Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 44 No. 5 (2023)

Smart Traffic Control and Management System using Machine Learning Techniques

[1]Shreeshayana R, [2]L. Lakshmaiah, [3]Kavya P O, [4]Anil D

[1] Department of Electrical and Electronics Engineering,
ATME College of Engineering, Mysuru, India.
[2]Department of Computer Science & Engineering (Data Science)
Nagarjuna College of Engineering & Technology, Bengaluru, India.
[3] Department of Computer Science & Engineering,
ATME College of Engineering, Mysuru, India.
[4] Department of Computer Science & Engineering,
CMR Institute of Technology, Bengaluru, India.

Abstract— This paper explores a Smart Traffic Control System incorporating dynamic signal switching and Intelligent Transport Systems (ITS) to combat urban traffic congestion. It focuses on dynamic signal adjustments based on real-time vehicle density, aided by YOLOv4 vehicle detection. This fusion of dynamic signal switching, ITS, and YOLOv4 aims to optimize traffic flow. The paper discusses technical aspects, benefits, and challenges, offering the potential to revolutionize urban transportation. With data-driven adaptability, this system promises to transform traffic into a more efficient urban ecosystem. The overall results found is satisfactory.

Keywords — Dynamic Signal Switching, Intelligent Transport System, Traffic, Vehicle Detection, Yolov4

1. Introduction

In the context of our rapidly expanding population and the corresponding surge in vehicular travel, a pressing challenge has emerged: traffic congestion. The increase in traffic has led to a cascade of issues including extensive delays, fuel wastage, prolonged queues, and a notable uptick in accidents, particularly at intersections. Traditional fixed-cycle traffic light controllers, which were once effective, have fallen short in addressing the escalating line of vehicles and prolonged wait times. This is evident in the continued reliance on traffic police officers to manage intersections, a practice that persists even in the presence of traffic lights. In an era marked by technological breakthroughs, solving such issues has become more achievable. An efficient traffic control system emerges as a pivotal tool in mitigating traffic congestion and its associated problems. The deployment of various traffic light systems has incorporated sensors to monitor real-time traffic density continuously. While similar mechanisms have been put in place in many countries, they often incur high costs since the need for in-road sensors and potential maintenance challenges [1]. This paper presents an alternative approach utilizing advanced computer vision technology to enhance traffic management and control more cost-effectively. Rather than relying on in-road sensors, we leverage the ubiquitous presence of CCTV cameras at intersections. By harnessing computer vision techniques, we enable efficient traffic control and management with minimal infrastructure requirements—merely requiring cameras and computers. The proposed system aims to build upon the existing CCTV camera infrastructure by implementing a PC vision-based approach. Our focus is on real-time monitoring, traffic control, and object detection. To achieve these objectives, we employ a pre-trained YOLO (You Only Look Once) Machine Learning Model.

YOLO is recognized for its exceptional accuracy and efficiency, combining aspects of Region-based Convolutional Neural Networks (RCNN) and SSD (Single Shot Detector) for superior performance. Notably, YOLO can detect objects in diverse orientations and positions, making it highly versatile [2]. Rather than the traditional approach of applying classifiers to individual images, YOLO processes images through a grid-based algorithm. This approach divides images into partitions and predicts object presence and confidence scores within each partition [3]. The use of IoU (Intersection over Union) evaluation metric enhances accuracy, especially for closely placed objects. Our system leverages the efficiency and precision of YOLO to detect and quantify traffic density. It functions by capturing real-time footage from CCTV cameras placed at intersections. The recorded pictures are separated into frames of uniform dimensions, and the YOLO model is applied to detect vehicles. The vehicle count obtained from the images guides the assignment of signal switching timings for each lane. This flexible strategy guarantees that the lane with higher vehicle density is given priority [4]. YOO framework works as follows: On each grid, image categorization and localization are applied. Then, YOLO forecasts the bounding boxes for objects and their accompanying class probabilities.

2. Literature Review

As of late, the mechanical development in different fields is developing quickly, especially in the field of transport, in particular Intelligent Transport System (ITS). ITS was a technique utilized in traffic plans to make proficient street-based transport system and it was applied in the developed nations. Example of ITS application is the utilization of CCTV cameras for reconnaissance [5].

Song et al., [6] proposed an approach for identifying urban traffic combines CNN to extract important data from GPS trajectory data with LSTM to collect dynamic elements. Against compare the prediction power of our hybrid model to Linear, CNN, CNN-LSTM, and enhanced CNN-LSTM, we ran a total of four trials. Higher prediction accuracy is accomplished by the use of more complex neural network topologies, however it will take additional time and computing power. To be able to reduce the training time, and thus enhance the suggested hybrid neural network.

Zhang et al., [7] describes about the congestion control by counting amount of vehicles on the lane as a whole. The primary goal is to perform edge detection using ‘canny Edge detection’ and determine the vehicle count by subtraction foreground and background image from the total area of vehicle and reduce traffic congestion. There will be a count of the vehicle density in relation to percentages and according to the count of the automobile on particular lane the green signal will be set for the calculated time. The advantage is there will be no time wastage due to free signal on empty road and adaption of the cycle period to entire region’s traffic.

Rathore et al., [8] proposed an automatic traffic control and monitoring system using a camera during any time. The majority of traffic information such as vehicle density, average speed, size and area of vehicle and counting total vehicles present were done using computer vision methods. First, utilising frame-difference algorithm objects in motion are separated from the scene and then texture information with grey scale intensity. Using morphological operators and top hat transformations Shadows are removed from the foreground objects as shadows of moving objects also belongs to the foreground.

[14] demonstrates a fresh approach to intelligent traffic control utilizing moving vehicle cameras. Here, a lane and vehicle identification system and a video processing module powered by a GPU are built as a first step in the process of finding violations for an inside-car fog-device. The model is shown in Figure 1. [15] LachiReddy et.al presented work where IR sensors are used to add up the total of vehicles, altering the time delay and providing drivers with traffic information via display boards at traffic intersections.

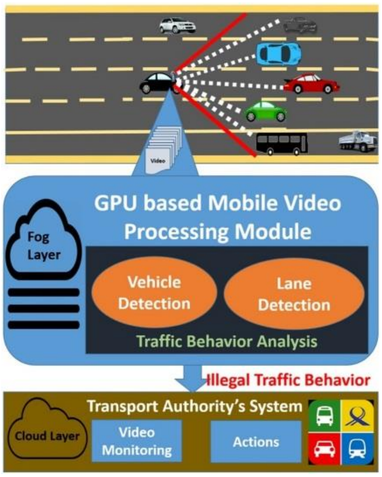

Figure-1: Driving Violation detection using Fog Device [14]

3. Methodology

The operational process of our system for managing traffic is orchestrated through a series of distinct stages, culminating in an efficient traffic flow strategy.

1. Capture Images: The foundation of our system lies in capturing real-time traffic footage through CCTV cameras. These video files are then segmented into frames, which serve as the input for subsequent processing. In this article, we exhibit the detection outcomes attained by applying the YOLO algorithm to these sample images.
2. Vehicle Detection: Vehicle detection constitutes a critical element in our methodology, as it defines the boundaries of vehicles within the specified images. Unlike prior detection systems that rely on multiple iterations over an image, our approach streamlines the process. Utilizing the YOLO V4 algorithm (You Only Look Once), we detect vehicles within a single pass. This technique optimizes performance, as YOLO V4 directly localizes vehicles and classifies them.
3. Traffic Light Control: The core of our traffic management system hinges on intelligent traffic light control. In a cross junction of four roads, video streams from each road are sent to the central server processing unit. Employing the YOLO algorithm, we assess the density of vehicles in each lane. Threshold values are then employed to prioritize lanes, determining the appropriate signal timing sequence (green, orange, red, and vice versa).

Our integrated approach encompasses capturing real-time footage, efficient vehicle detection using YOLO V4, and based on a vehicle, intelligent traffic light control densities and lane priorities. Through this methodology, we endeavour to streamline traffic management and enhance overall road safety and efficiency.

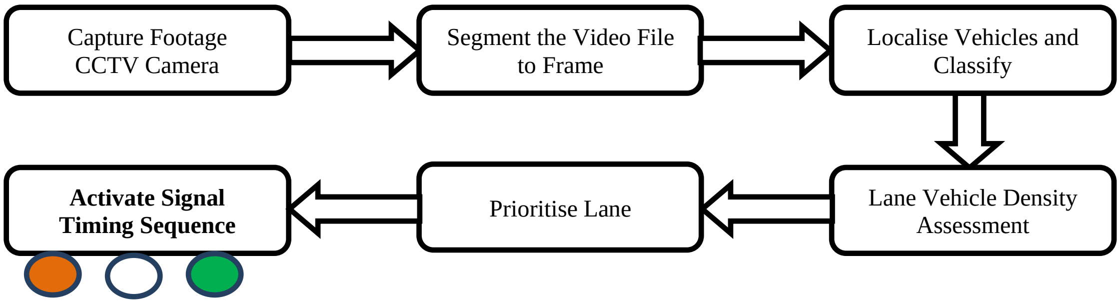

Figure-2: YOLO detection method

4. System Architecture

Our presented system implements Intelligent Traffic Management System using YOLO Machine Learning Model. Applying Machine Learning model will result in a very efficient management of the traffic, since the improved machine learning models get better as it learns over the period after its implementation [9]. Current work focuses on training the machine learning model and deploying it to receive the traffic count for better management of the traffic. Current identification frameworks reuse classifiers to perform location. The evolution of object detection frameworks has witnessed the progression from methodologies like deformable parts models (DPM) to more recent approaches such as R-CNN, each with its unique strategy for tackling the challenge. DPM, for instance, employs a sliding window technique, involving the application of a classifier at uniformly spaced regions across the entire image.

At first, the captured image from the input source is sent to the model and then the YOLO model detects the objects, and the model in-turn increments the count of the object. This process is repeated for each road and the signal switching takes place. The model now detects the image based on the classifiers and the confidence score. The detected objects are counted by the model, so that the vehicle count data is later used for dynamic signal switching in the traffic signals based on predefined threshold value condition. If the model passes the validation and testing part successfully then it can be deployed, else more training data must be passed into the model for better accuracy in object detection [10].

Next, from the Input Source the captured data is now transferred to our developed machine learning model which divides the image into MxM grids and it is classified as applied by our YOLO Model for each grid were based on the confidence score the machine learning model detects the one or more objects present in our YOLO Machine Learning Model.

5. Implementation

There are various favorable benefits to user involvement in information system construction and administration. First, users have greater chance to shape the systems and influence the result based on their needs and business goals if they are heavily involved in its design. Second, they are far more inclined to accept the transition process with open arms. Incorporating user skills and expertise enables better solutions. Our proposed system consists of 2 phases:

1. Vehicle Detection and Counting of Vehicles by YOLO Model

The architecture of our YOLO model encompasses 24 convolutional layers in conjunction with 2 fully connected layers. Its design incorporates 1x1 decrease layers followed by a 3x3 convolutional layer. The 7x7 grid layer, positioned on the rightmost side, constitutes one of the numerous bounding boxes that our YOLO model classifies. The model's algorithm is applied to each bounding box that it has classified. The input image received is divided into an S x S grid, where each matrix cell forecasts the bounding boxes for B and the associated confidence performance score. These confidence scores encapsulate both the model's certainty about the presence of an object within a box and the accuracy of its prediction [11].
The degree of confidence (C) can be computed using Equation below:

$$C = \Pr(Object) * IoU \quad \text{--}\textbf{Eqn.1}$$

Here, IoU represents the Intersection over Union between the predicted box and the ground truth. In the absence of an object within a cell, the confidence score is set to zero. Each bounding box is characterized by five predictions: (x, y), w, h, and confidence. The coordinates (x, y) signify the box's center, determined in relation to the grid cell bounds. 'w' represents the box's width, while 'h' denotes its height. In addition, every grid cell predicts C conditional class probabilities Pr(Class i | Object).
During testing, these class probabilities are combined with individual box confidence expectations to yield class-specific confidence scores for each box [12], as described by Equation below:

$$\Pr(Classi \mid Object) * \Pr(Object) * IoU = \Pr(Classi) * IoU \quad \text{----------------------------------}\textbf{Eqn.2}$$

Ultimately, the confidence score predictions are encoded in a format as shown in Equation below:

$$SxSx(B * 5 + C) \quad \text{--}\textbf{Eqn.3}$$

This intricate architecture and predictive approach enable our YOLO model to efficiently and accurately classify objects within bounding boxes, forming a critical component of our intelligent traffic management system.

2. Dynamic Signal Switching

Our developed YOLO model serves the purpose of efficiently enumerating the count of vehicles within a given input source. This sophisticated model undertakes the task of detecting vehicles depicted within images, thereby enabling an accurate quantification of the vehicles present. Through its advanced architecture and specialized training, the YOLO model discerns and localizes vehicles in the input source, effectively pinpointing their positions. Subsequently, it employs this information to generate a reliable tally of the total count of vehicles captured within the provided source. By effectively fusing cutting-edge machine learning techniques with robust image analysis, our YOLO model transcends the conventional methods of vehicle counting, offering a more precise and automated solution for quantifying vehicular presence within diverse scenarios. The count obtained from the source can now be passed into the python program for determining the threshold value of each lane which is predefined already. The python program now compares the count of vehicles from each lane and executes further steps in the next module.

The obtained data is then processed to the computer system in which we have written a python program that processes the input information that we have already predefined a threshold value based on the count of vehicles [13]. This data-driven approach optimizes the signal timings, dynamically adjusting them to alleviate congestion and reduce waiting times, ultimately leading to enhanced traffic management. The input from 4 lanes is detected and the lane with higher vehicle count is determined by our system. From the lane with denser traffic is Lane-3. System will open the signal of Lane-3 for 30 seconds and close after 30 seconds as depicted in Figure 3.

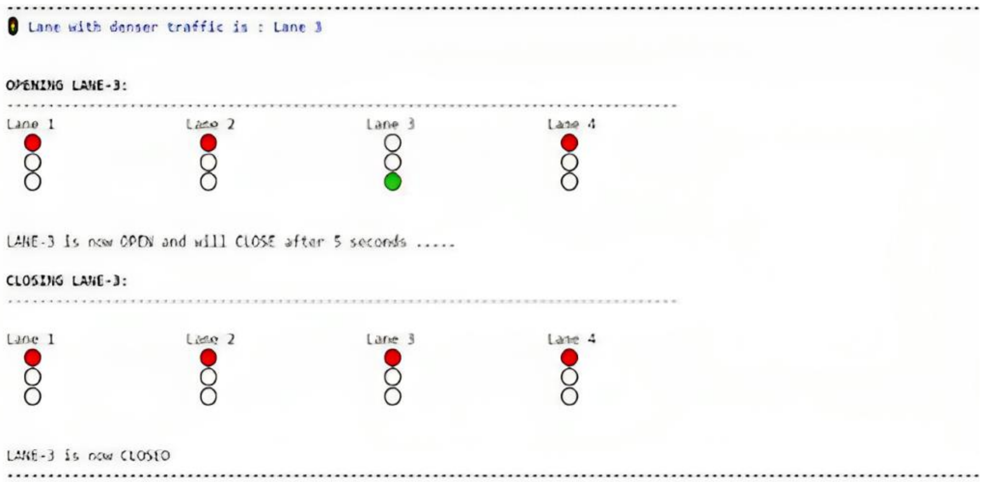

Figure-3: Dynamic Signal Switching – Output

The approach of integrating the dynamic signal switching system with the existing Traffic Management System's (TMS) CCTV cameras is both innovative and practical. By establishing this connection, your solution can tap into real-time traffic data and leverage the insights gained from the YOLO model's continuous learning process.

6. Results

The YOLO model has been meticulously trained across a spectrum of image sizes, each catering to distinct trade-offs between accuracy and speed. These sizes include 608x608 for heightened accuracy albeit at a slightly reduced speed, 416x416 striking a balance between moderate accuracy and speed, and 320x320 prioritizing high-speed detection albeit with slightly compromised accuracy. Interestingly, even in scenarios where a lane contains a limited number of vehicles and the camera angle affords a clear view of the vehicles, the smaller 320x320 image size configuration is capable of detecting the entirety of vehicles effectively. This phenomenon is demonstrated in Figure 4 and same is depicted in the Figure 5 with graphs showing detection speed with different image sizes. This underscores the adaptability and efficiency of the YOLO model, as it optimally adjusts its detection capabilities according to the contextual requirements of the situation. The model's versatility, coupled with the strategic camera positioning, enables accurate vehicle detection within constrained visual setups, even with the more speed-focused 320x320 image size configuration.

608*608(NOV: 15) 416*416(NOV: 13) 320*320(NOV: 12)

Figure-4: Different sizes of images: **608*608** (high accuracy, less speed), **416*416** (moderate accuracy, moderate speed, **320*320**(less accuracy, high speed)

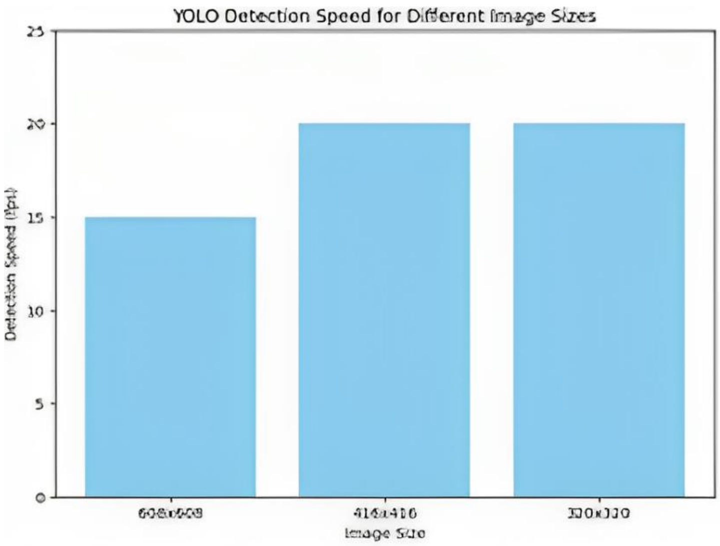

Figure-4: Graphs for Detection Speed with Different Image Sizes

The application underwent rigorous testing on a machine equipped with an AMD RYZEN 5 processor and 8 GB of RAM. The focus of the detection process was on identifying classes including 'car', 'motorcycle', 'bus', and 'truck', as these align with our specific interests. Our tests revealed that the detection process could be successfully executed with confidence thresholds of 0.50, 0.19, and 0.35, as illustrated in Figure 5 in the form of graph.

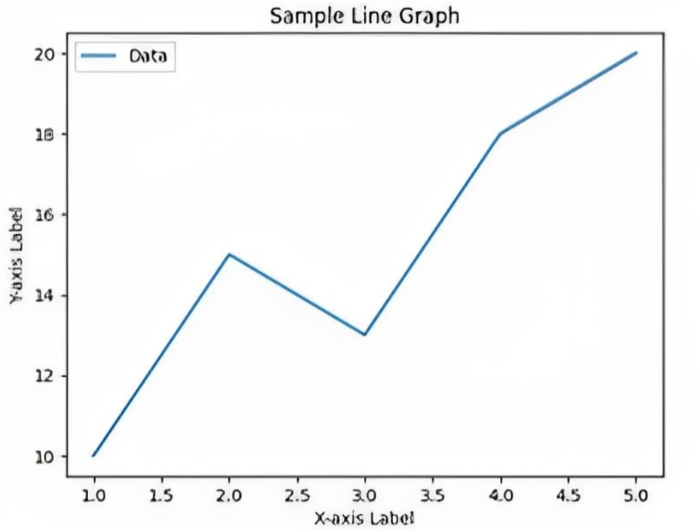

Figure-5: Graphs for Detection Speed with Different Image Sizes

Figure 6 shows the actual execution output. For optimal performance, achieving a smooth detection speed of around 15 to 20 frames per second (fps) necessitates the presence of robust hardware specifications. A processor of the caliber of an i5 or higher, coupled with graphics cards such as TITAN X NVIDIA and NVIDIA GT930, is imperative to maintain the desired level of operational efficiency. These high-end hardware components synergize to create an environment conducive to the seamless execution of the software, meeting the demands of real-time detection and processing tasks effectively. Figure 7 shows the videos used for detection of vehicles.

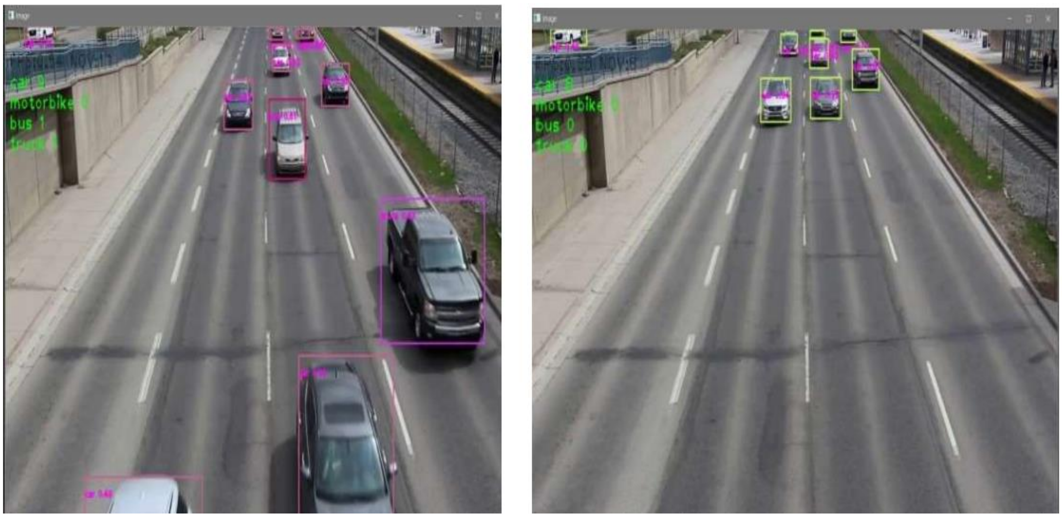

Figure-6: Detection result using YOLOV4 dataset

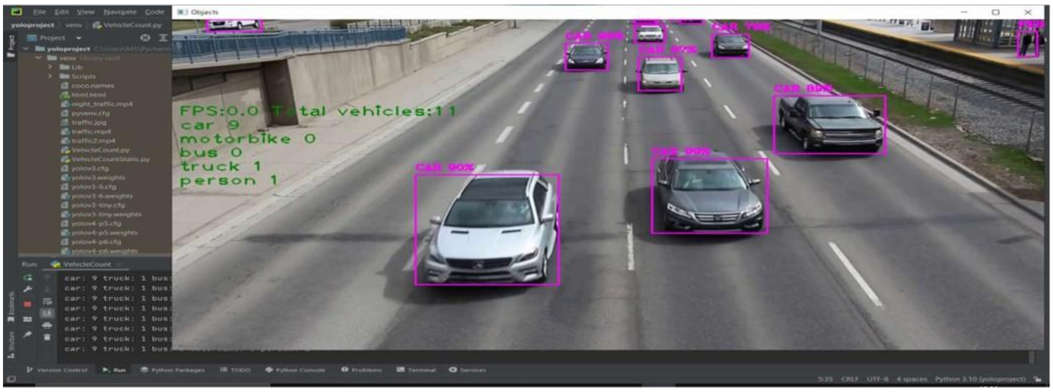

Figure-7: Videos used for vehicle detection

7. CONCLUSION AND FUTURE SCOPE

This article exhibits the persistent issue of traffic congestion in both urban and rural areas through the Intelligent Traffic Management system. Objective to leverage modern technology and more efficient traffic ecosystem is exhibited through results. The core of this effort involves harnessing machine learning models to optimize traffic flow and minimize disruptions on the road. While the initial training phase of the model may be time-consuming, it promises to significantly improve response times. Further, the proposed work not only addresses immediate congestion challenges but also sets the stage for a future where urban and rural transportation can seamlessly integrate with technological advancements. To enhance system reliability, a timer-based approach can be implemented for situations when the model fails to detect critical conditions, such as bad weather or low visibility initially. Additionally, the system can incorporate cloud computing support to log lane-specific traffic data, including date and time, facilitating more effective traffic analysis and road improvement strategies in the future.

REFERENCES

[1] Safiullin, Ravil, Vitaly Fedotov, and Alexey Marusin. "Method to evaluate performance of measurement equipment in automated vehicle traffic control systems." *Transportation Research Procedia* 50 (2020): 20-27.

[2] Ismagilova, Elvira, et al. "Smart cities: Advances in research—An information systems perspective." *International journal of information management* 47 (2019): 88-100.

[3] Kalva, Akhil Reddy, Jyothi Swarup Chelluboina, and B. Bharathi. "Smart Traffic Monitoring System using YOLO and Deep Learning Techniques." *2023 7th International Conference on Trends in Electronics and Informatics (ICOEI)*. IEEE, 2023.

[4] Chen, Chen, et al. "An edge traffic flow detection scheme based on deep learning in an intelligent transportation system." *IEEE Transactions on Intelligent Transportation Systems* 22.3 (2020): 1840-1852.

[5] Rajamoorthy, Rajasekaran, et al. "A novel intelligent transport system charging scheduling for electric vehicles using Grey Wolf Optimizer and Sail Fish Optimization algorithms." *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects* 44.2 (2022): 3555-3575.

[6] Song, Xiangbao, et al. "Combined CNN-LSTM network for state-of-charge estimation of lithium-ion batteries." *Ieee Access* 7 (2019): 88894-88902.

[7] Zhang, En-zhan, and Xia Zhang. "Road traffic congestion detecting by VANETs." *2nd International conference on electrical and electronic engineering (EEE 2019)*. Atlantis Press, 2019.

[8] Rathore, M. Mazhar, et al. "Smart traffic control: Identifying driving-violations using fog devices with vehicular cameras in smart cities." *Sustainable Cities and Society* 71 (2021): 102986.

[9] Gomathi, B., and G. Ashwin. "Intelligent Traffic Management System Using YOLO Machine Learning Model." *Disruptive Technologies for Big Data and Cloud Applications: Proceedings of ICBDCC 2021*. Singapore: Springer Nature Singapore, 2022. 119-128.

[10] Kumar, N. Suresh, and Amit Kumar Goel. "Detection, Localization and Classification of Fetal Brain Abnormalities using YOLO v4 Architecture." *International Journal of Performability Engineering* 18.10 (2022): 720.

[11] Megala, G., and P. Swarnalatha. "Efficient Object Detection on Sparse-to-Dense Depth Prediction." *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)*. Vol. 1. IEEE, 2023.

[12] Qiu, Qiwen, and Denvid Lau. "Real-time detection of cracks in tiled sidewalks using YOLO-based method applied to unmanned aerial vehicle (UAV) images." *Automation in Construction* 147 (2023): 104745.

[13] Tan, Tian, et al. "Cooperative deep reinforcement learning for large-scale traffic grid signal control." *IEEE transactions on cybernetics* 50.6 (2019): 2687-2700.

[14] M. Mazhar Rathore a, Anand Paul b 1, Seungmin Rho c, Murad Khan b, S. Vimal d, Syed Attique Shah, “Smart traffic control: Identifying driving-violations using fog devices with vehicular cameras in smart cities”, Sustainable Cities and Society, Elsevier, Volume 71, August 2021.

[15] P. LachiReddy, V. Divya, D. Swapna, D. ChinmayiSrinija, M. Rajesh, “Smart traffic controlling system”, Materialstoday, Proceedings, Science Direct, Volume 80, Part 3,(2023) :3702-370