AI ENHANCED TRAFFIC MANAGEMENT SYSTEM

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ABSTRACT:

This paper introduces an innovative approach to traffic management through the integration of artificial intelligence (AI) technology, emphasizing traffic density analysis, object detection, and emergency vehicle prioritization. Our model integrates advanced object detection algorithms with adaptive traffic density control, dynamically responding to real-time traffic conditions. Through deep learning methods, the system accurately identifies and tracks various objects, including 2, 3, and 4-wheelers, as well as emergency vehicles, in live traffic camera feeds. Leveraging traffic density analysis and object detection, the model intelligently adjusts traffic flow by optimizing lane assignments and implementing traffic strategies to enhance flow and safety. Notably, the system prioritizes emergency vehicles, ensuring rapid passage through intersections. Extensive experimentation and validation demonstrate the efficiency of our AI-based traffic control system in alleviating congestion, reducing travel times, and enhancing transportation efficiency in urban settings. This research contributes to the advancement of intelligent transportation systems, with promising implications for urban planning and sustainable development efforts.

KEYWORDS:

AI Traffic Control, Density based Traffic Flow Optimization, Vehicle detection and tracking using YOLOv8, Deep learning, AI based route planning, Emergency vehicle detection and prioritization.

INTRODUCTION:

In the era of rapid urbanization, traffic congestion has become a ubiquitous challenge in metropolitan areas worldwide. Traditional traffic signal control systems, operating on fixed schedules or basic timer mechanisms, struggle to adapt to dynamic traffic patterns, leading to inefficiencies, longer travel times, increased fuel consumption, and heightened emissions. As cities grow denser and vehicle populations swell, the need for intelligent traffic management solutions becomes ever more pressing.

This research paper introduces a paradigm-shifting approach to traffic signal control: leveraging artificial intelligence (AI) algorithms to dynamically adjust signals based on real-time traffic density. Unlike conventional signal systems, which rely on predetermined schedules or simple sensors that lack sophistication, our proposed system harnesses the power of AI to analyse and respond to the complex, ever-changing flow of vehicles on the road.

By integrating AI with traffic density data collected from cameras, the smart signal control system can make informed decisions in real-time. Through machine learning techniques, the system continuously learns from traffic patterns, optimizing signal timings to minimize congestion, reduce delays, and enhance overall traffic flow efficiency.

The significance of this research lies in its potential to revolutionize urban transportation systems. By intelligently adapting signal timings to match traffic density, the AI-driven approach promises substantial improvements in both traffic flow and environmental sustainability. Reduced congestion not only translates to shorter commute times and enhanced productivity but also contributes to lower fuel consumption and emissions, thereby mitigating the environmental impact of urban mobility.

Moreover, this research addresses the limitations of existing traffic management strategies by offering a scalable, adaptable solution that can evolve alongside the dynamic nature of urban landscapes. As cities continue to grow and evolve, the need for flexible, data-driven traffic control mechanisms becomes increasingly evident. By harnessing AI to optimize signal control based on real-time density data, this research represents a significant step towards building smarter, more resilient cities of the future.

Ultimately, this research contributes to the creation of more liveable, sustainable urban environments through the fusion of AI technology and Machine learning.

ADVANTAGES:

1. Heavy traffic jams are reduced.
2. Decrease in pollution.
3. Saves time which is wasted in traffic jams.
4. Saves fuel and money.

LITERATURE REVIEW:

One of the good research was published in International Journal of Scientific and Research Publications, IJSRP, Volume 8, Issue 2, February 2018 Edition [ISSN 2250-3153]. Here the research paper was aimed to solve traffic congestion in India. The major findings that they referred here are reducing the time of waiting in traffic jams and avoid to wait at no traffic roads. Every vehicle has a RFID enabled device that stores a vehicle identification number (VIN). VIN number that provides the information regarding the priority of the vehicle and type of the vehicle. Readers collects the information regarding the vehicles approaching towards the junctions. The Central processing unit calculates the volume and speed of vehicles on each road according to information collected by readers. (Ragha, 2018). The team tried to achieve this problem using Radio Frequency Identification Devices (RFID) technology. Also, they calculate the number of vehicles using the RFID reader when the vehicle moves near the reader.

In this system object-based detection system is used to accurately and easily identify the vehicle through the surveillance cameras which fixed on the particular traffic signal.

Apart from congestion detection and vehicle counts, various articles have been reviewed to study anomaly detection systems. Kamijo et al. in developed a vehicle tracking algorithm based on spatio-temporal Markov random fields to detect traffic accidents at intersections.

The model presented in their study was capable of robustly tracking individual vehicles without their accuracies being greatly affected by occlusion and clutter effects, two very common characteristics at most busy intersections which pose a problem for most models. Although traditionally, spot sensors were used primarily for incident detection, the scope of their use proved to be rather trivial for anomaly detection systems. Vision-based approaches have therefore been utilized far and beyond mostly due to their superior event recognition capability. Information such as traffic jams, traffic violations, accidents, etc. could be easily extracted from vision-based systems. Rojas et al. in and Zeng et al. in proposed techniques to detect vehicles on a highway using a static CCTV camera, while, Ai et al. in proposed a method to detect traffic violation at intersections. The latter's approach was put into practice on the streets of Hong Kong to detect red light runners. Thajchayapong et al. proposed an anomaly detection algorithm that could be implemented in a distributed fashion to predict and classify traffic abnormalities in different traffic scenes. Similarly, Ikeda et al. in used image-processing techniques to automatically detect abnormal traffic incidents.

PROBLEM IDENTIFICATION:

In densely populated countries like India and elsewhere, traffic congestion on four-lane roads often leads to prolonged waiting times at traffic signals, regardless of the density in individual lanes. This inefficiency significantly impacts daily commuters, delaying travel and contributing to frustration and productivity loss. Existing traffic management systems lack the adaptability to address lane-specific traffic density variations, resulting in suboptimal signal timing and further exacerbating congestion.
Furthermore, emergency vehicles such as ambulances and fire brigades face obstacles navigating through congested traffic, potentially delaying critical response times and jeopardizing public safety. The absence of a responsive mechanism to prioritize emergency vehicles exacerbates the challenges of urban traffic management.

To address these issues, we propose a system that leverages AI-enabled CCTV or traffic cameras to dynamically detect and analyse lane-specific traffic density on four-lane roads. By intelligently identifying congested lanes, the system autonomously adjusts signal timing to prioritize green signals for less congested lanes, optimizing traffic flow and reducing overall wait times. Additionally, the system incorporates a feature to expedite the passage of emergency vehicles by automatically triggering green signals in their path, ensuring swift and unhindered movement during emergencies.

Our project aims to revolutionize urban traffic management by harnessing AI technologies to enhance efficiency, minimize congestion, and prioritize emergency vehicles, ultimately improving the quality of life for commuters and ensuring public safety on the roads.

EFFECT OF AI:

Researchers from all over the world are working to introduce the use of Artificial Intelligence in managing road traffic in major cities to eliminate the issue of traffic congestion. Artificial Intelligence (AI) has emerged as a promising solution for
addressing the persistent challenges of traffic management in major cities.
AI can have following effects on traffic management: -

- Improved Traffic Flow: AI algorithms can analyse real-time traffic data and make dynamic adjustments to traffic signal timings, lane assignments, and route recommendations. This can lead to smoother traffic flow, reduced congestion, and shorter travel times for commuters.

- Enhanced Safety: AI can contribute to safer roads by predicting and preventing accidents. Through the analysis of historical accident data and real-time traffic conditions, AI systems can identify potential hazards and alert drivers or take autonomous actions to avoid collisions.
- Reduced Environmental Impact: AI-based traffic management systems can optimize traffic flow to minimize fuel consumption and emissions. By reducing idle time and congestion, these systems can contribute to lower levels of air pollution and greenhouse gas emissions in urban areas.
- Efficient Resource Allocation: AI algorithms can optimize the use of transportation infrastructure and resources, such as road capacity, public transportation services, and emergency response vehicles. This can result in more efficient use of taxpayer dollars and improved service delivery for residents.

HOW AI IS BETTER THAN CONVENTIONAL SYSTEMS:

AI traffic detectors offer several advantages over traditional traffic police, leading to reduced congestion and travel times, enhanced safety, and increased efficiency.
Firstly, AI traffic detectors can significantly improve traffic flow by efficiently managing signal timing. By collecting real-time traffic information through sensors, AI traffic systems can quickly direct this data to the traffic control subsystem, which manages traffic signals based on current conditions[1]. This results in reduced congestion and travel times, as traffic signals are optimized for the number of vehicles and pedestrians present.
Secondly, AI traffic detectors can enhance safety by minimizing the risk of accidents. By preventing sudden stops and red-light violations, AI traffic systems can reduce the likelihood of collisions. This is achieved through the use of wireless networks, which enable the detection of vehicles and pedestrians in real-time, allowing for the adjustment of traffic signals accordingly [1].
Thirdly, AI traffic detectors can increase efficiency by optimizing resource allocation. By reducing unnecessary signal cycles, AI traffic systems can ensure that traffic signals are only active when needed, reducing energy consumption and prolonging the lifespan of traffic infrastructure. This is achieved through the use of algorithms that analyse traffic patterns and adjust signal timing accordingly [1].
In addition, AI traffic detectors can prioritize emergency vehicles, such as ambulances, based on wireless sensor networks. This can significantly reduce response times and improve the chances of successful outcomes in emergency situations [1]. Furthermore, AI traffic detectors can predict possible traffic bottlenecks and clearance strategies using technologies like Big Data. This enables traffic management systems to proactively address potential issues, reducing congestion and improving traffic flow .
Finally, AI traffic detectors can improve the accuracy and speed of traffic sign recognition. By using deep learning models like YOLOv5, AI traffic systems can achieve 97.70% in terms of mAP@0.5 for all classes, outperforming traditional methods like SSD in both accuracy and recognition speed.

In conclusion, AI traffic detectors offer numerous advantages over traditional traffic police, leading to reduced congestion and travel times, enhanced safety, and increased efficiency. By collecting real-time traffic information, optimizing signal timing, prioritizing emergency vehicles, predicting traffic bottlenecks, and improving traffic sign recognition, AI traffic detectors can significantly improve the overall efficiency and safety of transportation systems.

PROPOSED MODEL:

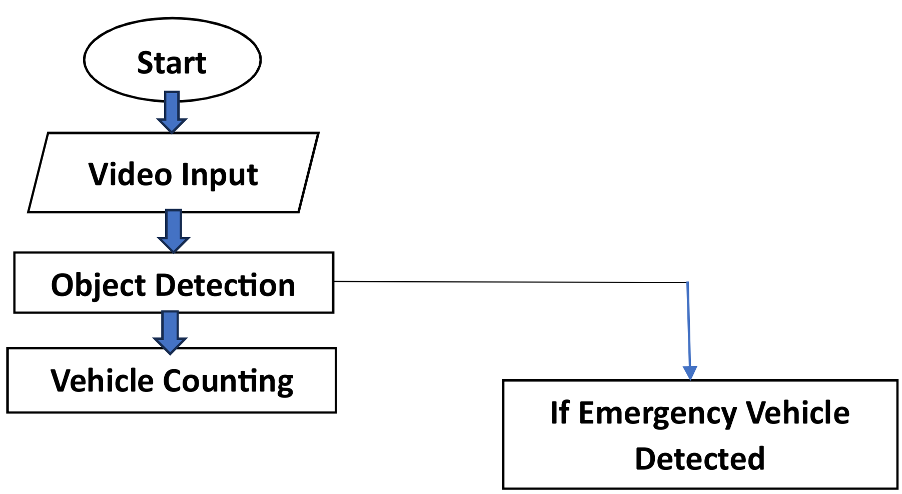
In our research paper on AI-based traffic control, we propose a comprehensive model that integrates object detection technology with dynamic signal adjustment based on traffic density analysis. Our model utilizes cutting-edge deep learning algorithms to detect and track various objects such as cars, trucks, 2-wheelers, 3-wheelers and emergency vehicles in real-time from traffic camera feeds. By accurately identifying and monitoring these objects, our system can dynamically adjust traffic signals, lane assignments, and other traffic management strategies tailored to current traffic conditions to optimize traffic flow and enhance safety.

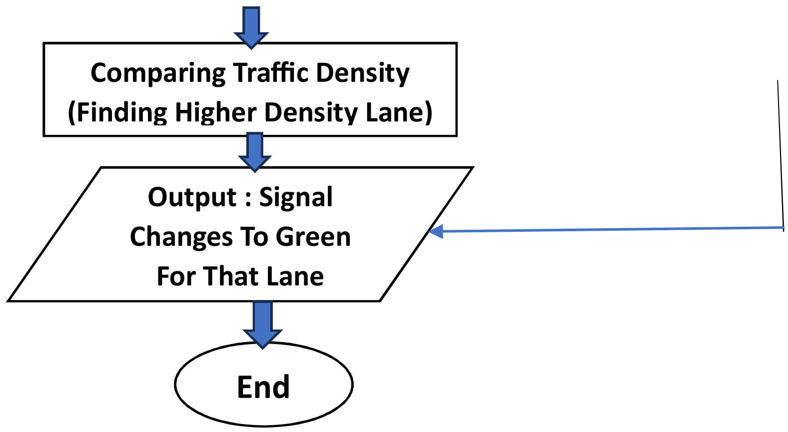
Measurement of traffic density is done using object detection technology. The computed traffic density is compared with other parts of the traffic in order to control the traffic signal smartly. In this model, there will be four cameras in one intersection for a four-way road. A high-definition camera placed on poles will observe the vehicular traffic flow continuously on a road then using frame by frame Real-time video analysis through our developed algorithm, we can detect how much cars are present on the road. Depending on the number of detected vehicles we have developed and implemented a sequential signal management system. The HD camera will be installed in the traffic light post at a height of 19-25 feet (for practical implementation) above the road. This camera will take the live video footage of the road and send it to a computer where video analysis (object detection) will be done. For a 4-way intersection, CPU will detect each and every car and will count the vehicle number in the road by using our developed algorithm. It will also do the same thing with another road by using another camera. CPU then compares vehicle number of both roads. The road which has more vehicles will get the preference and green light for that road will be on and red signal will be shown automatically to the other road.

Additionally, our model includes emergency vehicle detection and prioritization, ensuring efficient emergency response while maintaining traffic flow. Incase an Emergency Vehicle is detected in a lane, preference will be given to that particular lane and green light will be turned on for that road and red for all other roads to avoid delay and accidents.

Through this combined approach, our AI-based traffic control system aims to minimize congestion, reduce travel times, and improve overall transportation efficiency in urban areas.

Algorithms:





- Object Detection using YOLOv8:

  YOLOv8 proposed a new backbone network with a new anchor-free detection head, which means it predicts directly the centre of an object instead of the offset from a known anchor box. It also proposes a new loss function. The basic architecture of YOLOv8 consists of two major parts: the backbone for extracting feature maps and the head for detection. The backbone contains a series of convolutional layers for different image resolutions and sizes, and then the features detected are passed through the advanced head for detection based on a loss function.

- DeepSORT (Deep Simple Online and Realtime Tracking):

  DeepSORT (Deep Simple Online and Realtime Tracking) is a sophisticated tracking algorithm designed to track objects across multiple frames of a video or image stream. It excels at maintaining a consistent track of objects, even as they move through frames, providing valuable insights into their paths and behaviours.

  YOLO is a real-time object detection algorithm that uses a single CNN to predict the bounding boxes and class labels of objects in an image. YOLOv1 was introduced in 2015, which frames the object detection problem as a regression problem instead of a classification problem that classifies each pixel in the image. To eliminate duplicate detections, YOLO divides the input image into a grid and predicts the bounding boxes for the same class along with its confidence values; the output is then followed by a non-maximum suppression (NMS). There are 24 CNN layers in YOLOv1 architecture, then two fully connected layers.

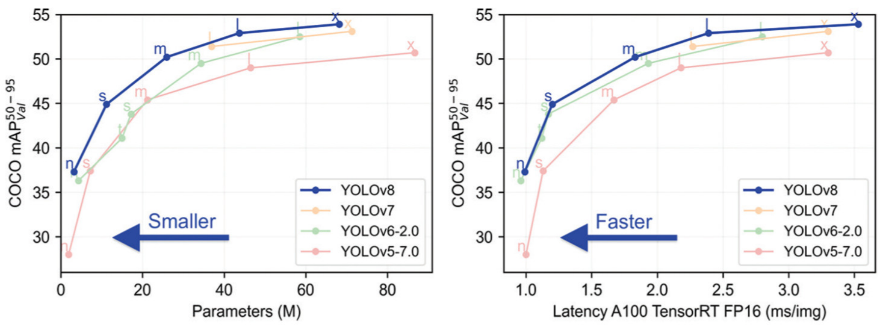


Fig1. YOLOv8 comparisons to its prior versions

A state-of-the-art algorithm based on a combination of feature pyramids, anchor-free detection, and multiple-scale training makes it compatible with YOLOv8. The algorithm tracks by associating every bounding box instead of only the high-scoring ones. Data association is the core of multi-object tracking, which first computes the similarity between trackelets and detection boxes. A tracklet is a sequence of detections that are likely to belong to the same object. The similarity metrics may include location, motion, and appearance features. The ByteTrack algorithm tracks objects with high or low values of confidence by presenting a BYTE method for each detection box. First, the high scoring boxes are tracked based on motion similarity or appearance similarity, and a Kalman filter is adopted to predict the location of the objects in the next frame. The similarity can be computed by the IOU or Re-ID feature distance between the predicted box and the detection box. After similarity computation, the matching strategy assigns identities to the objects. Algorithm 1 provides the pseudocode for the BYTE algorithm (Zhang, et al., 2022).

Algorithm 1: BYTE Algorithm

Input: V: video file; **D**: object detector; **θ**: detection score threshold
Output: T: tracks

Begin:
Step 1: Initialize T=0
Step 2: for frame f_k in V do
D_k □ $Det\ (f_k)$
D_{high} □ 0
D_{low} □ 0
Step 3: for d in D_k do
If d. score >θ then
D_{high} □ $D_{high} \cup \{d\}$
else
D_{low} □ $D_{low} \cup \{d\}$
Step 4: for t in T
$t.KalmanFilter(t)$
Step 5: Associate T and D_{high} using similarity1
Step 6: D_{remain} □ remaining boxes from D_{high}
Step 7: T_{remain} □ remaining tracks from T
Step 8: Associate T_{remain} in D_{low} using similarity2
Step 9: $T_{re\text{-}remain}$ □ remaining tracks from T
Step 10: T □ $T \backslash T_{re\text{-}main}$ // delete unmatched tracks
Step 11: for d in D_{remain} do
T □ $T \cup \{d\}$
end for
return
End

Requirements:

Computer & Cameras: A computer is used as a central device for various image processing operations and Cameras to capture the video to execute the project.

Operating system, IDE, programming languages like python and its libraries, Machine learning frameworks, DeepSORT, YOLOv8.

Implementation:

- Getting Video Inputs:

  Rather than immediately processing the entire video, the example starts by obtaining an initial video frame in which the moving objects are segmented from the background.

Fig.2 Sample Video

- Vehicle Tracking:

  The tracking stage depends on the results of the detection stage as the tracker tracks the detected bounding boxes of the vehicles. The ByteTrack algorithm is applied to track the moving vehicles in the scene based on their detected bounding boxes, and then the algorithm will assign a track identification number (track ID) for each tracked vehicle. The tracking stage is essential to the proposed system as it will be used in the vehicle counting process. The vehicle counting process starts after the detection stage and during the tracking stage. The counting process is performed in the predefined position line whose co-ordinates are fixed for a particular lane. At the entry line, the centre of each detected vehicle is calculated using the following equation:

$$(cx, cy) = (\frac{x + (x + w)}{2}, \frac{y + (y + h)}{2})$$

Where: (x, y) is the detected object's bounding box top left corner coordinates. (w, h) is the detected object's bounding box width and height. (cx, cy) is the centre coordinate of the detected object. Several important pieces of information are stored in a queue, including the car ID, the time of entering in seconds (TIME1), and the vehicle's calculated centre (CENTER1).

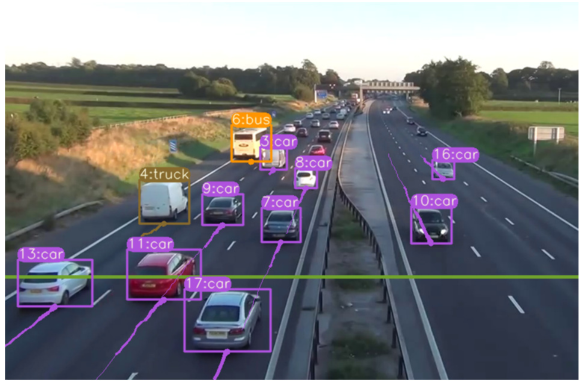


Fig3. Vehicle detection

- Performance Matrices:

Challenges and online competitions have pushed forward the frontier of the object detection field, improving results for specific datasets in every new edition. To validate the submitted results, each competition applies a specific metric to rank the submitted detections. Among the popular metrics to report the results, this section will cover those used by the most popular competitions, namely Open Images RVC, COCO Detection Challenge, VOC Challenge , Datalab Cup , Google AI Open Images challenge , Lyft 3D Object Detection for Autonomous Vehicles , and City Intelligence Hackathon . Object detectors aim to predict the location of objects of a given class in an image or video with a high confidence. They do so by placing bounding boxes to identify the positions of the objects. Therefore, a detection is represented by a set of three attributes: The object class, the corresponding bounding box, and the confidence score, usually given by a value between 0 and 1 showing how confident the detector is about that prediction. The assessment is done based on:

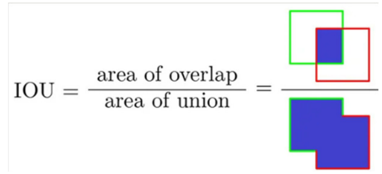
- A set of ground-truth bounding boxes representing the rectangular areas of an image containing objects of the class to be detected, and
- A set of detections predicted by a model, each one consisting of a bounding box, a class, and a confidence value.

Detection evaluation metrics are used to quantify the performance of detection algorithms in different areas and fields. In the case of object detection, the employed evaluation metrics measure how close the detected bounding boxes are to the ground-truth bounding boxes. This measurement is done independently for each object class, by assessing the amount of overlap of the predicted and ground-truth areas.

Consider a target object to be detected represented by a ground-truth bounding box Bgt and the detected area represented by a predicted bounding box Bp. Without taking into account a confidence level, a perfect match is considered when the area and location of the predicted and ground-truth boxes are the same. These two conditions are assessed by the intersection over union (IOU), a measurement based on the Jaccard Index, a coefficient of similarity for two sets of data. In the object detection scope, the IOU is equal to the area of the overlap (intersection) between the predicted bounding box and the ground-truth bounding divided by the

area of their union, that is

$$J(B_p, B_{gt}) = \text{IOU} = \frac{\text{area}(B_p \cap B_{gt})}{\text{area}(B_p \cup B_{gt})}$$



A perfect match occurs when IOU=1 and, if both bounding boxes do not intercept each other, IOU=0. The closer to 1 the IOU gets, the better the detection is considered. As object detectors also perform the classification of each bounding box, only ground-truth and detected boxes of the same class are comparable through the IOU.

By setting an IOU threshold, a metric can be more or less restrictive on considering detections as correct or incorrect. An IOU threshold closer to 1 is more restrictive as it requires almost-perfect detections, while an IOU threshold closer to, but different than 0 is more flexible, considering as detections even small overlaps between $B p$ and $B g t$. IOU values are usually expressed in percentages, and the most used threshold values are 50% and 75%.

- Precision and Recall:

Let us consider a detector that assumes that every possible rectangular region of the image contains a target object (this would be done by placing bounding boxes of all possible sizes cantered in every image pixel). If there is one object to be detected, the detector would correctly find it by one of the many predicted bounding boxes. That is not an efficient way to detect objects, as many wrong predictions are made as well. Conversely, a detector which never generates any bounding box, will never have a miss-detection. These extreme examples highlight two important concepts, referred as precision and recall, are further explained below.

Precision is the ability of a model to identify only relevant objects. It is the percentage of correct positive predictions. Recall is the ability of a model to find all relevant cases (all ground-truth bounding boxes). It is the percentage of correct positive predictions among all given ground truths. To calculate the precision and recall values, each detected bounding box must first be classified as:

- True positive (TP): A correct detection of a ground-truth bounding box;
- False positive (FP): An incorrect detection of a non-existing object or a misplaced detection of an existing object;
- False negative (FN): An undetected ground-truth bounding box.

Assuming there is a dataset with G ground-truths and a model that outputs N detections, of which S are correct ($S \leq G$), the concepts of precision and recall can be formally expressed as:

$$Pr = \frac{\sum_{n=1}^{S} \mathrm{TP}_n}{\sum_{n=1}^{S} \mathrm{TP}_n + \sum_{n=1}^{N-S} \mathrm{FP}_n} = \frac{\sum_{n=1}^{S} \mathrm{TP}_n}{\text{all detections}}, \qquad Rc = \frac{\sum_{n=1}^{S} \mathrm{TP}_n}{\sum_{n=1}^{S} \mathrm{TP}_n + \sum_{n=1}^{G-S} \mathrm{FN}_n} = \frac{\sum_{n=1}^{S} \mathrm{TP}_n}{\text{all ground truths}}.$$

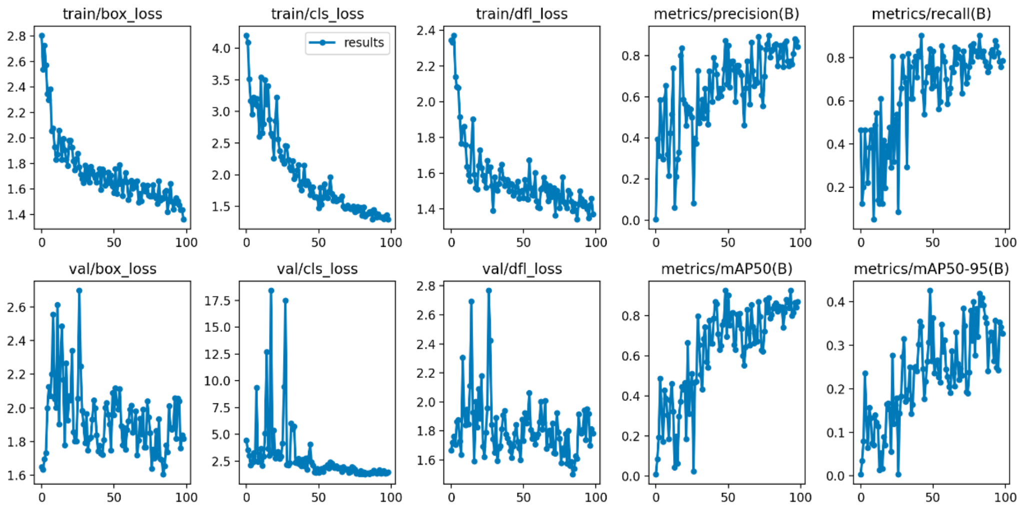


Fig4. Graphs obtained during training the model using YOLOv8

The horizontal axis of the graph is typically the number of epochs. An epoch is a complete iteration of the training dataset through the neural network during training. More epochs generally lead to better training of the model but can also lead to overfitting if done excessively.

The vertical axis in a typical YOLO (You Only Look Once) training graph would represent the loss value. Loss is a measure of how well the model is performing during training. Lower loss values indicate better model performance, while higher values indicate worse performance. The goal during training is to minimize the loss value.

"box_loss": This is the bounding box regression loss, which measures the error in the predicted bounding box coordinates and dimensions compared to the ground truth. A lower box_loss means that the predicted bounding boxes are more accurate.

"cls_loss": This is the classification loss, which measures the error in the predicted class probabilities for each object in the image compared to the ground truth. A lower cls_loss means that the model is more accurately predicting the class of the objects.

"dfl_loss": This is the deformable convolution layer loss, a new addition to the YOLO architecture in YOLOv8. This loss measures the error in the deformable convolution layers, which are designed to improve the model's ability to detect objects with various scales and aspect ratios. A lower dfl_loss indicates that the model is better at handling object deformations and variations in appearance.

The overall loss value is typically a weighted sum of these individual losses. The specific units of the vertical axis would be dependent on the implementation, but generally, they represent the magnitude of the error or the difference between the predicted and ground truth values.

- Process the rest of the video and count vehicles:

The camera installed detects the every vehicle on road and increases the number of count of vehicles. The co-ordinates of the position line are fixed and as the centre of the detected vehicles pass through the position line count is added ie. count=count+1.

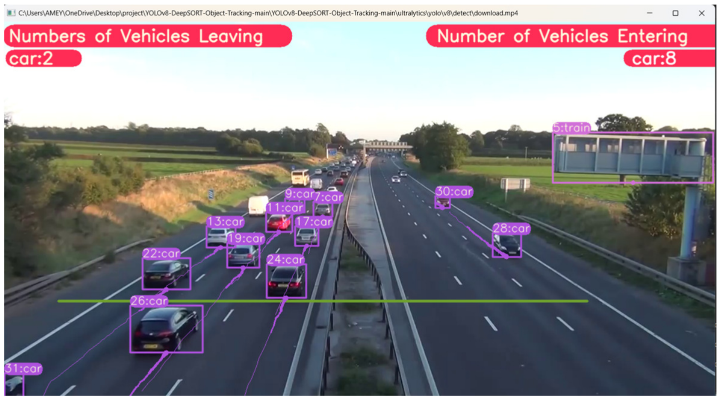


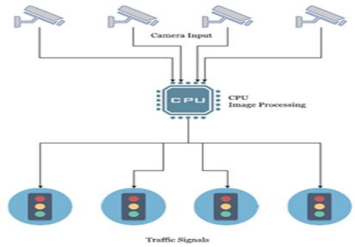
Fig5. Vehicle counting

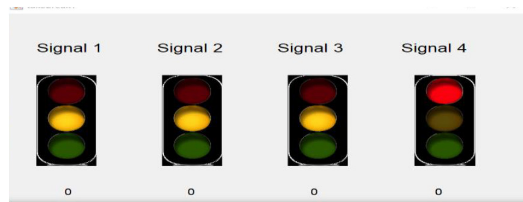
- Traffic light control:

According to the traffic density in a particular lane, the signals will be allotted after comparing the density of vehicles and threshold value. If there are zero vehicles, that signal will be skipped, if vehicle density is higher than that of the threshold value that signal will become green, and rest of the lanes will also act according to the comparison between car count and threshold value. And after leaving the traffic of high-density lane, the next lane which has highest density as compared to other lanes will be focused.

If in any lane an emergency vehicle is detected, that signal would immediately turn green and others will be red. So that, the emergency vehicle can pass quickly and there will be no chaos or accidents.

Car count	Thresholds Value
0	0
5	<10 and >1
20	<30 and >10
40	30>





CASE STUDY:

1] Singapore:

Singapore is a global leader in smart city initiatives and transportation innovation. Advanced System Implementation of the Electronic Road Pricing (ERP) system since 1998, using GPS and RFID technology to manage road congestion through variable tolls. Introduction of the Smart Mobility 2030 vision, integrating AI, IoT, and data analytics for predictive traffic management. Results Significant reduction in traffic congestion and improved air quality. Enhanced public transportation modal share through seamless integration with traffic management systems.

2] Los Angeles:

Los Angeles faces notorious traffic congestion challenges due to its sprawling urban landscape. The Los Angeles Department of Transportation (LADOT) deploys AI algorithms to manage traffic signals and control traffic flow. Machine learning models analyse historical traffic data to dynamically adjust signal timing based on real-time traffic conditions.

3] Netherlands (Amsterdam):

Amsterdam is known for its sustainable transportation initiatives and cycling-friendly infrastructure. Implementation of the Mobility as a Service (MaaS) platform, integrating various modes of transportation into a single digital platform. Use of AI-powered predictive modelling to optimize traffic flow and prioritize sustainable modes of transport.

CONCLUSION:

In conclusion, this research paper has outlined a pioneering project focused on the development and implementation of an AI enhanced traffic management system. By integrating object detection technology with adaptive signal management based on real-time traffic density analysis, our project aims to revolutionize urban transportation management, optimize traffic flow and reduce congestion, leading to improved travel times and overall efficiency. Through the utilization of advanced deep learning algorithms, we have demonstrated the system's capability to accurately detect and track various objects, enabling intelligent signal management, lane assignments, and traffic strategies. Additionally, our system prioritizes emergency vehicles and enhances safety for all road users. This project represents a significant advancement in intelligent transportation systems, promising safer and more efficient cities for the future.

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