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A Real Time Dynamic Approach for Management of Vehicle Generated Traffic

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Abstract: India, with a population of 1.3 billion and almost 300 million vehicles, is one of the biggest contributors to traffic jams, vehicle- specific pollution, and chronic lung diseases. To manage the footfall of these gigantic vehicles, continuous effort and research is taking place in the direction of both active and passive traffic management. This research paper aims towards showcasing a dynamic, fully autonomous deep learning model that uses real-time feeds from existing traffic junctions/ intersection cameras, process them and provide an intensity score based on the density of traffic in each adjoining lane.The proposed CNN model which is based on YOLO framework uses 10 seconds wait analysis time. The proposed system manages traffic, based on the intensity scores which assign traffic a Go time to each lane using an optimal traffic time in the range of 10-50 seconds.The model also scans for emergency vehicles in each lane, to provide a priority pass to such vehicles. Evaluation of model performance Mean Average Precision (mAP) is used.

Keywords: Traffic Management, Emergency Vehicle Detection, Intensity scores, Convolutional Neural Network, Optimal Traffic Time, Mean Average Precision, Intersection over Union

1. Introduction

With growing population, issues that arises in regard to traffic management is despite all the resources and finances being poured in can primarily be put into two categories: Firstly, the traffic jam avoidance rates have improved, yet not eradicated. Secondly, the huge number manpower is required to manage the traffic, have in any way not reduced. The problem here is not that police officers work long shifts in the heat, but rather that they are constantly exposed to harmful gases and pollutants while performing their duties for the nation.

A study looking at the pollution statistics in 2017, states that 1 in 7 policemen suffer from a respiratory problem in the nation's capital, Delhi. These problems have ranged from something as small as allergic rhinitis to diseases like severe asthma and Chronic Obstructive Pulmonary Disease or COPD. These diseases have been notoriously known for causing permanent and irreversible lung damage and can even lead to lung cancers in specific cases.

Taking all the aforementioned points into account objective of the research is to solve following issues:

- Minimise the traffic jam aggressions and lengths.
- Minimise the exposure of traffic police personnel from hazardous pollution.
- Providing a priority passage to first responder vehicles.

The main real-world issue stems from long waiting time at the signals. So there must be a suitable mechanism in which the waiting time can be adjusted dynamically based on the crowd in each lane.

As the traffic is manually monitored by a traffic cop instead of traffic signals. There is an urgent need of developing a smarter, cost-effective technical solution which can make accurate decisions without manual regulation. In this paper an analysis of the main sources of the congestion caused due to traffic is done. Instead of going by the traditional solutions such as, expanding roads, carpooling, use of public transportation and perhaps avoiding peak hours of traffic by rescheduling errands, an intelligent system needs to be adopted in order to curb the effect of traffic and regulate its flow. Also focus is on trying multiple techniques and finding the most suitable consistent manner to capture data via images, isolating vehicles using techniques like blob detection or YOLO. Since the system is based on the pre-existing network of routine surveillance cameras, therefore the whole analysis is done on account of the data acquired by them. A model that could specifically detect auto- rickshaws or cycle-rickshaws has not been included. The absence of lane discipline proved to be another obstacle in obtaining accurate density counts.

Significant contributions or highlights of this research work are listed below.

- Proposed model is based on real time to extract traffic data and traffic density using image processing techniques.
- To process the density data in real time in order to find the optimum traffic signal time, thus preventing traffics jams and chaos.
- To achieve the aforementioned goal with minimum human intervention.
- To provide the traffic police with right technology to control and monitor the traffic remotely.

2. Literature Review

This section identifies and discusses the contribution of existing literature as well as research carried out in the field of Smart Traffic Management Systems using different frameworks, models and methodologies. The literature review examines all the factors that have encouraged the advancement of research in this field. The root cause of the problem is undoubtedly the ever-increasing population in urban areas which has led to a rise in vehicle count on roads, hence triggering traffic congestion. Not only does it result in the wastage of time and fuel but also hampers the health of traffic police who are being exposed to hazardous gases 24/7. However, there was an overall decrease in the traffic levels during the last two years which entirely was a result of the coronavirus pandemic.

During the initial years of research, the process of object detection was based upon the daytime sequences using trade-offs between vanishing points and object collision methods. Further improvisations such as 2 nearest object detection were implemented in order to assess the density of traffic by using the time spatial image method. Authors emphasizes on using image processing techniques such as Y.O.L.O. (You Only Look Once) for calculating traffic density and detecting emergency vehicles. With the mention of emergency vehicles, it is important to realise how a valuable life could be lost due to poor traffic management. Thus, whenever an emergency vehicle is detected, the signal for that particular lane turns green and it is allowed to move first. Brown et al.[1)] showed the model experimented alongside with various object detection techniques, most notably Background Subtraction and Haar Cascade.

One of the major problems encountered is the inaccuracy of results due to the existence of mixed vehicles like Motorbikes (Non-Geared Motor Vehicles), Cars (Light Motor Vehicles) and Trucks (Heavy Motor Vehicles) and vehicles which are specific to India including but not limited to, auto-rickshaws, puled-rickshaws, street vendors and vehicles put together using frugal engineering in the lanes. The variety of vehicles and the absentia of lane discipline lead to false results by the model. This issue is resolved using an optimisation algorithm for signalling time at intersections under mixed heavy traffic as suggested by Lan, Chien-Lun, and Gang-Len Chang[2)].Now, the outcome of this model provides queue length and queue clearance time. Another crucial aspect affecting the video analytics is the lighting and weather conditions. Vision-based automatic vehicle detection under lighting conditions shown by Chan, Y-M. et al.[3)] .Night Time Traffic Surveillance Video by Hajimolahoseini et al.[4)] and Vehicular Traffic Density State Estimation by Tyagi, et al. based on Cumulative Road Acoustics [5)] are the various algorithms used to tackle this problem. Subclasses are defined to separate the daytime and night time samples. While defining, similar samples need to be skipped to avoid overfitting.

The AI-based traffic system and numerous machine learning frameworks have contributed practically to handling difficult challenges such as acquiring the correct prediction of traffic information in real-time as presented by P. Tungjiratthitikan [24)]. It is more likely to be affected by flow, speed and density. To achieve an optimal solution, the system should be equipped with all elements like sensors and data analytics capability shown by Dwivedy et al.[27)]. For efficient traffic signal policy, the neural network, reinforcement learning techniques are suggested by Dief et al.[25)] include the following algorithms-Multi-agent system and reinforcement learning framework. A Q-learning algorithm with feed forward neural networks with the longest queue is scheduled first at the intersection is proposed by Arel, Itamar, et al. [6)].

Trip modelling system for the prediction of travelling speed profile for the selected route based upon the analysis done by traffic information Park is proposed by Jungme, et al.[7)].

Distributed unsupervised traffic-signal control with hybrid computational intelligent techniques (Fuzzy Neural Network and Hybrid Multi-Agent System) for the management of large-scale traffic networks D. Srinivasan et al.[8)].Generalised Beta Gaussian Bayesian Network determines speed, density, and flow of traffic is presented by E. Castillo et al.[9)]. Discrete-Time Hidden Markov Model with classical Baum-Welch or Bayesian learning algorithm for inferring the traffic signal phases is shown by M. R. Gahrooei and D.B. Work et al.[10)]. Using Artificial Neural Network techniques based on Back propagation and Expert Fuzzy System for decision making an integrated system is proposed by M. Patel and N. Ranganathan [11)]. It provides an efficient performance for adaptable traffic control problems. Emerging technologies creating cooperative automotive systems have impacted the research in this field significantly. It has led to comparatively reduced investments and operational costs in the making. Communication technologies have aided the process of establishing a vehicular network to reduce the traffic congestion time is suggested by M. Lvet et al.[12], Menon et al.[13]. Chen, D et al.[14], Guerrero-ibáñez et al.[15] aimed toward advanced technologies, especially in the area of mobile computing, and wireless ad-hoc networks enabling the vehicles to communicate with other vehicles and the surrounding infrastructure (V2V, V2I).The automation of traffic signals is done using inductive loop detection as presented by Mandhare et al.[16]. For traffic detection, Wireless Sensor Networks are more useful. The traffic prediction is done with VANET's by S. Djahel et al.[17].

Researchers have made several attempts at traffic optimization used by Hassan et al.[26]. One of the difficulties is including forecasts for anticipated traffic conditions. Another problem is creating a flexible model that can deal with time, financial cost, convenience, and environmental damage, among other things. Correct detection of vehicle density on the road while maintaining high accuracy, which includes better algorithmic solutions for diverse cues, statistical and learning approaches, sensors, and telematics proposed by Balaji, S. R., and S. Karthikeyan[18].

The key challenges that India faces in implementing a Smart Traffic Management system are outlined in a World Bank study report which includes undeveloped road networks, government economic constraints, uncontrolled population growth, lack of resources for road function and maintenance, lack of demand for automation, lack of interest in decision-making and lack of user awareness shown by Seth et al.[19]. Emergency management, congestion management, advanced traffic control systems, traveller information systems, commercial vehicle operations, and advanced vehicle control systems are all smart traffic management system applications that must be prioritised in India proposed by Panwar et al.[23]. According to the study, pedestrian safety is closely related to human safety. There is no appreciable difference between persons (road users) who travel a short or long distance in a day, making it worrying for the risk of accidents since pedestrians find it difficult to recognise electric vehicles' presence on the road due to their quiet nature. Recognizing the severity of the consequences in the context of accidents is essential for enhancing global health as discussed by Patil et al.[28]

Taking into consideration everything that has been said about traffic congestion until now, one thing that it can certainly be concluded is that this problem is going to get worse in the near future. The negative effects include wastage of time and fuel, delays, inconvenience, economic losses, environmental pollution, stressed and frustrated motorists, stuck emergency vehicles and causing higher chances of collision due to such close proximity. Apart from this, the paranoia and intolerance suffered by the traffic cops because of long shift hours, societal isolation and a constant exposure to negative elements of the environment is a massive and real issue which often gets neglected. Most common causes of congestion are:

- Private car users.
- Undisciplined driving habits and the state of roads.
- Lack of information on traffic conditions.
- Urbanization.

Thus, the precise issue that the research paper will address is the poor traffic management in metropolitan cities. While a great amount of research has already been done in this area, a lot of new enhancements and strategies based on Artificial Intelligence, Machine Learning and Deep Learning suggested by Sharma et al. [20] [21] [22] have come forward to improvise the overall transportation systems' sustainability. Method suggested by Lingani et al.[29] detects, categorizes, tracks, and compute moving object velocity and direction using CNN model on still photos, recorded movies, and real-time live videos. The technical explanation states that as the traffic increases, traffic speeds go down very sharply. The phenomenon of traffic congestion with the help can be explained with the help of Fig.1.

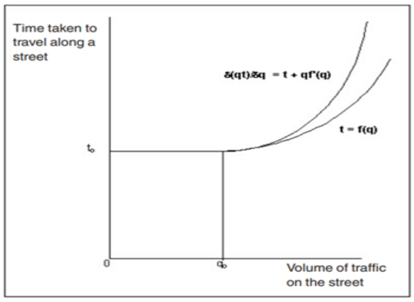


Fig.1: Effect of traffic congestion on speed.

In figure, the function t = f(q) represents the time (t) needed to travel along a street at different levels of traffic (q). The other curve, d(qt)/dq = t + qf'(q) is derived from that function. The difference between the two curves represents, for any volume of traffic (q), the increase in the journey times of the other vehicles which are in circulation due to the introduction of an additional vehicle. Modi et al[30] showed the use of various algorithms for optimising various aspects of the traffic management system, including smart traffic signal management, traffic flow prediction, traffic congestion detection and its management, and automatic detection of traffic signals, is covered in detail in this article, along with its methodology, review, challenges, and potential future applications.

This research tries to achieve this goal by deploying a smart traffic a management system, which works in real time to capture traffic density on various roads leading to junctions, studying their traffic patterns and dynamically controlling the traffic lights to provide the right duration of red and green light to minimize or even eradicate traffic jams caused by excessive traffic and poor traffic management. The system also provides for a manual control and real time surveillance of all traffic activities from a particularly closed and confined area rather than exposing personals to poor air quality in order to manage jams.

3. Proposed Methodology

Tracking multiple objects across frames is one of the most important challenges in machine learning. Object tracking deals with predicting positions and other relevant information with respect to the moving object. Object Detection, on the other hand, detects the target object in the image or video. It will produce results only if the target object is present while tracking is being done. Major components used in proposed system for managing traffic are explained as follows.

Object Detector: The foremost step towards the working of this model is the detection of vehicles in the lanes approaching the junction. This could be achieved using multiple techniques including but not limited to, laser scanners, routine traffic cameras. In order to make this model the most affordable solution to exist, the pre-existing architecture which is the routine surveillance cameras of the Integrated Traffic Management System is used. Such cameras are present at multiple 4 arm junction approach lanes throughout the metropolitan cities of India. Fig.2. shows the Camera positioning and exits show potential flow of traffic from various lanes upon green light. The cameras are sufficiently able to provide the correct resolution and frame rate as required by the algorithm. The detection of vehicles is done using the Y.O.L.O.v3 (You Only Look Once) which is a real-time object detection algorithm that uses a deep convolutional neural network to detect objects of choice in live feeds/images or videos.

Fig.2: Camera positioning and exits in a 4-arm junction.

Density Calculator: Post detection of vehicles, the process of density calculation begins. The process of density calculation can be conducted in two ways. The first is the traditional way to employ a tracker algorithm such as DeepSort along with Y.O.L.O. which primarily takes in the detected objects and provides unique identifications and labels to each vehicle in the subsequent frames, thus, in turn, returning the vehicle count in the region of interest. This algorithm is of high accuracy but is a resource monopoliser. For a smooth and real-time run, it requires a full- fledged Nvidia based GPU with a high CUDA Count. The second approach is a less resource intrinsic one. Instead of processing a whole live stream through the detector, time the incidents which trigger the Y.O.L.O. framework to run object detection on a singular frame rather than the whole video feed to calculate instantaneous density.Fig.3 shows timeline for triggering YOLO object detector in a 60 second scenario where lights go green in a round robin pattern.

In this manner, the tracking algorithms are skipped and thus save on precious resources. This approach can be completely executed over CPU processes and does not require a dedicated GPU component.

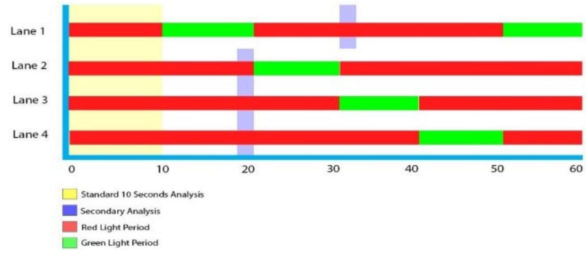


Fig.3: Timeline for triggering YOLO object detector.

Intensity Processing and Time Awarding: Once the traffic density in all the lanes is calculated, a simple ratio calculation is applied to all the densities which return an intensity score for each lane. Each junction is provided with a minimum and maximum Go Time. The minimum go time is nothing but the minimum amount of time for which any lane in the junction, irrespective of its density shall have a green light while the maximum go time is the maximum time limit for any lane. The product of the intensity score and minimum go time is the go time awarded to each lane.

Emergency vehicle detection: Emergency vehicle detection is one of the most crucial parts of traffic management system. The system has nothing but one purpose, to constantly look for emergency vehicles such as first responders, ambulances, fire trucks and law enforcement. Emergencies are one of the most time crucial situations and require immediate attention, only and only then the efforts of the first responders could be harnessed.

Passing data to the Traffic Controller: The complete scenario is then passed to a microcontroller that is used to operate the signal lights and timer clocks.Fig.4 shows basic system architectural walkthrough of the algorithms in place for vehicle density calculation and emergency response management.

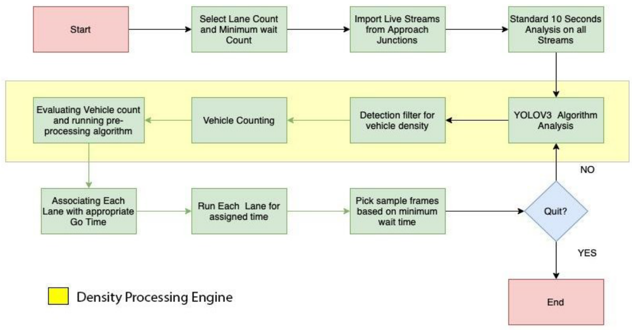


Fig.4: Basic system architecture for the model.

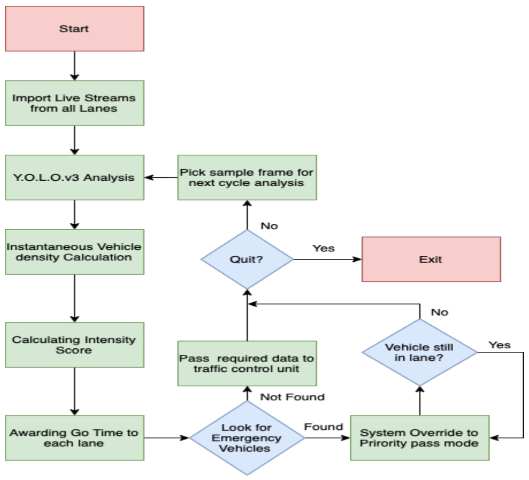


Fig.5: Final algorithmic workflow for implementation.

Fig.5 explains basic architecture used and workflow followed for experimental purpose using the modular Density Processing Engine.

Stream Intake: The stream intake is an essential aspect for producing efficient and accurate results. The camera must be installed in such a way that it captures the junction intake lane completely. The best positioning would be mounting them on each corner of intersection or placing them above the signals. The traffic flow does not change many from day to day thereby making predictions much easier. But in case of emergencies, accidents, major closures, the footage in real-time plays an influential role in making decisions on an urgent basis.

Streams captured by all the cameras into the system act as input to the proposed model. Fig.6 takes stream intake of live feed with pre-processing algorithms applied.

Fig.6: Stream intake of live feed.

Before passing them to the detector, it must be ensured that the features across all the streams are same. Features are the specific structures in the image such as points, edges, and objects and most importantly resolution and FPS. In case of inappropriate inputs or lack of input from any camera, the system quits immediately.

Deploying an object detector: YOLOv3 for real-time object detection. It identifies specific objects in videos, live feeds or images by using features learned by a deep convolutional neural network. Fig.7 shows results rendered by object detector based on pre-processed stream intake. The prediction uses 1x1 convolution therefore it is named as "you only look once". It is much faster than other networks and is much more stable and can easily upgrade to YOLO v4. Large data set has been used since the images of different vehicles are plentiful. RetinaNet could have been used as an alternative, but the training time of RetinaNet is greater than YOLOv3. In addition to this, the accuracy of detecting objects with YOLOv3 is comparatively more because it works excellently with large data sets.

Fig.7: Results rendered by object detector.

India is a diverse country and the labelling on ambulances differs from state to state because of varied cultural languages. There exist some data sets for foreign emergency vehicles because the language used is generally English and the vehicles look mostly identical. For a country like India, there is no such data set in existence. A custom YOLO model has been built to detect emergency vehicles. The dataset used for training the YOLO model was a prepared dataset which aimed at detecting ambulances and fire trucks. The initial dataset consisted of 20 base images obtained from internet. More images were taken in diversified day time setting environment with different features .These images were passed through Roboflow dataset for pipeline creation. As a result multiple copies were created with respect to change in orientation and image characteristics such as brightness, contrast, saturation. This resulted in a wide variety of image features and increased quantity of images.Fig.8 shows training result of proposed model which is annotated using Roboflow. This model gets revised from time to time, by analysing the data it gathers from recordings of real time traffic feed.

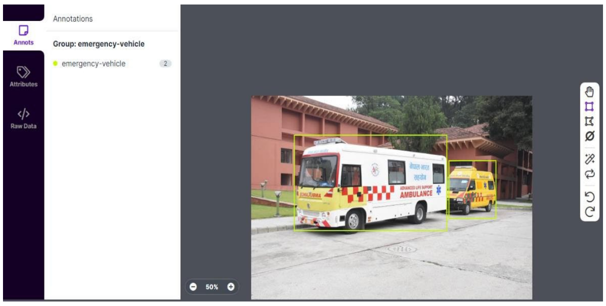


Fig.8: Training of custom model- Annotation of images

To get the object detector off, training images are collected from Google. Next, it was made sure that the number of objects in each class is evenly distributed and the objects chosen are distinguishable. The annotation of training images was done by drawing a box around the target object and later labelling the each box with the object class that was required to be predicted by the detector. There are many labelling tools available like CVAT, LabelIng, VoTT etc. Roboflow is used for annotation for the proposed model.

Fig.9: Testing model on Train-Test Set.

The accuracy of our model was 10% initially, but it shot up continuously training the model with custom built data set. Fig.9 shows results of custom model on Train-Test Set performed on the Google Collaboratory and Tensorboard.

Building Density Calculator: Following are the different strategies that could be deployed for density calculation. Applying DeepSort tracking for counting them while the vehicles moving towards the signals. The first is the traditional way to employ a tracker algorithm such as DeepSort along with Y.O.L.O. Fig.10 shows the result when Deep sort algorithm is used in collaboration with YOLO detector to provide unique identification-based tracking. It primarily takes in the detected objects and provides unique identifications and labels to each vehicle in the subsequent frames, thus, in turn, returning the vehicle count in the region of interest. This algorithm is of high accuracy but is a resource monopoliser.

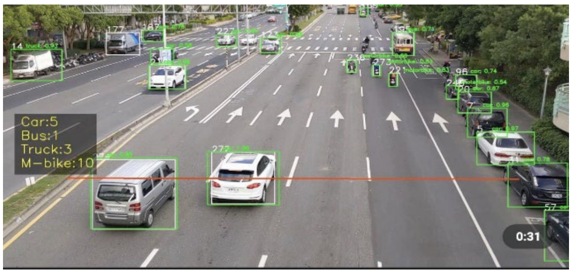


Fig.10: Identification-based tracking.

Counting stationary vehicles once they have stopped on the signal: Instead of counting each car while they are still moving can be resource intrinsic. Therefore, snapshots of vehicles were taken once they have accumulated on a red traffic signal and simply count the number of objects in the frame. Fig.11 shows object detection in the Density Processing Engine for calculation of stationary traffic at a signal post.

In this case only object detection algorithm is required and tracking algorithm is not required therefore the software is lighter.

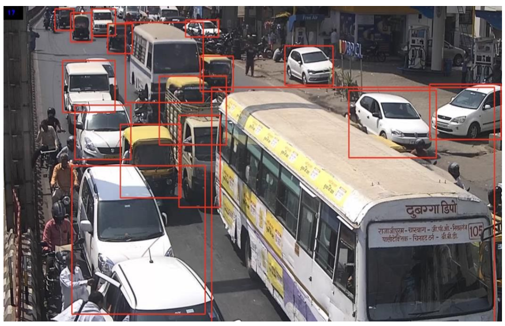


Fig.11: Counting stationary traffic on the signal post accumulation of vehicle

Density on the basis of how quickly a lane is filled with cars. Another approach could be determining the traffic intensity based on how quickly a lane gets crowded again post a period of Go Time. In this research the second method is considered as it is less resource intrinsic.

Intensity Processing and Time awarding: After calculating the density of every lane, a simple ratio and proportion formula is used to determine the intensity score. If a, b, c, d represents the densities in Lane1, Lane 2, Lane 3, and Lane 4 respectively, the formula to calculate minimum load and intensity scores of Lane 1, Lane 2, Lane 3, and Lane 4 is given as in Eq.2, Eq.3 Eq.4 and Eq.5.

Minimum Load= Minimum Value (a, b, c, d) (1)
Intensity Score of a= a/minimum load (2)
Intensity Score of b=b/ minimum load (3)
Intensity Score of c=c/ minimum load (4)
Intensity Score of d=d/ minimum load (5)

By comparing the density of each lane, first select the smallest value among all. The density of each lane will get divided by the minimum density value selected previously. The result obtained by dividing, will be the intensity score of each lane. This is called as feature scaling.

Next, each junction is provided with a minimum and maximum Go Time. Minimum Go Time is the standard go time for a junction for which the signal shall turn green, irrespective of any traffic density is set manually as shown in Fig.12.The product of intensity score and minimum go time is the go time awarded to each lane as shown in Table 1.

Table 1. Log of vehicle densities and go time awarded to each lane.

Parameters	**Lane 1**	**Lane 2**	**Lane 3**	**Lane 4**
Density	4	5	6	5
Intensity Score	1	1.25	1.5	1.25
Time Awarded(in seconds)	15	18	22	18
	Reanalysis of Lanes In Progress			
Density	14	9	8	9
Intensity Score	1.75	1.125	1	1.25
Time Awarded(in seconds)	26	16	15	16
	Reanalysis of Lanes In Progress			
Density	17	12	11	10
Intensity Score	1.7	1.2	1.1	1
Time Awarded(in seconds)	50	25	16	15
	Reanalysis of Lanes In Progress			
Density	13	11	7	25
Intensity Score	1.8	1.5	1	3.5
Time Awarded(in seconds)	27	23	15	50

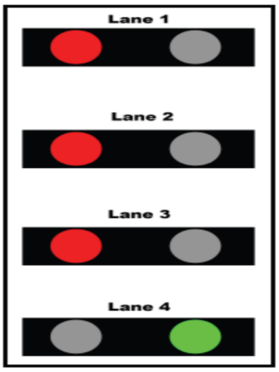


Fig.12: Depiction of current signal status

Emergency Vehicle Processing: While the Y.O.L.O. model detects all the vehicles in the lane doing a real-time analysis, the model is also looking for emergency vehicles or first responder's vehicles anywhere in the lane. If the algorithm happens to find one, an override function is triggered which provides for a priority pass to the emergency vehicle in the particular lane.

During this process, the entire lanes move out of the round-robin go time sequence and are all provided with a stop signal except for the distressed lane with the targeted vehicle. The override is employed until the targeted vehicle completely moves out of the lane.

5. Results and Discussion

In order to test the validity of the system, a simulation was set up in real life scenario using video feeds from surveillance cameras placed at the approach of the junction. The system boots into a 10-second wait analysis where all the signals are turned red and a density analysis is performed. This 10-second analysis provides for a base start and only occurs once on system boot. The feed was taken in by the algorithm and a minimum go time of 15 seconds and a maximum go time of 50 seconds were set. The algorithm then starts to run an internal clock in combination with the global world clock to trigger the Y.O.L.O. framework as and when required. Upon successful calculation of density from each lane, an intensity score is returned based on which a timer function provides each lane with a particular go time as shown in Fig.13. Further, these go times are supplied to the traffic controller unit which sends these chains of commands to their respective signals. During the process, a deep CNN model which has been specifically trained to detect Indian emergency services vehicles including Fire Trucks, Ambulances and Law Enforcement is also keeping an eye on each lane to check if any of the targeted vehicles are detected. If no such vehicle is detected, the system keeps running in a round-robin fashion. Interrupts can also be generated manually by the traffic operator to override the system completely and award each lane with the predetermined fixed time thus completely revoking the autonomous machinery.

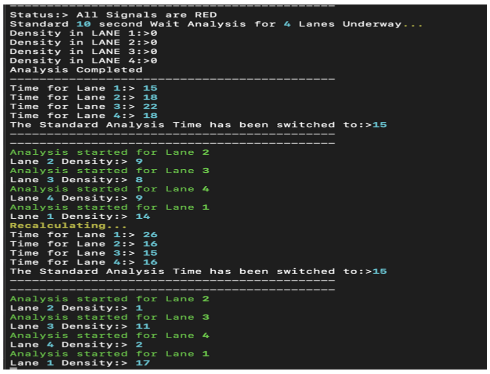


Fig.13: Traffic Management system with minimum Go time set as 15 sec.

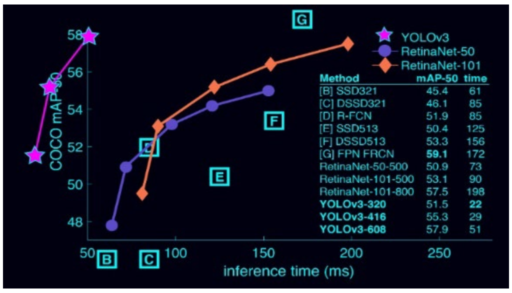
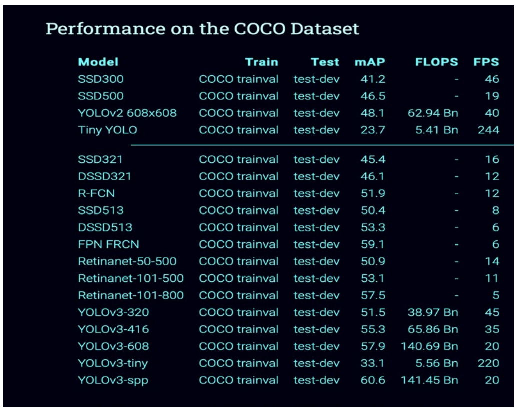


Fig.14: YOLO vs other models on grounds of time vs. mAP.

While detecting vehicles for density calculation the project used a YOLOv3. The model is trained over the coco dataset and classifies over 80 separate classes but it was streamlined to detect motor vehicles as shown in Fig.14. The model was built to detect classes which if taken into the context of the project include cars, trucks, buses and motorbikes. When the model was tested on the Indian road conditions it performed as per the above-mentioned standards but had low accuracy rates while detecting vehicles specific to Indian origin which include but are not limited to, Auto-Rickshaws, and Pulled-Rickshaws. The average accuracy of the model was brought down. This accuracy is planned to improve as the coco dataset is modified with the inclusion of a new dataset specific to Indian local vehicles.



Performance on the COCO Dataset

Model	Train	Test	mAP	FLOPS	FPS
SSD300	COCO trainval	test-dev	41.2	-	46
SSD500	COCO trainval	test-dev	46.5	-	19
YOLOv2 608x608	COCO trainval	test-dev	48.1	62.94 Bn	40
Tiny YOLO	COCO trainval	test-dev	23.7	5.41 Bn	244
SSD321	COCO trainval	test-dev	45.4	-	16
DSSD321	COCO trainval	test-dev	46.1	-	12
R-FCN	COCO trainval	test-dev	51.9	-	12
SSD513	COCO trainval	test-dev	50.4	-	8
DSSD513	COCO trainval	test-dev	53.3	-	6
FPN FRCN	COCO trainval	test-dev	59.1	-	6
Retinanet-50-500	COCO trainval	test-dev	50.9	-	14
Retinanet-101-500	COCO trainval	test-dev	53.1	-	11
Retinanet-101-800	COCO trainval	test-dev	57.5	-	5
YOLOv3-320	COCO trainval	test-dev	51.5	38.97 Bn	45
YOLOv3-416	COCO trainval	test-dev	55.3	65.86 Bn	35
YOLOv3-608	COCO trainval	test-dev	57.9	140.69 Bn	20
YOLOv3-tiny	COCO trainval	test-dev	33.1	5.56 Bn	220
YOLOv3-spp	COCO trainval	test-dev	60.6	141.45 Bn	20

Fig.15: mAp accuracies of CNN models vs.YOLOv3

Model Accuracy for Emergency Vehicle Detection:

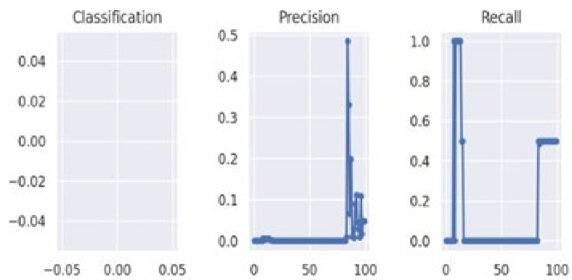


Fig.16: Precision vs. Recall of proposed model built for emergency vehicle detection.

The model for emergency vehicle detection is built from scratch due to absentia of any pre-existing ones. The data set is trained over the YOLOv5 framework. The evaluation metrics in terms of precision and recall of the model is represented in Fig.16. Mean Average Precision (mAP) is used for evaluation of object detection models. Fig.17 shows Mean Average Precision (mAP) for Intersection over Union (IoU) from 0.5 to 0.95 with a step size of 0.05.The mean of average precision (AP) values are calculated over recall values with a range of values 0 to 1.Higher accuracy is achieved for both the IoU thresholds 0.5 and 0.95 with mAp values in the range of 51.5 to 60.6.

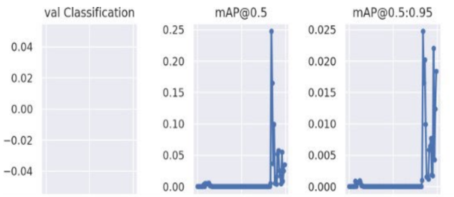


Fig.17: mAP of proposed model built for emergency vehicle detection.

The accuracy of the model is found to be very low, which is completely due to the absence of a high-resolution dataset, with emergency vehicles from each state labelled in different languages and painted accordingly. However, the system is set to improve as and when implemented since the everyday recordings generated by the traffic system shall be used as new data set to revise the model. We estimate that it will take at least 1 month for the model to reach a 60% accuracy rate and another 2 for being accurate enough to work independently without supervision.

Based on the experimental implementation certain issues that were encountered included:

Fig. 18: Improper position for density counting camera.

Since the system is based on the pre-existing network of routine surveillance cameras, at times we encountered the problem that the camera positions were not optimal as shown in Fig.18. The problem could easily be rectified by r adjustments to the physical position of the camera or zooming/cropping camera frame.

Fig.19: Absence of lane discipline leading to heavy motor vehicles hiding other small vehicles.

Another issue encountered during the run was due to the absence of lane discipline, the buses or trucks or vehicles of height greater than that of Light Motor Vehicles were able to cover the camera's capture frame thus hiding a lot of small vehicles behind them resulting in false density counts as shown in Fig.19. The problem could easily be tackled by enforcing lane discipline by vehicle size.

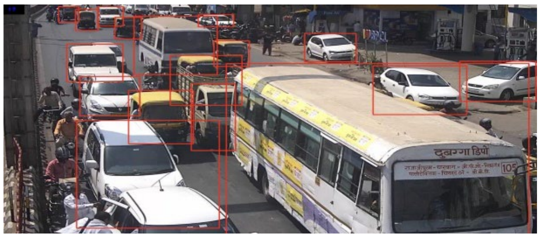


Fig. 20: Absence of a dedicated object detection model for Indian streets leads poor recognition of auto rickshaws and faulty density count.

The last major issue encountered was the absentia of a model that could specifically detect auto-rickshaws or cycle rickshaws which at times were missed during density calculation as shown in Fig.20.The problem could be solved easily by training the pre-existing model as and when the model is deployed.

6. Conclusion

Proposed CNN model for vehicle detection for traffic management is based on the calculation of Intensity Scores which uses Go time of maximum 15 sec. Model performances is evaluated on the prepared dataset and its performance is measured by using mean average precision as it a standard metric used for analysing accuracy of models for object detection. Results show that higher accuracy with mAp in the range of 51.5 to 60.6 at standard IoU threshold range of 0.5 to 0.95.

The future scope involves criminal tracking for rule violation and subsequent signal forwarding to the nearest police station. The collision detection and prediction system could be integrated easily. Number plate detection won't require any additional set of hardware or software changes. Any V.I.P. movement could be aided easily without the requirement of huge armies of traffic police. Another step towards the advancement of the research could include working towards an alternative approach for density calculation. Current research is based on calculation of density for finding the number of desirable objects in the frame. Another approach could be determining the traffic intensity based on how quickly a lane gets crowded again post a period of Go Time.

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