Grenze International Journal of Engineering and Technology, June Issue

AI-Driven System for Dynamic Traffic Management

Bhagyashri R Hanji[1], Shalini. S[2], Khushi Arunkumar Byakod[3], Kansihk Y[4], Gagan LM[5] and Jaysingh Rajpurohit[6]
[1,4-6]Information Science & Engineering, Global Academy of Technology, Bengaluru, India
Email: bhagyashri@gat.ac.in, kanishkyoganand78@gmail.com, gaganlm16@gmail.com, rjaysingh490@gmail.com
[2]Computer Science & Engineering, Dayananda Sagar Academy of Technology and Management, Bengaluru, India
Email: shalini.siddamallappa@gmail.com
[3]Electronics and Communication Engineering, JSSATE, Bengaluru
Email: khushibyakod15@gmail.com

***Abstract*— The Smart Traffic Management System is an AI-powered solution designed to optimize urban traffic flow by utilizing real-time vehicle detection and analysis. With rapid urbanization and increasing vehicular density, traditional traffic management methods often struggle to maintain efficiency, leading to congestion, longer travel times, and increased fuel consumption. This system leverages advanced computer vision techniques powered by You Only Look Once -YOLOv8, a state-of-the-art object detection model, to monitor, analyze, and control traffic dynamically. By detecting and classifying vehicles in real-time, the system enables intelligent traffic signal adjustments based on current traffic conditions rather than relying on fixed signal timers. At the core of this solution is an automated vehicle counting mechanism, which continuously tracks the number of vehicles passing through an intersection. The system sets predefined thresholds to determine traffic congestion levels and dynamically adjusts signal timings. This real-time decision-making capability reduces unnecessary waiting times, improves road efficiency, and minimizes fuel wastage caused by prolonged idling at signals. Additionally, the system incorporates user-friendly visualization, displaying real-time traffic status and signal changes, making it intuitive for both operators and the public. The proposed method is improvement over existing traditional methods and can be installed at densely populated areas, highways, smart urban cities. Valuable data analytics for urban planners, study long-term traffic patterns, optimize infrastructure development, and implement strategic improvements for better road networks is the main aim of the proposal. By integrating artificial intelligence, automation, and data analytics, this system presents a scalable, cost-effective, and efficient approach to managing urban mobility. It not only enhances commuter convenience but also contributes to sustainability goals by reducing carbon emissions through improved traffic flow.**

***Keywords*— Smart Traffic Management, AI-Powered Traffic Control, Real-Time Vehicle Detection, Dynamic Signal Optimization, Automated Vehicle Counting.**

I. Introduction

The critical challenge in today's modern days with exponential increase in vehicles on road, is efficient and smart management of traffic. The dynamic management of signal timing addresses real-time congestion, leading to unnecessary delays, fuel wastage, and heightened carbon emissions.

Grenze ID: 01.GIJET.12.2.396_21

This inefficiency calls for intelligent, data-driven solutions capable of dynamically adapting to fluctuating traffic conditions and optimizing road usage. By utilizing computer vision and artificial intelligence, this system can accurately detect and count vehicles in real-time, allowing for adaptive signal control that responds to live traffic conditions. The integration of YOLOv8, a state-of-the-art object detection model, ensures high-speed, high-accuracy vehicle recognition, making the system both effective and scalable. Instead of relying on pre-set timer-based signals, this system determines the optimal duration for traffic lights based on vehicle density, ensuring smoother traffic movement and minimizing waiting times. The user-friendly interface of the Smart Traffic Management System enhances accessibility for both traffic authorities and city planners. Its automated vehicle counting mechanism and congestion analysis provide valuable insights for improving urban infrastructure and long-term traffic planning. The real time data collected is cumulatively maintained in database extending the capability to perform data analytics and predictive modelling helping the officials to anticipate peak – hour congestion patterns and optimize city traffic accordingly. The combination of artificial intelligence, automation and instant decision-making features adds to the smart traffic management system. The idea here increases the user convenience and lays the foundation for an efficient, smart and eco-friendly transportation infrastructure.

II. Literature Survey

A real-time approach to monitor traffic is discussed in [1], using progressive deep learning methods using the YOLO object detection framework to detect vehicles, count them and classify-categorize them based on the types. The traffic management is improved with timely accurate data and decisions taken based on quick real time analysis improving the overall traffic system. The critical implementation challenges such as environmental sensitivity, calibration issues and accuracy constraints along with the benefits with respect to cost effectiveness and scalability compared to regular existing methods are emphasized by authors in paper [2]. A rigorous survey of various methods used to find moving objects in different applications including human computer interaction, autonomous vehicles, and surveillance. Approaches like background subtraction, optical flow, enhanced deep learning techniques-convolutional neural networks are used for categorization. Paper [4] details the third form of You Only Look Once (YOLO) Object detection procedure improved version of previous methods offering better accuracy, smaller object detection, increasing the object detection speed without letting down the quality of performance.

The network architecture is improved by adding a new backbone network, Darknet-53 making YOLOv3 more effective and reliable object detection in a variety of real-world scenarios. The writers of article [5] discussed improved ways to find objects improving speed and accuracy for real time applications with CSPDarknet53 as supporting pillar, PANet for feature fusion and SPP block to improve feature extraction. Real time optimized traffic control system using YOLOv3 is detailed in paper [6]. The results in article [7] depicts reduced average journey time and waiting time of travelers by adjusting traffic signal time. Deep learning models for vehicle classification and detection showing how technology helps in improving traffic monitoring and management in smart traffic management is discussed in paper [8]. Internet of Things and Image Processing are combined and proposed as an adaptive traffic management system in paper [9]. By analyzing real-time data from camera-monitored lanes using YOLO, the system calculates vehicle counts and adjusts traffic light timings, accordingly, aiming to reduce average wait times and improve traffic flow efficiency. The paper [10] proposes a method to detect and classify vehicles in densely crowded images using YOLOv5, addressing YOLO's limitations in detecting small, grouped objects by assembling four different models. The approach is evaluated on the Dhaka AI dataset, demonstrating improved performance over existing models.

Keeping in mind the existing work, the proposed implementation of an intelligent traffic management system using YOLO based object detection has demonstrated the potential for optimizing traffic signal control based on real-time vehicle density. By leveraging deep learning for object detection, the system effectively identifies and classifies vehicles, dynamically adjusting signal durations to improve traffic flow.

III. Proposed Work

The proposed AI-Driven Smart Traffic Management System introduces an innovative solution to optimize urban traffic flow using advanced AI techniques, specifically leveraging YOLOv8 for real-time vehicle detection and classification. Unlike traditional traffic control systems, this system dynamically adjusts traffic signals based on real-time traffic data, ensuring efficient traffic management and reducing congestion. The system can identify vehicles, assess traffic density, and control signal timing to minimize delays and improve road safety as detailed in figure 1.

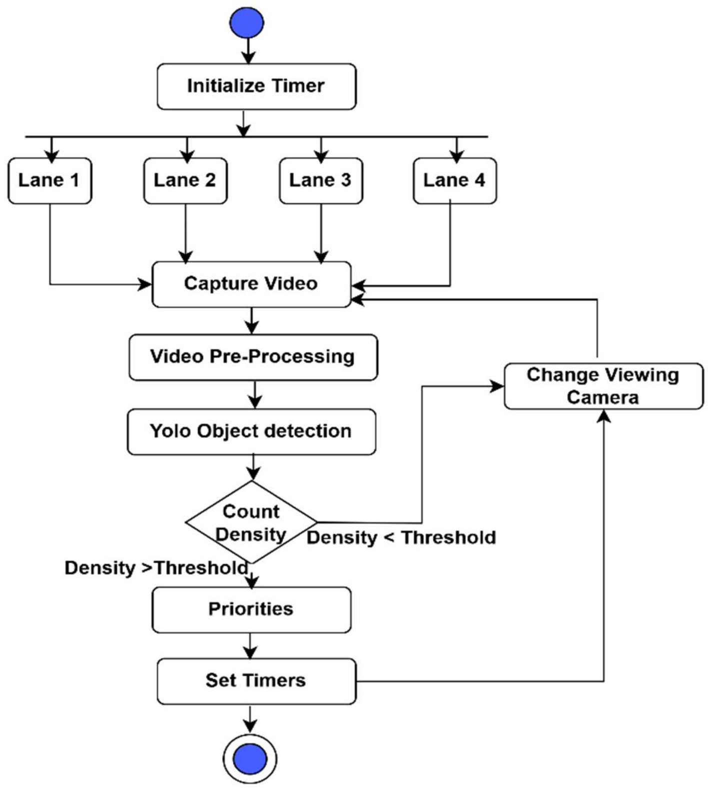

Figure 1: Process Flow Diagram

The platform offers scalability and adaptability for various urban environments, making it suitable for both small towns and large metropolitan areas. In addition to supporting a flexible signal control system that adapts to the traffic conditions of the moment, the integration of YOLOv8 offers high-accuracy identification of various vehicle types (such as cars, buses, and trucks). In order to provide smoother traffic flow during peak hours and less traffic congestion during off-peak periods, the system continuously monitors traffic and modifies the timing of red, yellow, and green lights based on vehicle count thresholds. Traffic managers may view real-time data visualizations, such as vehicle counts, traffic flow analytics, and signal statuses, thanks to the system's intuitive interface. Even people with little technical knowledge may easily observe and make decisions thanks to the user-friendly dashboard. For city authorities, the system serves as an effective tool for traffic optimization and urban planning, offering actionable insights to improve road safety, reduce traffic-related emissions, and enhance the overall commuting experience.

By leveraging AI and machine learning, the proposed system improves upon traditional traffic control methods by providing adaptive, data-driven solutions that enhance traffic management. It reduces the reliance on fixed signal timing and promotes efficient use of road infrastructure, contributing to the development of smarter, more sustainable cities. The Environmental Impact Reduction is directly proportion to reduction in Idling Tim e (IT) and Fuel Consumption (FC) as in equation 1.

$$EIR \propto \Delta IT + \Delta FC$$

$$Sustainability\ Index\ (SI) = f\ (\ EIR, EmissionReduction, Traffic\ Flow\ Efficiency)$$

$$Smart\ City\ Compliance\ Score\ (SCCS) \propto SI \text{ ----(1)}$$

The system architecture as shown in figure 2, follows a structured approach to managing traffic signals using YOLO object detection. Firstly, the timer is initialized to a value considered as a reference for signal duration. The camera monitors the parallel lanes and analyzes the traffic density. The quality of the input video is improved through preprocessing and further used for detection identified and vehicles are classified with YOLO object detection model. The number of vehicles on each line is counted after the object detection.

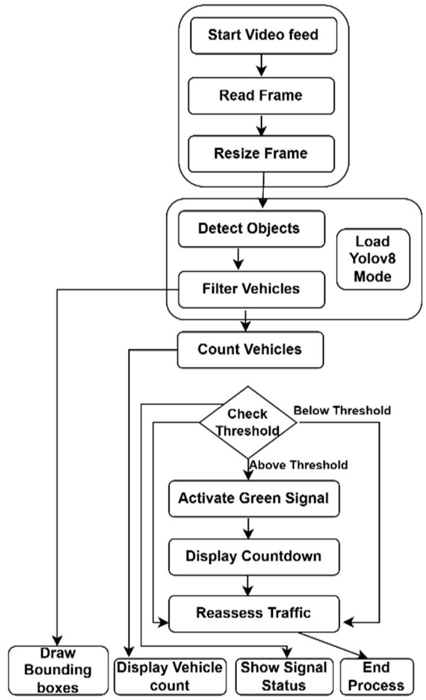

Figure 2: Process Flow Diagram

Based on the number of vehicle density detected a decision is made, if the vehicle density in one lane is less than the assigned threshold value, the next lane is monitored, further followed by the next lane. But if the density in any lane exceeds threshold, based on the density level the system sets priorities for lanes and accordingly calculates the time to be set for green light.

Figure 3: Simulation Results-Screenshot

The continuous feedback loop allows the system to optimize traffic flow, reducing waiting times and improving overall road efficiency. The simulation results are presented in figure 3. This implementation is designed to monitor traffic flow and regulate traffic signals using YOLOv8 for real-time object detection.
Using computer vision, the system improves traffic flow by changing signal timings based on real-time traffic, instead of using fixed time schedules. OpenCV is used to work with video input. Each frame is read and processed from the video file resizing it to fit to the screen properly with clarity and easily accessible. The YOLOv8 model which is trained on the dataset is a powerful model, used to detect objects from input video accurately for traffic monitoring. While the model can identify different types of objects, this setup focuses only on certain vehicles like cars, trucks, and buses—since they are important for controlling traffic signals.

The size and position of the detected object in a frame is defined by bounding box as shown in equation 2. The coordinates of the bounding box, confidence score and class label are extracted from each object being processed.

$$Object\ (i) = (B_i, C_i, L_i) \quad for\ each\ object\ i\ in\ frame\ F$$
$$where, B_i = \ (X_{min}, Y_{min}, X_{max}, Y_{max}) = Bounding\ Box\ Coordinates\ of\ Object\ i$$
$$C_i \in \ [0,1] = confidence\ score\ of\ detection$$
$$L_i \in \ \mathcal{L} = Class\ label\ from\ predefined\ label\ set\ \mathcal{L} \qquad \text{-------------(2)}$$

The confidence score indicates the accuracy of the detection. To ensure reliable results, only objects with a confidence score greater than 0.3 are considered valid vehicle detections as shown in equation 3.

$$Valid\ (i) = \begin{cases} True, If\ C_i\ > 0.3\ and\ L_i\ \in \{Class\ of\ vehicles\} \\ \qquad False, Otherwise \end{cases} \qquad \text{--------------(3)}$$

For each frame, the system counts the number of detected vehicles and updates the total vehicle count, providing a cumulative measure of traffic flow over time. The proposed method is based on a predefined vehicle threshold of twenty-three vehicles per frame which is set as a condition to toggle the traffic signal light. If the vehicle count exceeds threshold, the signal turns green for stipulated time of 15 seconds and the countdown timer is started. Once the timer reaches zero the system recalculates the traffic condition in the next fames and decides whether signal should continue with green or switch back to red. This dynamic approach ensures that traffic flow is managed efficiently, reducing unnecessary waiting times and improving overall road traffic conditions.

The processed video frame displays important information such as the number of vehicles detected in the current frame, total cumulative vehicle counts till current time, and traffic signal status. Bounding Box are drawn around the detected vehicle and cyzone library is used to display text overlays as shown in equation (4) ensuring clear and easy to understand information is displayed.

$$if\ Valid\ (i) = True, [for\ each\ valid\ detected\ vehicle\ i\ in\ frame\ F]$$
$$then : cyzone.drawBox(F, B_i)$$
$$cvzone.putText(F, Li + \ \ + str(Ci), position = B_i^{top\_left}$$
$$Where: B_i = Bounding\ box\ coordinates\ of\ vehicle\ i$$
$$L_i = Class\ Label, C_i = Confidence\ Score, f = Current\ Video\ or\ Image \qquad \text{-------------(4)}$$

The system continues processing frames in a loop until the user manually exits by pressing the 'q' key. This allows for continuous real-time monitoring of traffic conditions. The implementation is built using Python, with key dependencies including YOLOv8 for object detection, OpenCV for video processing, and cvzone for visualization enhancements.

By integrating these technologies, the system provides an intelligent approach to traffic signal control, moving away from traditional time-based signals and towards adaptive traffic management. The experimental results of the traffic management system using YOLO object detection demonstrate its ability to dynamically regulate traffic signals based on real-time vehicle density as in equation 5.

$$F_t = Frame\ at\ time\ t$$
$$D_t = \ \{(B_i, C_i, L_i)\} = Set\ of\ detected\ objects\ in\ F_t\ using\ YOLO$$
$$V_t = \ \{i | L_i \in VehicleClasses \wedge C_i > 0.3\}$$
$$= valid\ vehicle\ detection\ at\ time\ t$$
$$\rho_t = |V_t|, \qquad T_{green} = f(\rho_t)$$
$$where: \rho t\ is\ real\ time\ vehicle\ count,$$
$$f\ is\ signal\ timing\ function$$
$$Tgreen\ is\ duration\ of\ green\ signal\ for\ a\ given\ lane \qquad \text{------(5)}$$

The system processes video input from multiple lanes and applies YOLO-based object detection to classify vehicles such as cars, trucks, and buses. The density of traffic is determined by vehicle count on-road and the signal timings are adjusted accordingly. The method yields good results with YOLO which classifies and identifies different vehicles. The vehicles with confidence scores above thirty percent are considered for traffic density estimation. This method reduces false detection and improves the reliability of systems decisions. The total vehicle count is updated efficiently with successive frames allowing cumulative analysis of traffic trends.
The signal light is changed for a duration of fifteen seconds once the vehicle count exceeds threshold enabling the congested lane to clear. The signal color remains unchanged if the vehicle count is less than the threshold. The real-time display of signal status and vehicle count on the video frame allowed clear visualization of the system's decision-making process. The implementation of a dynamic green signal timer ensured that the system was responsive to fluctuations in traffic density, improving efficiency compared to traditional fixed-time signals as shown in figure 4 and 5.

Figure 4: Results depicting frame vehicles 22 and green signal for 13 seconds

Figure 5: Results Depicting Signal turning RED when the vehicle count is below threshold

The results highlighted the effectiveness of the system in adapting to traffic conditions in real-time. The detection accuracy remained high across different video frames, with minimal misclassifications. The system's ability to count vehicles dynamically and adjust signals accordingly demonstrated its potential for practical deployment in urban traffic management. The automated decision-making reduced unnecessary waiting times, making traffic flow more efficient. Queue length, Throughput, Average Speed Per Lane, Average Vehicle Wait Time, Carbon dioxide emission estimate and waiting time comparison of existing system with proposed system are the parameters considered for evaluation.

A. Queue Length

Little's formula L = λW is used queue length calculation, where L is the average queue length, λ is the arrival rate of vehicles, and W is the average time a vehicle spends in the system, AT is Arrival time, DT is the Departure Time. Figure 6 depicts approximately 30-35 percent improvement in vehicle waiting time at traffic queue.

$$QL = QL(t - \Delta t) + [AT(t) - AT(t - \Delta t)] - [DT(t) - DT\,(t - \Delta t]$$

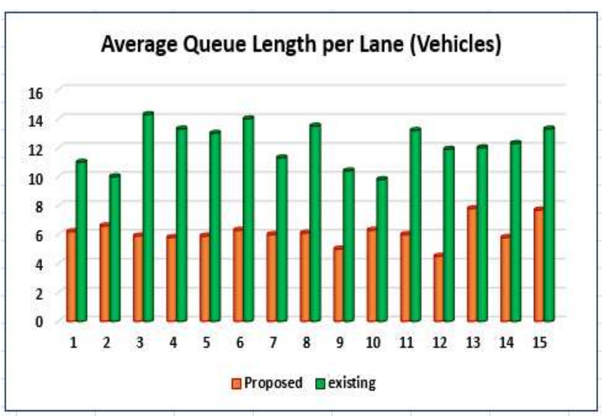

Figure 6: Average Queue Length per Lane

B. Throughput

Throughput is defined as number of vehicle Departures by green signal time (T0 to T1) i.e number of vehicles crossing stop-bar per unit time. Figure 7 shows around 50 to 60 percent improvement in throughput, i.e. number of vehicles crossing the signal.

$$Throughput\ (W) = Cumulative\ Departure(T_1) - Cumulative\ Departure(T_0)$$

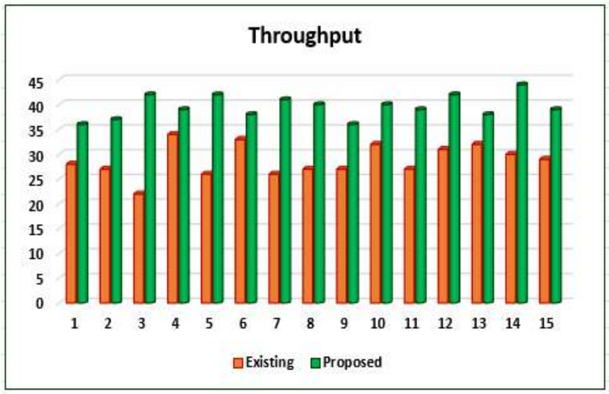

Figure 7. Throughput-Number of Vehicles passing the signal

C. Average Speed Per Lane

Average vehicle speed observed in a particular lane, measured in kilometers per hour (Kmph). It is the ratio of number of vehicles in bounding window W to the average vehicle speed.

$$ASPL = \frac{1}{\substack{number\ of\ vehicles \\ observed\ in\ window\ W}} sum\ of (avg\ speed\ of\ vehicles)$$

D. Average Vehicle Wait Time

This metric represents the duration a vehicle spends waiting at signal before leaving. It helps assess traffic efficiency and congestion levels. T_i^j is the time when vehicle joins the signal queue and T_i^s is the time when vehicle is served or leaves the signal. Figure 8 shows considerable improvement of 30 to 35% in average vehicle wait time of the proposed method.

$$WT = T_i^S - T_i^J$$

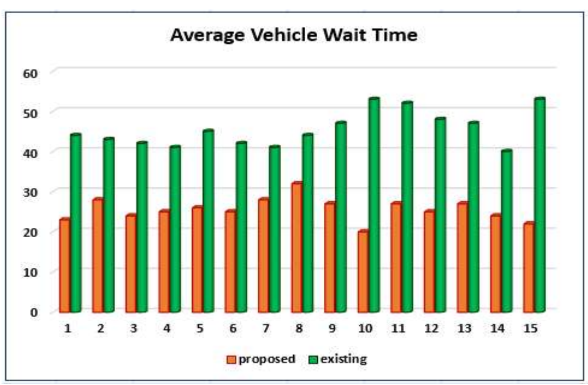

Figure 1. Average Vehicle Wait Time

E. Carbondioxide emissions estimate

This metric as shown in figure 9 is the calculation of Estimated level of carbon dioxide (CO_2) emitted by vehicles within the observed traffic system in grams per minute for idle and moving case. Proposed method shows an improvement of 20 to 25 percent over exisiting system.

$$Emission\ Rate\ (grams\ per\ minute) = (Emission\ Rate(Idle\ Time)) + (Emission\ Factor(Moving))$$

$$Emission\ Rate\ (Signal) = Sumof\ ((ER^{Idle\ Time} * T^{Idle\ Time}) + (EF^{Moving} * D))$$

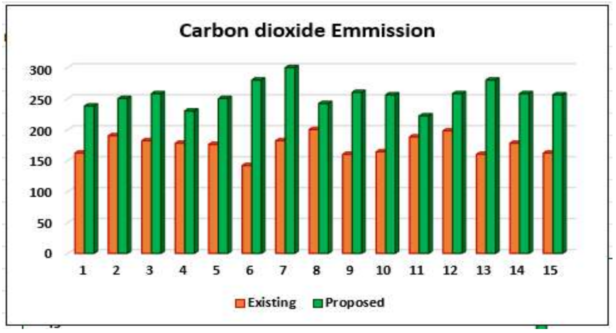

Figure 2. Carbon dioxide Emission Estimate

F. Traditional System Vs Proposed System

This metric focuses on the average vehicle waiting time comparison between conventional traffic management approaches and the newly proposed intelligent system. Here WT^{TS} and WT^{PS} is the waiting time of Traditional and Proposed System.

$$Improvement\ in\ Waiting\ Time = (WT^{TS} - WT^{PS})$$

$$Improved\ Percentage = 10 * \left(\frac{WT^{TS} - WT^{PS}}{WT^{TS}}\right)$$

IV. CONCLUSION

In conclusion, the proposed system presents a scalable and efficient solution to traffic congestion problems by utilizing AI-based object detection for intelligent traffic signal control. The results demonstrate that the model is effective in optimizing traffic flow while maintaining high detection accuracy. Future enhancements can focus on improving detection robustness under varying environmental conditions, integrating IoT-based traffic sensors, and implementing reinforcement learning techniques for even more adaptive signal control strategies. Additionally, more advanced traffic management algorithms could be incorporated to optimize traffic flow based on historical data, weather conditions, or time-of-day patterns. These enhancements could make the system even more effective in reducing traffic congestion and improving urban mobility. The system's ability to process video frames continuously and update signal timings in real-time enhances its practicality for real-world deployment. The integration of a dynamic green signal ensures that congested lanes receive priority, improving road efficiency. The framework can be further extended to incorporate additional features such as pedestrian detection, emergency vehicle prioritization, and adaptive signal control based on historical traffic patterns

REFERENCES

[1] Akhil Reddy Kalva, Jyothi Swarup Chelluboina, B. Bharathi. “Smart Traffic Monitoring System using YOLO and Deep Learning Techniques” , June 2023.
[2] David Fernandez Liorca, Antonio Hernandez, Ivan Garcia Daza. “Vision-based vehicle speed estimation”, March 2023.
[3] Joseph Redmon, Santosh Divvala, Ross B. Girshick, and Ali Farhadi . "YOLOv3: An Incremental Improvement" (Original YOLO Paper), original paper 2018.
[4] Xinyue Zhao, Guangli Wang, Zaixing He “A survey of moving object detection methods: A practical perspective” September 2022.
[5] Alexey Bochkovskiy, Chien-Yao Wang, Hongyu Liu. “YOLOv4: Optimal Speed and Accuracy of Object Detection”, (2020)
[6] N. Sharma, R. G. Meena, and A. A. Banerjee (Indian Institute of Technology, Kanpur). “Object Detection and Vehicle Tracking for Intelligent Traffic System UsingYOLO”, (2022)
[7] Ramkumar P., Sandeep P., S. Suganyadevi, “Smart Traffic Vehicle Monitoring and Signal Allocation using YOLO”, 2022.

[8] R. S. S. Anwar, S. S. Z. Rehman, and M. A. K. Azad (Indian Institute of Technology, Roorkee), "Vehicle Detection and Classification Using Deep Learning for Smart Traffic Management", 2021.
[9] Nitin Sakhare, Mrunal Hedau, Gokul B., Omkar Malpure, Trupti Shah, Anup Ingle, "Smart Traffic: Integrating Machine Learning, and YOLO for Adaptive Traffic Management System", 2024.
[10] Raian Rahman, Zadid Bin Azad, Md. Bakhtiar Hasan, "Densely-Populated Traffic Detection using YOLOv5 and Non-Maximum Suppression Ensembling", 20