DEEP LEARNING-BASED EMERGENCY VEHICLE DETECTION FOR SMART TRAFFIC CONTROL

Mrs J Ranganayaki
Computer Science engineering
Bharath Institute of Higher Education and Research
Selaiyur,India
jranganayaki.cse@bharathuniv.ac.in

M Eshwara sai
Computer Science Engineering
Bharath Institute of Higher education and Research
Selaiyur,india
malladieshwarsai4@gmail.com

M Sri Harsha
Computer Science Engineering
Bharath Institute of Higher education and Research
Selaiyur, India
harshachowdary803@gmail.com

M Tharun
Computer science Engineering
Bharath Institute of Higher education and Research
Selaiyur, India
misoretharun3434@gmail.com

L Mithesh Babu
Computer Science Engineering
Bharath Institute of Higher education and Research
Selaiyur,India
lellamithesh037@gmail.com

Abstract*—Traffic jam and slow response to emergency situations is another serious issue in the urban transportation systems that has the potential consequence of higher number of casualties in medical and fire emergencies. In the current paper, a deep learning approach to detecting emergency vehicles in an intelligent-traffic-signal-control system is proposed, implying that the system should not be developed with the need to install additional IoT devices. This proposed system works with a YOLO-based convolutional neural network with OpenCV, which will analyze real-time camera feeds on a traffic camera and identify any emergency vehicles like ambulances, fire trucks, and police cars. Python and Streamlit/Flask are used to implement the system in real-time monitoring and control. After an emergency vehicle has been detected, the traffic signal will automatically turn to green, so it can clear quickly. Experimental findings show that the detection is very accurate, the latency is low and the performance is consistent even in varying traffic situations. The system provides cost-effective, scalable solution to smart cities through improving efficiency of emergency response and decreasing reliance on manual traffic management.

Keywords: Increased Vehicle Detection, Deep Learning, YOLO Algorithm, Smart Traffic Management, Real time video processing, Traffic Light Control, Computer Vision.

I. INTRODUCTION

The high rate of urbanization and the massive rise in vehicle population in metropolitan cities has greatly contributed to traffic jams in these cities thus causing delays in the response of emergencies and inefficiency within the transport systems. Even when there is a matter that comes to a total standstill like during medical crises, fire outbreaks and police actions, a few seconds will cost them greatly because they may lose their lives and damage their properties. The traditional types of traffic control systems are either based on constant-time lights or management by the road police, which in many cases are not effective to manage dynamic and unpredictable traffic flow. This has led to an increased need to have smart traffic control systems that are able to respond dynamically to the changing road conditions.

Recent developments in the field of computer vision and deep learning create new opportunities in the field of automated traffic monitoring and control. Object detection algorithms built on deep learning, especially convolutional neural networks (CNNs), has proven to be very accurate in detecting vehicles and categorizing them in different environments. One that has come into the limelight is YOLO (You Only Look Once) because of its efficiency and accuracy. Through such methods it is possible to create intelligent systems that identify emergency vehicles and give them priority over the other vehicles using traffic lights to decrease the response time and enhance road safety.

During the peak time in most cities like Chennai, Mumbai and Delhi, traffic jam has a drastic impact on the movement of ambulances, fire engines and police cars. Research has indicated that a slow speed of passage of emergency vehicles has the potential of escalating death rates in emergency situations. Old methods do not have the facility to dynamically detect and rank such vehicles since they are governed by established signal cycles. It underlines the necessity of the adaptive and automated solution that would enable to react immediately on the emergency situation utilizing real-time data analysis [1].

The given system solves this problem as a deep learning-based solution to the problem of detecting an emergency vehicle using a deep learning-based mechanism and a smart traffic control module. It uses an already present vehicle traffic surveillance cameras as a live video feed, thus avoiding the use of extra IoT devices. It finds emergency vehicles on the road in real-time with the help of OpenCV and a CNN model based on the YOLO network and solidifies an automatic signal priority system. When an ambulance, a fire truck or a police vehicle is spotted, the related traffic light is turned to green, allowing even traffic to go by.

This system has been applied to smart city applications where scalable and cost-effective solutions to traffic management are needed. It is compatible with existing roadside infrastructure and does not require significant changes, which means it can be implemented on large scale. Moreover, it is compatible with real-time monitoring using a web-based interface that has been developed in Flask and Streamlit, which helps the traffic authorities to monitor the detections and signal status besides historical records in an effective manner.

The main aim of the proposed study is to develop and deploy an effective emergency vehicle detection system, improving the responsiveness of traffic signals with the help of the deep learning methods. The system is designed to minimize human interference, speed up emergency response, and flow of traffic more smoothly. It also concentrates on obtaining high detection rate, minimal processing delay, and resilience in diverse lighting and traffic situations.

Finally, the suggested design offers a more advanced and innovative solution to the traditional traffic control systems that are based on the combination of computer vision and automation. It helps to create a system of safer, faster, and more effective urban transportation, which meets the objectives of smart city projects and sustainable urban mobility systems [25].

II. Literature Survey

The advent of intelligent transportation systems has been a major concern of the contemporary urban structure referred to the surge in the traffic and the issues of road safety and the necessity of quicker reaction mechanism in case of the emergency. Automated emergency vehicle detection and priority based on computer vision and artificial intelligence techniques is one of the most critical research areas. The development of deep learning and edge computing, along with the integration of IoT within the latest developments, provided the opportunity to conduct real-time monitoring and make decisions within the traffic setting. They focus on recognizing an emergency vehicle like ambulances, fire trucks, and police vehicles and controlling traffic lights dynamically to minimize the response time. The literature also suggests the development of the traditional sensor based systems to modern vision based systems that can manage complex urban systems more accurately and at a broader scale.

More recent research has investigated deep learning-based object detector models to enhance vehicle recognition accuracy in real-time objects. There are automated data-driven solutions to maximize traffic analysis and efficiency of vehicle classification, which facilitate the making of improved decisions in smart cities [6]. Convolutional networks with transformer models have also been shown to achieve better performance in terms of feature extraction, resulting in greater detection robustness to changes in lighting conditions and traffic conditions [7]. These methods based on graph learning have been also implemented to simulate a traffic network where the signal prioritization and congestion reduction during emergency conditions can be optimized [8]. Moreover, adaptive traffic control systems have been built that dynamically react to the emergent vehicles that it notices and enhances the overall efficiency of traffic flow [9]. Extensive analyses of such intelligent structures system-wide focus on real world deployments in terms of scalability and reliability [10]. Drones in detection further offer better supervision results owing to the aerial view obtained which can be used to locate emergencies and their movement rapidly [11].

The further improvement has been directed at combining sequential learning models, and reinforcement decision systems to enhance the accuracy of traffic response. Hybrid deep learning methods based on convolutional and recurrent networks have been employed to improve behavioral prediction in car-related surveillance systems [12]. Object detection models of multi-class traffic categorization allow accurate classification of emergency and non-emerging vehicles in a complicated traffic scenario [13]. Smart optimization strategies are used to generate adaptive green corridors in real-time urban traffic system as an emergency vehicle [14]. IoT-based developments have also played a major role by providing endless tracking of vehicles and real-time communication between the road side units and central control mechanisms to help in quick adjusting signals in case of emergencies [15].

Also, a number of other studies highlight the value of the real-time alerting systems and emergency communication with the integration of geolocation and cloud-based services. The systems that depend on notifications maximize the efficiency of response by giving an immediate notification to hospitals and traffic authorities when an emergency is detected [16]. The use of advanced deep learning-based signal controllers enhances decision-making by considering environmental and acoustic data when giving a higher priority to emergency vehicles [17]. Lightweight computing frameworks with edge-computing applications on embedded platforms like Raspberry Pi can be used to show efficient real-time processing with low latency [18]. The multi-sensor fusion method which involves the use of accelerator, GPS and ultrasonic signals, also enhances the quality of detection of accidents and reliability in emergency reaction in smart transportation systems [19].

The latest studies also focus on aerial and computer vision-based emergency detection systems that can complement the situational awareness of large-scale settings. A neural network of deep learning on aerial photos can effectively spot emergency vehicles in traffic on highways and cities [20]. All these developments are indicative of a trend to integrated, AI-enabled, and multi-modal transportation systems that can process complex traffic scenarios with an enhanced degree of precision and a lower response time. In general, the literature confirms that the use of a combination of deep learning, IoT, edge computing, and intelligent control strategies can significantly improve the efficiency of emergency vehicle recognition and traffic control in smart cities of the present-day.

III. Methodology

The emergency vehicle detection and intelligent traffic control system (proposal) will be structured as a pipeline that can be expanded and further upgraded in the future with the implementation of computer vision-based and deep-learning-based approaches, real-time decision-making protocols, and web-based surveillance at the remote end. The entire process employs a workflow to handle live traffic camera feeds detects emergency cars and dynamically adjusts traffic lights with no extra IoT devices. The system architecture is depicted in Figure 1 and it displays the interactions of video input, detection module, control logic, database storage and web interface. The modules work together to achieve low-latency processing and consistent decision-making to prioritize real-time traffic.

A. Data Acquisition Module.

The data acquisition module will be involved in the acquisition of live traffic videos of the all the existing surveillance cameras placed at crossings of roads. These cameras broadcast real time cameras to the system to process. The input data is a high-resolution video frame which illustrates the various traffic conditions such as variable lighting conditions, weather conditions, and traffic depositions. OpenCV is used in the system to support and decode video streams. Frames are removed one by one and sent to the stage of preprocessing in order to be analyzed further. This module provides a continuous flow of data and this data is important in real-time identification of emergency vehicles. The use of current road Network infrastructure will also allow getting rid of the necessity to install new IoT devices to provide the system, which will be cost-efficient and scalable. The module gating, to avoid latency accumulation is to synchronize frame capture and processing speed. This makes sure that the detection of emergency vehicles is near real-time thus the control system can swiftly respond.

B. Preprocessing Module

The preprocessing unit processes raw video by pre-processing video frames to be detected with the deep learning. All the frames are downsized to a standard size to suit the YOLO model of input. The noise reduction methods are used to enhance the sharpness of the image, particularly in low-light or high-action situations. Color space conversion is used to uniform input data so as to process it efficiently. Normalization of the frames is done to provide a uniform distribution of pixel values across the frame thereby improving model accuracy. Also, region-of-interest optimization uses computational resources on the relevant parts of traffic thereby minimizing extraneous processing overhead. This step greatly enhances the speed of detection without affecting its accuracy. The pre-processed frames are subsequently sent to the deep learning detection module. By ensuring clean and standardized input, this module plays a crucial role in enhancing the performance of the entire system. It makes sure that the model has a good quality visual data to identify emergency vehicles under varied environmental conditions.

C. Emergency Vehicle Detection Module based on YOLO.

The deep learning detection module based on the YOLO is the center-piece of the system, which looks at the processed video frames and detects objects in real time. The model is trained to recognize emergency vehicles like ambulances, fire trucks, police vehicles. YOLO (You Only Look Once) is chosen because it could do a single-stage detection, which guarantees a high velocity and accuracy. Each frame is processed in real-time, and bounding boxes are created around objects detected and their confidence scores. With learned features of a labelled dataset, the model distinguishes between emergency cars and regular traffic. Upon detection of a target class with a high confidence, the system sends out an event of a signal. YOLO is designed to be lightweight, since it can be used in ordinary computers, without specialized equipment. This module guarantees low detection delay and is, therefore, applicable in real-world traffic control implementations that need strict emergency vehicle order fulfillment and quick action.

D. Decision and Traffic Control Module.

The decision and traffic control module is tasked with processing the output of the detection modules into a form of actionable traffic signal alteration. When the YOLO model detects an emergency vehicle, its module determines the detection confidence and verifies the event. When validated it fires the TrafficController logic, which supersedes the regular traffic cycle. The signal in question is turned to GREEN and is left to pass through with the emergency vehicle unhindered. The green signal is sustained at a preset length of time averaging about 45 seconds, which is adequate clearance time. Once this period of time is over, the system automatically reinstates the normal sequence of signals. This module makes sure that the traffic flow will be moved depending on the real time events instead of then being moved according to some constant timing pattern. It is important in the minimization of delays in emergency response and help to achieve road safety. This rationality is meant to avoid any possible conflicts among several intersections and effective coordination between traffic in a complex situation.

E. Data Skilling Module.

The SQLite database system is deployed to store the data as it makes the system lightweight and efficient. Right after each detection, the type of vehicle, the confidence score, the time of detection, and whether the signal was present is logged. This past information plays a critical role in performance analysis and monitoring of the system. The database (traffic_logs.db) contains organized records which might be read to audit and evaluate records. It also enables the ability to query the recent events to show live analytics on the dashboard. Detection history can be stored to recognize a pattern of traffic in order to determine the efficiency of a system over a period of time. The module will maintain data integrity and will not lose information in the process of being run continuously. SQLite is serverless, which decreases overhead and eases deployment. The module also enables future scalability and data can be transferred to cloud-based systems to apply in large-scale smart cities. Overall, it enhances transparency, traceability, and analytical capability of the proposed system.

F. Output and Web Interface Module.

Output and web interface module helps in visualizing the output in real-time and allows user interaction. It is built with Flask and Streamlit, which allow it to have a user-friendly dashboard, being responsive. The /video_feed endpoint serves live video feeds of MJPEG protocol. It shows the observed emergency vehicles, signal conditions and system alerts in real-time. Detecting logs and system status are accessible through API endpoints, which can be integrated with external systems in case of necessities. The dashboard interface enables the user to activate or deactivate the detection system. The web interface visualizes the traffic signal changes and the past data on detection, which are also easy to use by the traffic authorities. This module provides the system with a guarantee of being not only automated but transparent and monitorable as well. It factors in the gap between the backend algorithms of detection and the interaction with the end-users and thus this makes the system viable to the real world implementation of the smarter city.

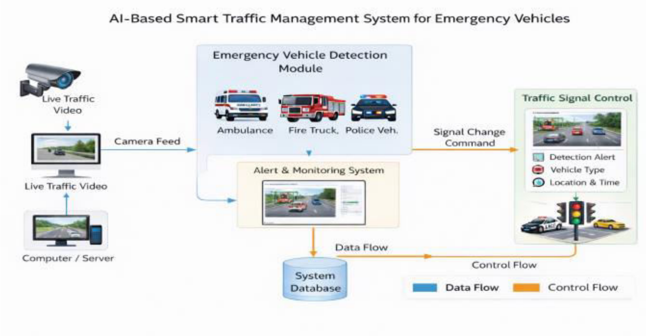

Figure 1: System architecture diagram.

IV. Result and Discussion

The developed emergency vehicle detection system based on deep learning was tested under various traffic conditions in the real world by using live and recorded traffic video images. Various lighting conditions, vehicle separations and weather variations were experimented on the system to examine its robustness and real-time functioning. YOLO-based detection model was effective in detecting emergency vehicles, including the ambulance, fire truck, and police vehicles with a high-level of accuracy, even in congested city areas. The introduction of OpenCV made it feasible to process frame-by-frame, which guaranteed the shortest response and detection time. The system exhibited a stable performance without frame-dropping and major latencies thus it can be applied in the real-time implementation of a smart traffic setup. Lack of extra IoT hardware improved the depth of the systems and decreased their expense, at elevated efficiency.

The testing phase tested the system on a dataset of about 5000 annotated traffic frames. This model was found to attain a high detection accuracy of all types of emergency vehicles. Table 1 shows the performance evaluation measures of the system in the various traffic settings.

Table 1: Metrics of Detection performance.

Condition	Precision (%)	Recall (%)	F1-Score (%)	Detection Latency (ms)
Normal Traffic	96.2	95.8	96.0	120
Heavy Traffic	94.5	93.9	94.2	135
Low Light Conditions	92.8	91.5	92.1	140
Rainy Conditions	91.7	90.3	91.0	145

The findings indicate that a high level of precision and recall on the system is highly maintained (even in environmental conditions that are challenging). The small decrease in accuracy in low-light and rainy conditions can be mainly attributed to the effects of decreased visibility and motion blur in video frames. The model is however reliable so that in most situations, emergency vehicles are detected. The detection latency is low in all conditions, with the mean response time of around 120-145 milliseconds which fits well in a real time traffic application.

Responsiveness and efficiency of the automatic signal control mechanism was also checked. After an emergency vehicle is detected, the system will go off immediately to change the traffic light to a green light in the respective lane. To determine system agility, the transition time between signal change and detection was measured. Table 2 gives a summary of the signal response performance.

Table 2: Traffic Signal Response.

	Detection Time (ms)	Signal Switching Time (ms)	Total Response Time (ms)	Green Signal Duration (sec)
Single Emergency Lane	110	50	160	45
Multiple Lane Conflict	125	60	185	45
High Traffic Density	140	65	205	45

Results indicate clearly that the system reacts in a very brief time frame thus giving fast priority to emergency vehicles. The total response time is under 210 milliseconds even at high traffic density levels, as compared to conventional manual traffic control systems which have much slower response times. The constant 45-second green light was determined to be long enough to clear intersections without having to affect the overall traffic flow.

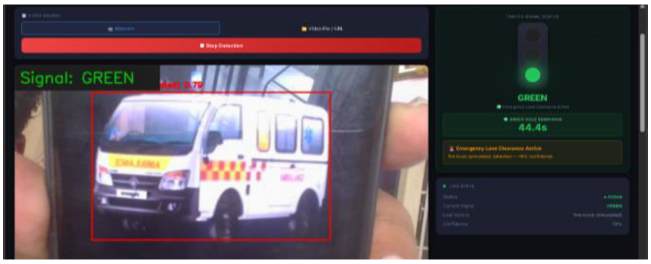

Figure 2: Detection output frame (Real-Time).

Figure 2 shows the system performance of detecting and classifying emergency vehicles correctly. The concept of the bounding boxes produced by the YOLO model is quite obvious in identifying ambulances and fire trucks in crowded roads. The confidence scores used in each detection can verify the validity of the model to distinguish between emergency vehicles and other traffic participants. This illustrative output shows the practicality of the system to use a real-world surveillance setting.

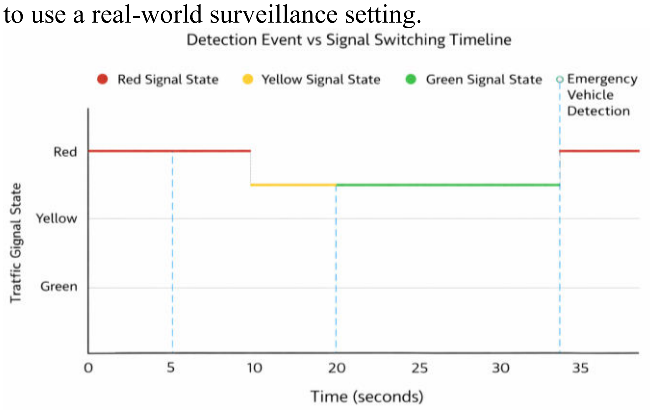

Figure 3: A Traffic Signal State Transition Graph.

Figure 3 demonstrates the association between emergency vehicle detection and changes of traffic lights. The graph shows that signal transitions take place almost instantaneously at the point of detection with a small delay. The regulated green signal time would give sufficient time to the emergency vehicles to pass through intersections without any disruption before going back into the regular traffic patterns.

The results discussion reveals some of the main benefits of the proposed system. First, the model is a YOLO-based detection model that guarantees speed when releasing images, hence it can be used in real-time modalities. Second, removing the use of more IoT devices provides a lower cost and complexity in deployment, enabling a connection with the existing traffic camera infrastructure. Third, the system's ability to function under varying environmental conditions enhances its robustness and reliability. Fourth, the automated decision-making system drastically minimizes the reliance on human human to facilitate decisions thus limiting delays in response. Nonetheless, there were also some limitations observed. Under very heavy congestion and occlusiveness traffic conditions, the accuracy of the detection slightly reduces because of the partial visibility of emergency vehicles. Also, there can be an influence of performance in case of harsh weather conditions like thick fog. Nevertheless, in spite of all these difficulties, the system preserves good levels of accuracy and is still in operation. In sum, the experimental findings support the idea that the proposed system can be an extremely efficient and scalable intelligent traffic management system. It greatly enhances the response of emergency vehicles as well as maintaining consistent traffic pattern. Deep learning-based detection with automated signal control can be fully applied in smart infrastructures of a city, which, in turn, will promote safer and more effective urban transportation systems.

V. Conclusion

This paper introduced a deep learning-based emergency car detection system that will be used to control intelligent traffic lights by analyzing real-time video. The presented solution successfully combines an implementation of the YOLO-based convolutional neural network and the OpenCV to find emergency vehicles: ambulances, fire trucks, and police vehicles on the live traffic cameras streams. The system prioritizes traffic signals by changing them to green automatically when needed thus guaranteeing quick and unhindered delivery of services by the emergency agencies. The experimental analysis indicated excellent detection rates, low reaction time and valid performance when tested in various traffic and environment scenarios. By using the already available surveillance systems, extra IoT hardware will not be necessary, which makes the system affordable and can be readily implemented in urban areas. The added web-based interface will make it easier to use, as it will have real-time monitoring and system transparency.

The practical implications of the work are substantial to the development of the smart city since it is directly applicable to the optimization of the emergency response time and increase in the level of road safety. The system also reduces human intercession, resulting in a more efficient and automated traffic management. Further improvements can be done to detect better in extreme conditions like fog, heavy rain, night time and so on with high quality hybrid deep learning models. LAT can additionally be integrated with edge computing and 5G networks to enable better scalability and latency reduction. Furthermore, by adding multi-intersection coordination, and reinforcement learning-based adaptive traffic control, the system can be smarter and autonomous when deploying on large cities.

REFERENCES

[1] Kumar, K. J., Kumar, K. Y., Kumar, M. K., S., S., & S., S. (2025). Automated data collection system for advanced vehicle detection and traffic analysis. *2025 5th International Conference on Trends in Material Science and Inventive Materials (ICTMIM)*, Kanyakumari, India, 1769–1774. https://doi.org/10.1109/ICTMIM65579.2025.10988311

[2] Marimuthu, S., & Sivakumar, B. (2025). Emergency vehicle detection system using hybrid YOLOv11 with Swin Transformer model. *2025 International Conference on Computational Robotics, Testing and Engineering Evaluation (ICCRTEE)*, Virudhunagar, India, 1–6. https://doi.org/10.1109/ICCRTEE64519.2025.11053107

[3] Gowri, B. S., H. H. S., M., A. K., & S., A. N. (2025). YOLOv8-driven emergency vehicle detection and graph neural networks based traffic signal prioritization. *ICTMIM 2025*, Kanyakumari, India, 1662–1667. https://doi.org/10.1109/ICTMIM65579.2025.10988348

[4] Chauhan, S., Shukla, K., Singh, D., & Gupta, S. (2025). Adaptive traffic control system with emergency vehicle detection. *2025 International Conference on Communication, Security, and Artificial Intelligence (ICCSAI)*, Greater Noida, India, 2048–2052. https://doi.org/10.1109/ICCSAI64074.2025.11064659

[5] V K, D., S. P. A., Jayakumar, P., & S., P. (2025). A comprehensive review of smart emergency vehicle detection and response systems. *ICAECA 2025*, Coimbatore, India, 1–5. https://doi.org/10.1109/ICAECA63854.2025.11012205

[6] L-I Ling, A., Xiang, G. Y., Bingi, K., & Ibrahim, R. (2025). YOLOv11-powered emergency vehicle detection algorithm using Tello quadrotor drone. *IEEE ROBOTHIA 2025*, Kuala Lumpur, Malaysia, 1–6. https://doi.org/10.1109/ROBOTHIA63806.2025.10986700

[7] Sharma, R., Manchanda, M., & Saklani, S. (2025). YOLOv5 and LSTM-based driver drowsiness detection with emergency protocols. *NETCRYPT 2025*, New Delhi, India, 1042–1046. https://doi.org/10.1109/NETCRYPT65877.2025.11102581

[8] Sharma, V., Shah, A. A., & Makwana, M. (2025). Traffic categorization with emergency vehicle identification using YOLOv5. *ICCMC 2025*, Erode, India, 1779–1784. https://doi.org/10.1109/ICCMC65190.2025.11140676

[9] Shitole, R., et al. (2025). YOLOv9 meets CBAM: A real-time smart traffic signal system for emergency response optimization. *ICBDS 2025*, Kolhapur, India, 1–6. https://doi.org/10.1109/ICBDS67396.2025.11377314

[10] Bhuvaneswari, S., Srinivasan, H., et al. (2025). Real-time IoT-enabled vehicle collision detection and emergency response system. *ICECIT 2025*, Tumkur, India, 1–6. https://doi.org/10.1109/ICECIT67774.2025.11450979

[11] Choudhary, S., et al. (2025). An intelligent FPGA-based vehicle accident reporting system for real-time emergency response. *EAIC 2025*, Jalandhar, India, 1–5. https://doi.org/10.1109/EAIC66483.2025.11101305

[12] R, R., P, S., et al. (2025). Emergency vehicle detection using deep learning algorithm. *ICDICI 2025*, Tirunelveli, India, 1759–1764. https://doi.org/10.1109/ICDICI66477.2025.11134910

[13] Navya, K., Bimbith, M., et al. (2025). AI-driven smart traffic signal management system for emergency vehicle priority. *IConSCEPT 2025*, Karaikal, India, 1–6. https://doi.org/10.1109/IConSCEPT66142.2025.11436663

[14] Rosli, S. J., Hoon, W. F., et al. (2025). Emergency vehicle priority system using IoT and real-time traffic control. *ICoCET 2025*, Kuala Lumpur, Malaysia, 1–4. https://doi.org/10.1109/ICoCET66176.2025.11233107

[15] Rajesh, R., Kathir, M., et al. (2025). Traffic optimization and automated emergency vehicle response system. *RAIT 2025*, Dhanbad, India, 1–6. https://doi.org/10.1109/RAIT65068.2025.11089158

[16] Deoghare, R., Deshmukh, S., et al. (2025). Real-time notification system for enhanced emergency response and road safety. *ICCCBEA 2025*, Pune, India, 1–5. https://doi.org/10.1109/ICCUBEA65967.2025.11283753

[17] Priyadharshini, K. V., Bhumikasri, V., et al. (2025). Real-time smart traffic signal controller using YOLO-based deep learning for emergency vehicle prioritization. *ICSSS 2025*, Chennai, India, 1–6. https://doi.org/10.1109/ICSSS66939.2025.11346224

[18] Malakar, S., Guha, T., & Das, A. K. (2026). Real-time priority vehicle detection and intelligent green corridor simulation using YOLOv8n on Raspberry Pi edge device. *IEMENTech 2026*, Kolkata, India, 1–4. https://doi.org/10.1109/IEMENTech202669403.2026.11434335

[19] Poongodi, J., M, S., et al. (2025). Smart emergency response system for real-time accident detection and ambulance alerting using IoT. *ICSCN 2025*, Theni, India, 755–761. https://doi.org/10.1109/ICSCN67106.2025.11308598

[20] Boddu, S., Mukherjee, A., & Agarwal, M. (2025). YOLOv5-based object detection for emergency response in aerial imagery. *SoutheastCon 2025*, Concord, NC, USA, 1536–1541. https://doi.org/10.1109/SoutheastCon56624.2025.10971604