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Real-Time Adaptive Traffic Controlling System

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***Abstract*-- In the period of innovative headways and mechanization, made conceivable by the wide-range utilization of Machine Learning, brilliant boulevards with an automated traffic lighting framework are the following most potential result that can cause a significant change in the day by day life traffic scenarios of the metropolitan. This paper talks about the broad utilization of two explicit object detection algorithms, to be specific YOLOv3 & YOLOv4, to process the live video feed of lanes, frame by frame and decide the blockage alongside the nearness of a crisis vehicle dependent on the expressed algorithms and make the traffic lights work in like manner. Tweaked preparing of the model makes the framework to be totally natural and mouldable. After blending this with a microcomputer and cloud benefits, a dependable and maintainable answer for the metropolitan can be accomplished.**

***Keywords* -- traffic-scenario, metropolitan, object-detection, YOLOv3, YOLOv4, live-video, emergency-vehicle, micro-computer, cloud-benefits.**

I. INTRODUCTION

The advancement of technology is making an impact on nearly everything in our daily spectrum of life. But the need for its application in the daily transportation system somehow has been restricted to the electronic and sensor-based IoT based applications, and subsequently, we lag in the adaptive automation of systems that are malleable. The scope of this paper is to draw attention to how the application of machine learning can bring about a change in the prevailing traffic system. With the explicit implementation of deep learning object detection algorithms namely YOLOv3 and YOLOv4 and pairing it up with sensors and microcomputers along with cloud computing, adaptive automation of the traffic control system is achievable that is completely reliable. The system monitors live video feed to process it and determine the congestion of vehicles and pedestrians on the streets, especially at crossings, and operates the traffic accordingly. Training upon a custom dataset, complete adaptiveness to emergencies, and likely situations have been achieved. Priorities to emergency vehicles like fire trucks and ambulances or detection of custom circumstances to which the system acclimates itself and functions accordingly through extensive training of the model to these factors.

II. BACKGROUND STUDY

There has been an alarming development in the field of smart cities. Automation has taken over a number of domains. Sensors provide real time data that makes the system adapt to the real life projections and function accordingly. Adaptability is a key feature of modern innovations in smart cities. Aspects like traffic lights, parking systems, can be automated to take a step towards smarter and more reliable solutions. The need for development is booming in this segment.

The traffic scenario in the current metropolitan cities is pretty chaotic. Due to the present traffic management system, a lane with lower number of vehicles or a lane with an emergency vehicle suffer equally and more like the other vehicles in the traffic. Through this piece of work, we would like to address the issue of not considering the pedestrian to vehicle ratio in a lane and sometimes the unfortunate event of the presence of an emergency vehicle in a traffic congestion.

In a referred project of the similar genre, the video arrangements from a camera were examined utilizing locale of the object and checking techniques to acquire the best way to detect and eliminate the traffic congestion. The registered vehicle thickness is contrasted with different fragments of the traffic to maintain an uncluttered traffic scenario [1]. Also, the present traffic management environment holds no accentuation on the live traffic situation [2]. In smart transportation frameworks, particularly in the metropolitan traffic scenario, crossing-point checking remains as a choice of the basic testing errands [3]. Also in small segment automation, through a lot of analysis reproducing a genuine situation, the empty parking space identification achievement pace of the proposed framework is assessed through a basic examination of the neighborhood and worldwide visual highlights and diverse classifier frameworks applied to the task [4].

In the emerging segment of Smart Cities, keen vision-based traffic espionage frameworks are accepting an inexorably significant job in highway monitoring and street management stratagem [5]. Lane center identification using quick extraction and high precision grouping of vehicle movement directions utilizing the action map has been a successful step [6]. A traffic observation framework is an earnest need to endure traffic that we experience day by day. Video gives a check of vehicles which assumes an imperative job in finding the gridlocks. It helps in distinguishing the item and tracks their movement to recognize their characteristic [7].

The still pictures of the street where the traffic ought to be controlled were successively coordinated utilizing picture matching with a vacant street reference picture. The emergency vehicle is identified[8]. Learning systems for the slow and unexpected "once-off" foundation changes are proposed to adjust different changes out of sight through the video [9]. A real-time traffic control framework has been introduced where the inclusion of vehicles in pictures from plausible spots where blockage can happen is determined to utilize picture handling devices to assign various occasions for the mass to pass [10].

A. Significance of the selected algorithm

While analyzing a number of algorithms and frameworks for this paper it was inferred that a straightforward and adaptable location calculation that improves mean average precision (mAP) with respect to the earlier outcome on VOC 2012 by application of high-limit CNNs. In case of scare training data, supervised pre-training for an auxiliary piece of work, trailed by space explicit calibrating, boosts execution significantly [11]. Also, Selective Search Algorithm joins the quality of a thorough search and segmentation. Rather than a solitary procedure to create conceivable item areas, the search is enhanced and utilization of an assortment of correlative picture partitioning to manage the same number of picture conditions as possible is done [12].

YOLO algorithms have been pioneers in terms of speed and accuracy in the field of object detection and video processing. On utilizing Tiny YOLO for location and quick movement estimation, test results show that the methodology has accomplished high precision at a stable 33.5 FPS on genuine traffic videos [13]. It was seen that in terms of handling time, YOLOv3 algorithm outflanks the algorithm of Faster RCNN in regards to aerial pictures of vehicles, although in exactness criterion they were found to be tantamount.[14]. Fine-grained arrangement of vehicles in seeing shrewd streetlights is basic for astute transportation and brilliant urban communities utilizing YOLOv3 for better precision and progressively explicit classification [15]. On further exploration of the domain, it was found that YOLOv4 not only proved to be a worthy competitor due to its sheer accuracy, but had the chance to come up as the algorithm of choice as far as this paper is concerned.

III. OVERVIEW OF PROPOSED ARCHITECTURES

A. YOLOv3

YOLO utilizes attributes learned by a deep convolution neural network to detect an object. YOLO9000, which was once considered as the fastest and most accurate algorithm for object detection was replaced by YOLO v3 and the former's speed was traded off for the latter's accuracy. YOLO v3 implements a variation of Darknet, which has a 53 layer network which is trained on Imagenet data-set. For detection, 53 additional layers are stacked onto it, producing a a total of 106 layer fully convolutional primary architecture for YOLO v3 with an unparalleled accuracy that remains yet to be surpassed. The architecture of YOLOv3 is shown below in Fig 1[16].

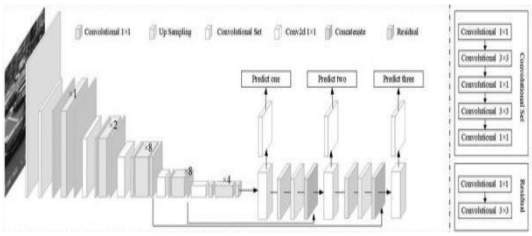

Fig 1: *YOLOv3 expanded Architecture (Mao, Rui-Sheng. 2019)*

B. YOLOv4

The architecture of YOLOv4 (Figure 2) comprises CSPDarknet53 as the foundation, additional module of spatial pyramid pooling, path-aggregation neck (PANet) along with YOLOv3 head. The block of spatial pyramid pooling, which is added over the CSPDarknet53, helps in increasing the receptive field and the most important context features are distinguished. Instead of Feature pyramid networks, the PANet is used as the technique for parameter aggregation for different levels of detector.

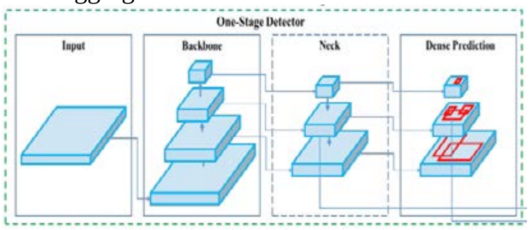

Fig 2: *YOLOv4 Architecture (Wang and Hong-Yuan Mark Liao. 2020)*

IV. IMPLEMENTATION OF PROPOSED ARCHITECTURES

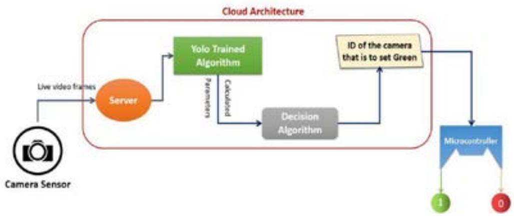

Fig 3: Work Flow Diagram

A. Pre-processing & Segregation of the image

As this project is an extensive work on the automation of the Traffic System and exploring ideas to make it as smooth as possible, we began our work by processing live video feed from the traffic security cameras, sending each frame of the video to the server after preprocessing it to our desired dimension. There, on running the YOLO trained model on it we get the concentration of traffic by both cars and pedestrians along with the count of emergency vehicles to decide the next status of the movement. We classified the detected objects into the custom classes with class labels: Pedestrian, Four-wheeler, Emergency Vehicle and Two-wheeler.

B. Preparing the Custom Dataset for training the algorithms

Custom datasets of street images by collecting frames of a real life traffic video and real life images relevant to the classes of detection, pedestrians, two-wheelers, four-wheelers and emergency vehicles like Ambulance and fire trucks were prepared. Then their respective label files with the bounding box details and class details were generated. The custom configuration files were developed with the relevant changes and the final model assembled was trained on this custom dataset prepared both for Yolov3 and YoloV4 algorithms. The model is trained extensively over a custom built dataset of 1,972 images with an average of 500 images catering to each class.

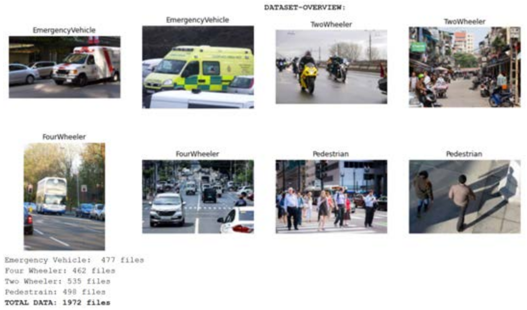

Fig 4: *Dataset Overview*

C. *Training the Yolov3 and Yolov4 algorithms and their corresponding specifications*

The configuration files were modified according to the custom training requirements.

- Filter value was set to 27 [(classes+5)*9]
- Class was set to 4
- Max batches was set to 8,000
- Steps was set to 6400

The whole algorithm was then trained from scratch with specifications according to our dataset and classes. We trained the architectures for detection of our concerned classes, two-wheeler and four-wheeler vehicles, pedestrians and emergency vehicles. As training the whole architecture is an extensive procedure, we saved the weights of both the algorithms at an interval of 1000 epochs for the Yolov3 and Yolov4 algorithms respectively.

D. The main findings for further action will be as follows

a. Total no of vehicles (Four-wheeler, Two-wheeler, Emergency Vehicle) & pedestrians.

b. The threshold value is set upon a rout-wise traffic scenario based on the traffic and emergency vehicle.

c. Now the traffic intensity is checked on either side and is compared with the threshold calculated.

d. Based on this and emergency vehicles the algorithm determines which side gets to move and the timer, based on the traffic density, is set for that side.

e. Meanwhile, the other side is monitored for comparison of traffic density and emergency vehicles.

f. If anomalies detected then that side gets the preference and the route alteration takes place keeping a precautionary time gap.

E. Working Algorithm and controlling the lights

When the algorithm is executed, the green and red lights are assigned to the respective signals. Then, the traffic is allowed to operate according to the specified algorithm until the timer goes off. Continuously the traffic density gets monitored and changes are made accordingly. In the meantime, if any unusual increase in traffic or any emergency vehicle is on the other side, the changes will be done accordingly. While the timer is on it will be observed if the traffic on the active side is comparatively lower than the other side. In that case, the switch of sides will take place. After the timer on one side is over, side switching takes place and the timer will be dynamically set depending on the traffic density. So, no side is going to suffer any abnormal waiting time or any uncontrollable queue. There can be manual intervention by the TCR (Traffic Control Room) through server communication.

F. Cloud Interaction & Output

The frames sent to the cloud server are fed to the trained algorithm which computes the traffic density with the subclass detection, and also the count of emergency vehicles on either side. This data is supplied to the decision making algorithm. In correspondence to this, the new status of the signals is generated in the form of binary Boolean logic. The microcontroller, connected to the cloud system, retrieves that Boolean logic to control the lights accordingly.

The traffic density is calculated, based on Vehicle count and Pedestrian count, depending on which of the ways is active. If a way is active i.e. in motion then only vehicles will be considered in determining the density since the pedestrians on the other side cannot cross. But on the inactive side, both vehicles and pedestrians will be taken under consideration in determining the traffic density.

The Status of the cameras is stored as “Status_Id” that defines whether the particular way they are catering to is in motion.

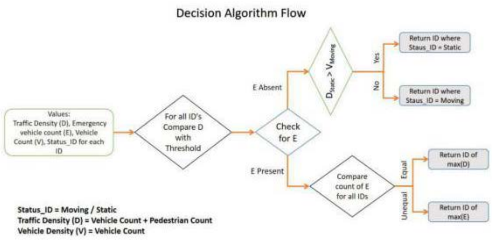

Fig 5: *Algorithm to make decision over the signal status*

V. RESULTS AND CONCLUSION

This research is focused on the training of YOLOV3 and YOLOV4 algorithms on custom data-set and classes, wherein we fed the architecture with the real-time images and live-video feeds of busy streets on an instantaneous basis. The algorithm shows high precision in detecting the classes it is trained on. Also based on this detection and classification and the density is computed for each class along with the overall traffic density. This value when fed to the decision-making algorithm produces the proper output on the status of the signals. The classification model which was trained on custom data-set and classes, seems to make accurate prediction and the overall traffic scenario is expected to move smoothly.

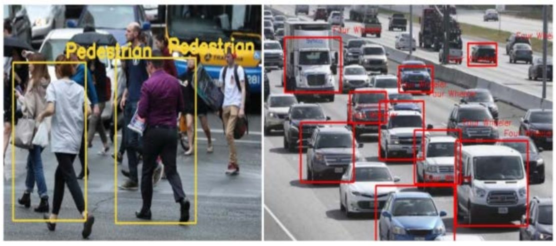

Fig 6: *Detection and classification by our trained YOLOv3 Model*

Fig 7: *Detection and classification by our trained YOLOv4 Model*

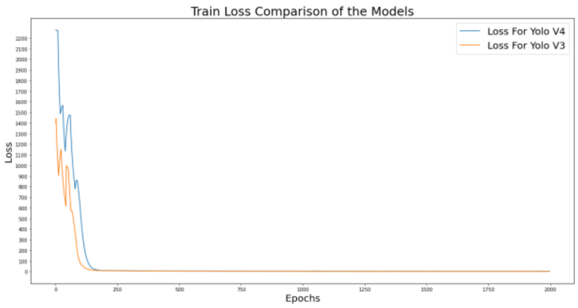

Fig 8: *Training loss comparison of the two custom trained models*

On the above Figure 8, we observe the training loss of the two selected architectures, it is observed that the initial loss value was quite large and which gradually reduced over the entire training procedure of 2000 epochs.

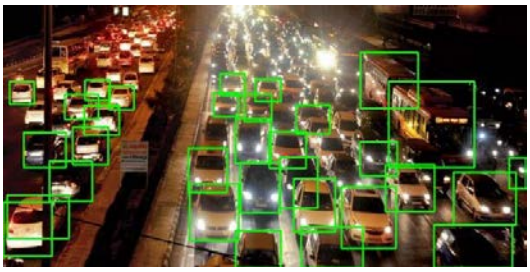

Fig 9: *Output of model in low light conditions*

Fig 10: *Performance in crowded scenarios*

In figure 9, we observe that the trained architecture of YOLOV4 makes pretty accurate predictions in densely populated low light situations. Whereas in figure 10, we observe its accuracy in detecting classes, like emergency vehicles, two-wheelers , pedestrians in crowded scenarios under broad daylight.

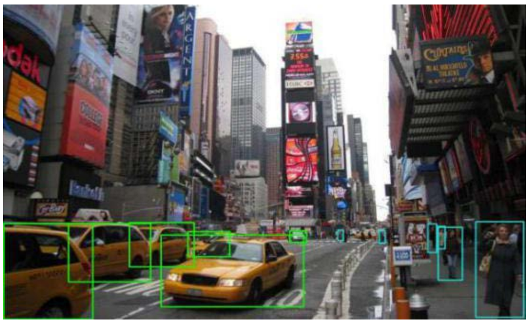

Fig 11: *Image given for Way 1*

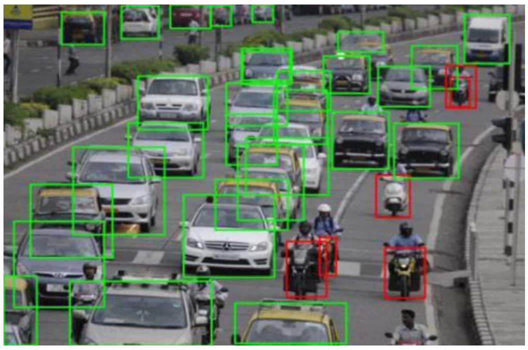

Fig 12: *Image given for Way 2*

Figure 11 and Figure 12 is a real-time input sample from two different ways of a crossing point to the model for testing. The total number of vehicles in figure 11 is found to be six, whereas no emergency vehicle was detected for figure 11 and number of pedestrians were found to be 6. Similarly, in Figure 12 the total number of vehicles is found to be 37 and no emergency vehicles or pedestrians were found. The algorithm proceeds to the decision making part, as the number of vehicles for Figure 12(Way 2) is more and checking all other necessary conditions(like presence of no emergency vehicle on either side), the model makes the decision to give Way 2(Figure 12) a green status. As the model is dynamic it automatically adapts to the situation and makes its decisions.

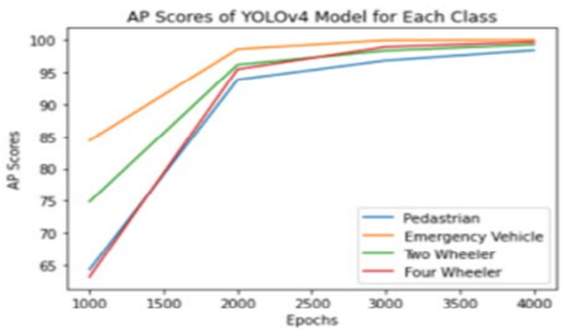

Fig 13: *AP Performance graph of YOLOv4*

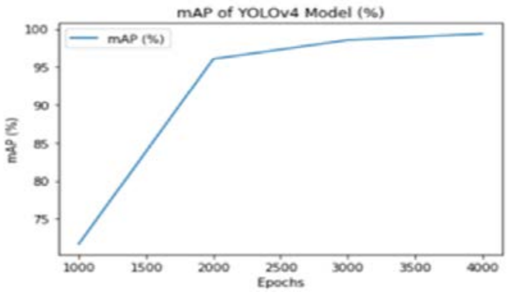

Fig 14: *mAP Performance of YOLOv4*

The above figure 13-14, depicts the relative comparison between average precision for all the separate classes (Figure 13) and overall Precision(Mean average Precision in Figure 14),after training it for a total of 4000 epochs. Thus we can observe from the Figure13&14 that the architecture performs with a fairly high accuracy for the given custom classes.

On further comparing both the algorithms based on their experimental findings,it was noted that, YOLO V4 has an increased processing speed in terms of object detection such as Frame Per Second(FPS) that is 10-12% more than that achieved in YOLO V3. Considering the trade-off between accuracy and computational power, YOLO V4 out performs YOLO V3. So, implementation of YOLOv4 algorithm was preferred over its previous version. Pairing it up with sensors and microcomputers, a reliable and adaptive automation of the traffic control system is achievable, especially during the era where population and metropolitan cities have shown an exponential growth which has resulted in complex traffic situations. This piece of work aims at providing a solution for a comparatively smooth and efficient movement of vehicles in and around the city, simultaneously giving preference to emergency vehicles and through this endeavor, we would like to cater to all these needs and provide a smart and sustainable solution.

VI. Future Scope

There are numerous prospects of automation and innovation in the field of smart-streets. By tweaking and modifying bits and pieces of this project, the abilities of a broader spectrum are achievable. Integrating auditory sensors and training it on audio files, abnormalities in a situation like accidents and even gunshots or other custom classes can be detected. A signal will be sent to the server along with the sensor ID on detection. The location can be fetched from the database using the ID associated with the camera or by linking it to the GPS navigation system. After a class is detected, a message will be transmitted to the nearest emergency support unit, with the location details for immediate action. Using image processing, we can achieve more accuracy. Conversion of audio frequencies to image frequency by creating the audio spectrogram of the audio frequencies can be achieved with the implementation of microcomputers. This allows making a more accurate and reliable CNN classification model. Integrating all these through a network through the cloud helps in monitoring the systems. It identifies problem or dispute units and even helps in the maintenance of the nodal units.

Reference

[1] P. Babaei, "Vehicles tracking and classification using Traffic zones in a hybrid scheme for intersection traffic management by smart cameras,"2010 International Conference on Signal and Image Processing, Chennai, 2010, pp. 49-53, doi: 10.1109/ICSIP.2010.5697440.

[2] X. Sevillano, E. Màrmol and V. Fernandez-Arguedas, "Towards smart traffic management systems: Vacant on-street parking spot detection based on video analytics,"17th International Conference on Information Fusion (FUSION), Salamanca, 2014, pp. 1-8.

[3] P. Girshick, J. Donahue, T. Darrell and J. Malik, "Region-Based Convolutional Networks for Accurate Object Detection and Segmentation," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 38, no. 1, pp. 142-158, 1 Jan. 2016.

[4] Uijlings, J.R.R., van de Sande, K.E.A., Gevers, T. et al. Selective Search for Object Recognition. Int J Comput Vis 104, 154–171 (2013).

[5] J. V. Arya, S. Tiwari and S. Behwalc, "Real-time vehicle detection and tracking," 2016 13th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON), Chiang Mai, 2016, pp. 1-6, doi: 10.1109/ECTICon.2016.7561327.

[6] R. Cucchiara, M. Piccardi and P. Mello, "Image analysis and rule-based reasoning for a traffic monitoring system," in IEEE Transactions on Intelligent Transportation Systems, vol. 1, no. 2, pp. 119-130, June 2000, doi: 10.1109/6979.880969.

[7] Prajapati, Mahendra & Pawar, Tanmay & Vala, Deepak. (2011). Position Detection of a Moving Vehicle using Images.

[8] Prakash, Uthara & Thankappan, Athira & Balakrishnan, Arun. (2018). Density Based Traffic Control System Using Image Processing. 10.1109/ICETIETR.2018.8529111.

[9] Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.

[10] He et al, “Spatial pyramid pooling in deep convolutional networks for visual recognition”, ECCV 2014Girshick, “Fast R-CNN”, ICCV 2015

[11] Q. Girshick, "Fast R-CNN,"2015 IEEE International Conference on Computer Vision (ICCV), Santiago, 2015, pp. 1440-1448, doi: 10.1109/ICCV.2015.169.

[12] P. Ren, K. He, R. Girshick and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137-1149, 1 June 2017, doi: 10.1109/TPAMI.2016.2577031.

[13] F. Oltean, C. Florea, R. Orghidan and V. Oltean, "Towards Real Time Vehicle Counting using YOLO-Tiny and Fast Motion Estimation,"2019 IEEE 25th International Symposium for Design and Technology in Electronic Packaging (SIITME), Cluj-Napoca, Romania, 2019.

[14] B. Benjdira, T. Khursheed, A. Koubaa, A. Ammar and K. Ouni, "Car Detection using Unmanned Aerial Vehicles: Comparison between Faster R-CNN and YOLOv3,"2019 1st International Conference on Unmanned Vehicle Systems-Oman (UVS), Muscat, Oman, 2019.

[15] Yang, F.; Yang, D.; He, Z.; Fu, Y.; Jiang, K. Automobile Fine-Grained Detection Algorithm Based on Multi-Improved YOLOv3 in Smart Streetlights.Algorithms 2020, 13, 114.

[16] Joseph Redmon and Ali Farhadi. (2018). YOLOv3: An Incremental Improvement.