

International Journal of Advanced Research in Computer and Communication Engineering

ISO 3297:2007 Certified $\,\,st\,$ Impact Factor 7.39 $\,\,st\,$ Vol. 11, Issue 7, July 2022

DOI: 10.17148/IJARCCE.2022.11757

Vehicle Detection and Tracking

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Abstract: Traffic surveillance may monitor and collect data about the flow of traffic on road networks, which is necessary for a number of applications in intelligent transportation systems (ITSs). One of the key issues with traffic monitoring is the accurate and quick detection and counting of vehicles.

Vehicle detection and monitoring have several applications. In order to enhance the infrastructure for everyone's comfort and convenience, public and private organizations may try to comprehend the traffic that passes through a particular area. Road widening, the placement of traffic signals, and the installation of parking spaces are a few examples of projects where traffic study is crucial.

In the past, manual tracking and identification were employed. Somebody will be posted there to count the vehicles and record their classifications. Sensors have been employed recently, although they only address the counting issue. Vehicle type cannot be determined via sensors

Keywords: Vehicle Detection, Deep Learning, DeepSort, YOLO, Video Processing.

I.INTRODUCTION

Despite the fact that it continues to result in unfathomable harms like over a million deaths, 20–50 million injuries, and trillions of dollars in losses annually worldwide, transportation remains the foundation of modern society and economies. The inductive loops used in conventional methods of detecting and monitoring road traffic provide some fundamental information on average speed, vehicle occupancy, and traffic flow. Real-time traffic control and monitoring cannot be provided by conventional methods. The transportation industry is only one of the industries that deep learning has the potential to disrupt. Deep learning techniques for automated traffic monitoring with applications in the detection of traffic congestion, road safety, and many more are included in the approaches for road transportation.

II. LITERATURE SURVEY

We have mentioned formerly that avenue transportation while connecting people and economies reasons essential damages to people, their fitness and lives, the economies and the planet environment. Traffic congestion caused by way of weather conditions, construction work, and other unforeseeable events alongside the roads, can restrict the efficiency of other services and reason feasible damages in urban cities. As cities and societies grow larger, it is important to come up with greater sensible solutions to assist their infrastructure. Intelligent Transportation System (ITS) is where ICT meets traffic management and transport to make smarter, extra knowledgeable decisions and enhance the first-class offerings provided by means of metropolis authorities Inductive loops are amongst the earliest strategies to measure road traffic.

Ali et al. [1] used inductive loop sensors to detect and becounted numerous automobile lane-less roads. They developed a couple of loop gadgets with a new shape for inductive loop sensors. Their answer was once in a position to sense vehicles and divide them with the aid of type. During testing, the system provided accurate counting of motors despite the heterogenous traffic conditions.

Jeng and Chu [2] combined inductive loop signature records with WIM data in their proposed solution. They aimed to track heavy vehicles by making use of IDL locations unfolding all over the network hence not proscribing the monitoring manner between two WIM stations.

Bhaskar et al. [3] an indicative-loop-based answer to controller site visitors lights. The solution addresses scenarios like reducingcongestion in a particular lane, using radio transmitter-receivers to make methods forpublic carrier cars such as firefighting and ambulance. One of the most common strategies for object detection is You Only Look Once (YOLO). The algorithm was introduced and outperformed different detection strategies in speed and accuracy. Since then, it has been under continuous enhancements to enhance itsperformance

According to Bochkovskiy et al. [4] YOLOv4 achieved exexcessive-performance compared with state-of-the-art object



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detection methods Naturally, such performance encouraged researchers to make the most its potential in transportation DeepSORT is the latest monitoring algorithm, extending SORT (Simple Online and Real-Time) tracking algorithm. The original algorithm was developed considering MOT task. With the foremost intention of supporting online and realtime applications. This means that the tracker partner detected objects from previous and current frames only.

Gao et al. followed the monitoring by detection paradigm. For their MOT, they used CNN and an attention module to perceive salient objects in visitors scenes. The approach proved to be aggressive with state-of-the-art methods. Gunduz and Acarman proposed another MOT algorithm which used CNN-based method as an alternative of confident- based strategies to extract bounding boxes. They performed data association by using solving min-cost flow problem assuming that motors action differs from other objects.

III METHODOLOGY

Deep Learning algorithms gaining popularity almost inall fields such as health care to predict patient disease condition, road traffic monitoring etc. To monitor trafficor to detect vehicle YOLOV4 has achieved highestvehicle detection rate but sometime this algorithm will give false detection rate and to overcome from this problem author of this paper adding DeepSort algorithm which will track actual presence of vehicles from video frame predicted by YOLOV4 so the false prediction perform by YOLOV4 can be avoid by using DeepSort algorithm.YOLOV4 and DeepSort get trained on 3 different datasets such as COCO, Berkeley and Dash Cam dataset. Author has experiment with this models by using real road traffic data obtained from Dash Cam but we don't have such dataset so we are using traffic video from Youtube.In propose paper video will be input to application and then application will extract frame from videos and give input to YOLOV4 for vehicle detection and detected vehicle frame will be further analysed by DeepSort algorithm to track vehicle and if vehicle tracked then DeepSort will put bounding box across tracked vehicle and increment the tracking count.

Detection

The detection in our model is performed using YOLOv4 detection algorithm. We choose YOLO because of its speed and accuracy especially with relatively larger objects. Due to the nature of our data, we believe that YOLO is a suitable choice.



Figure.1: YOLO V4

The architecture is made up of several components, but in general, they are as follows: The input, which comes first, is essentially the collection of training images that we will feed the network. The GPU processes these images inparallel batches. The Backbone and the Neck follow, doing feature extraction and aggregation. Together, the detection neck and detection head are referred to as the object detector.

Finally, detection and prediction are carried out by the head. The Head is principally accountable for the detection (both localization and classification).

Tracking

For the purpose of tracking, we are deploying DeepSORT, the enhanced version of the algorithm where the association metric issubstituted by an informed metric integrating motion and appearance information using Convolutional Neural Network

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Performance Metrics

We utilised precision, a well-known criterion, toassess the detection models in order to evaluate the detection outcomes. Follow is the definition of precision.

Precision = TP/TP (TP+FP)

The definitions of True Positive (TP) and FalsePositive (FP) are as follows:

True Positive (TP), which is the number of positiveobservations that the model predicts as positives.

False Positive (FP), or the proportion of negativedata that the model incorrectly interprets as positives

IV. EXPRIMENTAL RESULTS

Generate & Load YOLOv4-DeepSort Model: using this module we will generate and load the YOLOV4-DeepSort model

Upload Video & Detect Car & Truck: using this module we will upload test video and then apply YOLOV4 to detect vehicle and this detected vehicle frame will be further analyse by DeepSort to track real vehicles

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Figure 5 Load Model

Figure 6 input Video









Figure 9: Accuracy and precision



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V. CONCLUSION

The systems which have been proposed till now are intended to recognize simple human action such as walking, running and many more butnot suitable for crowded area. System which has been proposed is able to recognize unusual human action from crowd and action accordingly using motion influence map and OpenCV. The precision rate is bit higher than other and less researches have been made over this concept. Proposed system is able to work for Prior Appraisal against Crime. The accuracy is 96.42 % which is good enough for recognizing unusual activity in complex backgrounds. The proposed system is capable enough to efficiently recognize the unusual human activity from crowd by using OpenCV and Motion Influence Map, which enhances the accuracy and proficiency of the system up to a great extent. The Unusual Crowd Activity Detection can be implemented in various public places for prior and crime notification that enhances the casualty management. But accuracy is often important which requires enhancing for developing an ideal system that can be implemented practically.

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