at signal intersections to coordinate time distribution and ease traffic congestion. In the simulation experiment, we will use Pygame , a cross-platform set of Python modules which is used to create video games and different types of simulations.

Keywords: Traffic jams, traffic light system, traffic management, You Only Look Once(YOLO), intelligent monitoring, signal switching algorithm, artificial intelligence

I. Introduction

A report by the Boston Consulting Group estimates that the total cost of congestion in India in 2019 was a staggering $22 billion. This cost is expected to rise to an even higher $37 billion by 2030 if no action is taken. A recent study by TomTom Traffic Index has shown that Bengaluru, India's leading IT city, is the world's second most traffic-congested city. For instance, to travel a distance of 10 km within Bengaluru city limits, it takes close to 30 minutes, whereas the same distance can be covered in less than 13 minutes in Dubai [11]. However, Bengaluru is not alone in facing this traffic congestion problem, as other major cities of India also suffer from the same problem. One way to reduce the traffic congestion is by intelligently controlling traffic lights. Nowadays, most traffic lights are still controlled with pre-defined fixed-time plan and are not designed by observing real traffic. Recent studies propose handcrafted rules according to real traffic data. However, these rules are still pre-defined and cannot be dynamically adjusted w.r.t., real-time traffic. To dynamically adjust traffic lights according to real-time traffic, people have been using reinforcement learning technique [3]. Traditional reinforcement learning is difficult to apply due to two key challenges: (1) how to represent environment; and (2) how to model the correlation between environment and decision. To address these two challenges, recent studies have applied deep reinforcement learning techniques, such as Deep Q-learning (DQN), for traffic light control problem. You Only Look Once (YOLO), a cutting-edge real-time object detection system based on deep convolutional neural networks, does this. Then, in order to allow as many vehicles to pass safely with the least amount of waiting time, traffic signal phases are optimised based on data that has been collected, primarily queue density and waiting time per vehicle. YOLO can be implemented on an embedded controller with the Transfer Learning technique, allowing Deep Neural Network to operate on a small amount of hardware.

This system is divided into three modules: vehicle detection, signal switching algorithm, and simulation module. This image is sent to the vehicle detection algorithm, which makes use of YOLO, as seen in the figure below. To determine the traffic density, the number of vehicles in each class—such as cars, bikes, buses, and trucks—is counted. This density is one of the elements that the signal switching algorithm takes into account while determining the green signal timer for each lane. In accordance, the red signal times are adjusted. To prevent starving of a certain lane, the green signal time is limited to a maximum and minimum value [10]. To reflect a real-world urban intersection setting, all training and testing experiments were conducted in Pygame. The reminder of this paper is organized as follows: Literature Survey, Methodology, Discussion and Analysis , Conclusions, Future Scope and References.

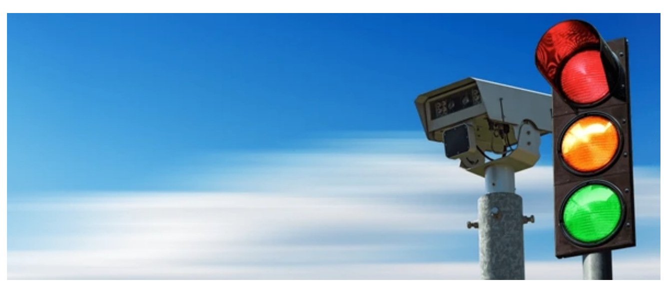

Figure 1. Implementation of smart traffic light system using CCTVs

II. Literature Review

Significant strides have been made in research leveraging reinforcement learning for the optimization of traffic signal control. The early stages of this exploration were marked by constraints, primarily stemming from simplistic simulations and computational limitations [1]. However, the landscape has since evolved, with advancements in both simulation technologies and computational power ushering in a new era of complexity and realism in traffic modeling tools. This evolution has paved the way for a rich diversity of research endeavors, each distinguished by its unique approach to reinforcement learning methodologies, state space definitions, action space formulations, reward mechanisms, simulation platforms, traffic

network configurations, and vehicle generation models.
Among the myriad of research trajectories, the definition of reward criteria has emerged as a pivotal aspect, with the quantification of queued vehicles standing out as a common metric [2][3]. Yet, recent investigations have transcended traditional boundaries, extending their purview to encompass holistic city-wide traffic control systems, often involving the coordination of multiple agents [4][5]. Concurrently, a subset of researchers has directed their focus towards safety considerations, striving to devise collision-free traffic models [6]. Furthermore, the comparative analysis between conventional traffic light systems and their smart counterparts has garnered attention, elucidating the potential benefits of adopting advanced control strategies [7]. Pioneering efforts by Nie [8] have exemplified this trend, as they developed an intelligent traffic light system leveraging object detection technology through camera surveillance to ascertain vehicle counts at intersections. Subsequent adjustments to traffic light sequencing based on real-time traffic density data underscored the adaptive nature of such systems. In a departure from conventional approaches. Overall, the YOLO model has emerged as a powerful tool in the realm of traffic light control systems, offering efficient object detection capabilities that enable real-time monitoring, adaptive signal control, pedestrian safety enhancements, and incident management. Its integration into research papers underscores its versatility and effectiveness in addressing the complex challenges of urban traffic management. Nie proposed the adoption of a fuzzy logic controller as an alternative to traditional reinforcement learning models for traffic light systems, positing its potential efficacy [9].

The integration of deep reinforcement learning and Smart Traffic Systems represents a nascent but promising frontier in the technological landscape, with ongoing research endeavors focused on unraveling the intricacies of driver behavior and human factors pivotal to the design of effective traffic light control systems. Moreover, the imperative of equity and social impact underscores the need for inclusive traffic control solutions that cater to the diverse needs of all road users, including pedestrians, cyclists, public transportation patrons, and marginalized communities. This holistic perspective not only enriches the discourse surrounding traffic engineering but also serves as a guiding principle for future research and development initiatives aimed at fostering safer, more efficient, and equitable urban mobility ecosystems .By leveraging YOLO's real-time object detection capabilities, researchers have explored innovative approaches to traffic monitoring, vehicle detection, adaptive signal control, pedestrian safety enhancement, and incident management. The studies reviewed demonstrate the potential of YOLO-based systems to revolutionize traffic management practices by providing accurate, timely, and actionable insights into traffic dynamics. As traffic congestion, road safety, and environmental concerns continue to pose significant challenges in urban environments, the adoption of YOLO-based solutions holds immense promise for optimizing traffic flow, improving safety, and enhancing overall transportation efficiency. Moving forward, further research efforts should focus on refining YOLO-based algorithms, integrating them into comprehensive traffic management frameworks, and conducting real-world deployments to validate their efficacy in diverse traffic scenarios. By continuing to innovate and collaborate across disciplines, we can harness the full potential of YOLO technology to create smarter, safer, and more sustainable urban mobility systems for the benefit of society.

III. Methodology

This section talks about the methodology followed for conducting this research work, employing the YOLO approach for effective traffic management system in vehicle movements:

1. Image Capture using CCTV:

The deployment of CCTV cameras is meticulously planned, considering factors such as traffic volume, intersection geometry, and visibility. Cameras are strategically positioned at vantage points to ensure comprehensive coverage of the traffic network.

Additionally, camera placement takes into account factors such as lighting conditions, weather resilience, and vandalism protection to ensure uninterrupted surveillance and reliable data capture.

2. Vehicle Detection using YOLO:

The proposed system uses YOLO (You only look once) for vehicle detection, which provides the desired accuracy and processing time. A custom YOLO model was trained for vehicle detection, which can detect vehicles of different classes like cars, bikes, heavy vehicles (buses and trucks), and rickshaws. The dataset for training the model was prepared by scraping images from google and labeling them manually using LabelIMG, a graphical image annotation tool. Then the model was trained using the pre-trained weights downloaded from the YOLO website. The configuration of the .cfg file used for training was changed in accordance with the specifications of our model. After making these configuration changes, the model was trained until the loss was significantly less and no longer seemed to reduce. This marked the end of the training, and the weights were now updated according to our requirements .These weights were then imported in code and used for vehicle detection with the help of Open CV library. A threshold is set as the minimum confidence required for successful detection. After the model is loaded and an image is fed to the model, it gives the result in a JSON format i.e., in the form of key-value pairs, in which labels are keys, and their confidence and coordinates are values.

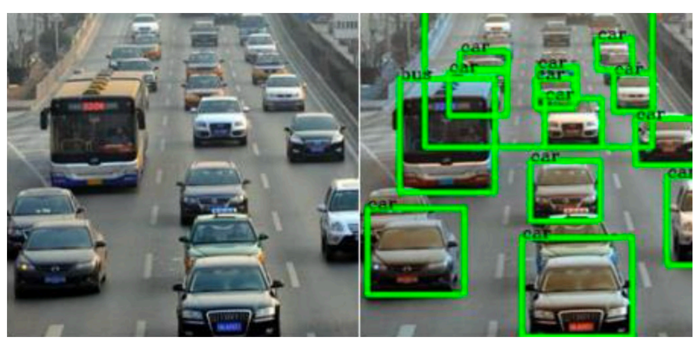

Fig 2: The bouding box algorithm of YOLO model

3. Traffic Density Calculation and Signal Switching Algorithm:

Upon detection of vehicles in the captured video frames, the relevant data, including vehicle counts and spatial distribution, is transmitted to a centralized server for further processing.
Switching Algorithm sets the green signal timer according to

traffic density returned by the vehicle detection module, and updates the red signal timers of other signals accordingly. It also switches between the signals cyclically according to the timers. The algorithm takes the information about the vehicles that were detected from the detection module, as explained in the previous section, as input. This is in JSON format, with the label of the object detected as the key and the confidence and coordinates as the values. This input is then parsed to calculate the total number of vehicles of each class. After this, the green signal time for the signal is calculated and assigned to it, and the red signal times of other signals are adjusted accordingly. The algorithm can be scaled up or down to any number of signals at an intersection.

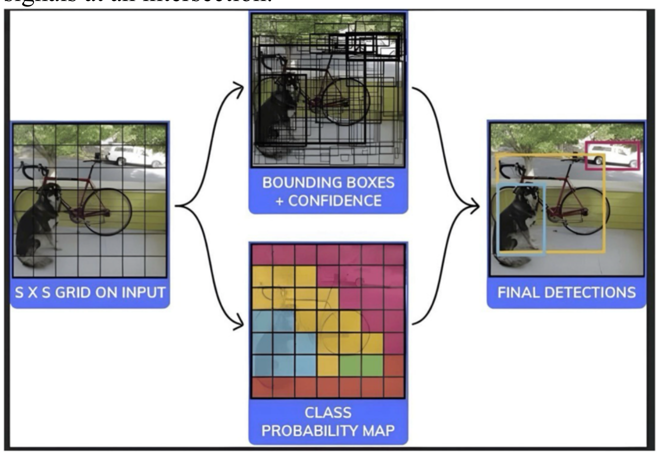

Figure 3. An illustration of the image's division and packaging using YOLO

4. Simulation Module:

Pygame is a series of cross-platform Python modules for making video games and simulations. It consists of computer graphics and sound libraries programmed to work with the Python programming language, which incorporates AI, mathematics, and Pygame, extending the excellent SDL library. This enables users to write full-featured games and multimedia applications in Python. Pygame is very compact, running on almost every platform and operating system. We use Pygame's functionalities to create vehicles at random and monitor their motion by updating their coordinates regularly. We use threading, a technique for performing several tasks at once. We keep the traffic signals up to date. Time functions are used to keep track of the time in seconds and do the job. Load is used to make images of cars, and bit keeps our eyes open.

5. Integration and Validation:

The vehicle detection module, signal switching algorithm, and simulation module are seamlessly integrated into a unified traffic light control system prototype.

The integrated system undergoes extensive testing and validation in both simulated and real-world traffic environments to evaluate its performance and reliability.

Field trials are conducted to assess the system's effectiveness in optimizing traffic flow, reducing congestion, minimizing delays, and improving overall road safety.

Real-time performance monitoring and feedback mechanisms are implemented to facilitate continuous improvement and refinement of the traffic light control system, ensuring its robustness and scalability in real-world deployment scenarios.

Through meticulous planning, rigorous testing, and iterative refinement, the proposed methodology aims to develop an innovative traffic management solution that leverages YOLO technology to optimize traffic flow, enhance road safety, and improve the efficiency of urban transportation networks.

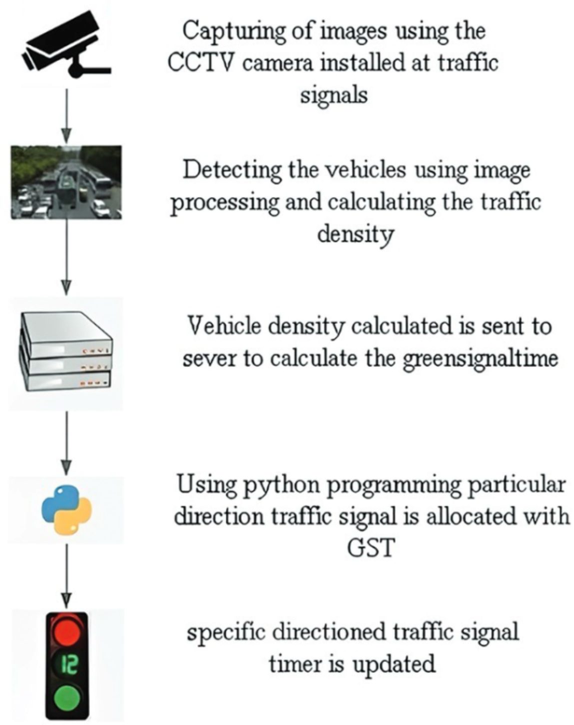

Figure 4: The image shows the working of the model how it will be able to run the traffic light system algorithm

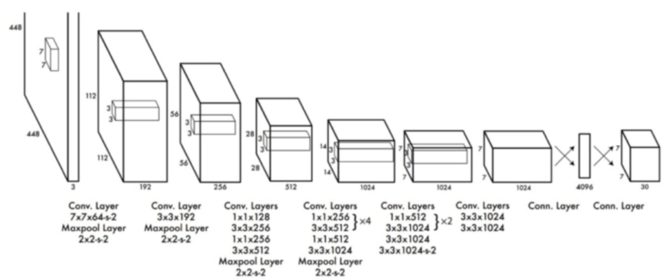

Figure 5. The image shows the working architecture of YOLO model

IV. Experiment analysis

Once the simulation was up and running, we compared the total number of cars that cross the intersection in the existing system over a 4-minute period and the proposed adaptive system with the same traffic distribution over a 25 minute period with 6 simulations, each lasting four minutes and with different traffic distributions.

The objective for a good AI-based traffic light system is to provide sophisticated control and coordination of traffic, reduce travel time and report in real-time and to report the vehicles in real-time and improve data analytics.

Table 1 shows the vehicle throughput in each of the four lanes in six different simulations each with a time span of four minutes. In this schema, the signal phases are visited sequentially in apre-determined manner (i.e., fixed duration and sequence)regardless of traffic conditions.

Table 2 shows the throughput of vehicles with the help of AI controlled traffic light system where the phases are visited in an adaptive manner based on real-time traffic conditions. The system is aimed at guiding vehicular movements through the

intersection more efficiently by minimizing queue length and wait time by maximizing throughput.
The following line graph demonstrates the difference in vehicle throughput in both the systems i.e., the current traffic light system and the proposed traffic light system over a period of 6 simulations in different traffic conditions.

CURRENT PROPOSED SYSTEM					
Simulation No.	Lane 1	Lane 2	Lane 3	Lane 4	Total
1	57	75	32	48	212
2	72	71	39	27	209
3	80	73	33	29	215
4	77	66	44	26	213
5	74	72	37	21	204
6	71	18	67	56	210
TOTAL					1263

Table 1: Data of throughput of vehicles in the current system

PROPOSED ADAPTIVE SYSTEM					
Simulation No.	Lane 1	Lane 2	Lane 3	Lane 4	Total
1	70	85	45	68	268
2	90	78	55	34	257
3	83	79	47	40	249
4	83	78	54	36	251
5	84	81	47	31	243
6	80	29	71	67	247
TOTAL					1515

Table 2: Data of throughput of vehicles in the proposed adaptive AI system

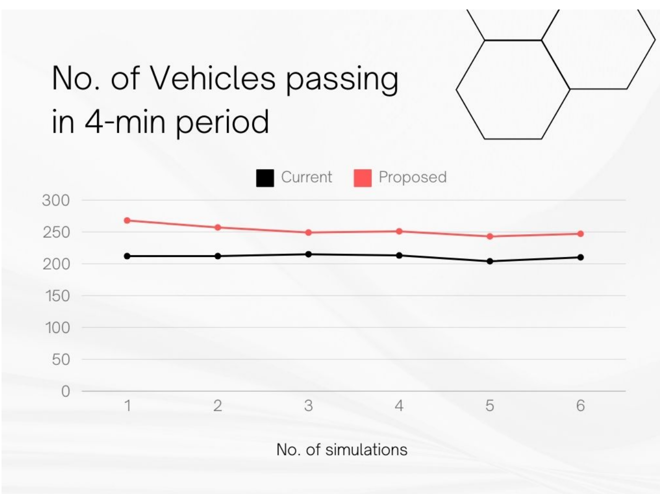

Figure 6: Line graph showing the comparison of vehicle throughput in both system

V. Conclusion

As a result, the suggested method makes sure that the way with more traffic is given a green signal for a longer period of time than the direction with less traffic by adjusting the green signal time adaptively based on the traffic density at the signal. This will lessen unneeded delays, traffic, and waiting times, all of which will cut down on fuel use and pollution.

The system exhibits a considerable improvement in terms of the amount of vehicles crossing the intersection, with simulation results showing a 23% improvement over the current method. Thus, to enable improved traffic control, this technology can be connected with the CCTV cameras in large cities.

VI. Future – Scope

Future work on traffic light control systems could explore several avenues for improvement and innovation. Integration of advanced AI techniques such as deep reinforcement learning (DRL) or multi-agent systems could enhance the system's ability to adaptively optimize signal timings in dynamic traffic environments. Additionally, incorporating vehicle-to-infrastructure (V2I) communication and dynamic adaptation to environmental factors like weather conditions could further improve traffic efficiency and safety. Future research could also focus on optimizing traffic light control for non-motorized modes of transportation and integrating with broader smart city initiatives for holistic urban mobility management. Real-time feedback mechanisms, adaptive control strategies, and comprehensive evaluations of social and environmental impacts should also be prioritized to ensure the development of more intelligent, sustainable, and inclusive traffic light control systems.

Acknowledgement

This work was supported in part by Maharaja Agrasen Institute of Technology, New Delhi, India and in part by The Department of Artificial Intelligence and Machine Learning of MAIT .This research paper was developed under the guidance of Dr. Tripti Lamba.

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