"AN EXPLORATION OF DETECTING METHODS FOR KEEPING TRACK OF AUTOMOBILE TRAFFIC"

Dr.M.Rajaiah,Dean Academics & HOD, Dept of CSE, Audisankara College of Engineering and Technology,Gudur.

Prof.V.Sreenatha Sarma,Dean ICT,Dept of CSE, Audisankara College of Engineering and Technology,Gudur.

Mr.S.Satwik, UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

Ms.T.Thanusha, UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

Ms.V.Hemalatha, UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

Ms.D.Rachana Pravalika, UG Scholar, Dept of CSE, Audisankara College of Engineering and Technology, Gudur.

ABSTRACT:

General traffic administration as well as infrastructure design may benefit from real-time vehicle surveillance on motorways, roads, and streets. This study introduces Traffic Detector ,a technology that makes use of deep learning methods to automatically monitor and classify vehicles on roads using a precise and stable camera. Despite being a well-established area visual programming research, improvements in neural networks for object recognition and categorization, particularly in the last years, made this area even more intriguing owing to efficacy of these methods. It is concentrated on region-based approaches like R-CNN (Region-based Convolutional Neural Network) and regression-based methods like YOLO (You Only Look Once) and also provided each enhanced versions in the subject of motor identification is being tackled by the quickly expanding domain of supervised learning approaches. Last but not least, we have a traffic offence detection module in place that examines traffic patterns and identifies various traffic offences in real-time. The Deep Neural Network (DNN) module of OpenCV accustomed implement the complete system. With excellent accuracy, We have indeed been fortunate in locating automobiles on the roads using YOLOv4. We used a quick YOLOv4-tiny model for motorcycle riders without helmets. Real-time vehicle tracking is accomplished using Deep SORT algorithm. For vehicle detection, YOLOv4 achieves a precision of 89%, while for helmet detection, YOLOv4-tiny achieves a delicacy of 96%. YOLOv6 97%. The backbone, neck, and head are the three crucial components the majority recent iteration, known as YOLOv5.YOLOv7 is anticipated to overtake YOLO v4This review paper aims to advance sophisticated deep learning frameworks for real-time vehicle detection.

Keywords*:* Deep learning, deep Sort Algorithm, Vehicle detection, R-CNN versions, YOLO versions, Object detection.

Introduction:

The volume of automobiles on the planet is growing quickly. The proportion of automobiles made in the last few years is way more than 70 million per year, according to data from the International Organization of Motor Vehicle Manufacturers This number is rising very quickly, and so are the amount of travel miles. This explosion in the level of transferring automobiles raises a wide range of challenges. Infrastructure, economic, and environmental management. To carry out the experiments, researchers are trained and evaluated on benchmark datasets such as KITTI, UA-DETRAC. The categorization of vehicles is then suggested using two efficient models (CFNN and Vector-CFNN) and a communication over a network fusion approach.

In our tests, the suggested technique achieved a precision of 90.45% on the Beijing Institute of Technology public dataset. The suggested YOLO-CFN and YOLO-V CFNN vehicle classification techniques' mean average accuracy and F-measure (F1) on the GRAMRTM data set are 99%, superior to those who use other techniques. Three methods of computer vision-based vehicle recognition algorithms set them apart: the motion-based method, the manually created feature method, and the supervised learning method. Motion-based techniques, for instance, structure separating, reference removal, and Optical Flow, separate moving objects from a static background based on their motion characteristics. Simple approaches for extracting the features based on handcrafted features gradients with an oriented histogram (HOG) One last strategy depends on reinforcement learning and employs a programmed a dnn that can accomplish precision tasks without the aid of a human when extracting features, such as R-CNN, fast R-CNN, faster R- CNN, mask R-NN, and mesh. Two-stage approaches are region based and include R-CNN. Using a focused search strategy to find the items in a photograph on a GPU, R-CNN was created to generate candidate regions. R-CNN was indicated because R-computing CNN's costs for screening as well as mentoring the image are high. It takes numerous places of significance from the source photo and extracts features from them. These extracted region suggestions are then sent to a fully convolutional network architecture.

A region proposal network (RPN) that receives end-to-end training and produces high quality region proposals got applied used to replace the slower RCNN algorithm. Faster R-CNN for object segmenting events is made possible by a system called Mask R-CNN. This framework is also utilized to predict object2 masks as a fresh branch, and it will train concurrently with the branch already in place for box-bounding identification. The goal of Mesh R-CNN is to forecast 3- dimensional network of triangles for detecting obstacles in real-world photos. There are currently only a few trials using mesh R-CNN in vehicle detection systems. Regression-based techniques, which including YOLO, YOLOv2, YOLOv3, YOLOv4, and YOLOv5, are a sort of one stage method. By detecting the input image only once, YOLO frame detection simultaneously accurately forecasts the anchor boxes and the class probabilities for these boxes, making it quickest and therefore most approach to real-time detection. Other detection techniques take longer than YOLOv2, and YOLOv3 can also be employed for small-scale vehicle objects. YOLOv4 is implemented use new tools for faster operation speed. A fresh PyTorch tutorial framework called YOLOv5 has been created for the advancement of object detectors. Although an article about YOLOv5 has not yet been released, there are tutorials that can be trained using customer datasets.This review paper reviews research related to detecting automobiles in real time. This provides a description of the concept detecting procedure.

The previous methods of vehicle recognition are as explained in. In the experimental findings from the studies are reviewed along with a comparison table. The usefulness of this review is highlighted in the final,Numerous techniques for monitoring automobiles rely on the qualities. A technique based on features dubbed scale-invariant feature transform (SIFT) and optical flow was used as a follow-up by Wang et al. An method called SIFT methods to retrieve attributes from photographs. The style of movement of the picture objects between two successive frames known as image sequences, is brought on by the movement of the object. Numerous techniques for automobile monitoring rely on the qualities. A technique based on features dubbed scale invariant feature transform (SIFT) and optical flow being employed as follow-up by Wang et al. An method called SIFT utilizes to recover attributes from photographs.

The style of movement of picture objects amid consecutive sets in a row known as In image sequences is brought on by the movement of the object. David Lowe created the scale-invariant feature transform (SIFT) in 1999 as a method of object recognition to find, define and compare regional characteristics in images.A few examples of applications are match moving, picture stitching, object identification, autonomous planning and guidance, and 3D modelling, gesture recognition, and video tracking.

Objective Of The System:

By studying the relevant methods from the preceding section, this section collects works on vehicle detection.Both conventional using ml algorithms and the deep learning technique known as representational machine learning are employed to construct vehicle identification systems. Traditional methods only have a few libraries to pick from and require human expertise to choose features. Deep learning methods are more popular than machine learning techniques because they can address an issue completely. When suggesting a mechanism for vehicle detection, the majority of the articles that use a deep learning-based approach will be examined in this article. Table I presents synopsis of the advancements in innovation used in paper evaluation.

Existing System:

R-*CNN*: The region-based series first series is R-CNN, or region-based convolutional network. To increase the precision of map, Ross Girshick released this detection technique in 2014. (Mean average precision). This plan combined two important concepts. For the purposes of segmenting and localization objects, it initially creates region recommendations using a large capacity convolutional network. Another method used to improve domain-specific fine-tuning performance is pre-training for labelled data challenges during training. Because it combined region suggestions, which are components of the source image, with a convolutional network, it was given R- CNN. The following is how the R- CNN framework functions, First, a select search approach is utilized to provide region-based proposals among alternative proposal methods (such as abjectness, category independent object proposals, limited parametric min-cuts, etc.). The following one is to compute feature vectors using a CNN for each wrapped proposal. The source picture must be converted to a fixed pixel size when computing features using forward propagation. The outcomes of scoring each method vector are then categorized using liner SVMs. Non- max suppression helps to solve the overlapping problem and create the corresponding bounding box. Based on the ILSVRC2013 dataset and the PASCAL VOC datasets, the tracking task is assessed. Despite the outstanding outcomes, the computation is not shared, and it moves at a slow pace. SPP nets (spatial pyramid pooling networks), which cannot be updated with convolutional layers, are utilized to increase the acceleration of R-CNN [22, 23] Fast RCNN: In the second series, fast R- CNN fixed the R-CNN and SPPnets' weaknesses. Ross Girshick and colleagues presented this new paradigm in 2015. The advantages of this architecture include better detection desired output value to the previous series, the chance to train on all network layers while using multi-task loss, and the helps to retrieve the methods with no needing to store them on disc.

Proposed System:

For YOLO, tracking is a straightforward regression problem that uses an source image to teach bounding box points and class possibilities. Each image is given a S-by-S grid by YOLO, and each grid forecasts N bounding boxes. YOLO uses the item tracking mechanism to track and follow real obstacles in pictures or videos. Joseph Chet Redmon is the one who truly invented the YOLO framework. With count of 45 frames by a second (fps), YOLO has the advantage of being very quick and more powerful for real-time applications. Tiny YOLO, a variant of the YOLO architecture that uses 9 convolution layers and can operate at a higher framerate, is a quicker version but has poor accuracy. Its open source implementation processing may commonly accomplish image illustration across its network. The YOLO framework is extremely quick, reliable for both real-time detection applications and autonomous car driving systems. The source image is divided into a S x S grid, with each grid overseeing identifying an object. The network provides an offset value for the bounding-box and class possibilities for each bounding-box that is taken in each grid. The specified bounding boxes are then utilized to locate the item in the picture that has a class possibility over a predetermined threshold. Most bounding boxes in a cell area can detect several objects. To leave just the highest probability bounding boxes, undesired bounding-boxes are deleted using non-max suppression methods. The YOLOv1framework produced superior outcomes to other detection techniques. Dark net is an open source, high-performance neural network implementation framework. It can be combined with CPUs and GPUs and was written in C and CUDA. Darknet helps sophisticated DNN implementations. The first repetition of YOLO uses the Darknet framework, which is limited in its applicability due to its training on the small ImageNet dataset. Detecting small-scale objects has various challenges. As a result, localization's an object can produce subpar outcomes.
*YOLOv2:*2016 saw the release of YOLOv2 under the moniker YOLO9000.With 19 CNN layers and 5 max-pooling layers, Darknet-19 was launched by YOLOv2. 9000 object classes can be discovered using this framework for real time object detection. One of the fastest object recognition models is YOLO, which can analyze frames at a rate of up to 150 FPS for minor networks while still recognizing objects. Even Though YOLO was not the most accurate model according to the mean average precision. It did well when trained on PASCAL VOC2012 and PASCAL VOC2007, with a map of 63%. However, the state-of-the-art Fast R-CNN at the period has a Map of 71%.]. PASCAL VOC2007.

YOLOv3: A natural object detection system called YOLOv3 (You Only Look Once, Version identifies things in films, live media, or still photos. To find an item, the YOLO supervised learning system leverages features that a deep CNN has11 learned. In April 2018, the third iteration of YOLO is released with some minor improvements. As a Darknet variant, this version has been increased to 53 layers. As a output of expanded capabilities at various scales, the product is of higher caliber. To obtain precise outcomes for class predictions, substitute the logistic classifier YOLOv2 soft - max. Using a logistics regressor to compute the score, which increased the bounding box, was another improvement.

YOLOv4: YOLOv4 is a onestage object identification model that enhances YOLOv3 with several new modules and trick bags and published in the literature. The tips and modules utilised are described in the components section below. CSPDarknet-53 (CSP terms CrossStage Partial) for backbone network of the feature extraction Spatial pyramid pooling (SPP) and path aggregationnetwork (PANet) for the neck YOLOv3 will be taken for the head. For greater accuracy, the two object detectors—combination of freebies and specials—are used. Therefore, this version could carry out effective detecting tasks on huge datasets.

YOLOv5: The backbone, neck, and head are the three crucial components the majority recent iteration, known as YOLOv5. Cross Stage Partial Networks (CSPNet) serve as the framework for extracting highly informative features from an input image. The PANet network helps to obtain highlight pyramids. The head's component is the same as in YOLOv3 and v4 versions. The main goal of YOLOv5 is to translate from the Dark net framework to the Tensor flow framework. YOLOv5 is implemented in the experiment using a modified dataset for object detection *YOLOv5*: The backbone, neck, and head are the three crucial components the majority recent iteration, known as YOLOv5. Cross Stage Partial Networks (CSPNet) serve as the framework for extracting highly informative features from an input image. The PANet network helps to obtain highlight pyramids. The head's component is the same as in YOLOv3 and v4 versions. The main goal of YOLOv5 is to translate from the Dark net framework to the Tensor flow framework. YOLOv5 is implemented in the experiment using a modified data set for object detection.

YOLOv6 Accomplishments On COCO val2017, YOLOv6-nano obtains 35.0 MAP.TensorRT FP16 dataset with 1242 FPS on T4 for inference bs32.On the COCO val2017 dataset, YOLOv6-s obtains 43.1mAP.utilisingTensorRT FP16 for bs32 inference at 520 FPS on T4 Similar methods are used in both projects to produce various model sizes. The primary distinction is that although YOLOv5 makes use of YAML, YOLOv6 defines the hyperparameters freely in Python, while YOLOv5 uses YAML. A preliminary look also suggests that YOLOv5 could be somewhat more customizable. But since YOLOv6 is so adaptable, future YOLOv6 versions may be bigger and make predictions that are even more accurate! The machine aid and machine learning community are buzzing about the YOLOv7 algorithm.

The most recent YOLO algorithm outperforms all earlier object detection algorithms and YOLO iterations in speed and precision. It can be taught significantly quicker on tiny datasets without any pre-learned weights than other neural networks and requires technology that is several times less expensive. As a result, YOLOv7 is anticipated to overtake YOLO v4, the previous state-of-the-art for real-time applications, to become the industry standard for obstacle tracking soon. The variations between the fundamental YOLOv7 versions The three separate YOLOv7 fundamental models are the YOLOv7, YOLOv7-tiny, and YOLOv7-W6: The primary model that has been tuned for standard GPU computation is YOLOv7. A simple a paradigm that edge GPU optimized is called YOLOv7-tiny. Computer vision models with the prefix "tiny" are lighter and more suited for Edge AI and deep learning workloads, making them suitable. for use with mobile computing devices or dispersed edge servers and devices. Applications of networked computer vision in the real world benefit from this concept. The edge-optimized YOLOv7-tiny employs leaky ReLU as the activation function as opposed to other models, which use SiLU as the activation function. YOLOv7-mask Instance segmentation is carried out using the YOLOv7 and Blend Mask integration. As a result, the MS COCOA dataset for edge detection was utilized to refine the YOLOv7 object identification model, which was trained across 30 iterations. It produces cutting-edge real instance segmentation outcomes.

LITERARTURE SURVEY:

On benchmark datasets (such as the PASCAL VOC dataset, the MS COCO dataset, ImageNet, etc.), the performance results of car tracking are assessed, and metrics scores are calculated using the recall and precision rate, F1-score, Average Precision (AP), mean Average Precision (mAP), intersection over union (IOU), and True Positive Rate (TPR) or Detection Rate (DR). The metrics evaluation is mostly used to assess how well detectors work with a given dataset. By separating training, testing, and validation, analysis is calculated. The hardware setting with regard to the test uses a graphics processing unit (GPU). The models are then put into action on frameworks Further traffic information can be gleaned from the pavement dynamic reaction under moving loads from moving vehicles, such as the weight, type, and acceleration of moving vehicles. One among the most often used methods for traffic monitoring, which can be separated into two categories, is the weight-in-motion (WIM) system. The high- speed WIM (HSWIM) system, used for vehicle congestion data collecting and traffic space control, is the prior type. Many issues in the automobile detection technology that could not be resolved using conventional techniques were resolved using deep- based techniques. However, there are still certain problems and difficulties to be resolved, such as dealing with occlusions, different weather scenarios, complicated scenes, and illumination variance issues. For real-time detection performance, a fast R-CNN algorithm can be offered, however YOLO frameworks are required for full real-time. Therefore, more sophisticated YOLO algorithms are employed to boost detection speed and accuracy. Modern techniques can now help solve problems on multiple scales.

TABLE I. ACHIEVEMENTS FOR REVIEWED METHODS WITH PROPOSED

Methods	**Proposed Year**	**Achievements**
Normalized color, Edge maps,the wavelet transform's components	2005	-is very powerful for detecting vehicles from static images byintegrated scheme.
Model for bendable parts in two vehicles [12]	2017	-makes more sure detection efficiency for real-timerequirements and partially occluded vehicles.
Inverse perspective mapping modified (MIPM), Hough transform, Gaussian mixture models (GMM)	2018	-are robust and more accurate compared to state-of-the-art methods in particular while interacting occlusions, illuminations and weather conditions.
CNN, Multi-layer feature fusion	2018	-is better detection accuracy and speed for real-time.
CNN, K-means, Feature concatenation	2018	-obtains a significant improvements which three times faster than faster R-CNN.
YOLOv2, Multi-layer feature fusion	2018	-proves abilities which are vehicle detection effectiveness andexcellent feature extraction.
Local binary pattern (LBP), Histogram, Clustering forest	2019	-outperforms state-of-the-art methods with significant and consistent improvements.
Multi-branch CNN	2019	can accurately detect for multi-scale the products and detection speed is fast for real.
CNN, Feature concatenation	2019	-is better than state-of-the-art models, except for YOLOv3.
Rapid R-CNN, Residual network	2019	-provides acceptable results for accuracy and execution time in real-time detection.
Improved faster R-CNN	2019	-improves comparing with original rapid R-CNN framework in both detection accuracy and

		inference time.
YOLOv3, YOLOv4	2020	-is suitable for traffic surveillance applications and effectively detects for multiple objects.
YOLOv4	2020	-is faster than contemporary object detectors
YOLOv5	2020	creates a grid to split photos. In the grid, each cell is in charge of finding items within of it.
YOLOv6	2022	schema for mono object tracking with a high performance, hardware-friendly, and effective architecture for industrial applications.
YOLOv7	2022	is the YOLO family's newest, highly powerful object detector.It is presently the most rapid and precise. real-time object detection, in agreement with study

Block Diagram

The below Figure shows the Block diagram of the proposed system.

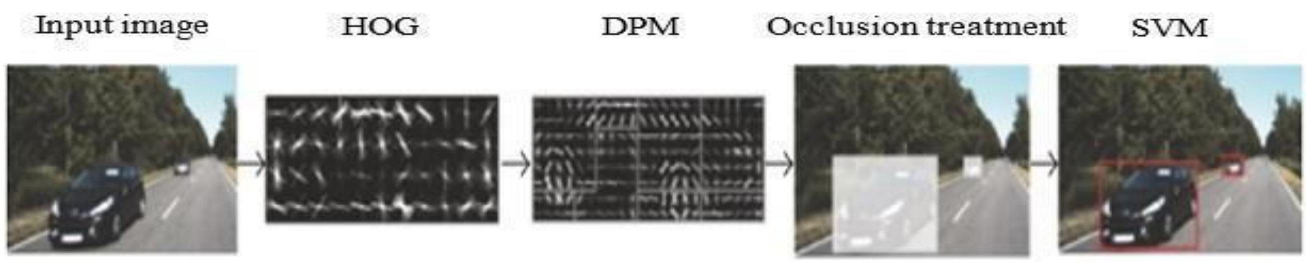

Fig. 1. Deep Model for Vehicle Tracking.

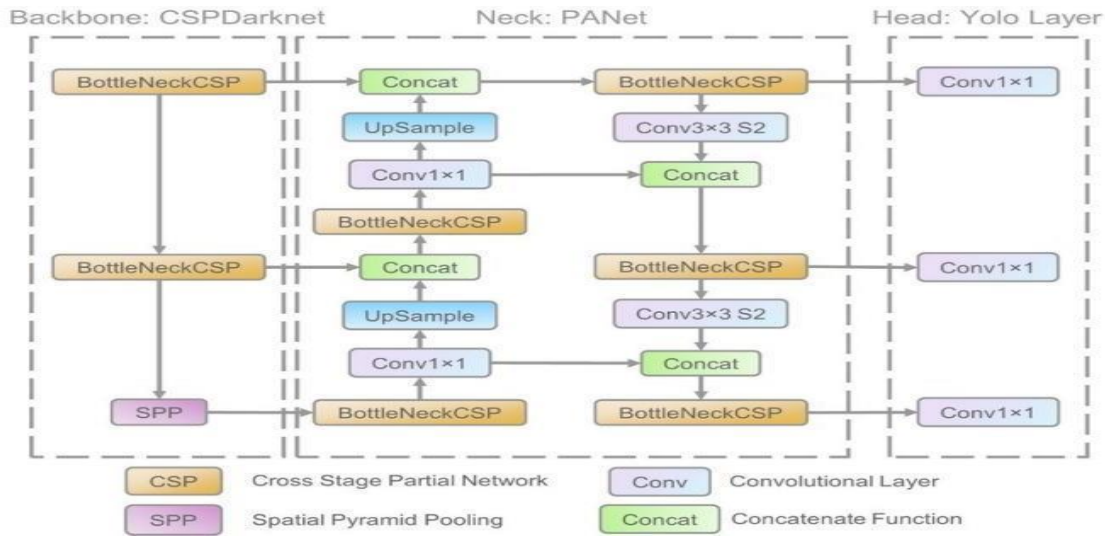

Fig. 2: YOLOv6 Working Process.

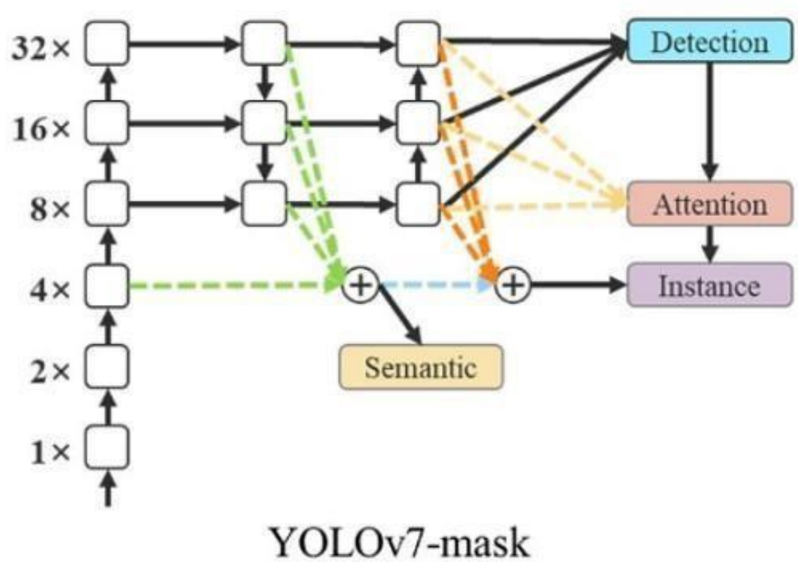

Fig. 3 . YOLOv7 Mask Image Segmentation Architechture.

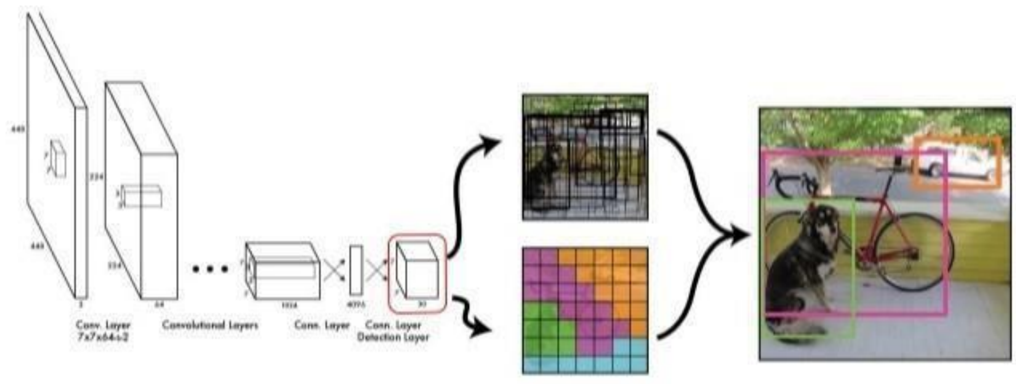

Fig. 4. YOLOv7 Architechture.

Hardware requirements:

- NVIDIA GPU
- 8GB RAM OR MORE
- LCD
- WIFI

Conclusion:

With cutting-edge techniques, deep learning- based automobile tracking technology has been developed for use in surveillance scenarios. Advanced vehicle detection techniques using RCNN and YOLO versions of contemporary deep learning frameworks have been examined in present article. The new frameworks can resolve several complex issues including multi-scale challenges and varied environmental circumstances. This review article is beneficial for real-time vehicle detection techniques in surveillance environments. This research primarily focuses on new object detectors and small-scale vehicle object detection. yolov6 and yolov7 has higher accuracy to detect the image and track it. These are the latest detecting techniques in recent times.

Future Work:

Regression-based techniques, which including YOLO, YOLOv2,YOLOv3, YOLOv4, and YOLOv5, are a sort of one stage method. By detecting the input image only once, YOLO frame detection simultaneously accurately forecasts the anchor boxes and the class probabilities for these boxes, making it quickest and therefore most approach to real-time detection. Other detection techniques take longer than YOLOv2, and YOLOv3 can also be employed for small-scale vehicle objects. YOLOv4 is implemented use new tools for faster operation speed. A fresh PyTorch tutorial framework called YOLOv5 has been created for the advancement of object detectors. Although an article about YOLOv5 has not yet been released, there are tutorials that can be trained using customer datasets.

References:

[1]] Linkai Chen et al., “An algorithm for highway vehicle detection based on convolution neural network”, *EURASIP Journal*, Springer,2018

[2] Rawat W, Wang ZH (2017) Deep convolution neural networks for image classification: a comprehensive review.

[3] Joseph Redmon, Ali Farhadi, “YOLO9000: Better, Faster, Stronger”, IEEE, 2016.

[4] M. Hassaballah, Mourad A. Kenk and Ibrahim M. Elhenawy, “On-Road Vehicles Detection using Appearance and Texture Information”, Egyptian Computer Science Journal Vol. 43 No.1, 2019.

[5] Luo-Wei Tsai, Jun-Wei Hsieh, and Kao-Chin Fan, “ Vehicle Detection Using Normalized Color and Edge Map”, IEEE, 2005.

[6] Minglan Sheng et al., “ Vehicle Detection and Classification Using Convolution Neural Networks”, *7th Data Driven Controland Learning Systems Conference*, IEEE, 2018.

[7] Jorge E. Espinosa et al., “ Detection of Motorcycles in Urban Traffic Using Video Analysis: A Review”, IEEE, 2020.

Author Profiles

Dr.M.Rajaiah, Currently working as an Dean Academics & HOD in the department of CSE at ASCET (Autonomous), Gudur, Tirupathi(DT).He has published more than 35 papers in Web of Science,Scopus,UGC Journals.

Prof.V.Sreenatha Sarma, Currently working as an Dean ICT in the department of CSE at ASCET Autonomous),Gudur, Tirupati(DT).

Mr.S.Satwik, B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur. He is Studying in computer science and engineering.

Ms. T. Thanusha, B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur. She is Studying in computer science and engineering.

Ms.V.Hemalatha, B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur. She is Studying computer science and engineering.

Ms.D.Rachana Pravalika, B.Tech student in the department of CSE at Audisankara College of Engineering and Technology, Gudur. She is Studying in computer science and engineering.