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Camera System for Over Speed Detection and License Plate Detection Using Machine Learning and Video Streaming Analysis

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Abstract: Now a days, road accidents and traffic issues are on the rise. Video-based vehicle detection technology can gather valuable data from video frames, like vehicle speed, type and license plates cost effectively and efficiently. This data can improve traffic management and enhance safety. Traditional speed detection systems still rely on traditional algorithms like YOLOv5 and SSD that lack in accuracy. Our proposed system uses cutting-edge technologies in machine learning and video steaming analysis. The system integrates YOLOv8 for precise vehicle detection, DeepSORT for robust tracking of vehicles, and EasyOCR in conjunction with YOLOv8 for accurate license plate number detection. On detecting the vehicle the speed of each vehicle is estimated and it's details are noted upon speed violation. Integration of these technologies improves traffic monitoring and reduces road accidents. The data collecting by these can later be used for alerting the drivers and as well as control teams.

Keywords: Vehicle detection, tracking, Vehicle speed detection, video streaming analysis, DeepSORT, YOLOv8 EasyOCR.

I. INTRODUCTION

Vehicle speed estimation has been considered as the most alarming aspect in traffic monitoring systems. It was found to be a topic for the intense research recently. Firstly, most roadways accidents are based on the speed limit violation, so we need to regulate roadways and prevent drivers from driving too fast. Actually, good traffic management reduces the traffic accidents and make the roadways safer. This goal is unachievable without the regulation of drivers that are violating. Although, several ways and means of determining the speed of vehicles have been introduced; there are still some obstacles in the way which necessitates further research to be conducted.

Also, many types of devices were created to measure their speed. The RADAR and LIDAR devices get aimed at the moving vehicles to measure the shift in the frequency of the wave from the reflected ray to estimate the speed. RADAR emits a beam of electromagnetic radiation at a selected frequency and direction of transmit. This wave bounces from the platform and returns to the radar, frequency is having a slight frequency difference than emitted which is called as the Doppler shift. Through recording of phase-difference between emitted and the reflected wave the measurement of target speed can be achieved.

Despite this RADAR does contain some weaknesses, too. On the one hand, it is inappropriate to differentiate various drivers speeding to the extent that a minimum 2s is required to capture them. Similarly, bigger vehicles nearby the radar would block the sight of smaller vehicle, thus giving rise to faulty measuring. It is possible that it generates incorrect lengths which would result in detecting traffic offenses. Lastly, RADAR technology has a major disadvantage of the lack of automatic transfer from the compilation of data for the recording information period.

Apart from RADAR technology, there are some other algorithms such as SSD, RCNN, DeepSort, EasyOCR and YOLO for more precise and effective traffic monitoring and enforcement approaches. Among these RCNN plays a pivotal role in refining traffic surveillance through its method of identifying and categorizing prospective vehicle areas using deep learning. This approach significantly boosts accuracy in intricate environments. Transitioning to the next algorithm, SSD (Single Shot Multibox Detector), offers swift real-time object detection with a single pass through a neural network. Its efficiency in capturing objects of varying sizes and high processing speed suits dynamic traffic environments.

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Additionally, SSD's adaptability to different lighting conditions and complex backgrounds enhances its effectiveness in traffic surveillance. Coming to YOLO algorithm we have different versions in that YOLOv3 outperforms SSD primarily due to its single-pass architecture, ensuring faster inference times and superior accuracy in object detection. Furthermore, advancements introduced in YOLOv4 and YOLOv5, such as improved backbone architectures and enhanced optimization strategies, further enhance their performance and efficacy, solidifying their superiority over SSD in various real-world applications, including traffic surveillance. Comparing to previous versions YOLOv8 outperforms YOLOv4, YOLOv5 and other versions in several key aspects, making it the preferred choice for object detection tasks. With advanced backbone architectures and optimization techniques. This superiority ensures better performance in challenging scenarios and real-time applications. In contrast, YOLOv4 and v5 may lag behind in accuracy and speed due to less advanced architectures and optimization strategies. Overall, YOLOv8 stands out as the most effective and reliable solution among the YOLO versions.

Here YOLO only detect vehicles after these we have to track the multiple vehicles which are detected for exceeding the speed limit for that we use SORT algorithm. The Sort algorithm is an efficient method for tracking objects in videos. Deep SORT surpasses SORT by utilizing deep learning techniques to enhance object tracking accuracy and robustness. Once a vehicle is detected and tracked, EasyOCR analyses the region of interest containing the license plate. Through the recognition of characters imprinted on the license plate, EasyOCR deciphers the vehicle's registration number, thereby facilitating automated enforcement measures.

Through the integration of these algorithms into a unified system, the capabilities for real-time traffic monitoring and enforcement undergo substantial enhancement. YOLO v8 work to detect vehicles, while Deep SORT seamlessly tracks them across consecutive frames. EasyOCR complements this process by swiftly recognizing license plates the seamless cohesion of these algorithms ensures precise and dependable detection and ultimately contributing to the enhancement of road safety and the efficiency of traffic management.

II. RELATED WORK

For our proposed system for speed estimation and license number detection various research papers have been covered ranging from using RADAR, LIDAR for speed estimation to using machine learning algorithms like SSD, RCNN and YOLO versions. Our analysis on these topics is briefly reviewed in this section.

1. RADAR and LIDAR approach

The RADAR and LIDAR devices get aimed at the moving vehicles to measure the shift in the frequency of the wave from the reflected ray to estimate the speed[6]. RADAR emits a beam of electromagnetic radiation at a selected frequency and direction of transmit. This wave bounces from the platform and returns to the radar, frequency is having a slight frequency difference than emitted which is called as the Doppler shift. Through recording of phase-difference between emitted and the reflected wave the measurement of target speed can be achieved.

Despite this RADAR does contain some weaknesses, too. On the one hand, it is inappropriate to differentiate various drivers speeding to the extent that a minimum 2s is required to capture them. Similarly, bigger vehicles nearby the radar would block the sight of smaller vehicle, thus giving rise to faulty measuring. It is possible that it generates incorrect lengths which would result in detecting traffic offenses. Lastly, RADAR technology has a major disadvantage of the lack of automatic transfer from the compilation of data for the recording information period.

2. Other Machine learning Algorithms

To address the limitations of RADAR technology in traffic monitoring and enforcement, various alternative algorithms such as SSD, RCNN and YOLO have been proposed[7][5]. Among these, RCNN plays a crucial role in enhancing traffic surveillance by accurately identifying and categorizing potential vehicle areas using deep learning techniques. Its ability to discern objects in complex environments significantly boosts accuracy, which is pivotal for effective traffic management and enforcement.

Transitioning to SSD (Single Shot Multi-box Detector), this algorithm offers rapid real-time object detection with a single pass through a neural network. Its efficiency in capturing objects of varying sizes and processing speed makes it well-suited for dynamic traffic environments. Moreover, SSD's adaptability to different lighting conditions and complex backgrounds further enhances its effectiveness in traffic surveillance, providing a versatile solution for comprehensive monitoring systems[12][7].

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While SSD excels in certain aspects, the YOLO (You Only Look Once) algorithm presents significant advancements in object detection. YOLOv3, in particular, outperforms SSD due to its single-pass architecture, ensuring faster inference times and superior accuracy. Subsequent versions like YOLOv4, YOLOv5 and YOLOv7 introduce improved backbone architectures and optimization strategies, further enhancing their performance in various real-world applications, including traffic surveillance. However, the latest iteration, YOLOv8, demonstrates superiority over its predecessors and other versions by excelling in several key aspects, making it the preferred choice for object detection tasks in traffic monitoring and enforcement systems.

TABLE I
COMPARISION BETWEEN RCNN, SSD AND YOLO OBJECT DETECTION ALGORITHMS

	Speed	**Accuracy**	**Ease of Implementation**
Faster RCNN	Not faster	Good	Not easy to implement
SSD	Faster than YOLO	Accurate than RCNN	Hard to implement compared to YOLO
YOLO	Faster than RCNN	Accurate than SSD and RCNN	Easy to implement

3. *Algorithms for tracking detected vehicles*

In addition to vehicle detection, tracking vehicles exceeding speed limits is crucial for effective enforcement measures. The SORT (Simple Online and Realtime Tracking) algorithm provides an efficient method for tracking objects in videos, leveraging both motion and appearance cues to associate object detections across frames. While SORT is widely used and effective, it has limitations, prompting the development of DeepSORT[4]. Deep SORT surpasses SORT by integrating deep learning techniques to enhance tracking accuracy and robustness. By incorporating appearance features learned from deep neural networks, Deep SORT can accurately associate object detections across frames, even in challenging scenarios with occlusions. This advancement enables more precise identification and tracking of speeding vehicles, contributing to enhanced traffic safety and enforcement efforts.

4. *Algorithms for license plate number detection*

Traditional license plate detection methods include edge detection. In that method it identifies areas with a high density of characters as potential license plates[9][10]. But it is inaccurate. Coming to neural networks they offer advantage by directly processing of raw pixel data but deep learning OCR approaches like Tesseract can be computationally heavy and less accurate with distorted images. Optical character recognition (OCR) systems are widely used. These systems typically involve character segmentation followed by classification using techniques like template matching or feature extraction. YOLOv8 models give high accuracy. So the combination of EasyOCR and YOLOv8 gives us high accuracy and efficiency in character detection[11].

III. PROPOSED METHODOLOGY

The proposed system examines all the limitations in vehicle detection, vehicle tracking and license plate number detection from the literature review and improves the system by using the appropriate algorithms for each different phase as specified next.

A. Vehicle detection

Vehicle detection algorithms can be categorized into traditional machine vision algorithms and more recent complex deep learning methods. Traditional methods typically rely on separating a vehicle from its fixed background image using motion detection techniques, such as background subtraction, continuous frame difference, and optical flow methods. Among these methods, YOLO has emerged as a widely-used and effective algorithm for object detection, offering impressive speed and accuracy.

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The latest iteration, YOLOv8, boasts improvements over previous versions, including training on a large dataset with high mean Average Precision and providing flexibility for speed-accuracy trade-offs through various model sizes. For real-time detection requirements and a vast training dataset, the YOLOv8 model is chosen, leveraging its enhanced performance and adaptability.

YOLOv8 highlights an improved architecture that builds upon its preprocessors, tending to limitations and consolidating progressed methods to boost execution. The model leverages different data augmentation strategies to improve generalizability and decrease overfitting, guaranteeing strong detection capabilities over diverse scenarios.

One of the key advantage of YOLOv8 is its high precision in identifying vehicles, accomplishing state-of-the-art comes about on question discovery benchmarks. Also, the model offers real-time speed, making it appropriate for applications requiring speedy decision-making, such as autonomous vehicles and robotics.

YOLOv8 is outlined to be lightweight and effective, requiring less computational assets compared to other models. This productivity makes it perfect for deployment on edge devices, guaranteeing ideal execution without compromising exactness.

A fundamental viewpoint of YOLOv8 is its open-source nature and solid community support. This fosters persistent improvement and change of the show, guaranteeing its significance and flexibility to advancing needs in the field of vehicle location.

The YOLOv8 algorithm for vehicle detection includes a few key steps that contribute to its proficiency and accuracy. At first, the input picture is isolated into a grid of cells, typically 13×13 or 26×26 in size. Each cell is then analyzed to predict bounding boxes around potential objects, along with their class names and certainty scores. To refine these forecasts and dodge overlap, YOLOv8 utilizes a strategy called non-maximum suppression (NMS), which chooses the foremost confident and non-overlapping bounding boxes for each object. The ultimate output of YOLOv8 comprises of a list of bounding boxes with their comparing class names and confidence scores, which can be utilized for different applications like vehicle counting, speed estimation, and traffic analysis.

The Algorithm for the YOLOv8(You Only Look Once version 8) is as follows:

Algorithm (YOLOv8)

Input:
 Image for vehicle detection

Output:
 List of refined bounding boxes with class names and confidence scores
1. Input Preparation:Take an input image for vehicle detection.
2. Grid Division: Divide the input image into a grid of cells, typically 13x13 or 26x26.
3. Prediction: For each cell in the grid, predict bounding boxes around potential objects (e.g., vehicles).Predict the class names (e.g., "car," "truck") and confidence scores for each bounding box.
4. Non-Maximum Suppression (NMS):Apply non-maximum suppression to refine predictions and remove overlapping bounding boxes.Select the most confident and non-overlapping bounding boxes for each object class.Discard bounding boxes with confidence scores below a certain threshold.
5. Output Formation: Form the final output as a list of refined bounding boxes with their corresponding class names and confidence scores.
6. Utilization:The output is used for various applications such as vehicle counting, speed estimation, and traffic analysis.

B. Vehicle Tracking

Object tracking is a critical component in video analysis, requiring the unique identification and continuous tracking of objects across frames. Despite its importance, object tracking faces various challenges such as occlusions, viewpoint variations, and non-stationary cameras. Traditional algorithms like Mean Shift and Kalman Filter have been employed for object tracking, leveraging spatio-temporal image brightness variations and prior forecasts to estimate object trajectories. However, these methods have limitations, such as reliability issues with Mean Shift beyond the neighbourhood region of interest and computational complexity with Optical Flow.

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In response to these challenges, deep learning approaches have gained prominence, with DeepSORT emerging as a popular algorithm for object tracking in conjunction with object detection algorithm YOLO. DeepSORT introduces a novel distance metric based on the appearance of the object, leveraging a dense layer trained on a dataset to generate appearance feature vectors. These feature vectors enable more accurate tracking by capturing object appearances and facilitating robust tracking across challenging scenarios. Through these advancements, DeepSORT enhances the reliability and accuracy of object tracking. DeepSORT provides a unique id for each detected vehicle and keeps track of it making it unique throughout the video stream.

DeepSORT's key advancement lies in its data association approach. Rather than exclusively depending on Intersection over Union (IoU), DeepSORT utilizes a sophisticated association metric that coordinating both motion data and appearance features. This progressed metric is utilized in conjunction with the Hungarian algorithm to match detections over frames precisely. By considering not only motion dynamics but also object appearances, DeepSORT minimizes identity switches and improves the reliability of object tracking.

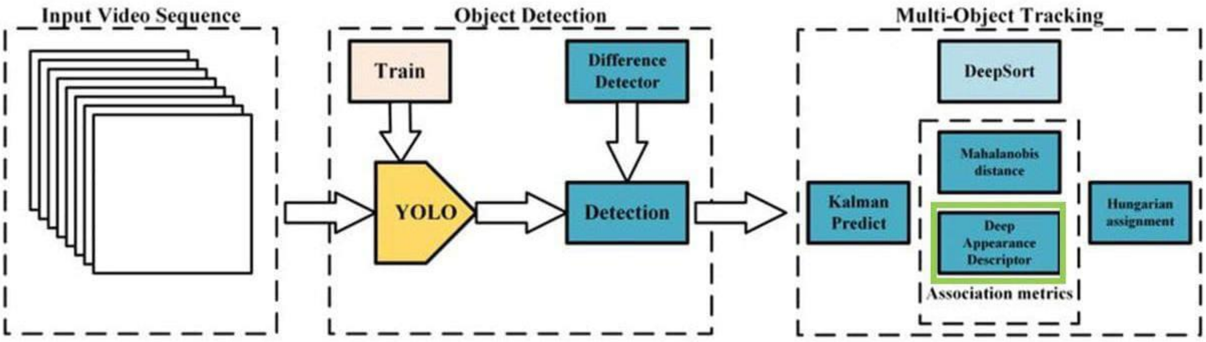

Fig. 1. Working of DeepSORT

Additionally, DeepSORT incorporates a Kalman filter for state prediction, assessing an object's position, speed, and acceleration based on its past state to anticipate its current state considering motion dynamics. This prescient capability guarantees smooth and continuous tracking indeed in challenging scenarios like occlusions or partial visibility.

Overall, DeepSORT's working mechanism includes combining object detection with advanced data association procedures based on appearance features and motion dynamics. This integration results in vigorous and accurate object tracking, making it a valuable tool for different applications requiring precise monitoring and tracking of objects in video streams.

C. Estimation of speed

For each detected vehicle tracker is initiated. Then the location of the vehicle of two consecutive frames is sent to the speed estimate function, where it calculates the speed of the vehicle based on distance between the two consecutive frames and time taken to travel the frames. For this simple Euclidean distance formula is used.

Distance = $\sqrt{[(x2 - x1)^2 + (y2 - y1)^2]}$

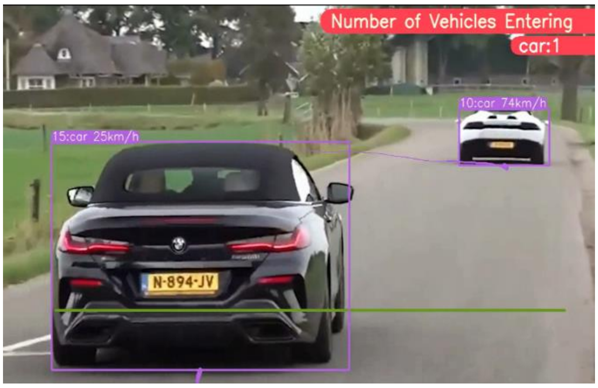

Fig. 2. Vehicle detection , tracking and speed estimation

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D. License Plate Detection

For license plate recognition YOLO, known for its high accuracy and real-time performance, has emerged as a widely used method for object detection, including license plate detection. In this study, the latest version of YOLO, YOLOv8, has been employed to capitalize on its advancements over previous versions. Model is trained by using YOLOv8 in a way to detect the region where the license plate exists on the vehicles.

E. License Plate Recognition

License Plate Recognition relies on Optical Character Recognition (OCR) systems to extract information from printed or handwritten text in scanned documents or image files, converting it into a machine-readable format for further processing. Various OCR techniques employ character segmentation followed by classification. Here we used EasyOCR approach which stands out as the optimal solution for character recognition, uniquely equipped to handle diverse image distortions and deliver high accuracy in real-time scenarios where traditional OCR methods may falter.

That’s why it emerges as a superior choice for character recognition tasks, offering efficient and accurate text extraction capabilities across various scenarios. In this first we convert the image to black and white then we highlight the part of license number. Then using easyOCR the characters are recognised. The approach we used to detect the license number using EasyOCR is as follows.

Algorithm (EasyOCR)

Input:
  Image `img`
  Coordinates (x, y, width, height)

Output:
  Recognized text as a string

1. Extract the specified region from the input image using the given coordinates.
2. Convert the extracted region to grayscale.
3. Use an Optical Character Recognition (OCR) reader to extract text from the grayscale image.
4. Filter and select the most appropriate text based on certain criteria (length and confidence score).
5. Return the recognized text as a string.

F. Alerting control teams

The data collected is processed and stored in a file. The data can be used to monitor the vehicle speeds. By this data we can get to know which vehicles are moving faster and crossing the speed limits.

This data is used to alert the nearby control teams. In our proposed methodology we had used twilio to alert the control teams by sending SMS about the details such as license number and its speed.

IV. ANALYSIS AND RESULTS

After the Training of data from our dataset using the YOLOv8 algorithm both for vehicle detection and license plate detection the confusion matrix are shown below. The graph shows the True Negative, False Positive values that we get after training the model.

The accuracy percentage of confusion matrix for vehicle detection using YOLOv8 is almost 97.98%.

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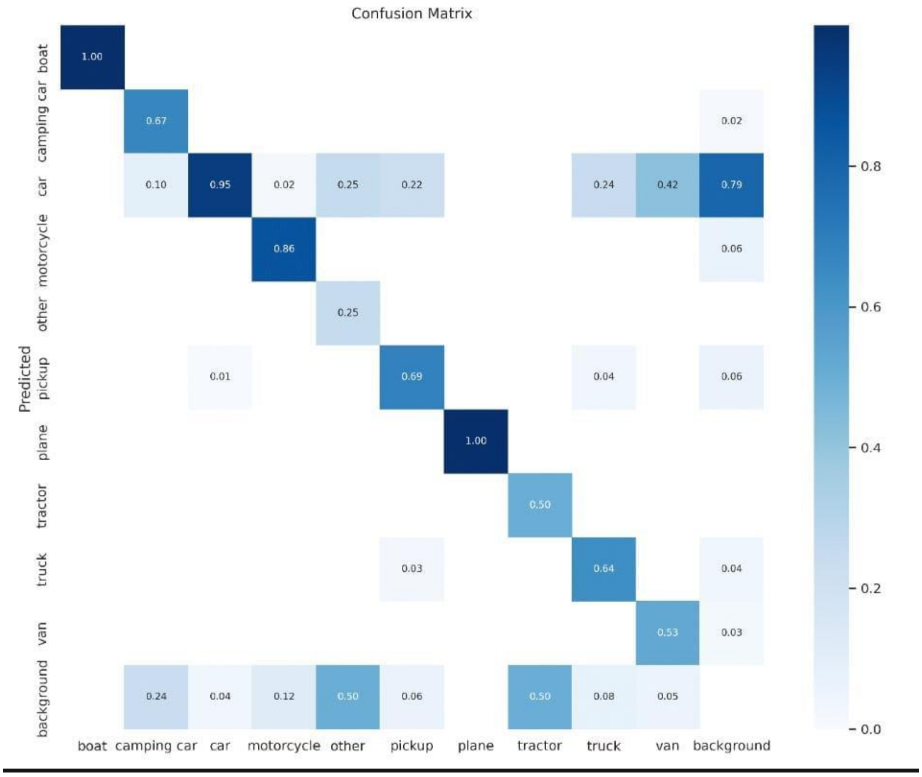

Fig. 3. Confusion matrix for vehicle detection

The accuracy percentage of confusion matrix for license plate detection using YOLOv8 is about 84%.

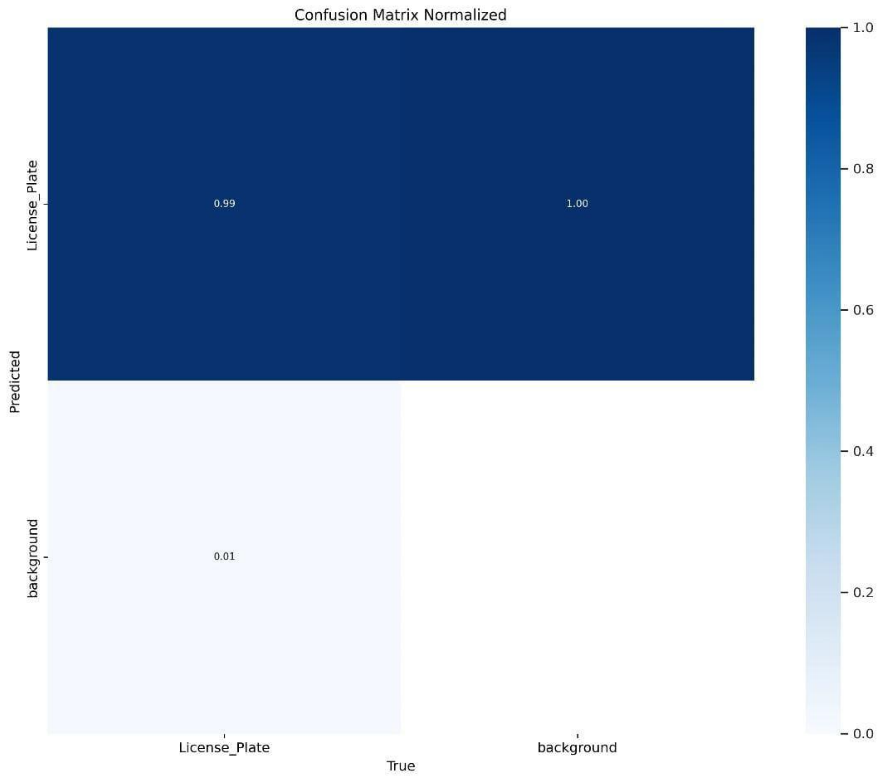

Fig. 4. Confusion matrix for license plate detection

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The mean average Precision and Box loss for the trained data is show below. The Mean Average Precision (mAP) extends the concept of average precision by calculating the average AP values across multiple object classes. This is useful in multi-class object detection scenarios to provide a comprehensive evaluation of the model's performance.

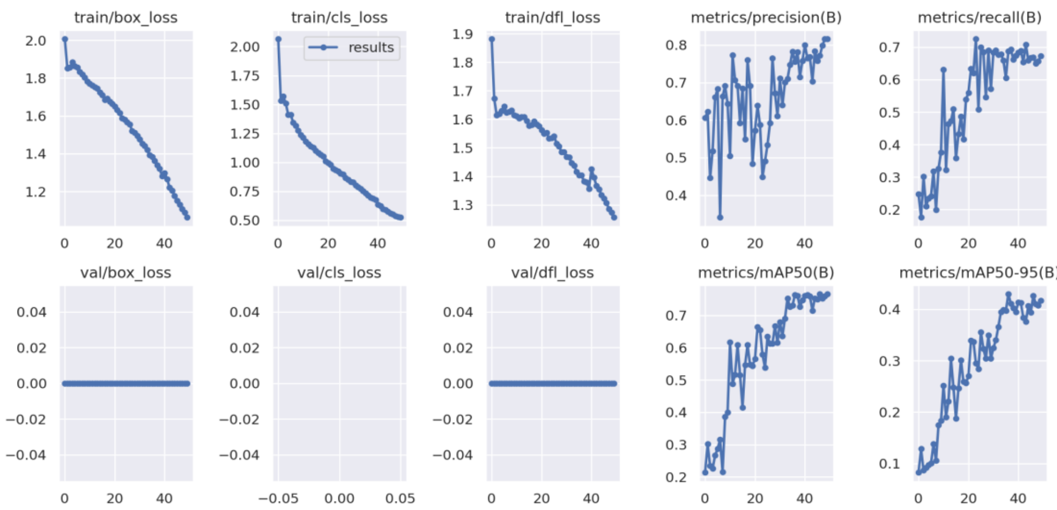

Fig. 5. Mean Average Precision and Box loss

The model performance metrics for YOLOv8x, YOLOv7x, and YOLOv5x based on mAP@0.5 and mAP@0.95 are as follows:

TABLE II
EVALUATION RESULTS OF CHARACTER DETECTION

Model	mAP@0.5	mAP@0.95
YOLOv8x	0.981	0.827
YOLOv7x	0.977	0.711
YOLOv5x	0.978	0.819

These metrics indicate that YOLOv8x outperformed YOLOv7x and YOLOv5x in terms of both mAP@0.5 and mAP@0.95, showcasing superior performance in object detection tasks across different Intersection over Union (IoU) thresholds.

Based on the experimental results the proposed methodology has the F1-Score for vehicle detection ranges from 90.8% to 98.2% across different vehicle classes, whith an overall mean F1-Score of 95.5%. The recall values of the vehicle detection using YOLOv8 vary between 90.1% and 98.9% for different vehicle classes, with a mean recall of 95.3%. And coming to precision, the precision metrics for vehicle detection with YOLOv8 fall within the range of 90.7% to 98.8% across various vehicle categories, with an average precision of 95.7%.

These values indicate the high accuracy, recall and precision achieved by the YOLOv8 model along with DeepSORT in detecting vehicles and tracking them across various vehicle categories. This highlights the effectiveness in object detection tasks of the proposed methodology.

V. CONCLUSION

In summary, integration of advanced machine learning with YOLOv8 for accurate vehicle detection, DeepSORT for robust vehicle tracking and EasyOCR for real license plate recognition Video-based vehicle inspection systems. Our research shows that the accuracy and efficiency of traffic monitoring increases using these state-of-the-art algorithms. Using YOLOv8 provides accurate vehicle identification, DeepSORT provides reliable vehicle tracking, and the combination of EasyOCR and YOLOv8 provides accurate license plate number identification.

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This integration not only improves traffic management, but also has the potential to reduce traffic congestion by detecting speed violations and detailed traffic information. Looking ahead, the success of these technologies in our plan will lead to subsequent and practical research in the field of traffic management and road safety. The information collected by the system can be useful to warn drivers and control groups about speed violations and improve overall safety measures. Additionally, the integration of YOLOv8, DeepSORT, and EasyOCR demonstrates the potential for further improvement of vehicle detection in video, paving the way for smarter and more effective inspection methods. As technology continues to advance, the use of advanced algorithms should create a safer environment and improve traffic flow in urban environments.

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