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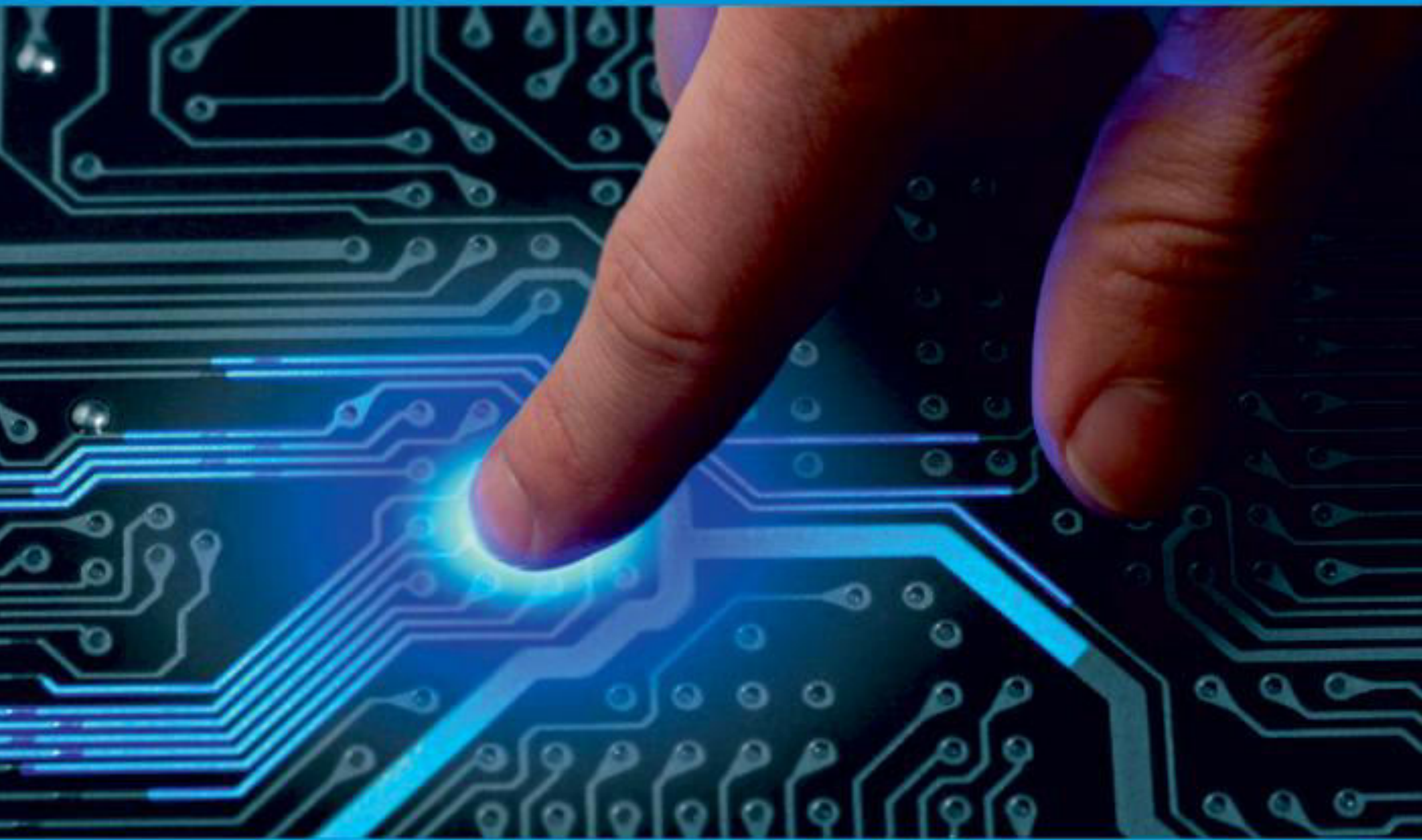
e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 7, July 2021

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 7.542

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 7.542

|| Volume 9, Issue 7, July 2021 ||

| DOI: 10.15680/IJIRCCE.2021.0907141 |

Vision-Based Vehicle Detection and Counting System Using Deep Learning in Highway Scenes

Kodudula Akhila[1] , Nayana R H[2] , Pooja[3] , Yashaswini SK[4]

Department of Computer Science & Engineering, Bangalore Institute of Technology, Bengaluru, Karnataka, India[1,2,3,4]

ABSTRACT: Intelligent vehicle detection and counting are becoming increasingly important in the field of highway management. However, due to the different sizes of vehicles, their detection remains a challenge that directly affects the accuracy of vehicle counts. To address this issue, this paper proposes a vision-based vehicle detection and counting system. In the proposed vehicle detection and counting system, the highway road surface in the image is first extracted and divided into a remote area and a proximal area by a newly proposed segmentation method; the method is crucial for improving vehicle detection. Then, the above two areas are placed into the YOLOv3 network to detect the type and location of the vehicle. Finally, the vehicle trajectories are obtained by the CNN algorithm, which can be used to judge the driving direction of the vehicle and obtain the number of different vehicles. Several highway surveillance videos based on different scenes are used to verify the proposed methods. The experimental results verify that using the proposed segmentation method can provide higher detection accuracy, especially for the detection of small vehicle objects. Moreover, the novel strategy described in this article performs notably well in judging driving direction and counting vehicles. This paper has general practical significance for the management and control of highway scenes.

KEYWORDS: Convolution neural network (CNN), Image segmentation, Vehicle detection, Vehicle counting, Highway management.

I. INTRODUCTION

Vehicle detection and statistics in highway monitoring video scenes are of considerable significance to intelligent traffic management and control of the highway. With the popular installation of traffic surveillance cameras, a vast database of traffic video footage has been obtained for analysis. Generally, at a high viewing angle ,a more- distant road surface can be considered.

The object size of the vehicle changes greatly at this viewing angle, and the detection accuracy of a small object far away from the road is low. In the face of complex camera scenes, it is essential to effectively solve the above problems and further apply them. In this article, we focus on the above issues to propose a viable solution, and we Apply the vehicle detection results to multi-object tracking and vehicle counting. Vehicle counting and detecting system can be used to trace vehicles, traffic monitoring and controlling, payment on highway troll.

We can also detect the speed of the vehicle on the lane. People will get knowledge about the types of vehicles entering and exiting and also will be able to get accurate information on the flow of traffic. Traffic flow is required in the urban transportation mainly in highways because its estimation is helpful in evaluating traffic state for management. Automatic vehicle counting is a key technique to monitor and estimate traffic flow. Therefore, vehicle counting is important and helpful to optimize the traffic signaling system.

II. RELATED WORK

Prof. Bartlomiej Placzek[1] The information concerning the presence of vehicles in the predefined detection zones on the traffic lanes is essential for the adaptive traffic control at signalized intersections. Major drawback is For a night time video sequence with very poor lightning. Prof.Ying-Che [2] Proposed idea was advanced driver assistance Systems have received considerable attention in recent decades, because many car accidents are caused mainly by driver's lack of awareness or fatigue. Major draw back is This is time consuming and impractical for a real time system. Prof. Linkal[3] Proposed idea Vehicle detection is a very important component in traffic surveillance and atomic driving. Drawback is R-CNN is slow and time consuming. Prof. Ahmad Arinaldi[4] MoG is used for background subtraction method to detect the moving vehicles in the image. Drawback is MoG background subtraction failed to detect vehicles that are overlapping Prof. Hai Wang[5] Yolov3 uses a single neural network to predict the bounding. Drawback is the detection accuracy of the model is low. Prof. Qiao Meng[6] This paper an efficient framework based on vehicle detection and tracking from aerial video is proposed. The moving-object detector can

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handle two situations static and moving background. Drawback is Many sensors need to be installed in urban areas the cost of this work is high. Prof. Sheeraz[7] The paper aims in background subtraction and detection of vehicle. Major drawback is system work with already captured videos but it need to be modified to be used for processing live video streams. Prof. Mingling[8] This paper an efficient framework based on vehicle detection and tracking from aerial video is proposed. The moving-object detector can handle two situations static and moving background. drawback is Many sensors need to be installed in urban areas the cost of this work is high. Prof. AISmadi[9] This paper provide a comprehensive review of the state-of-the- art video processing techniques for vehicle detection, recognition and tracking with analytical description. it uses tracking algorithm. Drawback is the main technical challenge from the application is perspective lies in the camera view and operating condition especially in urban traffic scenarios such as road sections and intersection Prof. Gram, Spain[10] This paper is to estimate the number of vehicles in an image of traffic congestion situation.it uses TRANCOS ,a novel database for extremely overlapping vehicle counting. Drawback is it has to overcome some limitation of the traditional MAE for object counting solutions. Prof. Yaduan[11] This paper is used to detect and recognize the vehicles from a video stream. The purpose of this article is to allow us to detect vehicles moving in front of camera placed under the rear view mirror and draw the trajectory lines of vehicle. the proposed algorithm uses deep learning approach based on the convolutional neural network. Drawback is R-CNN is slow and time consuming. Prof. Iman Asker[12] The proposed vehicle detector has been successfully trained by using Faster RCNN and R-CNN deep learning methods on the sample vehicle datasets and the vehicle detection process has been successfully performed by the trained vehicle detector being tested on the test data set. Drawback is R-CNN is slow and time consuming. been successfully performed by the trained vehicle detector being tested on the test data set. Drawback is RCNN is slow and time consuming. Prof. Mohammad[13] To enhance the system performance and to reduce time in deploying Deep Learning architecture, hence pretrained model of YOLOv3 is used in this research due to its good performance and moderate computational time in object detection. our proposed system capable to count the vehicles crossing the road based on video captured by camera with the highest accuracy.

III. PROPOSED ALGORITHM

In the proposed vehicle detection and counting system the highway road surface in the image is first extracted and divided into a remote area and a proximal area. The vehicle trajectories are obtained by CNN algorithm which can be used to judge the driving direction of the vehicle and obtain the number of different vehicles and respective count. The experimental results verify that using the proposed segmentation method can provide higher detection accuracy, especially for the detection of small vehicle objects

IV. SYSTEM ARCHITECTURE

Fig 1 represents First we giving video as input, then we using convolutional neural network, it is used to extract the feature points of detected object. Then it checks whether object matches if yes, it directly update the object feature and draw the tracks. If no again it checks whether the object matches within the 20 frames if Yes it update object features if no it deletes the object. After drawing tracks it checks whether the tracks is updated for more than 20 consecutive frames if yes continues tracking if no deletes the track. Several convolution neural network architectures were created by varying to classify Psoriasis as malignant or benign. 1) No. of layers and their configuration 2) No. of training steps and rate of learning 3) Activation functions 4) Optimizer. The structure of the CNN structures incorporates a progression of convolutional layers, pooling layers, a few power capacities, a single and deep fully associated layer. The size of the convolutional parts was monitored throughout all stages as a steady incentive. The number of channels was also balanced in the convolutional layers. Preprocessed dermoscopy images were fed into a wide range of CNN models at that stage. The structure of the CNN structures incorporates a progression of convolutional layers, pooling layers, a few power capacities, a single and deep fully associated layer. The size of the convolutional parts was monitored throughout all stages as a steady incentive. The number of channels was also balanced in the convolutional layers. Preprocessed dermoscopy images were fed into a wide range of CNN models at that stage. Deep convolutional networks (CNNs) has achieved amazing success in the field of vehicle object detection. CNNs have a strong ability to learn image features and can perform multiple related tasks, such as classification and bounding box regression. The detection method can be generally divided into two categories. The two-stage method generates a candidate box of the object via various algorithms and then classifies the object by a convolutional neural network.

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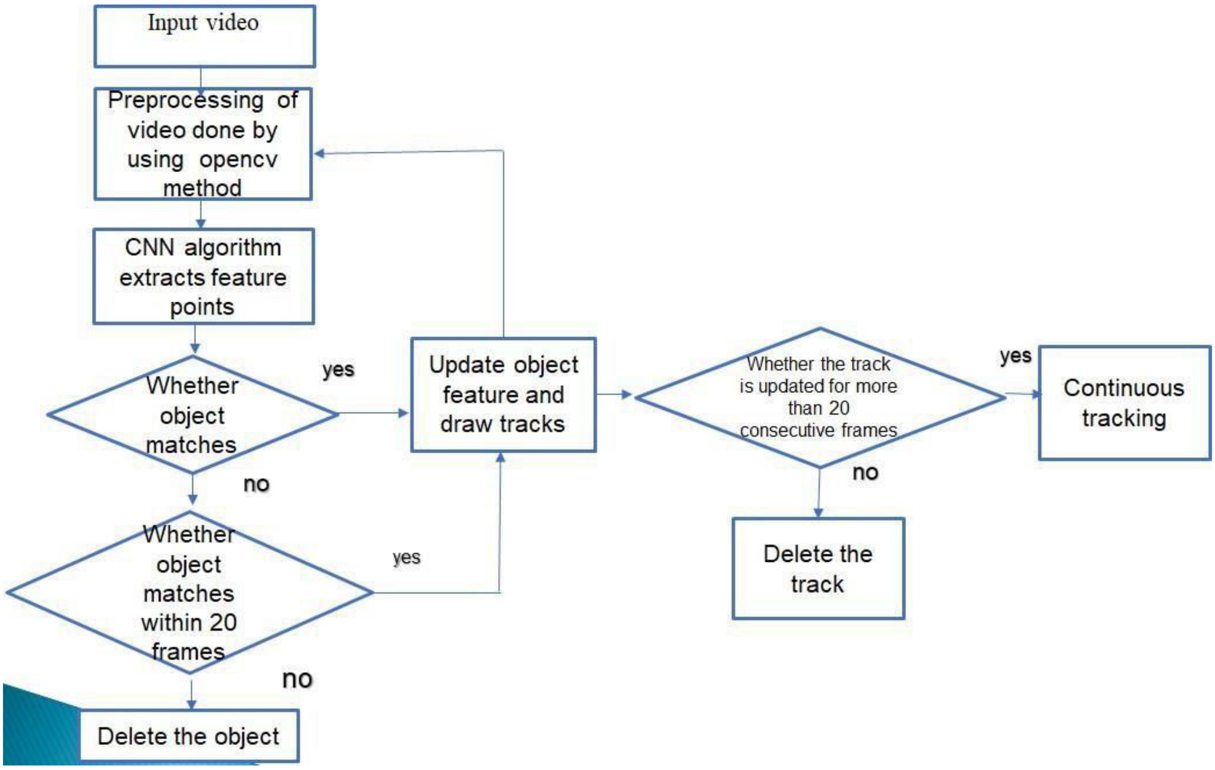

V. MODULES

Object detection: Deep convolutional networks (CNNs) has achieved amazing success in the field of vehicle object detection. CNNs have a strong ability to learn image features and can perform multiple related tasks, such as classification and bounding box regression. The detection method can be generally divided into two categories. The two-stage method generates a candidate box of the object via various algorithms and then classifies the object by a convolutional neural network. The onestage method does not generate a candidate box but directly converts the positioning problem of the object bounding box into a regression problem for processing. In the two-stage method, Region-CNN uses selective region search in the image. Multi-object tracking: This section describes how multiple objects are tracked based on the object box detected in “Vehicle detection usingYOLOv3”section. In this study, the CNN algorithm was used to extract the features of the detected vehicles, and good results were obtained. The CNN algorithm shows superior performance in terms of computational performance and matching costs. Matching of objects: The YOLOv3 deep learning object detection method issued to detect the vehicle object in the highway traffic scene. Finally, CNN feature extraction is performed on the detected vehicle box to complete multiobject tracking and obtain vehicle traffic information. The ORB algorithm extracts the detected box’s features and matches them to achieve correlation between the same object and different video frames. Finally, traffic statistics are calculated. achieve correlation between the same object and different video frames Updating object features and draw tracks When the number of matching points obtained is greater than the set threshold, the point is considered to be successfully matched and the matching box of the object is drawn. The source of the prediction box is as follows: feature point purification is performe using the RANSAC algorithm, which can exclude the incorrect noise points of the matching errors, and the homography matrix is estimated. We define a threshold T that refers to the maximum pixel distance of the detected Centre point of the vehicle object box, which moves between two adjacent video frames. The positional movement of the same vehicle in the adjacent two frames is less than the threshold T. Therefore, when the center point of the vehicle object box moves over T in the two adjacent frames, the cars in the two frames are not the same, and the data association fails. Considering the scale change during the movement of the vehicle, the value of the threshold T is related to the size of the vehicle object box. Different vehicle object boxes have different thresholds. This definition can meet the need so vehicle movement and different input video sizes. T is calculated by Equation, in which box height is the height of the vehicle object box. T = box height/ 0.25 We delete the trajectory that is not updated for ten

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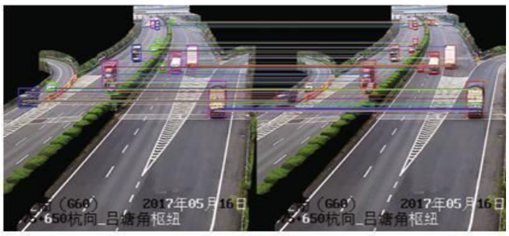
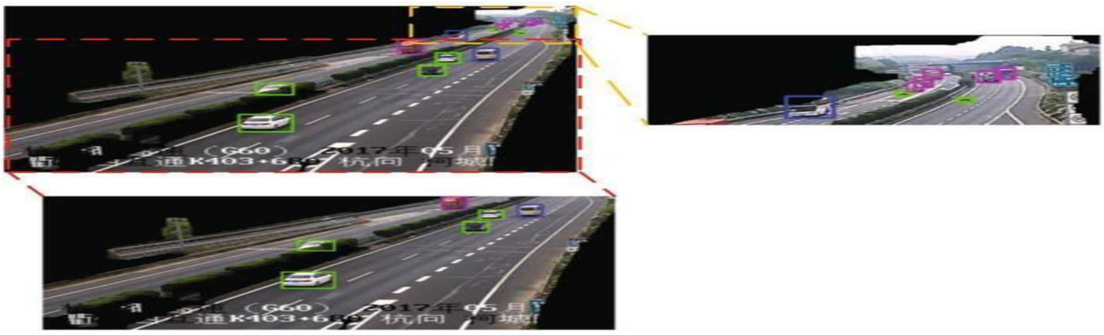
consecutive frames, which is suitable for the camera scene with a wide-angle of image collection on the highway under study Tracking and counting: After obtaining the object box, we performed vehicle tracking based on the ORB feature point matching method and performed trajectory analysis. In the experiment, when the matching point of each object was greater than ten, the corresponding CNN prediction position was generated.

VI. RESULT AND DISCUSSION





(a)

(b)

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VII. CONCLUSION

With the remarkable potential of object detection and counting will be implemented with the help of CNN, the proposed system can recognize vehicle of all type. The experimental results verified that the proposed vehicle detection and tracking method for highway surveillance video scenes has good performance and practicabilty. To address the problem of the small object detection and the multi-scale variation of the object, the road surface area was defined as a remote area and a proximal area. The two road areas of each frame were sequentially detected to obtain good vehicle detection results in the monitoring field. The position of the object in the image was predicted by the CNN feature extraction algorithm based on the object detection result. Then, the vehicle trajectory could be obtained by tracking the CNN features of multiple object.

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