

PAPER • OPEN ACCESS

Intelligent Traffic Light Control System Based On Traffic Environment Using Deep Learning

To cite this article: Moolchand Sharma *et al* 2021 *IOP Conf. Ser.: Mater. Sci. Eng.* **1022** 012122

View the [article online](#) for updates and enhancements.

You may also like

- [A new cellular automaton for signal controlled traffic flow based on driving behaviors](#)
Yang Wang, , Yan-Yan Chen et al.

- [Optimizing the traffic control system of Sultan Agung street Yogyakarta using fuzzy logic controller](#)
L N A Mualifah and A M Abadi

- [Research and Application of Microcirculation Theory in small cities](#)
Kuanxiang Xi, Weixiong Zha and Wenqian Ji

ECS Toyota Young Investigator Fellowship

For young professionals and scholars pursuing research in batteries, fuel cells and hydrogen, and future sustainable technologies.

At least one \$50,000 fellowship is available annually.
More than \$1.4 million awarded since 2015!

 Application deadline: January 31, 2023



Learn more. Apply today!



INTELLIGENT TRAFFIC LIGHT CONTROL SYSTEM BASED ON TRAFFIC ENVIRONMENT USING DEEP LEARNING

Moolchand Sharma^{1*}, Ananya Bansal², Vaibhav Kashyap², Pramod Goyal², Dr. Tariq Hussain Sheikh³

^{1,2}*Maharaja Agrasen Institute of Technology, GGSIPU, Delhi, India*

³*Government Degree College Poonch, Jammu & Kashmir, India*

moolchand@mait.ac.in^{1*}, ananyabansal0@gmail.com², sirvaibs231098@gmail.com²,
pramodgoyal38@gmail.com², tariqsheakh2000@gmail.com³

ABSTRACT

At present, the traffic control frameworks in India, need insight and go about as an open-loop control framework, with no input or detecting system. Present technologies use Inductive loops and sensors to detect the number of vehicles passing by. It is a very inefficient and expensive way to make traffic lights adaptive. Using a simple CCTV camera can improve the conditions. The visual tracking of objects is amongst the most critical areas of computer vision and deep learning. The objective of this work was to develop the traffic control framework by presenting a detecting system, which gives an input to the current system, with the goal that it can adjust the changing traffic density patterns and provides a vital sign to the controller in a continuous activity. Using this method, improvement of the traffic signal switching expands the street limit, saves time for voyaging, and prevents traffic congestion. The framework additionally goes for consolidating exceptional arrangements for clearing the path for emergency vehicles. In this paper, we will detect and track vehicles on a video stream and count those going through a defined line and to ultimately give an idea of what the real-time on-street situation is across the road network. Our real target is to advance the deferral in the travel of vehicles in odd hours of the day. It uses the YOLO (“You Only Look Once”) object detection technique to detect objects on each of the video frames And SORT (Simple Online and Real-time Tracking algorithm) to track those objects over different frames. Once the objects are detected and tracked over different frames, a simple mathematical calculation is applied to count the intersections between the vehicle's previous and current frame positions with a defined line.

However, accuracy drops when vehicles are either close together or have large shadows, dark vehicles do not always meet the detection criteria, and night scenes are challenging to resolve as headlight beams can create large areas that meet threshold criteria. We are focusing on the Indian roads where the traffic conditions are harsh and abrupt. We have already tested it on a live feed from various traffic prone roads and have found satisfactory results. Other Adaptive Traffic Light Systems were not able to work on the Indian traffic conditions. Our model has the edge over the other by performing at par on Indian roads. We'll increase or decrease the timer according to the conditions of the roads. This will tremendously improve the traffic conditions at a very low cost. Inductive loops are a feasible but expensive method. So, this system reduces costs and provides quick results.

KEYWORDS: Computer Vision, Deep learning, Inductive loops, YOLO, SORT



Content from this work may be used under the terms of the [Creative Commons Attribution 3.0 licence](#). Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

1. INTRODUCTION

A relentless increment in the population mainly in India, the number of vehicles and autos builds quickly, which prompts the congested road issue. This proposed framework will have a compelling job to evade the crowded road. Under common conditions, traffic signals control, for the most part, has two deformities:

1. The consideration of emergency cars is not there. As traffic signal control frameworks are the lack of crisis measures, the intersection dependably meets congested driving conditions and prompts unnecessary financial losses[1][2].
2. Overwhelming Traffic Congestions: With an expanding fleet of automobiles out on the road, overwhelming transit clogs have generously expanded in significant urban communities. This happened ordinarily at the primary intersections regularly toward the beginning of the day that is in office hour and at night after office hours, after the available time. The significant impact of this issue is the expanded time wastage of the general population[3].
3. No traffic yet standing still: Since the traffic signal stays red for the current timespan, the street clients have to hold up until the traffic light goes to green. On jumping a red light, they need to pay fines. The answer to this issue is building up a framework that recognizes traffic streams on every street and sets the time for changing the signals automatically. Also, the effective interaction of traffic flags in neighboring intersections is likewise crucial [4][5].

Innovation for smart traffic management was undertaken at Carnegie Mellon University for deployment in a test project in Pittsburgh, targeting minimization of road traffic emanations arising from the targeted area. Dissimilar to other unique control flags that update the plans and stages of traffic signals by the values hardcoded in the controller, the proposed framework consolidates the latest technologies with human-made brainpower. The signs interact with each other, thereby adjusting to the evolving traffic scenarios to minimize the time vehicles waste waiting. Benefiting from the fiber-optic camcorders similar to the ones used efficiently in unique controlling frameworks, this proposed method checks the number of vehicles. It makes changes progressively to stay away from blockages as much as possible. Initial outcomes from the pilot project are encouraging: the amount of time wasted by drivers lingering at traffic signals was reduced by 40, and to traverse the targeted area reduced by 25%.

Our proposed model will detect and track vehicles on a video stream and count those going through a defined line and to ultimately give an idea of what the real-time on-street situation is across the road network. Our real target is to advance the deferral in the travel of vehicles in odd hours of the day. It uses the YOLO object detection technique to detect objects on each of the video frames And SORT (Simple Online and Real-time Tracking algorithm) to track those objects over different frames. If we have less traffic or there is more traffic than usual, our model will optimize the light by increasing or decreasing the duration of the light. Traffic situation can be further optimized once we have the real-time count of the vehicles by just applying previous dynamic scheduling algorithms like the [6]:

1. BEST-GREEN time configuration
2. The scheduling algorithm
3. The enhanced scheduling algorithm

These algorithms will help schedule the traffic lights appropriately [7]. The paper is lined up as: The study about the existing technologies is discussed in Section 2. The proposed methodology explaining intelligent

traffic light control systems is detailed in Section 3. Implementation and results are explained in Section 4. Finally, section 5 consists of conclusions followed by References.

2. LITERATURE REVIEW

The development of the Self-Intelligent Traffic Light Control System based on Traffic Environment using Machine Learning is required as the current traffic lights are making use of technologies that are using much older microcontrollers providing low efficiency and no flexibility. Such traffic light management systems suffer from problems as they execute certain previously defined lines of code that cannot offer the adjustability of updation being executed in real-life scenarios. The current traffic management systems provide hard-coded & previously set intervals of time for different signals, and that makes the system very rigid. The Self-Intelligent Traffic Light Control System based on Traffic Environment using Machine Learning System delivers excellent results on various parameters like performance, efficiency, and along with the superb flexibility and sustainability [8] [9].

Millions of cars, trucks, and other motorized two-wheelers travel on busy roads of towns and metropolitan cities every single day. Innumerable factors like different financial, societal, and cultural nuances decide the levels and the growth of traffic jams and blockages. The levels mentioned above of congestion have a direct correlation with road accidents, wastage of travel time, the financial burdens of transportation as well as proving to be a hindrance to the first responders in case of any emergency. Damages because of crammed roads take various forms like reduction in efficiency and productivity of employees, wastage of taxpayer's time, loss of economic opportunities, slow-down of delivery services. All of these factors contribute to increased costs. To overcome the challenges caused by these traffic jams, it would be advisable to construct state-of-the-art infrastructure and simultaneously make the existing infrastructure smart [10][11].

Another method posed forward reinforcement learning methods, in particular the Q-learning model-free algorithm, to manage and avoid the gridlocks with a limited ability to detect auto-mobiles. The conclusions of their research showcased that these learning methods are a promising avenue to better manage road traffic scenarios under partial detection scenarios, such as traffic control systems using DSRC technology. This becomes an encouraging and required change in an area very reluctant to change. The statistical outcomes on scanty, intermediate, and heavy rates of arrival indicate reinforcement learning can manage every density of vehicular road traffic. Even though the methods for optimizing road traffic on scanty arrival and massive arrival are, quite discrete, outcomes prove reinforcement learning can make use of the 'particle' property of the vehicular traffic, along with the 'fluid' property, thereby it can provide a quite remarkable and comprehensive optimization technique[12][13].

One of the potential problems of such vehicular traffic management systems has been to put forward a traffic management system that considers the vehicular traffic at any traffic signal to be isolated from all other traffic signals near-by in the city. Traffic congestion is a practical problem resulting in substantial delays and extra fuel costs for drivers. It is generally recognized that improvements to traffic signal control provide the biggest payoff for reducing congestion on surface streets and that adaptive control strategies capable of responding to traffic conditions in real-time hold the most potential for improvement[14]. This assumption of their proposed methodology will cease to be the most optimal solution in a scenario when such a traffic signal is not independent of all other near-by traffic signals. Their values, which were fed to the machine learning model, exclude the size of the queues as well as the time wasted in them. Hence, if there is a scenario wherein the outgoing lanes are gridlocked, the traffic exiting the traffic signal would require waiting in a queue in the lane, leaving the traffic signal. In situations like this, their model failed to provide the most optimal solution. The methods put forward have the ability to be transformed to apply it to inter-connected traffic signals. The present traffic management systems use as input the - time spent in

the queue as well as the length of the queue for every traffic signal, and the results are given as the returns linked to every possible phase of the traffic light. The methods proposed can be widened to interconnect with multiple traffic signals near-by at the same time. This interconnected ecosystem will be made up of numerous traffic signals in the desired area in place of multiple independent traffic signals. This method would take as input the queue length and the time of waiting in queues for every street of every traffic signal of the targeted region [13][15].

To research autonomous vehicles, a new method was put forward in which they used deep learning algorithms. They led to the conclusion that their traffic signal detection had a direct correlation to easier and optimal paths for programmed vehicles in urban scenarios and had allowed for better traffic management systems for these automated vehicles on which the research was conducted. As accurate for almost all deep learning algorithms, a blatantly simple approach to enhance the efficiency of the model, is to gather and classify a more extensive training data set. In particular, sample images from areas outside the area of primary research should augment the capability of the vehicular traffic control system to scale. At the same time, parallel processing of the data in the detector, as well as tracker, should help in meeting higher demands[16][17].

There are also some clear limitations related to the use of the YOLO model for the detection of vehicles at any traffic signal. This model applies strict spatial constraints on the box in which the object is bound since every cell in the grid can only predict two boxes as well as be a part of a single class. The causes mentioned above limit the count of objects close-by that this model can predict. This model faces issues with not so large objects that are present in groups, for instance, a large number of ants. As the YOLO model is trained to predict how to bound boxes, it faces issues in generalizing to objects in exaggerated or unusual sizes or views. This model takes into consideration comparatively coarse features to predict the boxes bounding objects because the internal architecture contains various down sampling layers from the input image [18][19].

3. PROPOSED WORK/ METHODOLOGY

After studying the various ongoing research on the adaptive traffic light solutions, we emerged with a plan of action to complete our proposed methodology. Our methodology has been summarized in Figure 1. We have used YOLO and SORT to detect and track vehicles on a video stream and count those going through a defined line. The process has been explained in the following flowchart.

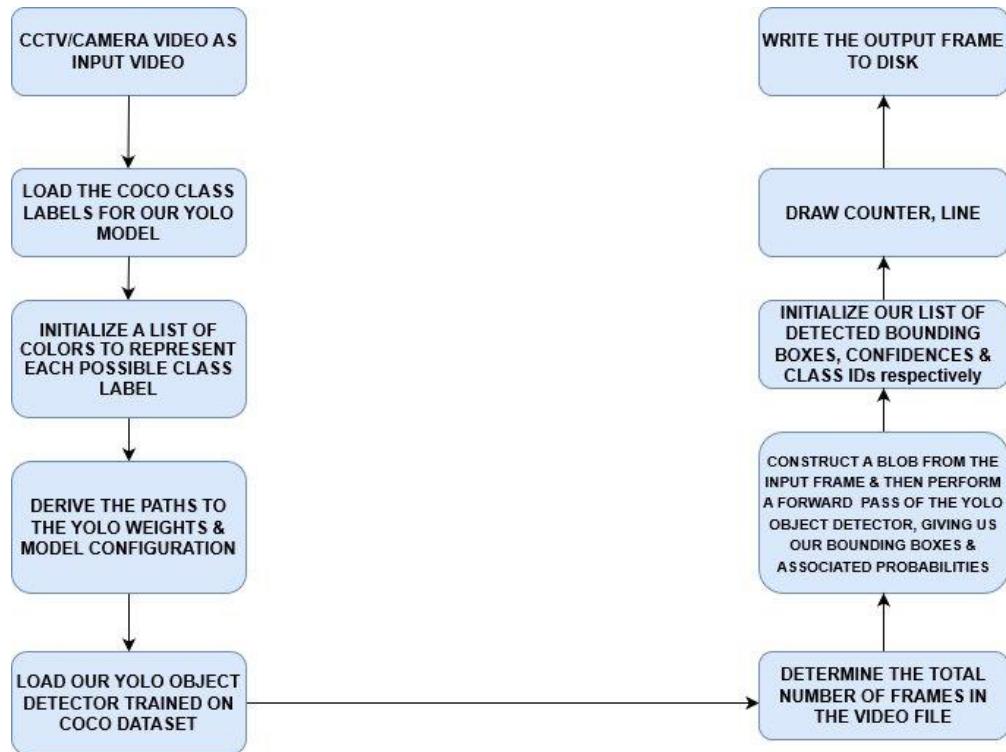


Figure 1: Flowchart explaining the proposed methodology

3.1 Our Proposed Traffic Light Control System :

Previous works for self-intelligent traffic light systems were based majorly on using induction loops, which is very costly or using microcontroller circuit sensors, which are not so accurate. So, we have proposed a model that is cost-effective and is most accurate when compared to all present models.

This paper aims to detect and track vehicles on a video stream and count those vehicles going across a predefined line. By using the count of vehicles on each side of the traffic light, we have optimized the traffic lights by assigning them time according to the traffic behavior in real-time. If we have less traffic or there is more traffic than usual, our model will optimize the light by increasing or decreasing the duration of the light. We have used YOLO and SORT algorithms on the live video feed to get the vehicle count in real-time.

3.2 Traffic Light Duration Optimization Problem :

The capacity to anticipate traffic scenarios is significant for ideal management. For instance, if it is known that we would realize that some street will wind up clogged after some time, this data could be transmitted to street clients that can go around this street, consequently enabling the entire framework to diminish from blockage. Even for single intersections, there may be no optimum ideal arrangement. With various intersections, the issue turns out to be significantly increasingly mind-boggling, as the condition of one light impacts the progression of traffic towards numerous different lights. Another fact for the complication is the way that the progression of traffic always shows signs of change, contingent upon the season of the

day, the day of the week, and the season. Roadwork and mishaps further impact intricacy and execution; fixed-cycle controllers constrain most traffic lights. A cycle of setups is characterized in which all traffic gets a green light eventually. The split time decides to what extent the lights should remain in each state. Occupied streets can get inclined by modifying the split time. Our project intends to Eliminate the postponement of Roads by lessening Traffic on the street, consequently utilizing Machine Learning. It decides traffic on every street by using camcorders. Using that traffic data, we can deal with the significant time and handle the traffic out and about. On every street, we place camera sensors that identify the vehicle and give current traffic data on every street. The traffic level on every street balances the planning of the signal. The street which has more vehicles present than another street then this street allot a green sign and for others have red is allocated. It likewise gives the extra usefulness of discharging the crisis vehicle on its event that implies when a crisis vehicle is seen. For national improvement, it is important to lessen traffic jams on the major streets.

3.3. Learning from real-time traffic :

The capacity to anticipate traffic conditions is significant for ideal control. For instance, if we know that we would realize that some street will wind up clogged after a certain amount of time, this data could be transmitted to street clients that can go around this street, consequently enabling the entire framework to diminish from blockage. Our model can learn from day to day behavior of traffic at a particular time. If a certain road has some congestion at the same time of the day, then after some days, our model will learn, at which time it does have congestion and will increase/decrease accordingly.

3.4. Our Proposed Model :

The motto of our project is to track and detect vehicles on a live video stream and count the vehicles going through a defined line of intersection.

It uses:

- (i) **YOLO** to detect objects on each of the video frames.
- (ii) **SORT** to track those objects over different frames.

Once the objects are detected and tracked over different frames, a simple mathematical calculation is applied to count the intersections between the vehicle's previous and current time frame positions with a defined line.

3.4.1 YOLO

By applying object detection, we'll not exclusively have the option to figure out what is in a picture, yet also where a given item resides! YOLO partitions the info picture into an $S \times S$ lattice. Every lattice cell predicts just one object. Every network cell predicts a fixed number of boundary boxes. For every framework cell, it predicts B boundary boxes, and each case has one box confidence score. It recognizes one object just paying little heed to the quantity of boxes B, and it predicts C conditional class probabilities (one for every class for the likeliness of the item class).

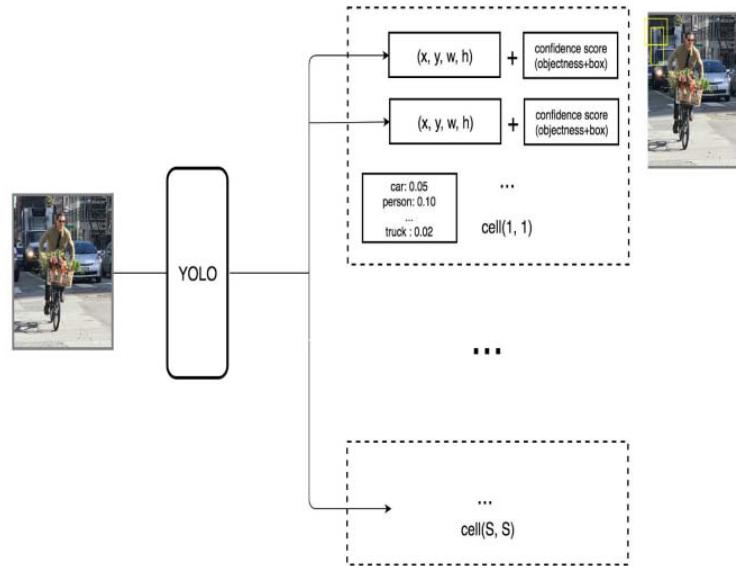


Figure 2: YOLO application on an image

As shown in Figure 2, the Boundary box has five elements: (x, y, w, h) and a score for the box confidence. This score tells us the probability of the box to contain an object and accuracy also. x and y are offsets. Every cell has 20 conditional class probabilities.

YOLO's prediction has a shape of $(S, S, B \times 5 + C) = (7, 7, 30)$.

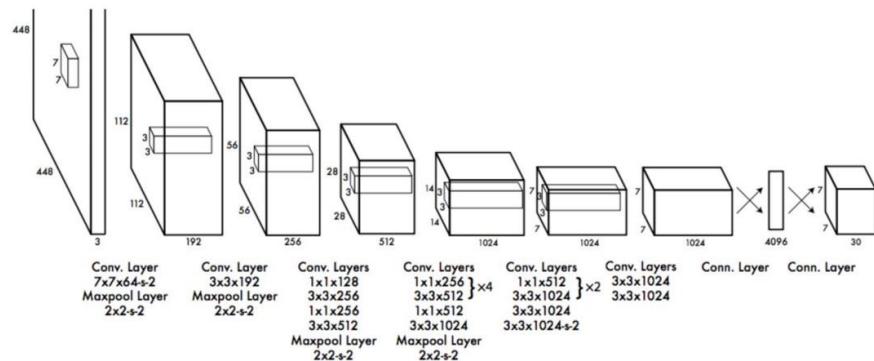


Figure 3: YOLO convolution layers

The real idea behind You Only Look Once is to assemble a convolutional neural network system for anticipating a $(7, 7, 30)$ tensor, as shown in Figure 3. It utilizes a CNN system to decrease the spatial measurement. YOLO plays out a linear regression using a couple of completely associated layers for making $7 \times 7 \times 2$ boundary box predictions. To make the last prediction, we keep those with high box certainty scores (more than 0.25) as our previous predictions.

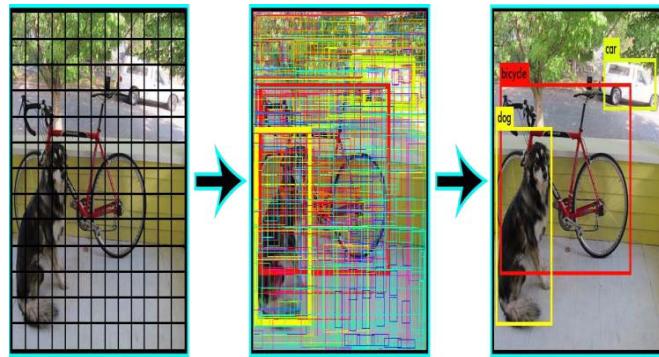


Figure 4: Categorization of objects using YOLO

The class confidence score for every prediction box is calculated by using equation 1:

$$\text{Class confidence score} = \text{box confidence score} * \text{conditional class probability} \quad (1)$$

It's used to measure confidence in both ends, classification, and localization. Mathematical definitions used by YOLO: The image is divided into a $S \times S$ grid, as shown in Figure 4. Every cell on the grid predicts B bounding boxes and the scores for confidence these boxes are calculated by using equation 2.

$$C = \Pr(\text{object}) * \text{IoU} \quad (2)$$

IoU: Intersection over Union between the predicted box and the ground truth. If no object exists in a cell, its confidence score should be zero. Each bounding box consists of five predictions: x , y , w , h , and confidence where (x, y) : Coordinates representing the center of the box. These coordinates are calculated concerning the bounds of the grid cells, as explained in equation 3.

$$\begin{aligned}
 x &: x \text{ coordinate of center} \\
 y &: y \text{ coordinate of center} \\
 w &: \text{width of bounding box} \\
 h &: \text{height of bounding box} \\
 c &: \text{Confidence}
 \end{aligned} \quad (3)$$

Each grid cell also predicts C conditional class probabilities. These scores show both the probability of that class and how well the box fits the object using the mentioned formula, as shown in equation 4.

$$Pr(\text{Object}) * Pr(\text{Object}) * IoU = Pr(\text{Class } i) * IoU \quad (4)$$

By using all the formulas and conditions, a YOLO model is successfully implemented, as shown in Figure 5.

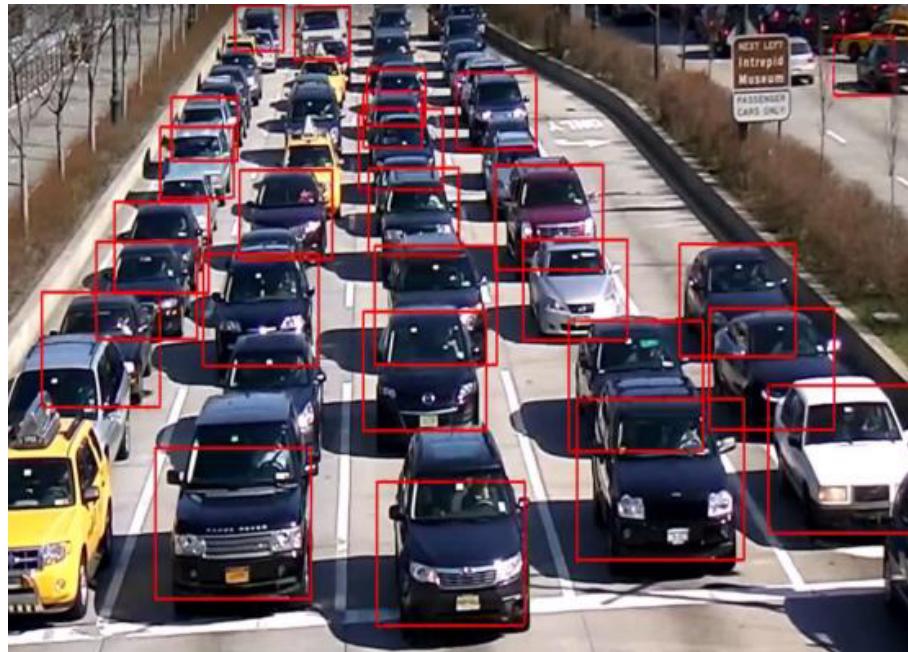


Figure 5: YOLO applications on cars as objects

3.4.2. SORT:

A simple online and real-time tracking algorithm for 2D more than one object tracking in video frames. It is designed for online tracking applications where only past and current frames are available, and the

method creates object identities on the fly. While this minimalistic tracker doesn't handle occlusion or re-entering objects, its purpose is to serve as a baseline and testbed for the development of future trackers. SORT was initially described in an arXiv tech report. At the time of the initial publication, SORT was ranked the best *open-source*, multiple object tracker, on the MOT benchmark. The real-time working of SORT has been illustrated in Figure 6.

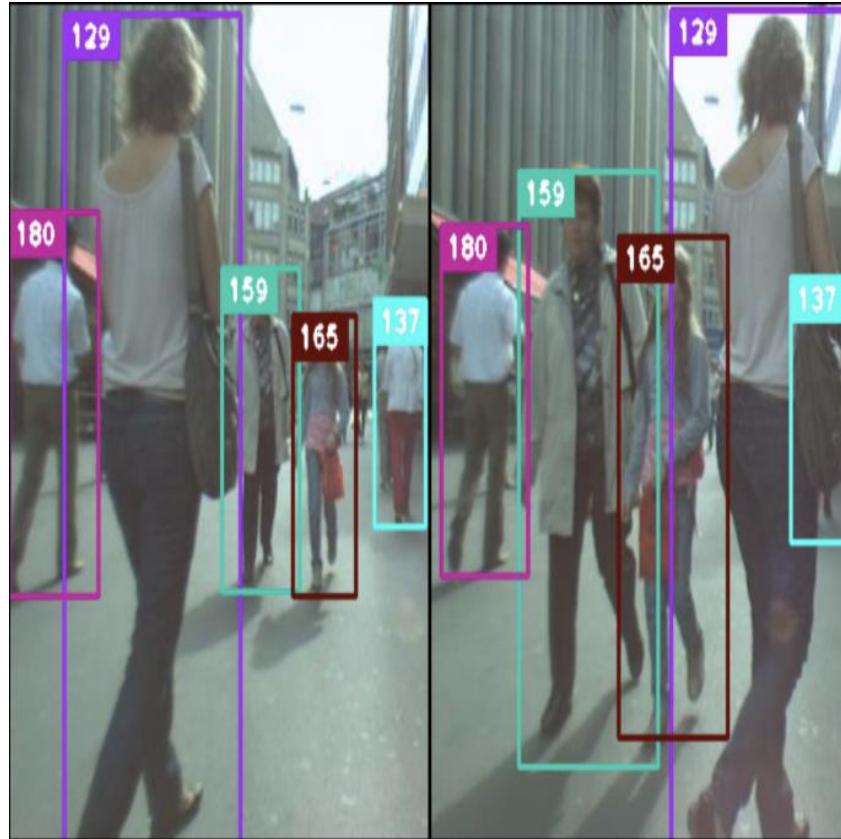


Figure 6: Real-time working of SORT over moving objects

We coordinate appearance data to improve the efficiency of SORT. Because of this augmentation, we can follow objects through longer times of impediments, successfully diminishing the number of switches. Sort can track numerous objects in real-time, however, it merely associates objects already detected across different frames based on detection results coordinates.

4. IMPLEMENTATION AND RESULTS

4.1. Experimental Setup

The configuration of the laptop used for this project is: 6th Generation i5 clocked at 3.0GHz with Catalina MacOS and 8 Gigabytes RAM. Our model performance on live feed captured by a video camera in Indian road conditions. We have used a reference line to calculate the number of cars passing through that line. That line is placed 100-120 meters before the red light using our code.

4.2 Results:

Our goal was to categorize if the object is a vehicle or not instantly, and YOLO works better when compared with other real-time object detectors. YOLO has been compared with various detectors, and comparison is shown in Figure 7.

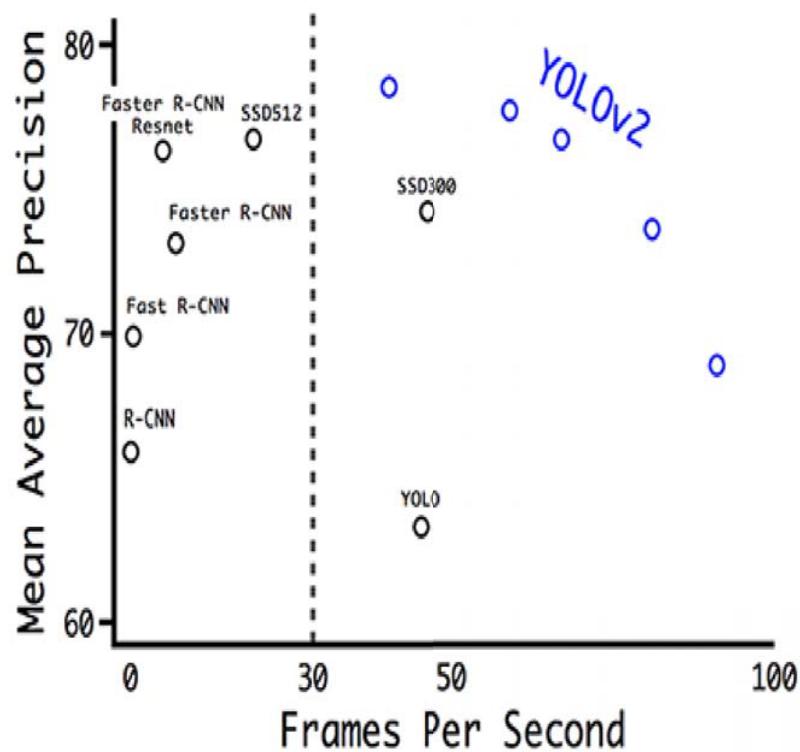


Figure 7: Accuracy comparison for different detectors: Comparison to prove that YOLOv2 is better than other algorithmic models

Also, YOLO performs at par when compared with Faster R-CNN and RetinaNet. The formation of a WordTree is described in figure 8, which shows how COCO and ImageNet form the WordTree. Figure 9 illustrates the Feature Comparison table in between YOLO and YOLv2 and proves with time YOLO has been improved.

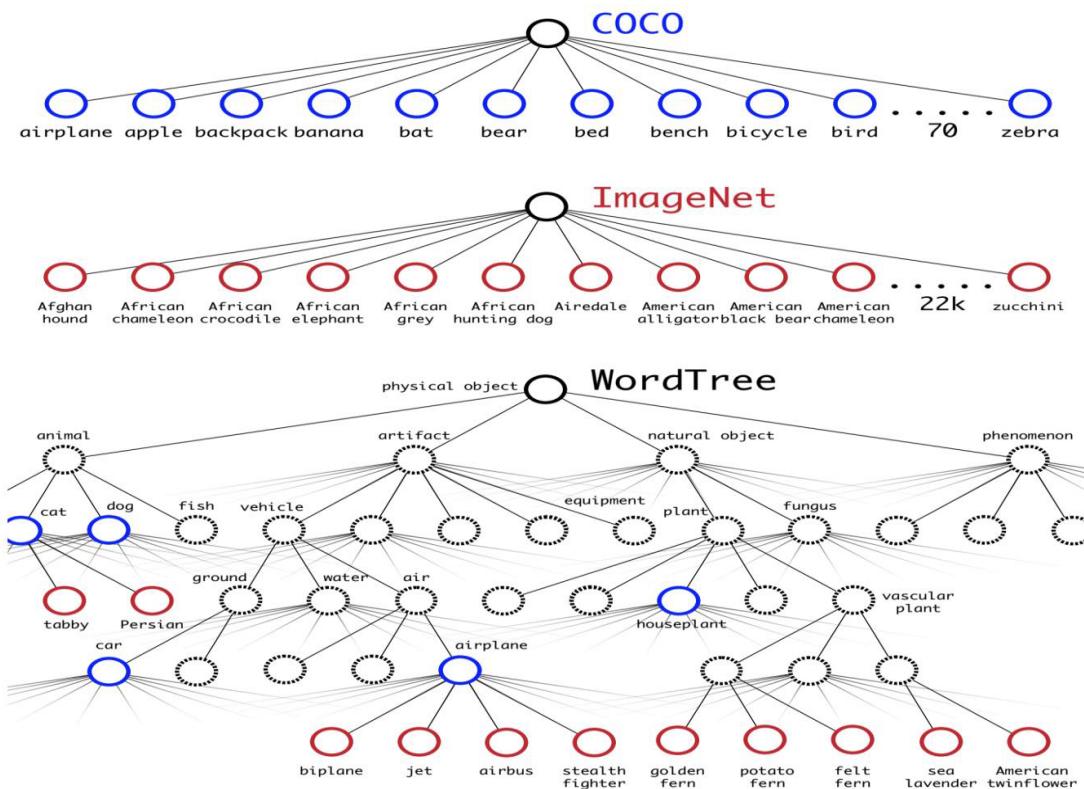
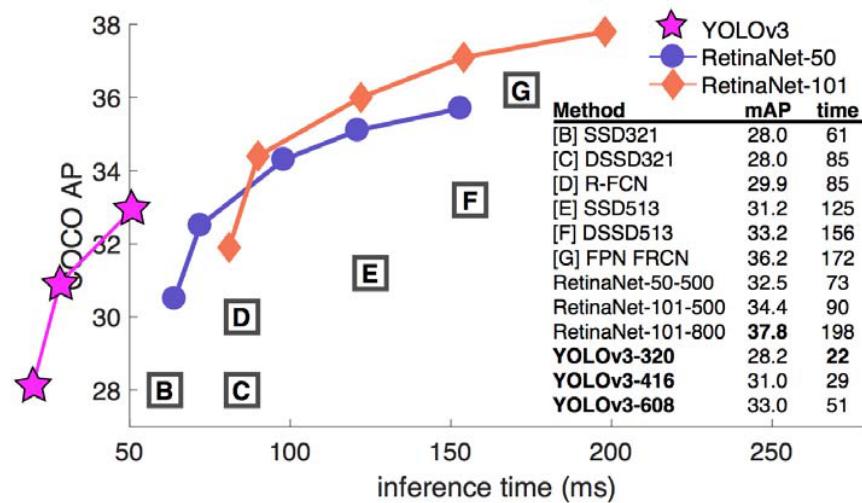


Figure 8: Combination of COCO and ImageNet labels form a hierarchical WordTree

	YOLO							YOLOv2
batch norm?	✓	✓	✓	✓	✓	✓	✓	✓
hi-res classifier?		✓	✓	✓	✓	✓	✓	✓
convolutional?		✓	✓	✓	✓	✓	✓	✓
anchor boxes?		✓	✓					
new network?			✓	✓	✓	✓	✓	✓
dimension priors?				✓	✓	✓	✓	✓
location prediction?					✓	✓	✓	✓
passthrough?						✓	✓	✓
multi-scale?							✓	✓
hi-res detector?								✓
VOC2007 mAP	63.4	65.8	69.5	69.2	69.6	74.4	75.4	76.8
								78.6

Figure 9: Feature Comparison between YOLO and YOLov2

Similarly, Figure 10 shows YOLov3 performs very well in the fast detector category when speed is important.

**Figure 10:** Performance of YOLov3 is quite efficient in the fast detector category when speed is important.

With the help of machine learning, we improved the traffic control framework by presenting a detecting system, which gives an input to the current system; so it can adjust the changing traffic thickness designs and gives the vital sign to the controller continuously. We have already tested it on a live feed from various traffic prone roads and have found satisfactory results. Other Adaptive Traffic Light Systems were not able to work on the Indian traffic conditions. Our model has the edge over the other by performing at par on Indian roads. Also, various time Dynamic scheduling algorithm of traffic lights like the

1. BEST-GREEN time configuration
2. The scheduling algorithm
3. The enhanced scheduling algorithm

can be applied to our proposed model, and an optimized dynamic self-intelligent framework can be further designed using our model [17].

5. CONCLUSION

The goal of this work is to improve the traffic control system by developing a Self-adaptive algorithm to control road traffic based on deep learning. This new system facilitates the movement of cars in intersections, resulting in reducing congestion, less CO₂ emissions, etc. We have evaluated and compared our model YOLO with other existing models on various grounds as far as YOLOv3 is a good detector. It's fast and accurate also. But by using YOLO, we have solved our purpose to identify objects on the roads. As shown in figure 12, our model works very well on the Indian roads; the counter is increased by one every time a car passes by the Yellow Line, which is placed a few meters before the red light crossing. By using our model, 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. As future work, we will include pedestrians as input into the Adaptive Traffic Light Control to minimize their waiting time. Another axis is to add sensors fusion to the controller and not limited to the camera, which will give more adaptability and robustness to our system face different weather state.



Figure 12: Actual snapshot of test video on Indian roads

REFERENCES

- [1]. Dia, H. (2002). *An agent-based approach to modelling driver route choice behavior under the influence of real-time information*. Transportation Research Part C: Emerging Technologies, 10(5-6), pp. 331–349. Doi:10.1016/s0968-090x(02)00025-6
- [2]. GAO, F., & WANG, M. (2010). *Route Choice Behavior Model with Guidance Information*. Journal of Transportation Systems Engineering and Information Technology, 10(6), pp. 64–69. Doi:10.1016/s1570-6672(09)60072-6
- [3]. Morikawa T., Miwa T., Kurauchi S., Yamamoto T., Kobayashi K. (2005) *Driver's Route Choice Behavior and its Implications on Network Simulation and Traffic Assignment*. In: Kitamura R., Kuwahara M. (eds) *Simulation Approaches in Transportation Analysis*. Operations Research/Computer Science Interfaces Series, vol 31. Springer, Boston, MA, Doi: 10.1007/0-387-24109-4_13
- [4]. WEN, W. (2008). *A dynamic and automatic traffic light control expert system for solving the road congestion problem*. Expert Systems with Applications, 34(4), pp. 2370–2381. Doi:10.1016/j.eswa.2007.03.007
- [5]. Hossan, S., Nower, N.(2020). *Fog-based dynamic traffic light control system for improving public transport*. Public Transp. Doi:10.1007/s12469-020-00235-z

- [6]. P. Shanmugaraja, K. Chokkanathan, J. Anitha, A. Parveen Begam, N.Naveenkumar (2019), "Dynamic Packet Scheduler for Queuing Real-Time and Non-Real Time Internet Traffic" International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-8 Issue-3.
- [7]. G. R. M., Krishna, D., Shreyas, T. R., & Asnath Victory Phamila, Y. (2018). *Road Congestion based Traffic Management System with Dynamic Time Quantum*. 2018 International Conference on Recent Trends in Advanced Computing (ICRTAC). Doi:10.1109/icrtac.2018.8679287
- [8]. 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
- [9]. Rotake, Dinesh & Karmore, Swapnili. (2012). *Intelligent Traffic Signal Control System Using Embedded System*. Issue 3.
- [10].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
- [11].Ali Alheeti, Khattab M. (2011). *Intelligent Traffic Light Control System Based Image Intensity Measurement*. Issue 3.
- [12].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
- [13].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.
- [14].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.
- [15].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.
- [16].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.
- [17].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.
- [18].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, Doi: 10.1109/ICIRCA.2018.8597266.
- [19].Hossai & Lee. (2019). "Deep Learning-Based Real-Time Multiple-Object Detection and Tracking from Aerial Imagery via a Flying Robot with GPU-Based Embedded Devices." Sensors, 19(15), 3371. Doi:10.3390/s19153371