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Vehicle Detection and Tracking Using YOLOv8 and Deep Learning to Boost Image Processing Quality

Priyanka Ankireddy[1,],V. Siva Krishna Reddy[2,*], Dr.V. Lokeswara Reddy[1,]

[1]Department of CSE,K.S.R.M. College of Engineering (Autonomous), Krishnapuramu, Kadapa, Y.S.R. (District), Andhra Pradesh, India.

2 Dr.V.Lokeswara Reddy, Professor &HoD, Department of CSE, K.S.R.M. College of Engineering, Kadapa, AndhraPradesh India.

*Corresponding Author e-mail id: vskreddy.ysrafu@gmail.com

Abstract: The ability to recognize and track cars is a vital part of traffic surveillance systems, and is critical for the efficient management of traffic and the safety of drivers and passengers. Finding and following the path of vehicles is the primary goal of this research. The goal of this research is to develop a system that can recognize cars in photos and videos automatically. Deep Learning, a technique that may include fuzzy logic, neural networks, and evolutionary algorithms, has various applications, one of which is the detection and tracking of automobiles. We will utilize YOLOv8 and the Kalman filter or the DeepSORT algorithm to follow vehicles throughout the course of a movie using deep learning for this project. This is the main topic of the article. Afterward, the DeepSORT algorithm forms the backbone of the vehicle detecting system. By adding focus loss as an optimization component to the original DeepSORT method, we are able to improve the performance of feature extraction. Therefore, the procedure begins with a series of training procedures applied to photos from the publicly accessible road vehicle dataset. After that, we employ YOLOv8 and the DeepSORT algorithm to follow the vehicle identification model, and their combined efforts show how effective they are. To locate it, one must examine the detection rates achieved by both models on different types of automobiles. The fundamental objective of this study is to develop an automated technique for detecting and tracking autos in both static and dynamic scenes. Once the network model has been trained, it is applied to the analysis of the camera video from the car, and the detection performance is evaluated experimentally. The study's findings show that the technique's success rate in recognizing automobiles has grown to 98.48%. In addition, using DeepSORT as the vehicle tracker results in decreased mistake rates.

Keywords: Vehicle Detection, Image Processing, Vehicle Tracking, Deep Learning, Object Tracking.

1. INTRODUCTION

Both the vehicle information system and the intelligent traffic system make use of automatic vehicle data recognition. Since the beginning of this decade, it has attracted substantial interest from academics because to developments in digital image technology and gains in processing capabilities. Many cutting-edge traffic management solutions rely heavily on automatic vehicle detection technologies [1, 2]. Systems like this include automated vehicle collision detection, lane departure warnings, traffic signal controllers, and traffic density estimators, to name a few. The strain on those in charge of managing the population and its associated infrastructure grows with each passing year. The pace at which the global population is expanding is astounding. As a consequence, manufacturing of automobiles and other mechanical gadgets skyrocketed. However, it's crucial to handle new problems like traffic, accidents, and other situations with extreme caution. In order for humanity to continue making progress toward their objectives, new discoveries and inventions have had to be developed and implemented. Congestion on main thoroughfares and in big cities is a prime example. Some of the solutions used to this issue include a traffic signal and a sign.Autonomous cars, face recognition systems, and picture segmentation are just a few examples of the many real-world uses of computer vision technology [1-3].

2. RELATED WORKS

Vehicle detection technology is analogous to target detection technology. Both vehicle detection and target detection aim to accomplish similar core goals, which may be broken down into the locations and types of targets. Historical data-based algorithms, deep learning-based algorithms, YOLO-based algorithms, and path-following algorithms are the four primary categories of vehicle identification algorithms.

i. Traditional Vehicle Detection Algorithm

Traditional techniques of vehicle detection also make use of a vehicle identification system that is based on a very simple application of machine learning. This system can identify vehicles based on their individual characteristics thanks to the integration of a vehicle-centric algorithm and a machine learning algorithm [4-6]. Conventional techniques for identifying automobiles include frame difference methods, streamer methods, and background modeling techniques [7, 8]. These methods are currently in heavy use. Several more methods exist for detecting vehicles. While such an algorithm may provide very accurate identification results in a controlled laboratory setting, it does have some restrictions in the real world due to factors like lighting and weather [9, 10].

ii. Vehicle Detection Algorithm Based on Deep Learning

R-CNN with slow, medium, and quick speeds R-CNN is a common technique for two-stage target identification [11, 12]. After producing a predetermined number of targets based on regional suggestion, the most notable feature of this technique is the use of a convolution neural network to deal with prospective targets. In order to accomplish sparse sampling, (ER-CNN first takes the original picture as input and uses candidate areas. Once potential areas have been located, a convolutional neural network (CNN) collects features, and a support vector machine (SVM) assigns labels. R-CNN has dramatically enhanced detection accuracy while making the bounds of the algorithm much more controllable compared to the gold standard target detection technique [13, 14]. Faster R-CNN [15, 16] is an improved version of Fast R-CNN that speeds up region formation by using the properties of an RPN network. To begin, it checks the candidate box's collection of features against a multi-task loss function to ensure it's enough for the detection job at hand. If that's the case, it moves on to step two. This allows us to give a name to the thing we've detected.

iii. Vehicle Detection Using YOLO (You Only Look Once)

Initially, YOLO [17] approached object identification as a regression issue inside a single neural network. Due to its better performance, the approach has quickly become the gold standard in the field of object detection. Consistent development since YOLO's inception has resulted in five generations of the architecture, from YOLO [18] through YOLOv2 [19], YOLOv4 [20], and YOLOv8 [21]. The original YOLOv1 combined the three processes of feature extraction, object localisation, and classification into a single operation. Despite its high mAP, this network was

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SOTA in terms of mean average accuracy. The foundation of the first YOLO design was a series of convolutional layers followed by maxpool layers. The network is now adaptive to picture resolution thanks in large part to the elimination of the fully-connected layer that existed at the very end of YOLOv1. The third iteration, dubbed YOLOv3, was created by building upon and refining the features introduced in the prior two versions. Two prior generations, ResNet [22] and the feature-pyramid network (FPN) [23], served as inspiration for this new generation's architecture. The COCO-2017 dataset is amenable to rapid models such as YOLOv5, the DeepSORT method [24], single shot multibox object detection (SSD) [25], and Center Net [26], all of which are capable of achieving comparable mAPs. It is possible to gather the mAPs using any of these models in conjunction with YOLOv3. This form of tracking relies on precise detection and the lack of occlusion [27], since a single camera can only catch one side at a time. The difficulty in correctly identifying these components has, to some degree, aided the development of deep learning models that can recognize objects despite partial occlusion. Even if the item is partly concealed by a bigger one, modern CNNs can still generate an accurate prediction of it. Many deep learning networks, such as Faster-RCNN [20], SSD, and YOLO, have been used in the context of real-time MOT. The purpose of this research is to evaluate the efficiency of YOLOv5 and YOLOv8 in order to create a real-time method for monitoring autos that use multi-threading techniques to handle several video streams on a single GPU [28].

iv. Vehicle Tracking

In order to find a picture sequence that best matches an object, conventional tracking techniques first detect objects in the early frames, and then explore the surroundings for characteristics that correlate to those items. Conventional detectors including contour-based target identification [29], the Harris corner detector [30], symmetric integral and fluctuating transform (SIFT), and feature point-based approaches [31,32] all suffered from the same problem of false detection. Better performance was achieved, however, by using DL models to identify the objects first, and then going to match features through the traditional tracking approaches. We use DeepSORT, a tracking methodology, in combination with low-confidence track filtering, to implement the strategies presented in [33] for tracking through detection. Consequently, the number of false positives produced by the original DeepSORT algorithm decreased. Recently, [34] proposed using 3-D constrained multiple kernels to follow objects recognized by a YOLOv5 network. The use of Kalman filters made this possible. The development of more sophisticated tracking algorithms has led to a notable improvement in object tracking accuracy in recent years. However, these methods need a large amount of computing resources to execute. Our study provides a straightforward approach to object-centroid tracking for monitoring the detection efforts of YOLO-based DL networks over several lanes of traffic in real time. This study also evaluates the differences between YOLOv5 and YOLOv8 in terms of performance to help develop a real-time system for monitoring cars that can handle several video streams on a single GPU by using multi-threading methodologies [35].

3. PROPOSED METHODOLOGY

The suggested procedure consisted of three separate actions. To begin, YOLOv8 takes N frames at consistent intervals to locate moving vehicles for analysis. To gather and evaluate characteristics of objects, we next utilize K-

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means clustering and the KLT tracker to follow the corner points as they travel over N-frames. The article concludes by detailing a dependable method for assigning vehicle trajectories to each of the highlighted bounding boxes. This method ensures that the labels applied to the trajectories of individual vehicles are unique from one another. You can view a diagram of the suggested solution architecture in Figure 1.

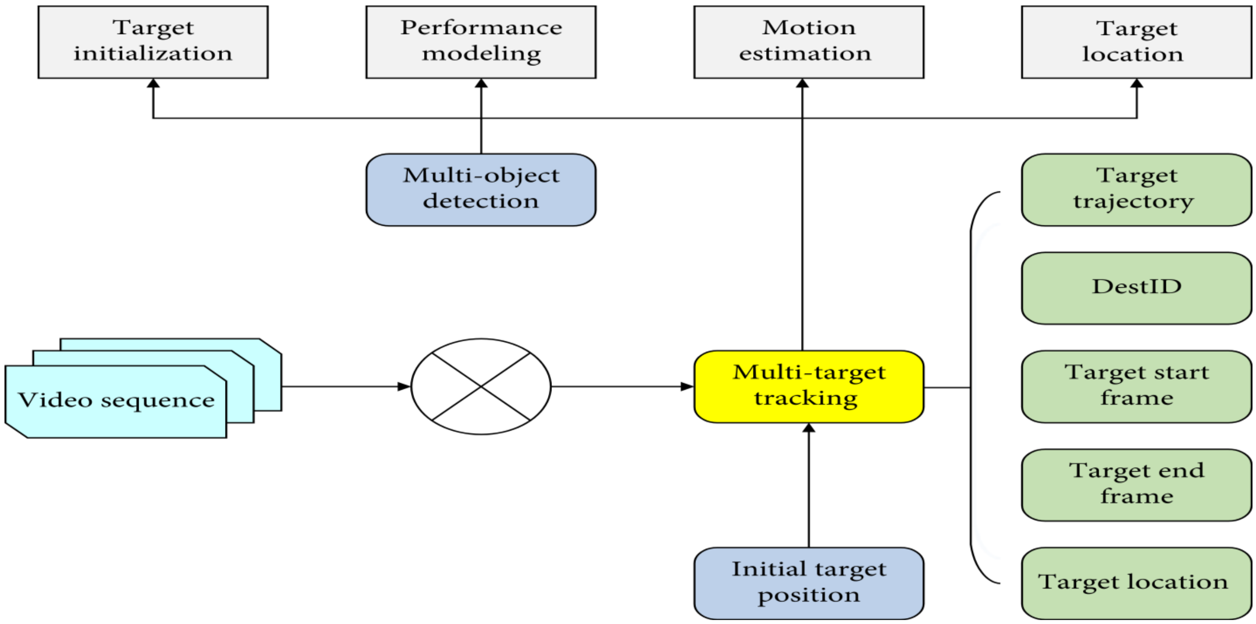

Figure 1. Architecture of vehicle detection and tracking model

i. Vehicle Detection

To expedite the detection procedure, we use the YOLOv8 architecture and transfer learning in this study. Our hard work has finally paid off with the completion of this layer. In [22], you can find a more thorough description of the transfer learning approach. [22] Our choice to use transfer learning meant that the Resnet-50 [16] would serve as the basis for our neural network model on the YOLOv8 platform. To further understand how the YOLOv8 and DeepSORT algorithm models for vehicle recognition work, consider the block diagram shown in Figure 2. This shows the model's inner workings in great detail. The convolutional neural network ResNet50 was trained using over a million photos from the ImageNet dataset.

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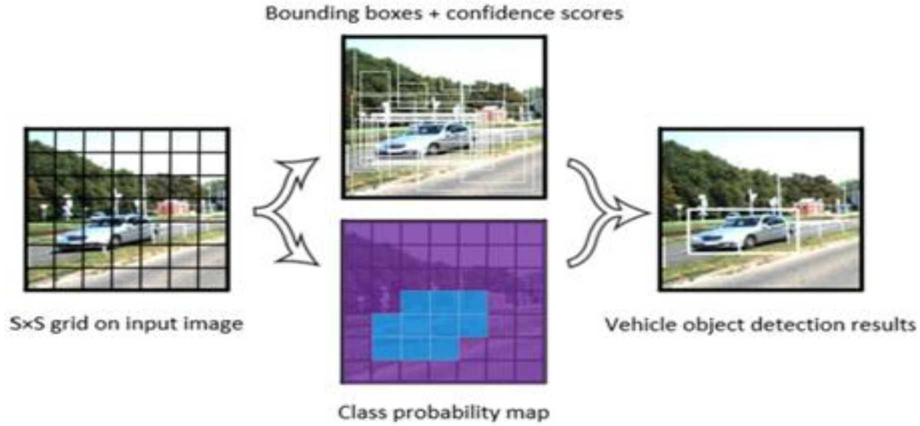

Figure 2. Architecture of YOLOv8 and DeepSORT algorithm vehicle Detection models

ii. Vehicle features refinement and clustering

At this point, we don't only group automobiles together, we also separate them from their backgrounds by wiping them clean. Processing speed and precision in matching features are both increased by optical flow tracking. As a result, we monitor the feature points between frames f and f + 1 using the optical flow Kanade-Lucas method [2]. Combining two successive images creates a new set of optical flow vectors, V, with elements Vi = (Mi, i), where S and are defined as follows:

$$M_i = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (1)$$

$$\theta_i = Arctan\left(\frac{y_2 - y_1}{x_2 - x_1}\right) \quad (2)$$

The notation for the previous frame's X and Y coordinates is X1 and Y1, whereas the notation for the following frame's X and Y coordinates is X2 and Y2. Displacement magnitudes and angles are represented by the vectors M and, whereas each value in V represents a single corner point Pi seen between frames f and f+1. The detecting noise is a common reason why trackers fail. Due to the short amount of time (9 frames) that noisy detections may be followed, this study only considers a foreground detection to be a vehicle object if it has been tracked for a sufficient amount of consecutive frames. Then, k-means clustering is used to group the remaining automobiles in the image's foreground. You may get further information at [36].

iii. Vehicle Counting

After identifying the most trustworthy characteristics, we put them into their own categories for each car. We assign unique ID numbers to each of these vehicle components and track them until they are no longer visible.

4. IMPLEMENTATION OF VEHICLE DETECTION AND TRACKING USING YOLOv5

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Small target objects, certain size scaling in the process of continuous detection, the complexity of the vehicle environment, too many targets in a single image in the dataset, and overlapping of targets are just some of the difficulties encountered when attempting to detect the vehicle target using the vehicle dataset. Furthermore, the effectiveness of a vehicle identification system relies on achieving a number of criteria, making it crucial to use the proper detection technique.

i. Analysis of Algorithm Selection

Think about it In Table 1, we compare the detection rates and accuracy ratings of a number of widely used target identification techniques. Table 1 shows that Faster R-CNN has a higher detection accuracy than other one-stage detection networks, but a considerably different detection rate.

Training Set	Algorithms			
	FRCNN	YOLO	DeepSORT	YOLOv8
VOC2007 + 2012	0.765	0.772	0.823	0.801
VOC2007 + 2012	0.958	0.963	0.986	0.965
VOC2007 + 2012	0.865	0.871	0.897	0.899
VOC2007 + 2012	0.784	0.789	0.864	0.897
Training Set	2010	2010	2010	2010
MAP	78.4	68.8	83.3	98.48
FPS	21	49	43	54

Table 1. Comparing the detection-rate and accuracy-rate of a number of popular target-detection algorithms.

ii. Designing the Model

a. Initialization Operation of Candidate Box

The most important part of the detection process, network training, requires initialization of the network model's parameters.

b. Detection Module of Network

YOLOv8, supported by DarkNet-53, can parse the input data and pull out useful features. The network is able to extract more feature information because of its deep-level structure. But as seen in Figure 3, there are also problems for the network at extremely deep levels.

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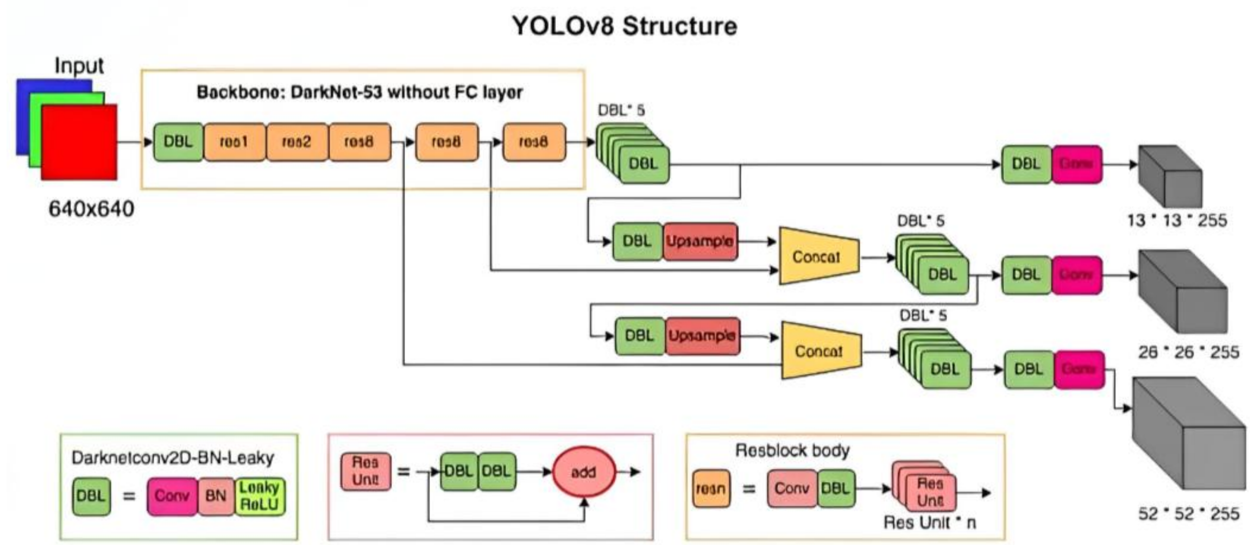


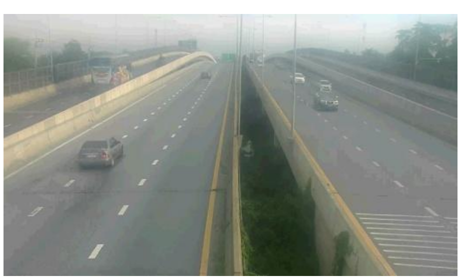
Figure 3. Network architecture of YOLOv8 with a backbone ofDarkNet-53.

5. EXPERIMENTAL RESULTS AND ANALYSIS

This section primarily compares the speed and performance of the proposed vehicle recognition and tracking method against that of current high-performance CF trackers using publicly accessible datasets, and analyzes the results. In this subsection, we will compare the performance of the proposed algorithm for vehicle recognition and tracking to that of the high-performance CF trackers.

i. Dataset selection

When developing a system for target identification using a deep learning technique, the selection of an appropriate dataset is a crucial and challenging step. In this study, we are developing a model and have chosen to train it using the BDD100K picture dataset. Figure 4 displays some representative data from the set. All of the images included in the offered data were taken from a moving vehicle on a public route. These pictures show a broad variety of vehicles, as well as human and non-human victims. We only shot at six of the 10 target categories available to us. Vehicles, buses, passengers, trucks, motors, and bicycles all count as means of transportation.



(a)

(b)

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(c)


(d)

Figure 4. Data images of BDD100K

ii. Processing of Data

Both a "picture" and a "label" portion make up the downloaded data. All the fresh information was actually saved as JSON files, and each JSON file does indeed map to an image with the same name.

iii. Detection of Model

To complete the process of building a vehicle detection model, one must first train the model before loading the trained weight onto the model to carry out the actual detection. The training technique may make use of the parameter sets shown in Table 2. Target identification throughout the three backbone network layers is where YOLOv8 often shines in both training and detection. These are the lowest, middle, and highest tiers of the network's central infrastructure.

Models	mAP/%	Vehicle Detection and Tracking/FPS	Memory size
FRCNN	94.4	20	200.3
YOLOv5	86.7	30	243.6
DeepSORT	95.5	35	15.7
YOLOv8	98.4	39	15.9

Table 2. Parameter settings of the training process on various models

iv. Result Analysis of vehicle detection and tracking

To guarantee a high-performing trained model, it's important to choose a few parameters before beginning the detection network training process. After applying our improved YOLOv8 algorithm, we compared its performance to that of other state-of-the-art object recognition methods, such as Faster R-CNN, YOLOv5, the DeepSORT algorithm, and YOLOv8 using the same configuration environment and dataset. This was done to verify that the improvements we had seen with our new YOLOv8 algorithm were really the consequence of that method. We capture FPS using an NVIDIA GTX1660Ti graphics processing unit. Table 4 displays the results for both the Track Maintenance dataset and the BDD100K dataset.

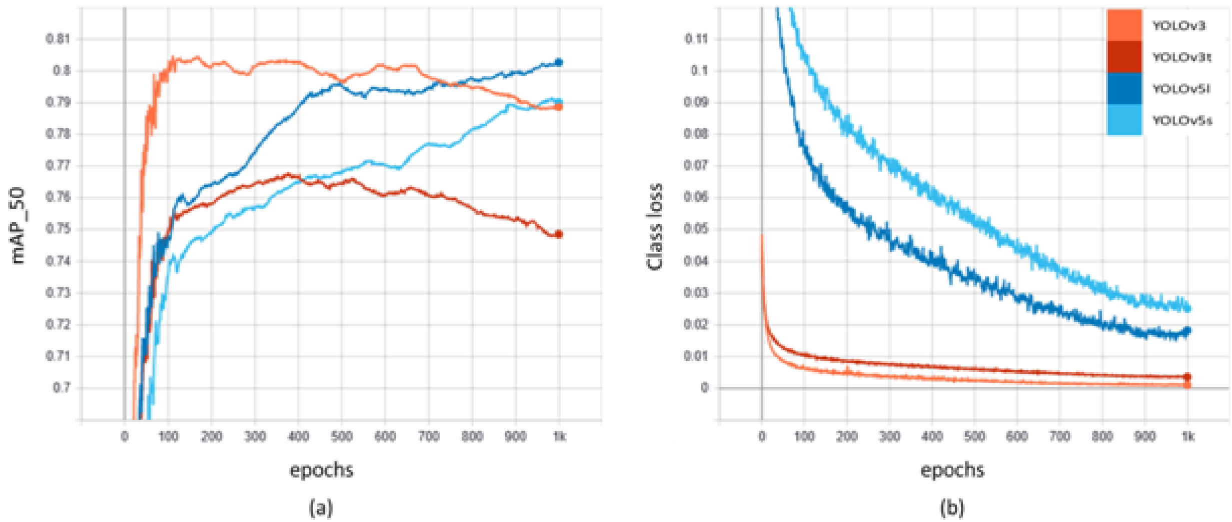

figure 5. Training results of FRCNN, SSD, YOLOv5t, YOLOv8l, and YOLOv8s on the BDD100K dataset.
(a) mAP at IoU = 50 (b) loss of classification.

We can see from figure 5 that our method outperforms Faster R-CNN, YOLOv5, the DeepSORT algorithm, and YOLOv8 in terms of recognition accuracy. Figure 5 depicts the monetary value of loss when training is complete.Adjusting the learning rate in accordance with the breakpoint continuation strategy is necessary to keep training going, even if the final results won't be that different from the second portion of Figure 6.The detection box scores in Figure 6 remain constantly above 0.7, indicating that the model can correctly categorize the great majority of cars. The detection impact of trucks is around average, that of bus types is a little lower, and that of detection boxes is typically minimal. In Figure 7, we can see how well the network can recognize both people and bicycles.

Figure 7 demonstrates that although the detection model does not substantially affect either the person or bicycle categories, the human category scores much higher than the bicycle category scores. The extension of available box possibilities and the subsequent increase in "person" detection box accuracy are other noteworthy developments. Figure 8 demonstrates the detection method's outcomes, providing evidence that the bus category detection effect is general. During the course of the inquiry, this evidence may become apparent.

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Figure 6. Detection of vehicles on the road from different camera views by day scenes and night scenes

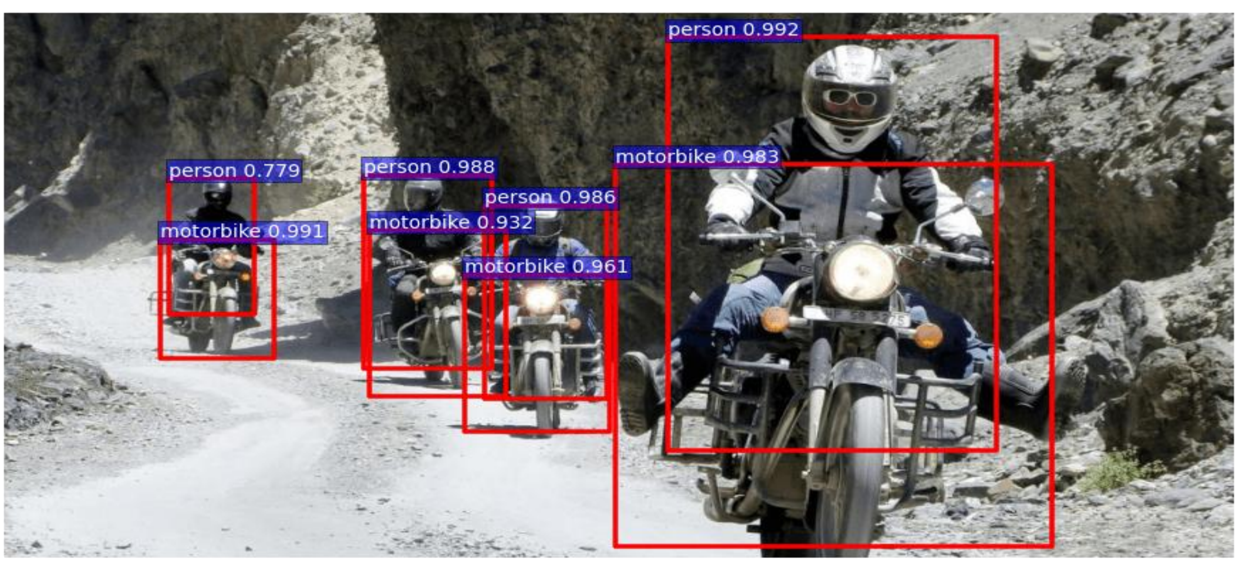

Figure 7. Illustrating the detection on bike category and person category

Figure 8. Vehicle detection on bus category

6. CONCLUSION

In this study, we use deep learning to automate the process of music production. We also suggest updating the YOLOv8 and DeepSORT algorithm to better detect racers and their gear. We apply the YOLOv8 and DeepSORT algorithm extensively to boost the classification loss and mAP at IoU of the different sets of training data. Newer versions of YOLO, YOLOv8, and the DeepSORT algorithm allow for faster convergence and more precise identification of obstructed vehicle objects and tiny vehicle objects. These benefits are cumulative. The experimental findings for the recently developed YOLOv8 and DeepSORT technique demonstrate a great degree of resilience. By applying these algorithms, we are able to perform thorough inspections of construction workers and equipment, addressing the problem of low detection accuracy for complex scene issues like occluded vehicle objects and small vehicle objects, and meeting the practical requirements for vehicle detection in the context of track construction safety. The findings of this work provide credence to the practical use of intelligent detection tools and lend momentum to the thorough investigation and advancement of track safety vehicle detection technology. In terms of both vehicle identification and tracking accuracy, the combined use of YOLOv8 and DeepSORT was shown to be the most successful solution based on the metrics that were examined.

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