Task 2 - Vehicle Detection Report

- ## Introduction

Traffic signal control systems play a vital role in managing vehicular traffic at intersections, aiming to enhance road safety and efficiency. These systems use a combination of traffic lights, sensors, and timing algorithms to regulate the flow of vehicles and pedestrians. However, in many countries, including ours, traffic signal control systems face several challenges such as congestion during peak hours, lack of synchronization between signals, and inadequate detection of vehicles, especially at night or in adverse weather conditions. These issues often lead to increased travel times, fuel consumption, and pollution, highlighting the need for more advanced and adaptive traffic management solutions.

To address these challenges, several technical solutions have been devised. One approach involves implementing adaptive traffic signal control systems that adjust signal timings based on real-time traffic conditions. These systems use various sensors, such as inductive loops, cameras, and radar, to gather data on vehicle presence and flow. Another solution is the use of synchronized signal timing, or "green wave," which ensures a smoother flow of traffic along main corridors by coordinating the signals to minimize stops. Additionally, some cities have implemented intelligent transportation systems (ITS) that integrate traffic management with other modes of transportation, providing a holistic approach to traffic control. The major steps in these techniques typically include data collection, analysis, and real-time adjustments to signal timings.

Vehicle detection systems are crucial in modern traffic signal control, providing the data necessary for adaptive and intelligent traffic management. These systems utilize machine learning algorithms and computer vision techniques to accurately detect and classify vehicles in real-time. For instance, convolutional neural networks (CNNs) can process images from traffic cameras to identify different types of vehicles and assess traffic density [11]. This information can then be fed into adaptive signal control algorithms to dynamically adjust signal timings, reducing congestion and improving traffic flow [4]. The process is a proposed solution for the given task in the below block diagram. It takes images captured by the lane CCTV as the input and produces a traffic signal as the output.

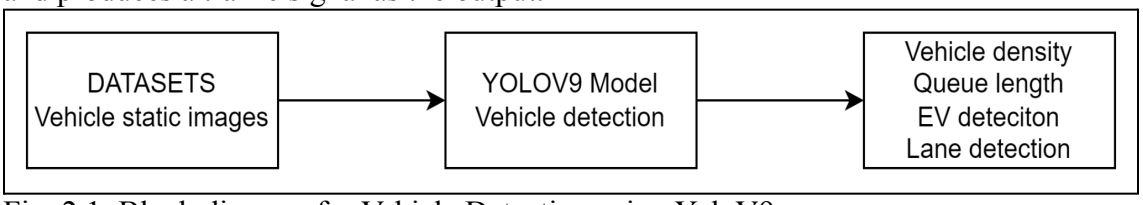


Fig. 2.1: Block diagram for Vehicle Detection using YoloV9.

- **Literature Survey**

Sl. No	Title of the paper	Year of publication	Problem Statement	ML Technique used	Final Outcome
1	Vehicle detection and counting of a vehicle using openCV [1]	2021	The trouble of getting the initial background is the mistake of continuous background update and the trouble of controlling the update speed in moving vehicle location of traffic video. With the expanding number of streets and traffic everywhere, traffic observation and control utilizing current advancements has become a necessity. Vehicle detection is the key task in this area and counting of vehicles plays an important role.	1. Adaptive background subtraction, binarization, and morphological activities are used to detect a moving vehicle. 2. Blob tracking to coordinate with vehicles in the current frame and those in the past outline.	1. The exactness of the proposed vehicle counting technique changed from 95-99%, based on the video input. 2. Once the vehicle passes into the virtual detection zone, it will be detected and counted in sequential order.
2	Machine learning-driven intelligent and self-adaptive system for traffic management in smart cities [2]	2022	Traffic congestion is becoming a serious problem with the large number of vehicles on the roads. In the traditional traffic control system, the timing of the green light is adjusted regardless of the average traffic rate at	1. OpenCV is used for counting the vehicles from the input image. Here in this work, the OpenCV.cdn module is used to count the number of vehicles. 2. YOLOv3 is a state-of-the-art model	1. The YOLO object detection model was trained on 42 authentic traffic images of two main junctions of the city of Jabalpur. The mean time taken for detecting the vehicles per image is 1.36s. The time taken in object detection mainly depends on the

			the junction. In order to handle road traffic issues, an intelligent traffic management solution is required. This article represents a self-adaptive real-time traffic light control algorithm based on the traffic flow. We present a machine-learning approach coupled with image processing to manage the traffic clearance at the signal junction.	for real-time object detection. YOLOv3 predicts 4 coordinates for each bounding box around an object. Training is performed with a sum of squared error loss.	incorporated processing hardware. 2. For correct predictions, it is necessary to take an image that shows vehicles as discreetly as possible, not overlapped by any other object. 3. It can be inferred that the proposed intelligent traffic management system based on the single image processing is self-adaptive, highly accurate, fast and has the potential to be implemented in traffic clearance at the junctions.
3	Dynamic Traffic Control System with Reinforcement Learning Technique [3]	2020	Traditional reinforcement learning is hard to apply because of two key difficulties: (1)how to represent condition; and (2)how to model the correlation among condition and choice. To address these two difficulties, investigations have applied deep reinforcement learning techniques, for	1. Phase-gated model learning: The operator will take the state, which is the representation of the condition, as model info. The earth typically incorporates the current traffic light phase and traffic conditions. 2. A highlight extraction algorithm to show signs of improvement in	1. **Peak hour vs Non-peak hour:** On the given day, there is more traffic on WE bearing than SN for more often than not, during which a perfect traffic light control strategy is relied upon to provide a longer time for WE guidance. And during top hours (around 7:00, 9:30 and 18:00), the policies gained from our technique give a longer time for the green light

			example, Deep Q-learning (DQN), for traffic light control problems. Late deep reinforcement learning approaches gained promising ground for the traffic light control problem. Our methodology expands this profession by making important element extraction algorithms for giving better performance of classification.	performance. 3. Object Recognition utilizing Speeded-Up Robust Features (SURF) is made out of three stages - feature extraction, feature depiction, and feature coordinating.	on WE than non-top hours. In the early morning, the vehicle appearance rates on SN are larger than the rates on WE, and our strategy consequently gives a longer time to SN. 2. **Weekday versus Weekend:** The policy gives fewer green lights on WE (more green lights on SN) during weekend daytime than it gives on weekdays. This is on the grounds that there is more traffic on SN than on WE during weekend daytime.
4	Adaptive Traffic Light Based on Yolo-Darknet Object Detection [4]	2019	Nowadays roads and streets are getting overcrowded, especially in bigger cities. Hence the main goal of our project is to build a traffic monitoring system that is able to detect the movement of cars and to track and count the different vehicles by analyzing a camera picture with the help of computer vision. With a vision-based adaptive traffic light system, the device that	1. The detection is done by the Darknet object detection framework. Darknet is one of the open-source object detection frameworks that have YOLOv3. 2. The ROI masking was done through OpenCV.	1. We could run detection at a 2,4 fps average when using the YOLOV3 dataset, and around 15.5 fps average when using the Tiny version of the YOLO detector. This result shows that the YOLO detector is lightweight enough and very possible to run better on a better high-performance system. 2. The ROI successfully managed the system to only detect the part of the

			is needed is only a camera and a computer. This means this system will cost less because most intersection or traffic lights already have some CCTV, we just need to calibrate the camera and install the proprietary software for a self-regulating traffic light.		road that we want to control. OpenCV helps the system only detect a lane that we want to control from two or more lane roads. Therefore, it also helps to reduce system resources because detection only occurs in certain sections, not in the whole scene
5	A Sound-based Machine Learning to Predict Traffic Vehicle Density [5]	2021	Traffic flow mismanagement is a significant challenge in all countries, especially in crowded cities. An alternative solution is to utilise smart technologies to predict traffic flow. In this study, the frequency spectrum describing traffic sound characteristics is used as an indicator to predict the next five-minute vehicle density. Sound frequency and vehicle intensity are collected during a thirteen-hour data gathering. The collected sound intensity and frequency are then used to learn three machine-learning	Three machine learning algorithms were trained and tested upon selection of the best MLA to predict short-term traffic flow Support Vector Machine (SVM), Artificial Neural Network (ANN), and Random Forest (RF). The performance of the three machine-learning algorithms in prediction was evaluated using RMSE.	1. RF yielded the least RMSE value of 10.67, by SVM with an RMSE value. Lastly, ANN yielded the highest RMSE value. Consequently, the machine learning algorithm that yielded the least RMSE for sound frequency is Random Forest. 2. In the cross-validation process, Random Forest has a consistent performance where it yielded the lowest RMSE among the three algorithms, which is the same as the result in the first learning phase. Hence, it can be validated that Random Forest (RF) is the best machine-learning

			models and random forests and to predict vehicle intensity.		algorithm to predict short-term traffic flow.
6	Traffic Density Estimation Using Machine Learning Methods [6]	2021	The Intelligent Transportation System (AUS) is expressed as a system that provides users with better information and safer, more coordinated, and smarter use of transportation networks with different transportation modes and traffic management. One of the most important components of AUS models is the determination of traffic density which is a difficult problem as it affects other interconnected intersections and varies in time. In this study, the long-term short memory network (LSTM) model, one of the deep learning methods, is proposed to estimate the traffic density of a certain region using open data of Istanbul Metropolitan Municipality.	1. **Linear regression method:** A multiple linear regression model was used because the number of independent variables in the traffic dataset was more than one. 2**. Decision tree:** Regression trees were used because they work with constantly changing data. 3. **Random forest:** the algorithm is an ensemble learning algorithm consisting of the output of multiple decision trees. Each node branches by choosing the best among the randomly selected variables in the node. 4. **Deep learning:** An artificial neural network is formed by the combination of neural nodes. 5. **Long short-term memory (LSTM):**	1. Experimental evaluations of linear regression, decision trees, random forest, classical deep learning, and LSTM methods were made using real data from IMM. RMSE and MAE values were used as evaluation criteria to examine the performance of the methods. 2. The LSTM method made predictions with lower error rates compared to other methods. The standard deviation value of the LSTM method gave better results compared to other methods. This shows that the LSTM method works more stable. 3. The graph with the highest overlap between the predicted value and the actual value of a number of vehicles estimated by decision trees, deep learning, linear regression, LSTM and random forest method - belongs to the

				The LSTM deep learning algorithm is known as a recurrent neural network introduced to eliminate the disadvantages of the RNN architecture.	study using the LSTM method.
7	Smart Traffic Control System using YOLO [7]	2019	Traffic congestion is becoming a serious problem with a large number of cars on the roads. Vehicle queue length waiting to be processed at the intersection is rising sharply with the increase of the traffic flow, and the traditional traffic lights cannot efficiently schedule it. A real-time traffic light control algorithm based on the traffic flow is proposed in this paper. In fact, we use computer vision and machine learning to have the characteristics of the competing traffic flows at the signalized road intersection.	1. YOLO is a clever convolutional neural network (CNN) for doing object detection in real time. 2. A deep neural network (DNN) is an artificial neural network (ANN) with multiple layers between the input and output layers. The DNN finds the correct mathematical manipulation to turn the input into the output. 3. A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers.	The new system facilitates the movement of cars in intersections, resulting in reduced congestion, fewer CO2 emissions, etc. The richness that video data provides highlights the importance of advancing the state-of-the-art in object detection, classification and tracking for real-time applications.
8	A Smart Traffic Management System for	2017	Traffic congestion is a growing problem everyone faces in their daily life. A real-time	The system uses technologies like loads cells for counting and	The equipment is cost-effective and it helps reduce waiting and traveling times hence

	Congestion Control and Warnings Using Internet of Things (IoT) [8]		traffic information collection and monitoring system to solve the problem of monitoring and controlling road vehicles is proposed.	detecting vehicles, RF transmitters and receivers for detecting EVs, IoT for efficient information transmission	saving fuel and money. A provision for emergency vehicles to pass the signal is also a major cause of concern.
9	Smart Traffic Management System with Real Time Analysis [9]	2018	This paper aims to overcome traffic congestion caused by ineffective traffic management systems. The traditional systems allot timings irrespective of the actual density. The system proposed ensures traffic lights respond to real-time values of traffic, thereby allowing proper management of time and resources.	The main components of the traffic management system include a camera, yellow, green and red indicators, the IOT platform for analytics (ThingSpeak) and ultrasonic sensors. Raspberry Pi serves as the edge device that is used to communicate with the cloud.	Every time the Raspberry Pi finds the level of traffic it updates the values to ThinkSpeak. These values can be converted in the form of a database, which serves as a source of information. This together with the help of ultrasonic sensors and image processing techniques, an approximate level of traffic can be found out that is equivalent to real time values of traffic. This can be used to assess and control the traffic lights in real time.
10	Traffic Management System Using YOLO Algorithm [10]	2023	The issue of traffic congestion is becoming worse day by day. The typical traffic lights are unable to effectively regulate the growing number of vehicular traffic; therefore, we mixed computer vision and	YOLO version 7 is a fundamental model that lends itself to conventional GPU computing the fastest. The YOLOv7-tiny model is a straightforward one, and its edge GPU is optimized. Tiny	Different sorts of cars have been successfully spotted and distinguished. The program may also keep track of how many vehicles are parked at the traffic light at any given moment. By dynamically adjusting the duration of

			machine learning to mimic complicated incoming traffic at signalized intersections.	computer vision models are easier to execute on dispersed edge servers and devices, or mobile computing devices.	the green signal based on the volume of traffic, the proposed system could help reduce congestion and improve the overall traffic flow. This could lead to shorter travel times and significant energy savings.
11	Intelligent Traffic System Using Machine Learning Techniques: A Review [11]	2023	To create a Machine Learning-based Intelligent Traffic System that can monitor and regulate traffic flow efficiently. This system involves the use of cameras and sensors placed on roadways to collect real-time data on traffic flow and identify congestion points. The collected data is then processed and analyzed using machine learning algorithms to generate actionable insights that can be used to optimize traffic flow.	Traffic sign detection uses YOLO to identify traffic signs in the video and Alex Net to categorize them, alerting drivers to approaching road conditions and rules. Based on traffic flow analysis and traffic sign detection, the prediction and warning system forecast future traffic conditions and provide real-time notifications for drivers	The evaluation procedure revealed that the suggested smart traffic control system can effectively manage high traffic volumes and provide accurate real-time forecasts. It was also observed that the system could facilitate ambulance movement past congested traffic, thereby potentially saving lives. However, the review procedure highlighted the need for improvements in security, scalability, and reliability
12	Smart Traffic Light System by Using Artificial Intelligence [12]	2019	With an enormous increase in population, traffic congestion is becoming a highlighting issue. The key component to this solution will be	It utilizes the microcontroller of Arduino added to GPS (Global Positioning System) and GSM (Global System for Mobile	By assigning the model distribution to the system it was found to: 1.Reduce the number of cars in specified time intervals by 55%. 2.Increase average speed of cars in the system by

			proposing a traffic signal which can perceive a heavy traffic area and highlight a schedule of which lane at what time is busy and causing congestion issues. The next step will be analyzing that data and perceiving a logical and minimal schedule on which intelligence can be performed.	Communications) shields. The GPS shield is utilized to get the present area of the ambulance, while the GSM shield is used to exchange the GPS readings to the server center for preparation and choice.	55%. 3.Decrease the number of stops a car had to make while in the system by 29%. 4.Decrease average time a car had to spend in a system by 65%. 5.Decrease average waiting time of cars to pass the intersection by 38%.
13	Ambulance detection using image processing and neural networks [13]	2021	Ambulance Detection using Image Processing and Neural Network is a vehicle detection and tracking system, which recognizes the ambulance amidst the traffic congestion. From the past few years, the range of vehicle usage of the road is growing each day that results in traffic congestion. Hence making it hard for the emergency vehicle to pass through the traffic at the earliest possible time.	The only piece of hardware used is the surveillance camera. YOLOv3 and CNN are used as it makes work much more compatible with countries where road width is irrelevant for separate ambulances.	Preparing a dataset for the program to train and assess from was done, and it was used by the program to identify the Ambulance amidst all the vehicles. Upon sensing that the captured vehicle is an ambulance, we successfully got the program to turn that traffic light into green, while others were turned red.

14	Smart Traffic Management For Ambulance [14]	2022	During rush hours, emergency vehicles like ambulances get stuck in jams. Due to this, these emergency vehicles are not able to reach their destinations on time, resulting in the loss of human lives. We are willing to develop a system which is used to provide clearance to ambulances when they are stuck in traffic jams. Here we clear the path of the emergency vehicle hence it can reach the destination in time.	Microcontroller, Raspberry Pi and its camera module, Image Sensor, Arduino Uno	Emergency vehicle stuck in a traffic condition is detected with a detection algorithm and then the traffic signal gets an alert by which it changes the signal to green from red For the video part, the already setup CCTV is used.
15	Emergency Vehicle Detection on Heavy TrafficRoad from CCTV Footage Using Deep Convolutional Neural Network [15]	2019	Sometimes emergency vehicles like ambulance, firefighters get stuck in the traffic causing threat to life in many cases. It is important to give priority to this car and help to clear its path. But it is difficult or sometimes impossible for trafficpolice to handle this. For this reason, we need an automated system that will be able to detect an emergency car in heavy traffic, let the controller know or	Object detection and classification is done using YOLO-V3 with Darknet-53 architecture. transfer-learning is used (use a deep convolutional neural network which is pre-trained with a big dataset) as a feature extractor with a newly defined fully connected layer on top of the pre-trained model.	The model can be embedded with CCTV to track emergency vans and give priority in that road to pass the emergency van. With this automated process, no human effort will be required to manually help such a scenario. The model has achieved impressive results in detecting and identifying emergency cars of all kinds.

			automatically navigate other cars to clear its path.		

● Proposed Methodology/Solution

The proposed vehicle detection system employs the YOLOv9 model from Ultralytics for robust and efficient vehicle detection. YOLOv9's advanced architecture ensures high accuracy and real-time processing, crucial for traffic monitoring applications [10]. The system processes video feeds to detect vehicles, calculate vehicle density, and measure queue length in various lanes. Additionally, the model is trained to identify emergency vehicles, enabling the system to prioritize and manage their presence in traffic. This comprehensive approach provides valuable insights for traffic management, enhancing road safety and optimizing traffic flow by dynamically adjusting signals and lanes based on real-time vehicle data and emergency vehicle detection [15].

In developing a dynamic traffic signal controller using multi-agent reinforcement Learning (MARL), the integration of advanced models like YOLOv8 and CNN is pivotal. The YOLOv8 model is employed for real-time vehicle detection and density estimation, providing essential input for the traffic signal controller to make informed decisions. By accurately assessing traffic conditions, YOLOv8 enables the controller to optimize signal sequences effectively. Additionally, the CNN model enhances vehicle detection accuracy, ensuring reliable traffic data input. The MARL framework allows multiple agents to interact with the traffic environment, learning optimal signal policies that minimise waiting times and improve overall traffic flow.

A significant aspect of this system is the feedback loop mechanism, which evaluates the controller's performance by measuring reduced waiting times for vehicles. The incorporation of emergency vehicle handling is also a critical feature, where the CNN and GPS data feed into the V2I communication system, allowing the MARL model to prioritize emergency vehicles through signal preemption. Edge computation ensures real-time processing of traffic data, while cloud storage facilitates efficient data management and scalability. This comprehensive approach leverages cutting-edge technology to enhance the efficiency and responsiveness of urban traffic signal control systems.

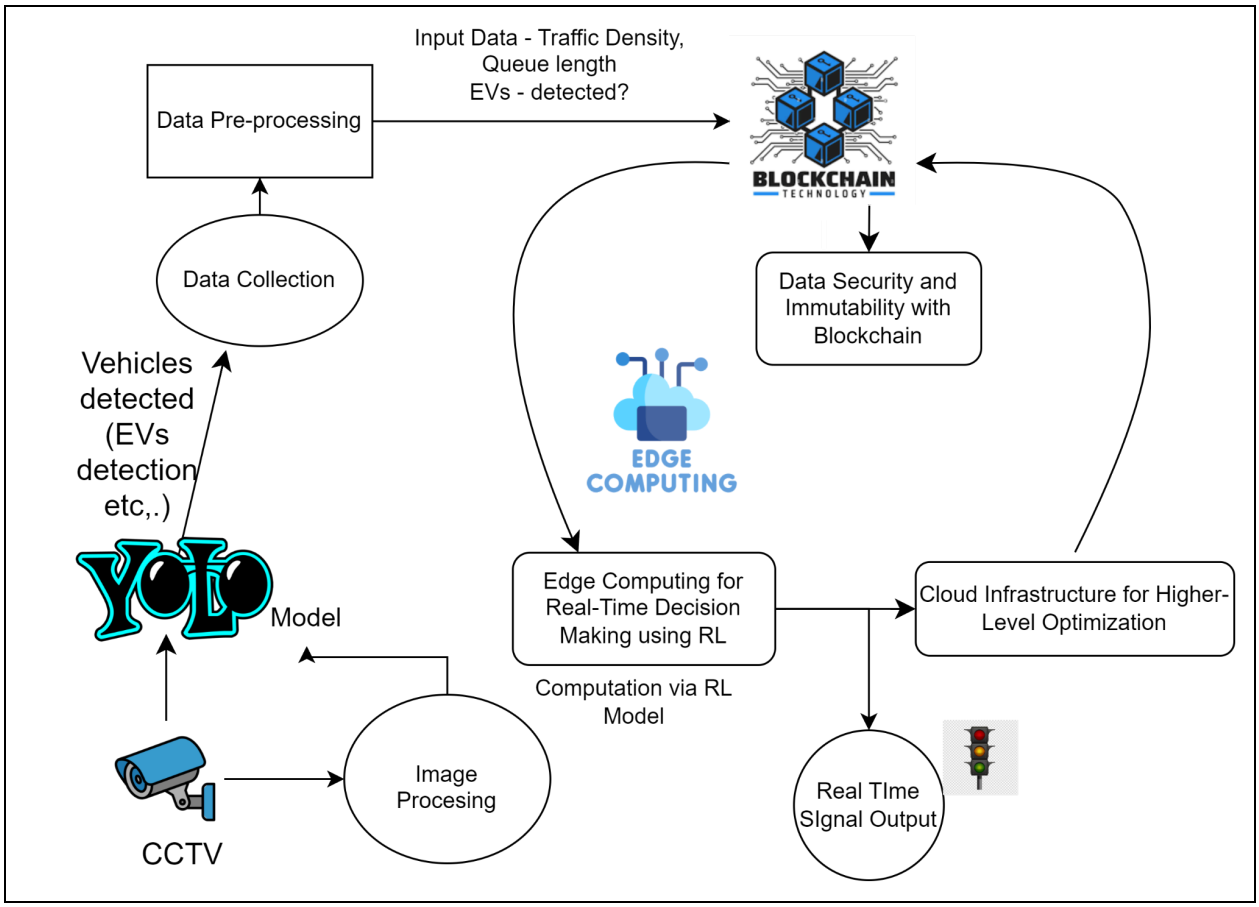


Fig. 2.2: Block diagram for the dynamic traffic signal controller using machine learning techniques and computer vision.

In this project, we develop a dynamic traffic signal controller using advanced image processing and machine learning techniques. RoboFlow is employed for image preprocessing, annotation, and augmentation, ensuring high-quality input data. We utilise the YOLOv9 model for real-time analysis of vehicle density, queue length calculation, and emergency vehicle detection. This approach enables adaptive signal timing, improving traffic flow and reducing congestion. By accurately identifying and responding to varying traffic conditions, the system enhances overall traffic management and safety, particularly for emergency vehicles needing prioritised passage. The detailed process is represented in the form of a block diagram below.

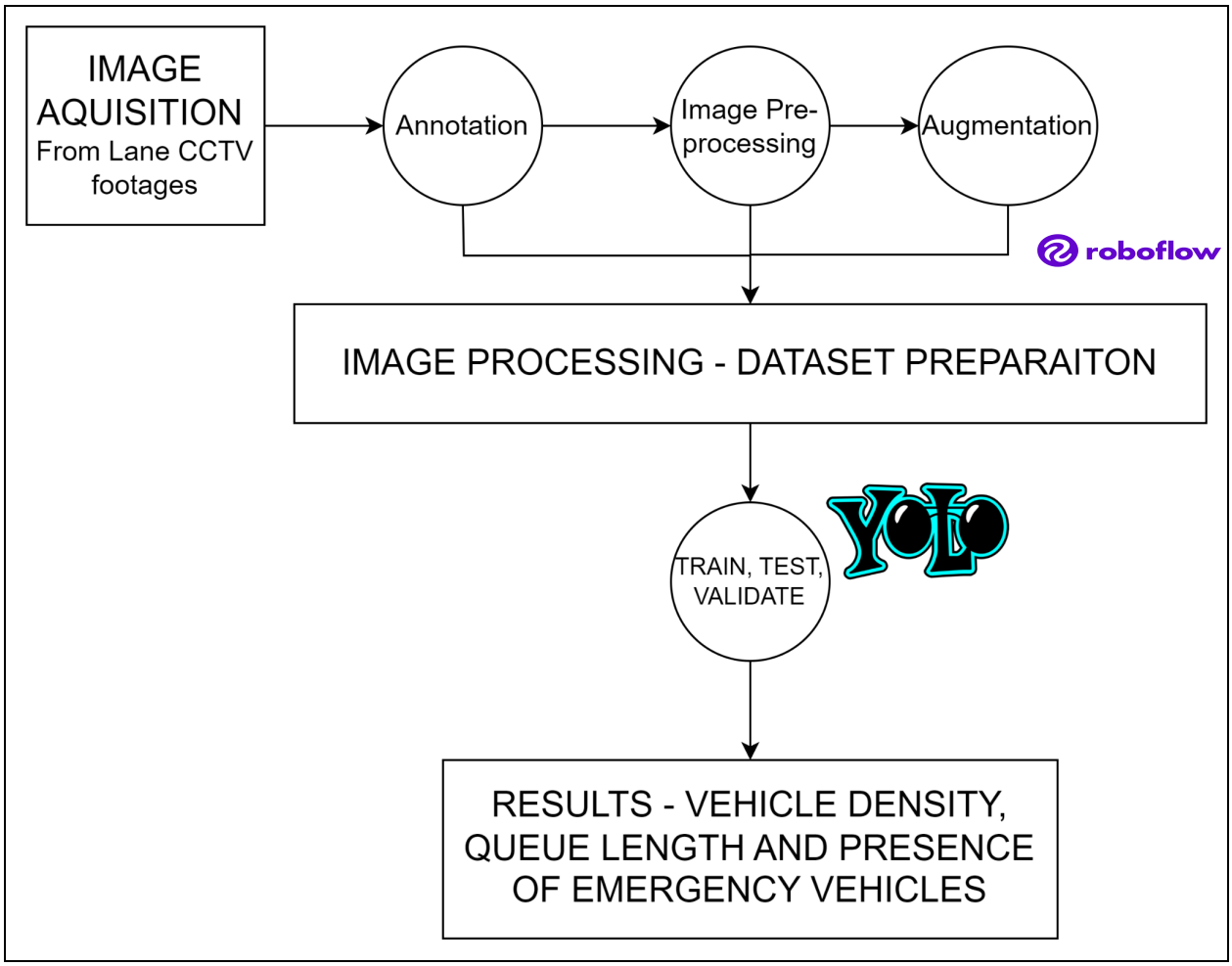


Fig. 2.3: Block diagram for vehicle detection using YOLOV9 and image processing using Roboflow.

- **Novelty of the solution**

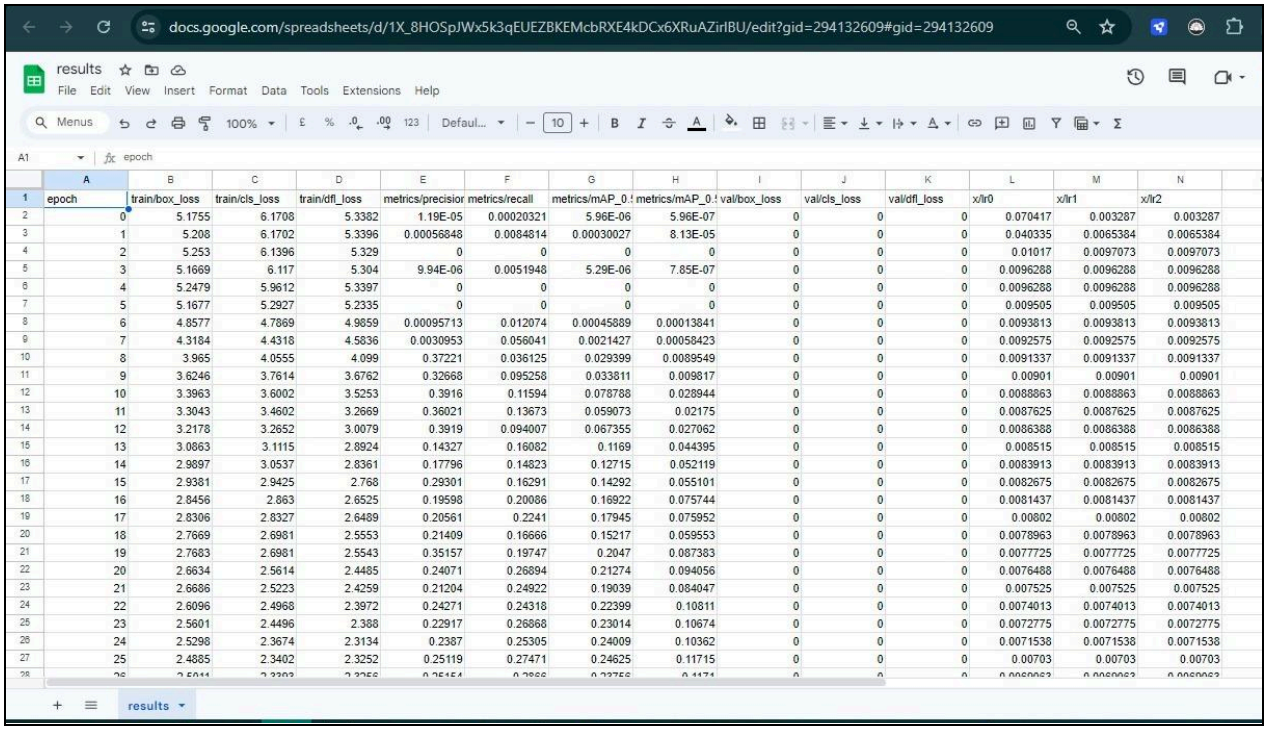
Our proposed dynamic traffic signal controller introduces several novel elements compared to existing machine learning solutions. While traditional systems rely on static timers or simplistic vehicle counting methods, our approach leverages advanced image preprocessing, annotation, and augmentation via RoboFlow, ensuring high-quality and diverse training data. The integration of the YOLOv9 model, renowned for its superior accuracy and speed in object detection, enhances the system's ability to analyze vehicle density, and queue length, and detect emergency vehicles in real time.

The element of novelty lies in our comprehensive use of state-of-the-art techniques to create an adaptive traffic control system. By incorporating real-time data analysis and machine learning, our solution dynamically adjusts traffic signals based on current conditions, rather than pre-set intervals. This results in optimized traffic flow, reduced congestion, and improved response times for emergency vehicles, setting our methodology apart from existing, less adaptive ML solutions.

- **Results**

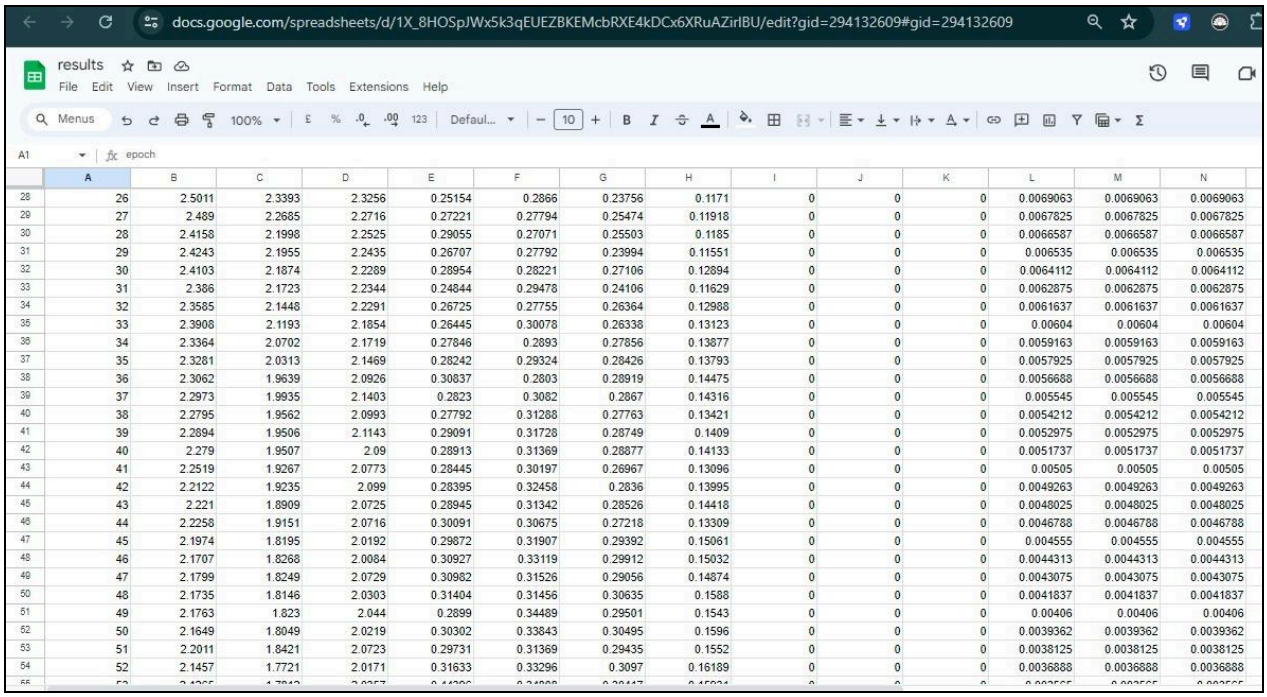
Task 2.1: Vehicle detection and counting

After training the model on the custom dataset for 75 epochs to detect vehicles, the following are the key results:

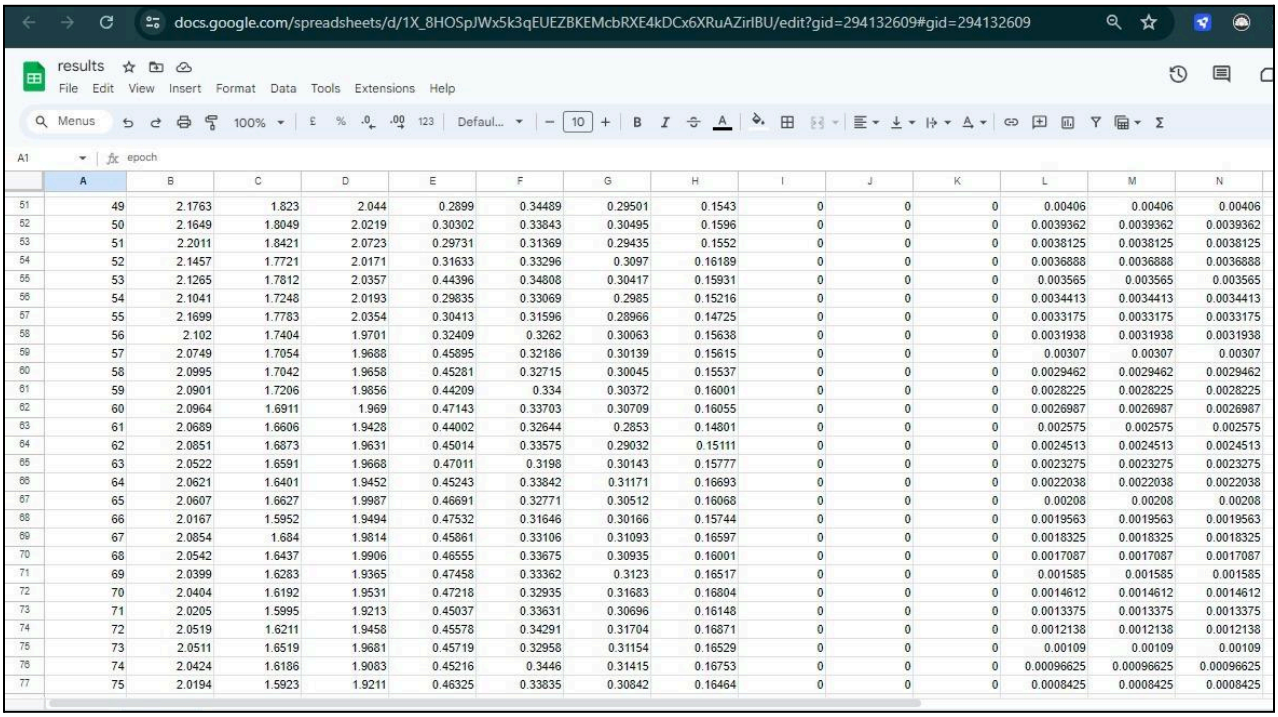


	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	epoch	train/box_loss	train/cls_loss	train/dfl_loss	metrics/precisior	metrics/recall	metrics/mAP_0.!	metrics/mAP_0.!	val/box_loss	val/cls_loss	val/dfl_loss	x/lr0	x/lr1	x/lr2
2	0	5.1755	6.1708	5.3382	1.19E-05	0.00020321	5.96E-06	5.96E-07	0	0	0	0.070417	0.003287	0.003287
3	1	5.208	6.1702	5.3396	0.00056848	0.0084814	0.00030027	8.13E-05	0	0	0	0.040335	0.0065384	0.0065384
4	2	5.253	6.1396	5.329	0	0	0	0	0	0	0	0.01017	0.0097073	0.0097073
5	3	5.1669	6.117	5.304	9.94E-06	0.0051948	5.29E-06	7.85E-07	0	0	0	0.0096288	0.0096288	0.0096288
6	4	5.2479	5.9612	5.3397	0	0	0	0	0	0	0	0.0096288	0.0096288	0.0096288
7	5	5.1677	5.2927	5.2335	0	0	0	0	0	0	0	0.009505	0.009505	0.009505
8	6	4.8577	4.7869	4.9859	0.00095713	0.012074	0.00045889	0.00013841	0	0	0	0.0093813	0.0093813	0.0093813
9	7	4.3184	4.4318	4.5836	0.0030953	0.056041	0.0021427	0.00058423	0	0	0	0.0092575	0.0092575	0.0092575
10	8	3.965	4.0555	4.099	0.37221	0.036125	0.029399	0.0089549	0	0	0	0.0091337	0.0091337	0.0091337
11	9	3.6246	3.7614	3.6762	0.32668	0.095258	0.033811	0.009817	0	0	0	0.00901	0.00901	0.00901
12	10	3.3963	3.6002	3.5253	0.3916	0.11594	0.078788	0.028944	0	0	0	0.0088863	0.0088863	0.0088863
13	11	3.3043	3.4602	3.2669	0.36021	0.13673	0.059073	0.02175	0	0	0	0.0087625	0.0087625	0.0087625
14	12	3.2178	3.2652	3.0079	0.3919	0.094007	0.067355	0.027062	0	0	0	0.0086388	0.0086388	0.0086388
15	13	3.0863	3.1115	2.8924	0.14327	0.16082	0.1169	0.044395	0	0	0	0.008515	0.008515	0.008515
16	14	2.9897	3.0537	2.8361	0.17796	0.14823	0.12715	0.052119	0	0	0	0.0083913	0.0083913	0.0083913
17	15	2.9381	2.9425	2.768	0.29301	0.16291	0.14292	0.055101	0	0	0	0.0082675	0.0082675	0.0082675
18	16	2.8456	2.863	2.6525	0.19598	0.20086	0.16922	0.075744	0	0	0	0.0081437	0.0081437	0.0081437
19	17	2.8306	2.8327	2.6489	0.20561	0.2241	0.17945	0.075952	0	0	0	0.00802	0.00802	0.00802
20	18	2.7669	2.6981	2.5553	0.21409	0.16666	0.15217	0.059553	0	0	0	0.0078963	0.0078963	0.0078963
21	19	2.7683	2.6981	2.5543	0.35157	0.19747	0.2047	0.087383	0	0	0	0.0077725	0.0077725	0.0077725
22	20	2.6634	2.5614	2.4485	0.24071	0.26894	0.21274	0.094056	0	0	0	0.0076488	0.0076488	0.0076488
23	21	2.6686	2.5223	2.4259	0.21204	0.24922	0.19039	0.084047	0	0	0	0.007525	0.007525	0.007525
24	22	2.6096	2.4968	2.3972	0.24271	0.24318	0.22399	0.10811	0	0	0	0.0074013	0.0074013	0.0074013
25	23	2.5601	2.4496	2.388	0.22917	0.26868	0.23014	0.10674	0	0	0	0.0072775	0.0072775	0.0072775
26	24	2.5298	2.3674	2.3134	0.2387	0.25305	0.24009	0.10362	0	0	0	0.0071538	0.0071538	0.0071538
27	25	2.4885	2.3402	2.3252	0.25119	0.27471	0.24625	0.11715	0	0	0	0.00703	0.00703	0.00703

Fig 2.4: Epochs results after training (1-25) [Epochs set to 75]



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
28	26	2.5011	2.3393	2.3256	0.25154	0.2866	0.23756	0.1171	0	0	0	0.0069063	0.0069063	0.0069063
29	27	2.489	2.2685	2.2716	0.27221	0.27794	0.25474	0.11918	0	0	0	0.0067825	0.0067825	0.0067825
30	28	2.4158	2.1998	2.2525	0.29055	0.27071	0.25503	0.1185	0	0	0	0.0066587	0.0066587	0.0066587
31	29	2.4243	2.1955	2.2435	0.26707	0.27792	0.23994	0.11551	0	0	0	0.006535	0.006535	0.006535
32	30	2.4103	2.1874	2.2289	0.28954	0.28221	0.27106	0.12894	0	0	0	0.0064112	0.0064112	0.0064112
33	31	2.386	2.1723	2.2344	0.24844	0.29478	0.24106	0.11629	0	0	0	0.0062875	0.0062875	0.0062875
34	32	2.3585	2.1448	2.2291	0.26725	0.27755	0.26364	0.12988	0	0	0	0.0061637	0.0061637	0.0061637
35	33	2.3908	2.1193	2.1854	0.26445	0.30078	0.26338	0.13123	0	0	0	0.00604	0.00604	0.00604
36	34	2.3364	2.0702	2.1719	0.27846	0.2893	0.27856	0.13877	0	0	0	0.0059163	0.0059163	0.0059163
37	35	2.3281	2.0313	2.1469	0.28242	0.29324	0.28426	0.13793	0	0	0	0.0057925	0.0057925	0.0057925
38	36	2.3062	1.9639	2.0926	0.30837	0.2803	0.28919	0.14475	0	0	0	0.0056688	0.0056688	0.0056688
39	37	2.2973	1.9935	2.1403	0.2823	0.3082	0.2867	0.14316	0	0	0	0.005545	0.005545	0.005545
40	38	2.2795	1.9562	2.0993	0.27792	0.31288	0.27763	0.13421	0	0	0	0.0054212	0.0054212	0.0054212
41	39	2.2894	1.9506	2.1143	0.29091	0.31728	0.28749	0.1409	0	0	0	0.0052975	0.0052975	0.0052975
42	40	2.279	1.9507	2.09	0.28913	0.31369	0.28877	0.14133	0	0	0	0.0051737	0.0051737	0.0051737
43	41	2.2519	1.9267	2.0773	0.28445	0.30197	0.26967	0.13096	0	0	0	0.00505	0.00505	0.00505
44	42	2.2122	1.9235	2.099	0.28395	0.32458	0.2836	0.13995	0	0	0	0.0049263	0.0049263	0.0049263
45	43	2.221	1.8909	2.0725	0.28945	0.31342	0.28526	0.14418	0	0	0	0.0048025	0.0048025	0.0048025
46	44	2.2258	1.9151	2.0716	0.30091	0.30675	0.27218	0.13309	0	0	0	0.0046788	0.0046788	0.0046788
47	45	2.1974	1.8195	2.0192	0.29872	0.31907	0.29392	0.15061	0	0	0	0.004555	0.004555	0.004555
48	46	2.1707	1.8268	2.0084	0.30927	0.33119	0.29912	0.15032	0	0	0	0.0044313	0.0044313	0.0044313
49	47	2.1799	1.8249	2.0729	0.30982	0.31526	0.29056	0.14874	0	0	0	0.0043075	0.0043075	0.0043075
50	48	2.1735	1.8146	2.0303	0.31404	0.31456	0.30635	0.1588	0	0	0	0.0041837	0.0041837	0.0041837
51	49	2.1763	1.823	2.044	0.2899	0.34489	0.29501	0.1543	0	0	0	0.00406	0.00406	0.00406
52	50	2.1649	1.8049	2.0219	0.30302	0.33843	0.30495	0.1596	0	0	0	0.0039362	0.0039362	0.0039362
53	51	2.2011	1.8421	2.0723	0.29731	0.31369	0.29435	0.1552	0	0	0	0.0038125	0.0038125	0.0038125
54	52	2.1457	1.7721	2.0171	0.31633	0.33296	0.3097	0.16189	0	0	0	0.0036888	0.0036888	0.0036888



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
51	49	2.1763	1.823	2.044	0.2899	0.34489	0.29501	0.1543	0	0	0	0.00406	0.00406	0.00406
52	50	2.1649	1.8049	2.0219	0.30302	0.33843	0.30495	0.1596	0	0	0	0.0039362	0.0039362	0.0039362
53	51	2.2011	1.8421	2.0723	0.29731	0.31369	0.29435	0.1552	0	0	0	0.0038125	0.0038125	0.0038125
54	52	2.1457	1.7721	2.0171	0.31633	0.33296	0.3097	0.16189	0	0	0	0.0036888	0.0036888	0.0036888
55	53	2.1265	1.7812	2.0357	0.44396	0.34808	0.30417	0.15931	0	0	0	0.003565	0.003565	0.003565
56	54	2.1041	1.7248	2.0193	0.29835	0.33069	0.2985	0.15216	0	0	0	0.0034413	0.0034413	0.0034413
57	55	2.1699	1.7783	2.0354	0.30413	0.31596	0.28966	0.14725	0	0	0	0.0033175	0.0033175	0.0033175
58	56	2.102	1.7404	1.9701	0.32409	0.3262	0.30063	0.15638	0	0	0	0.0031938	0.0031938	0.0031938
59	57	2.0749	1.7054	1.9688	0.45895	0.32186	0.30139	0.15615	0	0	0	0.00307	0.00307	0.00307
60	58	2.0995	1.7042	1.9658	0.45281	0.32715	0.30045	0.15537	0	0	0	0.0029462	0.0029462	0.0029462
61	59	2.0901	1.7206	1.9856	0.44209	0.334	0.30372	0.16001	0	0	0	0.0028225	0.0028225	0.0028225
62	60	2.0964	1.6911	1.969	0.47143	0.33703	0.30709	0.16055	0	0	0	0.0026987	0.0026987	0.0026987
63	61	2.0689	1.6606	1.9428	0.44002	0.32644	0.2853	0.14801	0	0	0	0.002575	0.002575	0.002575
64	62	2.0851	1.6873	1.9631	0.45014	0.33575	0.29032	0.15111	0	0	0	0.0024513	0.0024513	0.0024513
65	63	2.0522	1.6591	1.9668	0.47011	0.3198	0.30143	0.15777	0	0	0	0.0023275	0.0023275	0.0023275
66	64	2.0621	1.6401	1.9452	0.45243	0.33842	0.31171	0.16693	0	0	0	0.0022038	0.0022038	0.0022038
67	65	2.0607	1.6627	1.9987	0.46691	0.32771	0.30512	0.16068	0	0	0	0.00208	0.00208	0.00208
68	66	2.0167	1.5952	1.9494	0.47532	0.31646	0.30166	0.15744	0	0	0	0.0019563	0.0019563	0.0019563
69	67	2.0854	1.684	1.9814	0.45861	0.33106	0.31093	0.16597	0	0	0	0.0018325	0.0018325	0.0018325
70	68	2.0542	1.6437	1.9906	0.46555	0.33675	0.30935	0.16001	0	0	0	0.0017087	0.0017087	0.0017087
71	69	2.0399	1.6283	1.9365	0.47458	0.33362	0.3123	0.16517	0	0	0	0.001585	0.001585	0.001585
72	70	2.0404	1.6192	1.9531	0.47218	0.32935	0.31683	0.16804	0	0	0	0.0014612	0.0014612	0.0014612
73	71	2.0205	1.5995	1.9213	0.45037	0.33631	0.30696	0.16148	0	0	0	0.0013375	0.0013375	0.0013375
74	72	2.0519	1.6211	1.9458	0.45578	0.34291	0.31704	0.16871	0	0	0	0.0012138	0.0012138	0.0012138
75	73	2.0511	1.6519	1.9681	0.45719	0.32958	0.31154	0.16529	0	0	0	0.00109	0.00109	0.00109
76	74	2.0424	1.6186	1.9083	0.45216	0.3446	0.31415	0.16753	0	0	0	0.00096625	0.00096625	0.00096625
77	75	2.0194	1.5923	1.9211	0.46325	0.33835	0.30842	0.16464	0	0	0	0.0008425	0.0008425	0.0008425

Fig 2.5: Epochs results after training (25-50) [Epochs set to 75]

Fig 2.6: Epochs results after training (50-75) [Epochs set to 75]

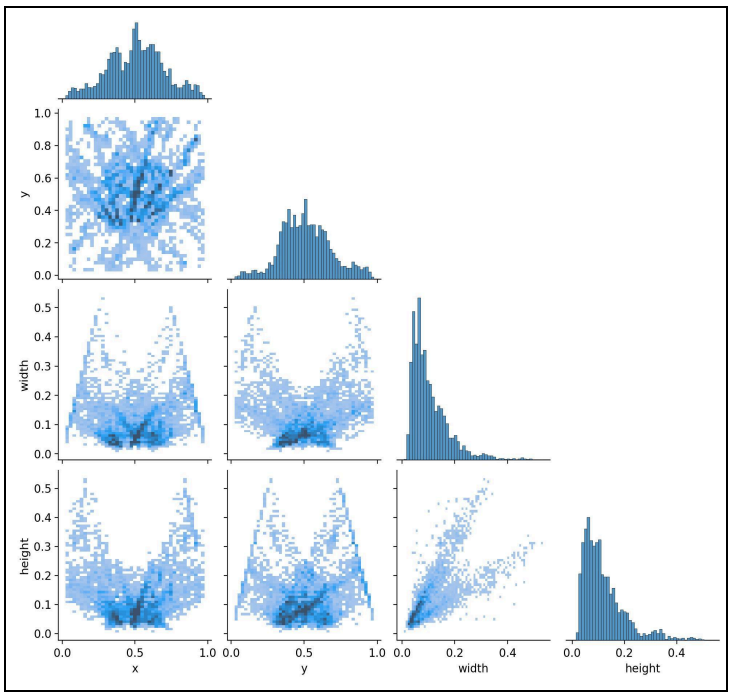


Fig 2.7: Labels Correlogram

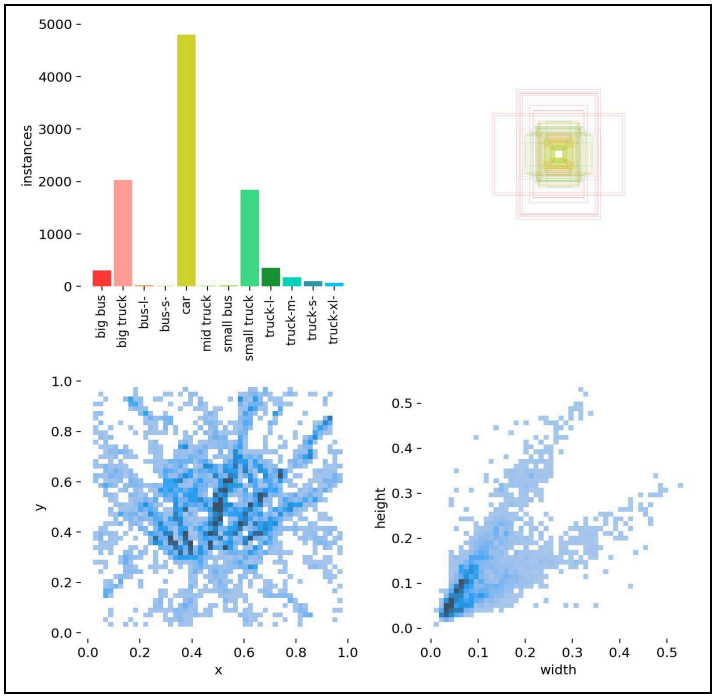


Fig 2.8: Labels used in the training

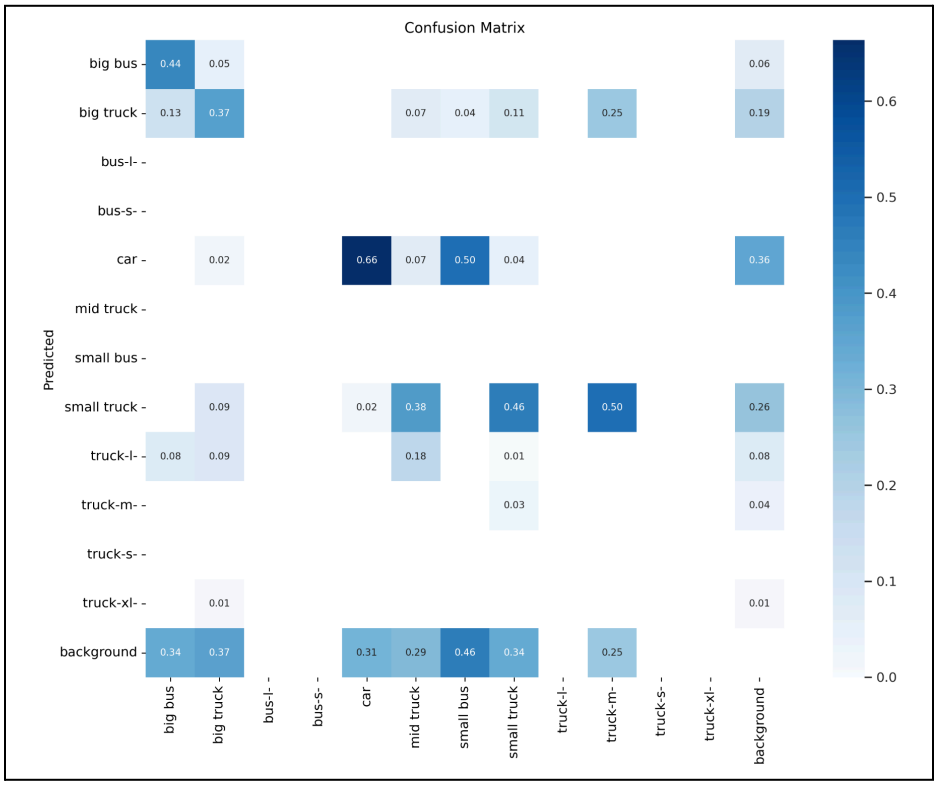


Fig 2.9: Normalized confusion matrix after training

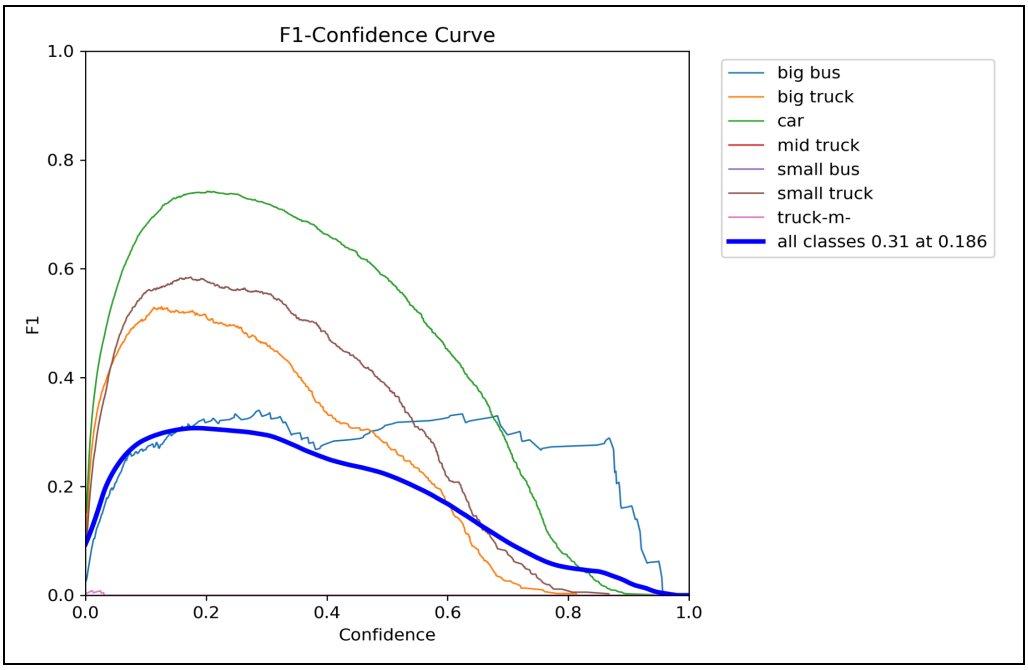


Fig 2.10: F1-Confidence Curve after training

Fig 2.11: Prediction on a Test image

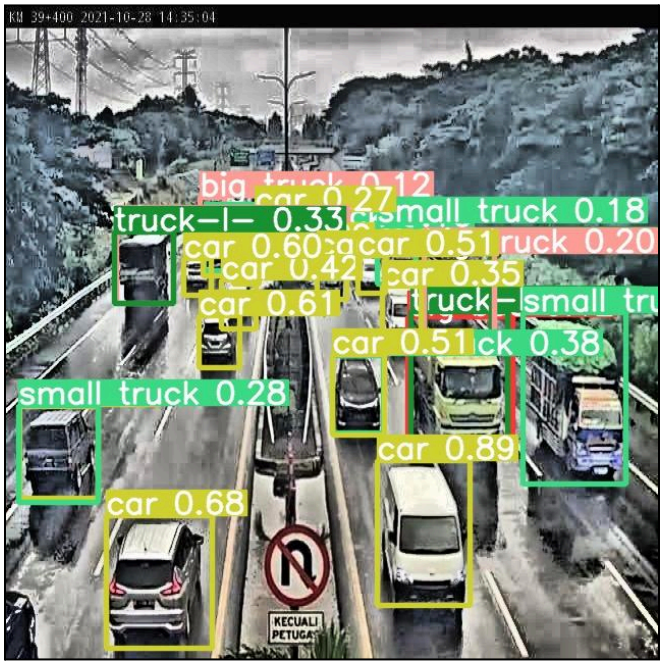


Fig 2.12: Prediction on a Validation image

Task 2.2: Emergency Vehicle Detection

With a similar approach, we deduced a working model for emergency vehicles such as ambulances, fire trucks and police vans for lane prioritization. The process described in Fig. 2.3 was applied for the same which involved the extensive usage of RoboFlow for image processing and datasets and YoloV9 for training and model preparation. These models can be readily used in any Python inference and put into use. The following two images are the results of annotation and labelling of the datasets ran on Google Colab with GPU units.

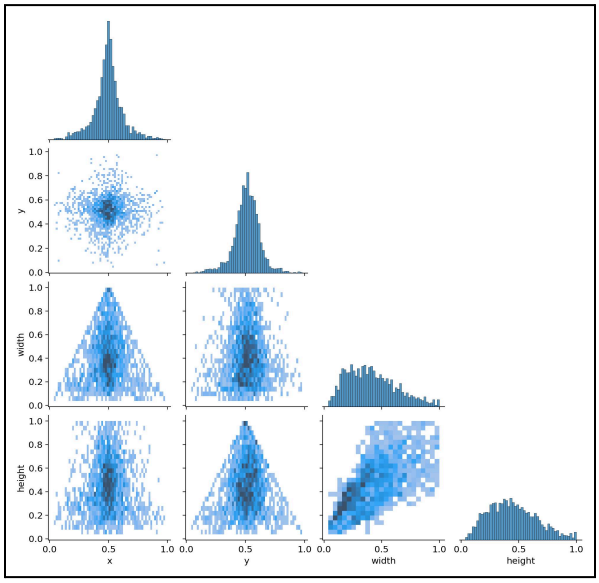


Fig 2.13: Labels Correlogram

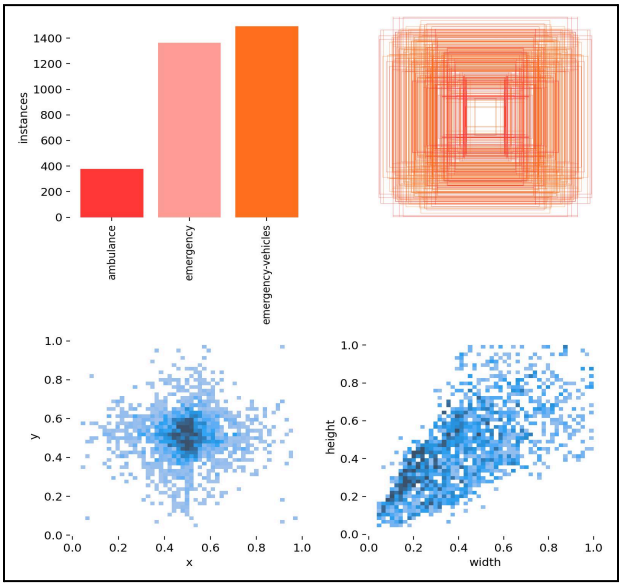


Fig 2.14: Labels taken for training

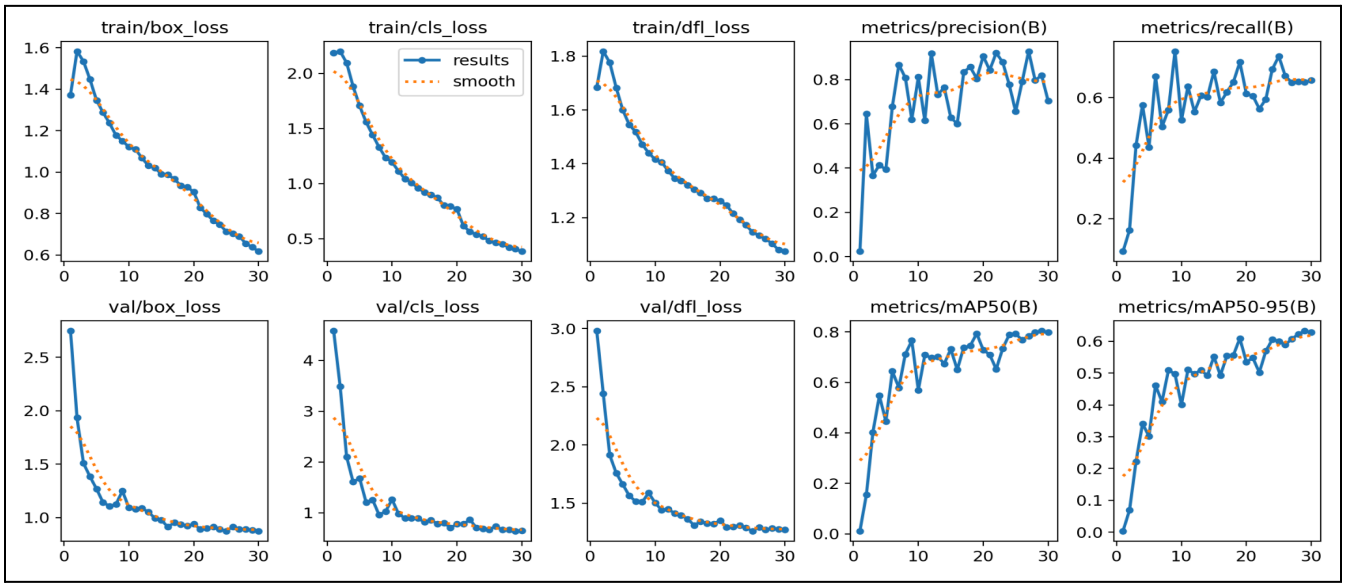


Fig 2.15: Results after training

Fig 2.16: Training batches (batches of 8) taken for training the YOLOV9 model.

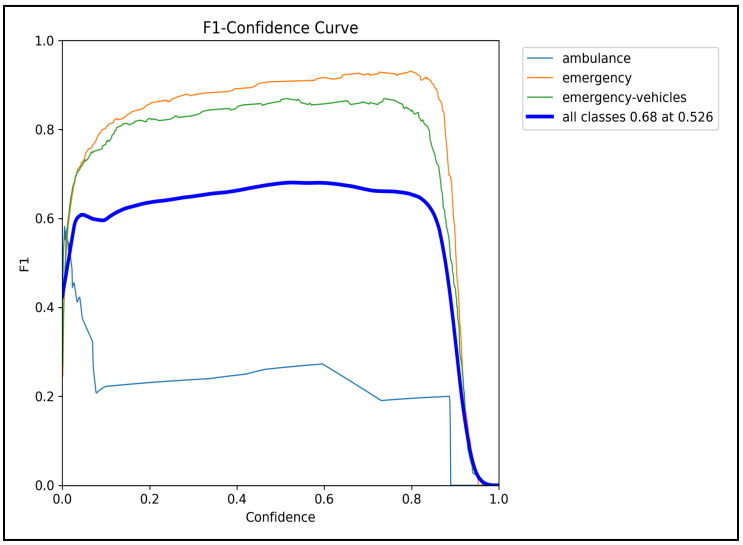


Fig 2.17: F1-Confidence Curve after training

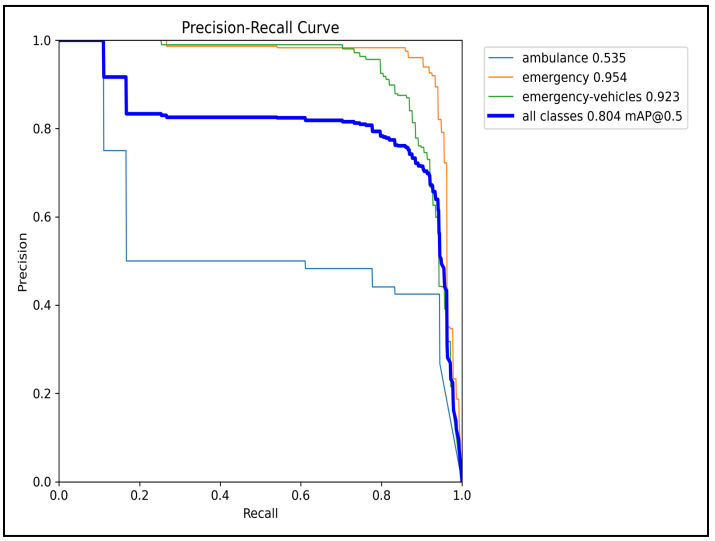


Fig 2.18: PR Curve after training

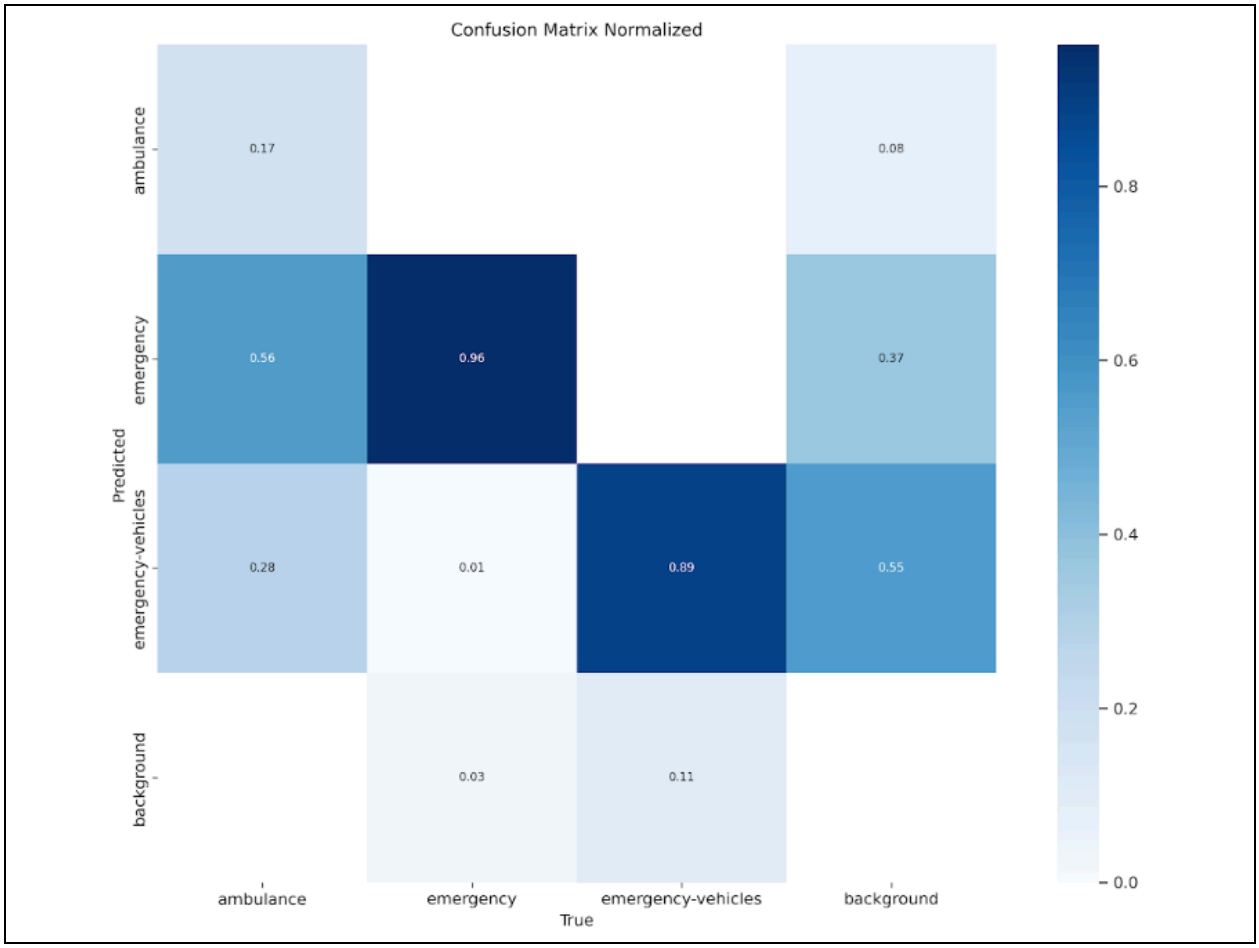


Fig 2.19: Normalized confusion matrix after training

epoch	train/box_loss	train/cls_loss	train/dfl_loss	metrics/precisior	metrics/recall(B)	metrics/mAP50(	metrics/mAP50-	val/box_loss	val/cls_loss	val/dfl_loss	lr/pg0	lr/pg1	lr/pg2
1	1.373	2.186	1.6841	0.02398	0.09265	0.01123	0.00381	2.7482	4.5834	2.9795	0.00047508	0.00047508	0.00047508
2	1.5833	2.2018	1.8179	0.64469	0.1628	0.15509	0.06931	1.9358	3.4916	2.4401	0.00092001	0.00092001	0.00092001
3	1.5347	2.0966	1.7757	0.36721	0.44224	0.40196	0.2221	1.5074	2.1009	1.9123	0.0013335	0.0013335	0.0013335
4	1.4472	1.8827	1.6821	0.41434	0.57579	0.54703	0.3412	1.3829	1.6068	1.7575	0.0012875	0.0012875	0.0012875
5	1.3475	1.7064	1.5999	0.39385	0.43634	0.4455	0.30132	1.2685	1.6801	1.6614	0.0012404	0.0012404	0.0012404
6	1.2883	1.5585	1.5453	0.67783	0.66999	0.64408	0.46179	1.143	1.2049	1.5645	0.0011932	0.0011932	0.0011932
7	1.237	1.4428	1.5182	0.86748	0.50376	0.57881	0.4099	1.1054	1.2547	1.5142	0.0011461	0.0011461	0.0011461
8	1.1779	1.3313	1.4718	0.80832	0.55972	0.71163	0.50972	1.1241	0.9589	1.5105	0.0010989	0.0010989	0.0010989
9	1.1508	1.2357	1.4405	0.62024	0.75282	0.76534	0.49696	1.2483	1.0245	1.5885	0.0010517	0.0010517	0.0010517
10	1.1214	1.1948	1.416	0.81129	0.52598	0.56895	0.40124	1.0903	1.2597	1.5014	0.0010046	0.0010046	0.0010046
11	1.1114	1.114	1.4069	0.61483	0.63671	0.70825	0.51047	1.0796	0.979	1.441	0.00095743	0.00095743	0.00095743
12	1.0684	1.0429	1.3735	0.91751	0.55299	0.69785	0.49805	1.0881	0.89344	1.4507	0.00091027	0.00091027	0.00091027
13	1.0314	1.0097	1.3462	0.73187	0.60644	0.70137	0.50927	1.0506	0.8908	1.4114	0.00086312	0.00086312	0.00086312
14	1.0204	0.96027	1.3374	0.76449	0.60161	0.67393	0.49247	0.99441	0.88884	1.3962	0.00081596	0.00081596	0.00081596
15	0.99126	0.92156	1.3211	0.6291	0.68633	0.73137	0.55216	0.97471	0.81556	1.3635	0.0007688	0.0007688	0.0007688
16	0.98828	0.9011	1.3049	0.59994	0.58323	0.65014	0.49267	0.91189	0.85624	1.3103	0.00072164	0.00072164	0.00072164
17	0.96643	0.87211	1.2926	0.83477	0.61795	0.73843	0.55446	0.95218	0.77972	1.3414	0.00067449	0.00067449	0.00067449
18	0.93522	0.80159	1.2716	0.85696	0.6512	0.74507	0.55647	0.93605	0.7943	1.3271	0.00062733	0.00062733	0.00062733
19	0.92788	0.79413	1.2702	0.80459	0.71707	0.79357	0.60928	0.92197	0.70698	1.3231	0.00058017	0.00058017	0.00058017
20	0.90447	0.76814	1.2619	0.90555	0.61257	0.7284	0.53503	0.93851	0.77478	1.3502	0.00053302	0.00053302	0.00053302
21	0.82789	0.6154	1.2467	0.84282	0.60584	0.70986	0.54787	0.88949	0.77475	1.2945	0.00048586	0.00048586	0.00048586
22	0.79828	0.56437	1.2149	0.9207	0.56298	0.65194	0.50218	0.89697	0.86604	1.2986	0.0004387	0.0004387	0.0004387
23	0.76547	0.54049	1.1933	0.87872	0.59447	0.73399	0.56899	0.91254	0.70195	1.311	0.00039155	0.00039155	0.00039155
24	0.7467	0.51888	1.1723	0.77813	0.69333	0.78818	0.6058	0.88981	0.68232	1.287	0.00034439	0.00034439	0.00034439
25	0.71408	0.48252	1.146	0.65593	0.73639	0.7924	0.60023	0.87365	0.66994	1.2612	0.00029723	0.00029723	0.00029723
26	0.70399	0.46346	1.134	0.79103	0.67118	0.76768	0.58848	0.91261	0.73624	1.2932	0.00025007	0.00025007	0.00025007
27	0.69068	0.44967	1.122	0.92803	0.64987	0.78386	0.60792	0.88821	0.665	1.2702	0.00020292	0.00020292	0.00020292
28	0.65633	0.4227	1.1039	0.79722	0.65206	0.79888	0.62188	0.89	0.66888	1.2828	0.00015576	0.00015576	0.00015576
29	0.63804	0.40599	1.081	0.81901	0.65045	0.80398	0.63284	0.88256	0.64077	1.2755	0.0001086	0.0001086	0.0001086
30	0.61791	0.38534	1.0749	0.70391	0.65658	0.79891	0.62831	0.87397	0.64552	1.2707	6.14E-05	6.14E-05	6.14E-05

Fig 2.20: 30 Epochs results after training

Fig 2.21: A collage of the prediction of test images by the trained model

Fig 2.22: Collage of prediction on the validation set by the trained model

As we can see in the above two pictures, the model predicted the emergency vehicles with great accuracy. Also, we can see that the F1 score for all emergency vehicles in general is around 0.8, hence proving our model's upper hand.

- **Compared Methods**

Our model suggests a smart traffic signal system, which can automatically determine which lane needs a higher green light time based on real-time conditions. In a junction, detecting which lane has a higher volume of traffic and green lighting that lane will reduce the overall traffic congestion significantly, compared to the existing signal systems used.

Comparing this model to other proposed models such as those mentioned in the literature survey (Vehicle detection and counting of a vehicle using openCV, Adaptive Traffic Light Based on Yolo-Darknet Object Detection, etc.) we see that many of them use older versions of YOLO [16]. We have taken one of the latest versions of YOLO (v9), to utilize all the new features available. Yet another paper (Dynamic Traffic Control System with Reinforcement Learning Technique) uses Deep-Q Learning using phase-gated technique, and Speeded-Up Robust Features (SURF) for object detection. We have implemented OpenCV and YOLOv9 into our model. One of the key focuses in our model is the detection of Emergency Vehicles (EVs) and prioritising lanes based on this information along with other data such as queue length and traffic density. In the papers mentioned above, detecting EVs is not a feature. Our model can benefit many people with this feature as vehicles like ambulances, police, etc can pass through the traffic quicker and avoid potential casualties/danger. Additionally, implementing blockchain technology into the system for extra security and protection of data is also done.

Our model suggests a smart traffic signal system, which can automatically determine which lane needs a higher green light time based on real-time conditions. In a junction, detecting which lane has a higher volume of traffic and green lighting that lane will reduce the overall traffic congestion significantly, compared to the existing signal systems used.

Comparing this model to other proposed models such as those mentioned in the literature survey (Vehicle detection and counting of a vehicle using openCV, Adaptive Traffic Light Based on Yolo-Darknet Object Detection, etc.) we see that many of them use older versions of YOLO [16]. We have taken one of the latest versions of YOLO (v9), to utilize all the new features available. Yet another paper (Dynamic Traffic Control System with Reinforcement Learning Technique) uses Deep-Q Learning using phase-gated technique, and Speeded-Up Robust Features (SURF) for object detection. We have implemented OpenCV and YOLOv9 into our model. One of the key focuses in our model is the detection of Emergency Vehicles (EVs) and prioritising lanes based on this information along with other data such as queue length and traffic density. In the papers mentioned above, detecting EVs is not a feature. Our model can benefit many people with this feature as vehicles like ambulances, police, etc can pass through the traffic quicker and avoid potential casualties/danger. Additionally, implementing blockchain technology into the system for extra security and protection of data is also done.

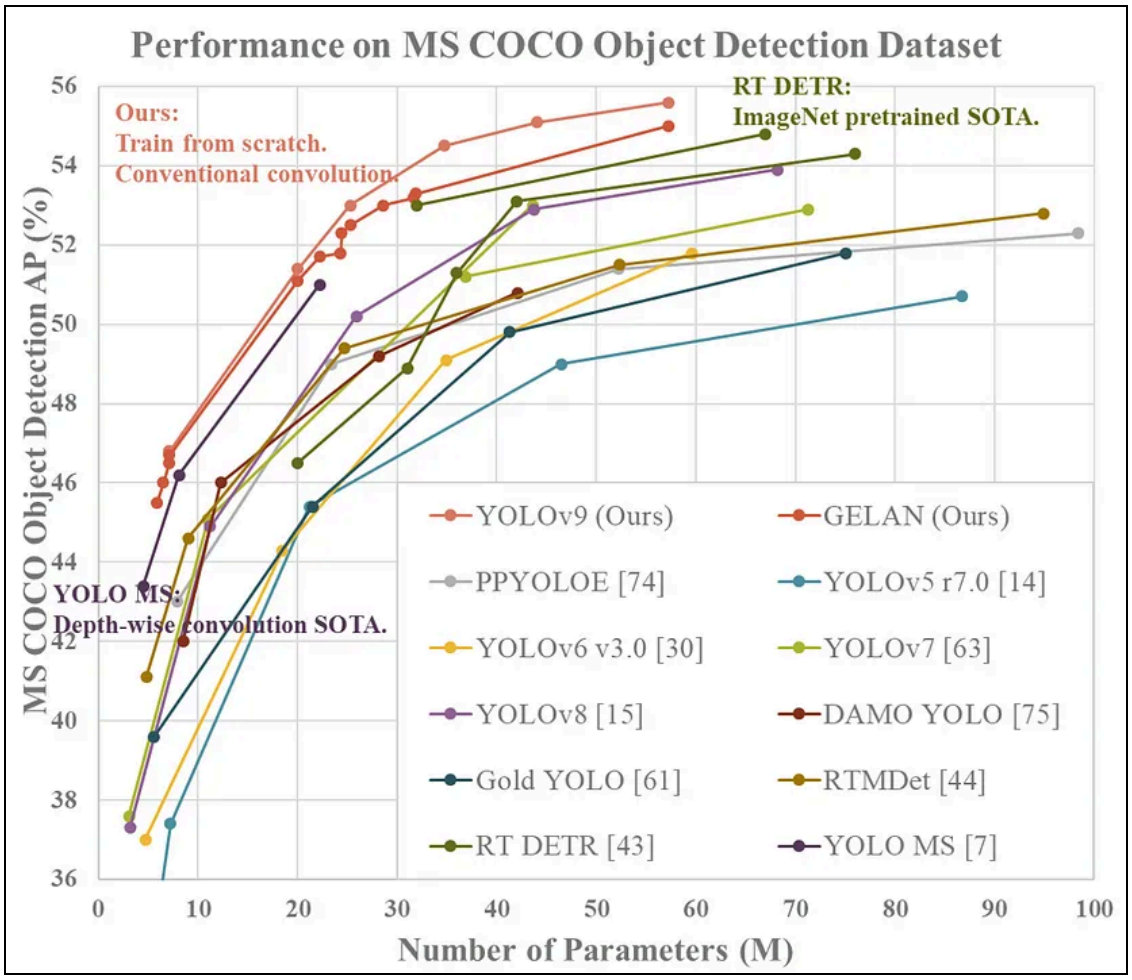


Fig 2.23: Reporting performance from "YOLOV9 performance reports" [16]

- **Conclusions**

The highest number of instances created was that of the cars, with around almost 5000. Following this are big and small trucks, with about 2000 instances each. Other vehicle types had significantly small numbers of instances.

In the confusion matrix, we can see that most of the cars are correctly predicted. Some of the smaller vehicles are wrongly predicted as cars. Trucks and buses also have some confusion. A large number of vehicles are getting predicted as background. This is so as many vehicle types have been underrepresented in the dataset.

By analysing the F1 score, it can be concluded that the bus reached a maximum of 0.35 value which is the least of all the vehicles. The Rest of the vehicles had a good value of average precision and recall that made up the F1 score.

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