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Adaptive Traffic Management System using CNN (YOLO)

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Abstract: The huge number of vehicles on the roadways is making congestion a significant problem. The line longitudinal vehicle waiting to be processed at the crossroads increases quickly, and the traditionally used traffic signals are not able to program it properly. Manual traffic monitoring may be an onerous job since a number of cameras are deployed over the network in traffic management centers. The proactive decision-making of human operators, which would decrease the effect of events and recurring road congestion, might contribute to the easing of the strain of automation.The traffic control frameworks in India are now needed as it is an open-loop control framework, without any input or detection mechanism. Inductive loops and sensors employed in existing technology used to detect the number of passing vehicles. The way traffic lights are adapted is highly inefficient and costly in this existing technology. The aim was to build a traffic control framework by introducing a system for detection ,which gives an input to the existing system (closed loop control system) in order to adapt to the changing traffic density patterns and to provide the controller with a crucial indication for ongoing activities. By this technique, the improvement of the signals on street is extended and thus saves time by preventing traffic congestion.

This study proposes an algorithm for real-time traffic signal control, depending on the traffic flow. In reality, the features of competitive traffic flow at the signposted road crossing are used by computer vision and by machine learning. This is done by the latest, real-time object identification, based on convolutional Neural Networks network called You Look Once (YOLO). Traffic signal phases are then improved by data acquired in order to allow more vehicles to pass safely over minimal wait times, particularly the line long and the time of waiting per vehicle.This adjustable traffic signal timer is used to calculate traffic density utilizing YOLO object identification using live pictures of cameras in intervals and adjusts the signal timers appropriately, therefore decreasing the road traffic congestion, ensuring speedier transit for persons, and reducing fuel consumption. The traffic conditions will improve enormously at a relatively modest cost. Inductive loops are a viable but costly approach. This method thereby cuts expenses and outcomes quickly.

Keywords: YOLO, convolution neural networks, machine learning, closed loop control system

I. INTRODUCTION

A key difficulty in many towns is the traffic congestion and fixed-cycle light controls do not resolve the excessive time at the crossing. Instead of a traffic light, we often see a cop managing movements. He sees the state of the road and determines the period permitted for each direction. A constant increase in the number of vehicles and cars, particularly in India, is rapidly creating, which leads to crowded road problems. This proposal will have an impassive task to avoid the busy road. Traffic control signals have mainly abnormalities under typical circumstances:

1) The emergency automobiles are not considered. The lack of crisis precautions ensures that the intersection meets crowded driving circumstances confidently and causes unnecessary financial losses.
2) Overwhelming traffic congestions: Overwhelming transit blocks have spread across large urban neighborhoods as an increased flood of cars is on the road. This usually happens at the major crossings frequently at the start of business time and at night, after the available time. The major effect of this problem is the increased waste of time for the general population
3) There is still no traffic: The road customers have to stop till the traffic light becomes green since the travel signal remains red for the current time period. They have to pay for jumping a red light. The answer to this question is to provide a framework that identifies streams on all streets and determines the time to automatically change the lights. In the nearby junctions, efficient interaction of traffic flags is also critical

For adaptive traffic light systems such as a magnetic telemetry sensor, there is a solution to monitor how busy traffic can be monitored in real-time. In England and Australia, this type of system has been adopted. However, it is costlier and ineffective because the system must be planting directly in the motorway itself, the sensor may also be a problem if something happens and the sensor must be rectified, given that the sensor has been installed within the road.This human feat motivates us to build an Adaptive Traffic Light Control that takes account of real-time traffic and manages the intersection intelligently.

The suggested context consolidates the newest technology with human-made brain power, which is unlike the other special control flags which update the plans and phases of traffic signals by hardcoding the controller values. The signs interact, responding to shifting traffic conditions minimizes waiting time for vehicles This offers up a new option for an adaptive road light system based on vision with the advancement of computer vision technologies. With a vision-based adaptive light. It implies it will cost less since most junction or traffic lights already have some CCTV camera so it only needs to calibrate the camera and install proprietary traffic light software. We need two major components for such a system: eyes to see how the road is in real-time, and a brain **to work on** it. A central traffic signal system has two primary tasks: to move as many users as possible across the intersection and as little friction as possible amongst these users. These algorithms assist to properly program the traffic lights.

Our suggested model would identify, track and count cars on a video stream that go across a given line and offer a sense of what is happening on the road network in real-time. Our genuine aim is to make progress at unusual hours on the deferment in automobiles. The detection approach for items on each video frame employs the YOLO method. And SORT to track these items throughout different frames (Simple online and real-time tracking algorithms). If we have less traffic or traffic than normal, our model optimizes the light by raising or reducing the light life. Traffic situation may be better improved if we just use past dynamic scheduling method such as the real-time count of the vehicles

BEST-GREEN time configuration 2.The enhanced scheduling algorithm

These algorithms will help schedule the traffic lights appropriately. The suggested method adapts the green signaling period to the density of the traffic on the signal and ensures that a green signal is allocated in a direction with more traffic for a longer time compared to fewer traffic directions.

II. LITERATURE SURVEY

Development of the self-intelligent traffic light control system, based on the traffic environment using machine learning, is needed since the existing traffic lights utilize technologies that employ far older, efficient, and unflexible microcontrollers. These traffic lighting systems are having issues in executing some already established code lines that cannot allow the update to be adjusted in real-life circumstances. The present traffic systems offer hard-coded and previously defined time periods for various lights, which makes the system highly inflexible. The Traffic Environment-based Self-Intelligent Traffic Light Control System employing a machine learning system provides outstanding outcomes in a variety of aspects such as performance, efficiency, and excellent adaptability and sustainability.[1][2]

Every day, millions of automobiles, trucks and other two-wheelers are traveling on the busy city and metropolitan highways. Covering the degrees and expansion of traffic congestion and blockades, countless elements like economical, sociological, or cultural subtleties determine. The above-mentioned congestion levels are directly related to traffic accidents, travel wastage, transportation expensive load and are an obstacle to the first responders in any event. Damage from closed roads takes several forms, such as reducing employees' efficiency, wasting the time of taxpayers, losing economic possibilities, slowing down delivery service. All of these variables lead to higher prices. It would be advisable to build state-of-the-art infrastructure and at the same time to make the current infrastructure clever in order to address the problems posed by such delays.[3][4]

Another way to control and avoid grid lock-ups with a limited capacity to identify mobiles was to develop reinforcement learning methods, notably the Q-learning model-free algorithm. The findings of the research demonstrate that these learning approaches provide an encouraging means of managing road traffic situations more effectively under incomplete detection scenarios, such as DSRC traffic management systems. In a region particularly unwilling to change, this creates encouraging and necessary changes. Statistical results on small, medium, and high arrival rates suggest that strengthening learning can handle all the densities of road transport by vehicle. Although the techniques for optimizing road traffic on a short-term arrival and huge arrival are very discreet, the results show that strengthening learning can make use of the 'particle' characteristic of car traffic and the 'fluid' property.[5][6]

III. PROPOSED SYSTEM

The proposed system have optimized traffic lights by assigning them time ,based on traffic conduct in real-time by utilizing the count of vehicles at either side of the signal.If we have less traffic or traffic than normal, our algorithm will optimize light by raising or reducing light time. For real-time count, we employed YOLO and SORT algorithms on the live video feed. (i)YOLO to detect objects on each of the video frames.(ii)SORT to track those objects over different frames.

Our suggested system uses an image from traffic junction CCTV cameras as input to calculate real-time traffic density utilising image processing and object detection.

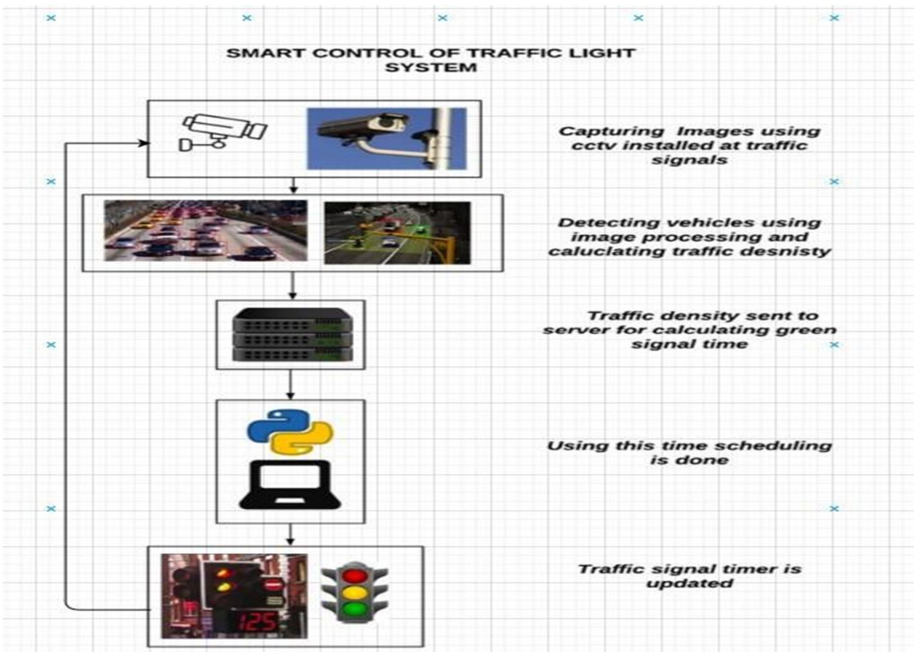
Vehicle Detection, Signal Switching Algorithm, and Simulation are the three parts that make up this system.

1) *Vehicle Detection Module:* This module is in charge of counting the number of vehicles in the image that the camera sends back.As an output, it will provide you the number of vehicles in each vehicle class, such as car, bike, bus, truck, and rickshaw.
2) *Signal Switching Method:* This algorithm changes the times of all signals to red, green, and yellow.These timings are based on the number of vehicles of each class received from the vehicle detection module, as well as a number of other criteria such as the number of lanes, the average speed of each class of vehicle, and so on.
3) *Simulation Module:* To model traffic lights and automobiles passing through a traffic intersection, a simulation is built from the ground up using the Pygame package.

This image is passed on to the vehicle detection algorithm, which uses YOLO, as indicated in the diagram below.

The number of vehicles of each class, such as cars, bicycles, buses, and trucks, is counted in order to compute traffic density.This density, along with a few other criteria, is used by the signal switching algorithm to set the green signal timing for each lane. The red signal times have been modified to reflect this.In order to prevent lane starvation, the green signal time is limited to a maximum and minimum value.

To showcase the system's effectiveness and compare it to the present static system, a simulation is also created.



A. Vehicle Detection Module

1) For vehicle detection, the suggested system employs YOLO (You Only Look Once), which gives the requisite accuracy and processing speed.Vehicle detection was trained using an unique YOLO model that can detect vehicles of various classes, including automobiles, bikes, heavy vehicles (buses and trucks), and rickshaws.
2) To create the dataset for training the model, we scraped images from Google and manually labelled them with LabelIMG, a graphical image annotation tool.After that, the model was trained using the YOLO website's pre-trained weights.
3) The setting of the.cfg file used for training was altered to match our model's specifications.By altering the 'classes' variable, the number of output neurons in the last layer was set equal to the number of classes the model is expected to detect.
4) This was four in our system: car, bike, bus/truck, and rickshaw.The number of filters must also be adjusted using the formula 5*(5+number of classes), which in our case is 45.
5) The model was trained after these configuration adjustments were made until the loss was greatly reduced and no longer appeared to be decreasing.The training came to an end at this point, and the weights were adjusted to our specifications.
6) Using the OpenCV library, these weights were then imported into code and used for vehicle detection.The minimum level of confidence required for successful detection is set as a threshold.It gives the result in JSON format when the model is loaded and a picture is provided to it.i.e., in the form of key-value pairs, with labels acting as keys and confidence and coordinates acting as values.From the labels and coordinates acquired, OpenCV may be used to draw bounding boxes on the images.

B. Signal Switching Algorithm

The Signal Switching Algorithm adjusts the red signal timers of other lights based on the traffic density given by the vehicle detecting module, and sets the green signal timer accordingly.It also cyclically alternates between the signals based on the timers.The information about the vehicles observed by the detection module, as stated in the preceding section, is sent into the algorithm.This is in JSON format, with the key being the identified object's label, and the values being the confidence and coordinates. The total number of vehicles in each class is then calculated using this data.
Following that, the signal's green signal time is calculated and assigned, and the red signal times of other signals are altered as necessary.Any number of signals at an intersection can be scaled up or down using this approach.

The following factors were considered while developing the algorithm:

1) The processing time of the algorithm to calculate traffic density and then the green light duration – this decides at what time the image needs to be acquired
2) Number of lanes
3) Total count of vehicles of each class like cars, trucks, motorcycles, etc.
4) Traffic density calculated using the above factors
5) Time added due to lag each vehicle suffers during start-up and the non-linear increase in lag suffered by the vehicles which are at the back [13]
6) The average speed of each class of vehicle when the green light starts i.e. the average time required to cross the signal by each class of vehicle [14]
7) The minimum and maximum time limit for the green light duration - to prevent starvation

C. Working of the Algorithm

The default time for the first signal of the first cycle is established when the algorithm is first run, and the algorithm sets the timing for all other signals of the first cycle and all signals of subsequent cycles.The detection of cars for each direction is handled by a different thread, while the current signal's timer is handled by the main thread.When the current signal's green light timer (or the following green signal's red light timer) reaches 0 seconds, the detecting threads take a picture of the next direction.The result is subsequently parsed, and the next green signal's timer is set.
All of this occurs in the background, while the main thread counts down the current green signal's timeout. This enables for a seamless timer assignment and hence eliminates any latency.The following signal becomes green for the period of time defined by the algorithm whenever the current signal's green timer reaches zero.When the time of the signal that will turn green next is 0 seconds, the image is taken.
This provides the system a total of 5 seconds (the value of the yellow signal timer) to process the image, detect the number of cars of each class present in the image, compute the green signal time, and set the times of this signal and the red signal time of the following signal correspondingly. The average speeds of vehicles at startup and their acceleration times were utilised to identify the best green signal time based on the number of cars of each class at a signal, from which an estimate of the average time each class of vehicle takes to cross an intersection was found.

The formula below is used to compute the green signal time.

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

where:

1) GST is green signal time
2) NoOfVehiclesOfClass is the number of vehicles of each class of vehicle at the signal as detected by the vehicle detection module,
3) AverageTimeOfClass is the average time the vehicles of that class take to cross an intersection, and
4) NoOfLanes is the number of lanes at the intersection.

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To make traffic management more successful, the average time each type of vehicle takes to cross an intersection can be set according to the location, i.e., region-wise, city-wise, locality-wise, or even intersection-wise based on the features of the intersection.

For this, data from the relevant transportation agencies can be evaluated.The signals are switched in a cyclic pattern rather than in the order of densest to least dense.This is in line with the current system, which requires individuals to change their routes or cause any confusion because the signals turn green one after the other in a fixed pattern.

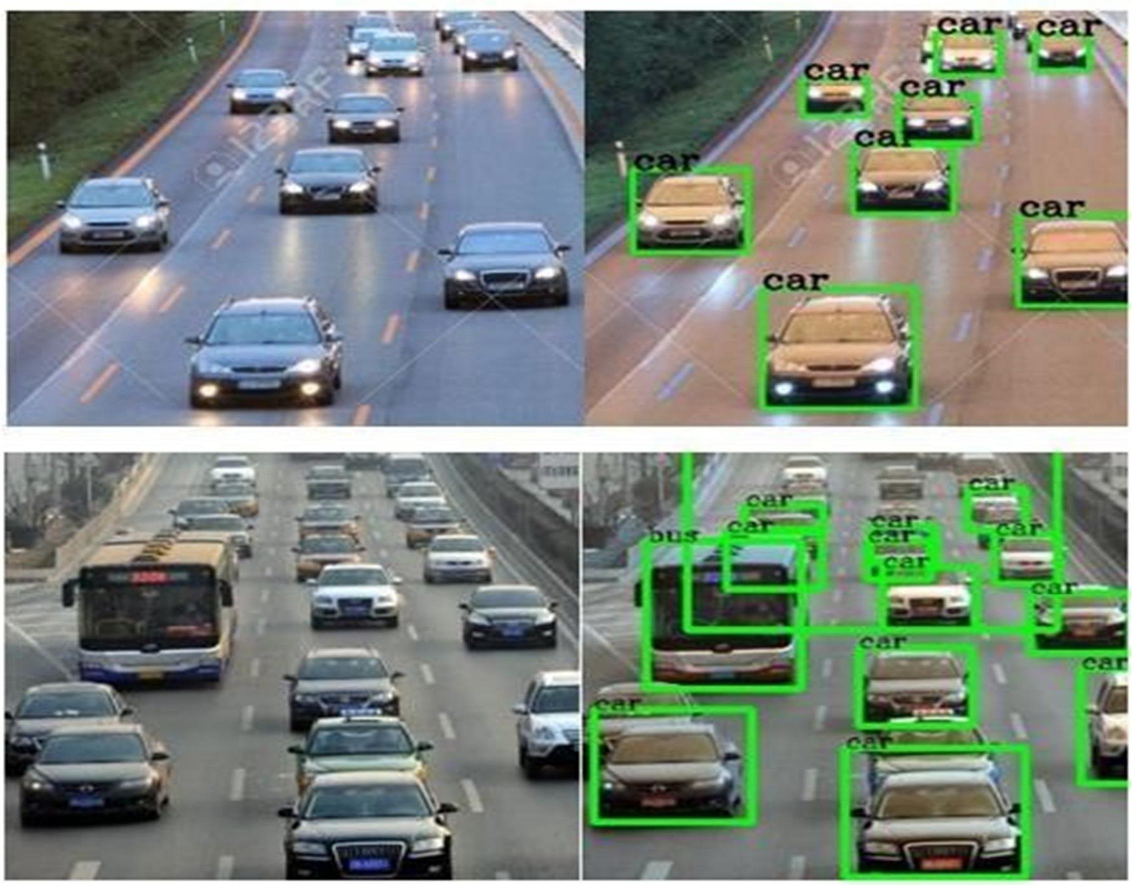
The order of the signals is also the same as it is now, and the yellow signals have been taken into account. Order of signals: Red → Green → Yellow → Red

D. Simulation Module

To imitate real-life traffic, a simulation was created from the ground up using Pygame.It aids in visualising the system and comparing it to a static system that already exists.It has a four-way intersection with four traffic lights.On top of each signal is a timer that displays the amount of time until the signal changes from green to yellow, yellow to red, or red to green. The number of vehicles that have crossed the intersection is also displayed next to each light.Automobiles, bicycles, buses, trucks, and rickshaws arrive from all directions.Some of the vehicles in the rightmost lane turn to cross the intersection to make the simulation more realistic. When a vehicle is generated, random numbers are used to determine whether it will turn or not.It also has a timer that shows how much time has passed since the simulation began.

IV. RESULTS

A. Output of the Vehicle Detection Module



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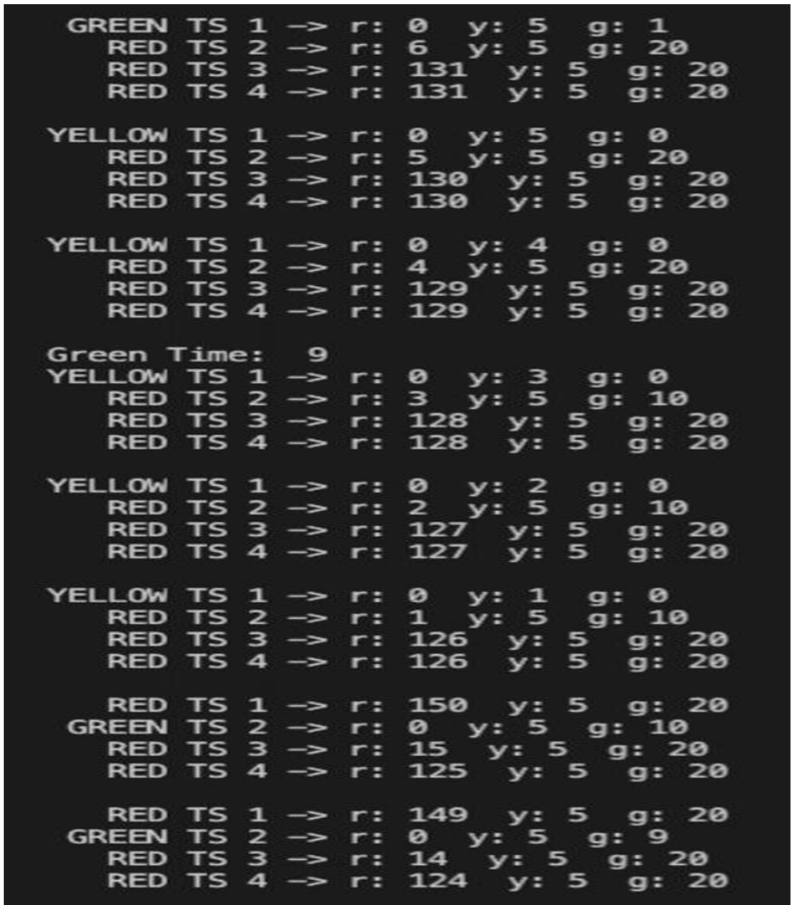
B. Output of the Signal Switching Algorithm



```
  GREEN TS 1 -> r: 0   y: 5   g: 1
    RED TS 2 -> r: 6   y: 5   g: 20
    RED TS 3 -> r: 131   y: 5   g: 20
    RED TS 4 -> r: 131   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: 130   y: 5   g: 20
    RED TS 4 -> r: 130   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: 129   y: 5   g: 20
    RED TS 4 -> r: 129   y: 5   g: 20

 Green Time:  9
 YELLOW TS 1 -> r: 0   y: 3   g: 0
    RED TS 2 -> r: 3   y: 5   g: 10
    RED TS 3 -> r: 128   y: 5   g: 20
    RED TS 4 -> r: 128   y: 5   g: 20

 YELLOW TS 1 -> r: 0   y: 2   g: 0
    RED TS 2 -> r: 2   y: 5   g: 10
    RED TS 3 -> r: 127   y: 5   g: 20
    RED TS 4 -> r: 127   y: 5   g: 20

 YELLOW TS 1 -> r: 0   y: 1   g: 0
    RED TS 2 -> r: 1   y: 5   g: 10
    RED TS 3 -> r: 126   y: 5   g: 20
    RED TS 4 -> r: 126   y: 5   g: 20

    RED TS 1 -> r: 150   y: 5   g: 20
  GREEN TS 2 -> r: 0   y: 5   g: 10
    RED TS 3 -> r: 15   y: 5   g: 20
    RED TS 4 -> r: 125   y: 5   g: 20

    RED TS 1 -> r: 149   y: 5   g: 20
  GREEN TS 2 -> r: 0   y: 5   g: 9
    RED TS 3 -> r: 14   y: 5   g: 20
    RED TS 4 -> r: 124   y: 5   g: 20
```

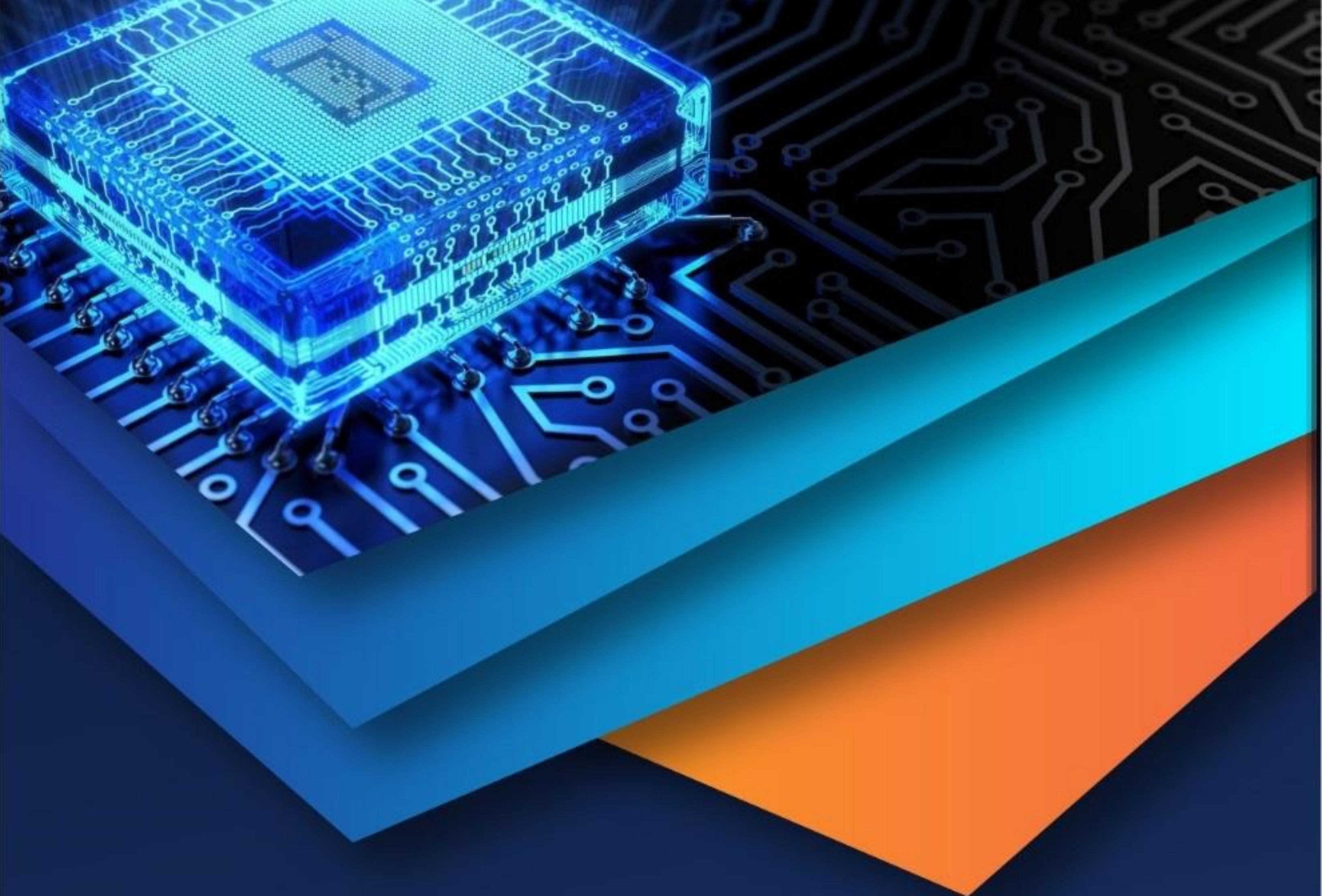
C. Output of Simulation

V. CONCLUSION

This system enhances the traffic control system by the development of a self-adaptive road traffic algorithm based upon deep learning. This new method promotes intersection flow of automobiles, which reduces congestion, reduces CO2 emissions, etc. For different reasons, we tested and compared our YOLO model with other current models as a good detector. It's quick and precise, too. However, we have solved our objective of identifying things on the roadways by employing YOLO. Vehicle counting is a process to estimate the road traffic density to access the traffic conditions. Vehicle counting is a technique to calculate the density of road traffic for traffic access. In this context, the video-based counting technique is presented, the processing of video by YOLO, tracking, and counting is done in three phases, for example, object detection. YOLO obtained renewable results into the field of object recognition and green precision into cogitative tracking speed. This suggested approach makes traffic congestion simpler, precise, and early and can produce highly precise results.our model works very well on the Indian roads, not only we'd save time but also a lot of money and infrastructure costs when compared with the expensive and impractical method of Inductive Loops

REFERENCES

[1] Chavan, S. S., Deshpande, R. S., & Rana, J. G. (2009). Design of Intelligent Traffic Light Controller Using Embedded System. 2009 Second International Conference on Emerging Trends in Engineering & Technology. Doi:10.1109/icetet.2009.76
[2] Rotake, Dinesh & Karmore, Swapnili. (2012). Intelligent Traffic Signal Control System Using Embedded System. Issue 3.
[3] Nellore, K., & Hancke, G. (2016). A Survey on Urban Traffic Management System Using Wireless Sensor Networks. Sensors, vol. 16, Issue 2, 157. doi:10.3390/s16020157
[4] Ali Alheeti, Khattab M. (2011). Intelligent Traffic Light Control System Based Image Intensity Measurement. Issue 3.
[5] Bakker B., Whiteson S., Kester L., Groen F.C.A. (2010) Traffic Light Control by Multiagent Reinforcement Learning Systems. In: Babuška R., Groen F.C.A. (eds) Interactive Collaborative Information Systems. Studies in Computational Intelligence, vol 281. Springer, Berlin, Heidelberg, Doi: 10.1007/978-3-642-11688-9_18
[6] R. Zhang, A. Ishikawa, W. Wang, B. Striner, and O. K. Tonguz (2020), "Using Reinforcement Learning With Partial Vehicle Detection for Intelligent Traffic Signal Control," in IEEE Transactions on Intelligent Transportation Systems, Doi: 10.1109/TITS.2019.2958859.
[7] Xie, Xiao-Feng & Smith, Stephen & Barlow, Gregory. (2012). Schedule-Driven Coordination for Real-Time Traffic Network Control. ICAPS 2012 - Proceedings of the 22nd International Conference on Automated Planning and Scheduling.
[8] M. B. Natafgi, M. Osman, A. S. Haidar and L. Hamandi (2018), "Smart Traffic Light System Using Machine Learning," 2018 IEEE International Multidisciplinary Conference on Engineering Technology (IMCET), Beirut, pp. 1-6, Doi: 10.1109/IMCET.2018.8603041.
[9] M. K. Mainali, K. Hirasawa, and S. Mabu (2010), "Evolutionary approach for the traffic volume estimation of road sections," 2010 IEEE International Conference on Systems, Man and Cybernetics, Istanbul, pp. 100-105, Doi: 10.1109/ICSMC.2010.5642212.
[10] K. Behrendt, L. Novak, and R. Botros (2017), "A deep learning approach to traffic lights: Detection, tracking, and classification," 2017 IEEE International Conference on Robotics and Automation (ICRA), Singapore, pp. 1370-1377, Doi: 10.1109/ICRA.2017.7989163.
[11] G. Chandan, A. Jain, H. Jain, and Mohana(2018), "Real-Time Object Detection and Tracking Using Deep Learning and OpenCV," 2018 International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, pp. 1305- 1308,



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