An Application of Deep Learning Algorithm for Automatic Detection of Unexpected Accidents Under Bad CCTV Monitoring Conditions in Tunnels

[1]Prof.Vishal Shinde, [2]Miss.Sneha Shet, [3]Miss.Sneha Chauhan, [4]Miss.Suryanjali Verma

[1]Asst. Professor,[2,3,4]UG Student,[1,2,3,4]Computer Engg. Dept. Shivajirao S Jondhle College of Engineering and Technology, Asangaon, Maharashtra, India. [1]mailme.vishalshinde@gmail.com, [2]snehashet919@gmail.com, [3]snehachauhan328@gmail.com,[4]suryanjali.v@gmail.com

Abstract- Object Detection & Tracking System (ODTS) is combined with a popular deep learning network which is known as Faster RCNN (Faster Regional Convolution Neural Network), for Detecting the Object and Conventional Tracking of objects an algorithm is introduced and is applied for detecting and monitoring unexpected events automatically on CCTVs, the unexpected events can be Wrong-Way Driving or Stopping, Person getting out of the vehicle or Fire. The ODTS accepts frames of video in time as input in order to obtain resultsof Bounding Box (BBox) by Detecting objects and it compares the Bounding Boxes of the previous and current video frames for assigning an ID that is unique to every object which is moving and detected. This system is making it attainable to trace any object which is moving in time, this is unusual to achieve in frameworks of conventional object detection. With the help of ODTS, a deep learning model was trained with a dataset that consisted of event data in the tunnels to (AP) Average Precision values of 0.7161 for Person, 0.8479 for Car, and 0.9085 for Fire. A deep learning-based model in Object Detection Tracking System (ODTS) was given training with a dataset that consisted of images of events in the tunnels to (AP) Average Precision values of 0.7161 for Person, 0.8479 for Car, and 0.9085 for Fire. Based on a model of deep learning which was trained by using four videos of accidents, the system of CCTV Accident Detection in the tunnel which was based on ODTS was tested. The system detected all the accidents at intervals of just 10 seconds. The important point to be noted is that the capacity of accident detection could be improved automatically without making any modifications in thesource code because the training dataset will become rich.

Keywords— Faster RCNN for Detecting objects, Algorithm for Object tracking, Object Detection & Tracking system, CCTV Accident Detecting System, Detection of Unexpected Events.

I. INTRODUCTION

The position, as well as the size of targetobjects that appears on videos or images, canbe found by using the technology of object detection. For security system and CCTV monitoring, detection of cancer and mainly in self-driving of vehicles have been appeared by various applications. For tracking objects it is important to define object class and position in a provided static image by object detection. It can be implied that the results ofobject tracking should be deeply dependent on object detection performance.

This technology is effectively used for tracing of pedestrians and the vehicles in motion, monitoring of accidents in traffic cameras, monitoring of criminal and security in local areas of concern, etc. In this paper with the use of automatic object detection ,case study on analysis along with control oftraffic conditions have been carried out.

Based on a system of on-road vehicle detection, the development of a car which was self-driving was initiated. The detection of vehicle objects is done by CNN and it classifies the vehicle type. The center point of tracking is changed rely on the detected vehicle object's position on the image, the tracking algorithm of the vehicle object will track the vehicle object. The space between visualized vehicle object and the driving car is calculated by the system similar to a birds- eye view of a vehicle object which is displayed on the monitor.

This system's process helps to view the vehicle object's position in such a way that it can help assistance of self-driving system and the vehicle object in 0.4m horizontal and1.5m vertical, tolerance at the camera is localized.

 DOI : 10.35291/2454-9150.2022.0151

In another detection system which depends on deep learning with a combination with SVM (Support Vector Machine) and CNN was created to monitor the vehicles which were moving on roads or highways by satellite's help. Using input value of satellite image, the feature is extracted by the system from the satellite image by use of CNN and binary classification with Support Vector Machine is performed for detection of the vehicle Bounding Box.

In short, this system applies Bounding Box obtained by detection of an object based on images or videos and algorithm applied to the system compared with faster RCNN and Gaussian Mixture Model SVM (Support Vector Machine). It is found that faster R- CNN was detecting the vehicle's type and position more accurately. Thus, it could be said that the deep-learning-based method of detecting objects is preferable for the algorithm based approach.

Therefore it may be deduced that all cases of development in this paper are about dealing with information about the object, it shows outstanding performance with help of deep learning.

Hence an effort is made in this paper for generating an object detection along with tracking system (ODTS), that can obtain information of moving target objects by combining object tracking algorithm with object detection process based on the deep learning.

II. AIMS AND OBJECTIVE

a) Aim

To develop a system that automatically detects unexpected accidents under poor CCTV monitoring circumstances in tunnel byapplying the deep learning algorithm.

b) Objective

This system has ability to track a object which is in motion in time, which is not usual to be achieved in conventional object detection frameworks b) For saving lives Objective Immediate and exact accident detection is important and more efficient traffic incident management Traffic crashes can result inproperty damage, death, injuries and nonrecurrent congestion.

Exact and speedy detection of accident will help to improve the undelayed incident management, this will minimizes fatalities/ injuries on account of crash occurrence .So, improving the said such accident detection procedure is required and important for traffic incident management.

Hence an effort is made in this paper for generating an object detection along with tracking system (ODTS), that can obtain information of moving target objects by combining object tracking algorithm with object detection process based on the deep learning.

III. LITERATURE SURVEY

Paper 1: Bird's eye views localization of surrounding vehicles.

A new framework for detection and localization of vehicle with partial representation is proposed using geometryand stereo vision. A tracking algorithm that detects every partially visible vehicles is introduced .To track vehicles which are partially visible, detection of vehicle edge which is on the ground is done by this algorithm. Detecting edge of vehicle on the ground is called as grounded edge, afterwardsa reference point is selected for Kalman filter tracking. Tracking and detection of the vehicles which are partially visible is successfully carried out by this proposed system.

Paper 2: Robust vehicle detection by combining deep features with exemplarclassifications.

In this paper, the possibility of exploitation of deep neural features for robust vehicle detection is examined. It is assumed that a detection framework for vehicle combines powerful instance classifier based on Exemplar SVMs (E-SVMS) with feature learning based on DNN (DeepConvolutional Neural Network) to achieve powerful detection of vehicle in images provided by satellite. DNN is adopted to learn differential image features, which have a high learning capacity.

Paper 3: Detection and classification of vehicles for traffic video analytics.

Traffic video analysis system is explained in this paper. This system uses techniques of computer vision. The system is especially designed to instinctively collect important statistics for regulators and policymakers in a fashion which is computerized . These statistics consists of counting of vehicles, type classification of vehicle ,vehicle speed estimation by monitoring lane usage, and videos. The core of this system is detecting and classifying vehicles detected in videos of traffic.Two models are implemented for this purpose

1. MoG + SVM based system

2. Faster RCNN based system

Paper 4: Online Self-Supervised Multi- Instance Segmentation of DynamicObjects.

This study comes up with a mechanism for continuously separating moving objects using just a vehicle-mounted monocular camera and no previous knowledge of the object's visual appearance, location, or shape.In contrast to many tracking-by-detection- based systems, our system can detect moving objects with no previous knowledge of their visual presence, location, or shape. Additionally, the classifier is utilised to generate labels from earlier frames of the same object, which intensifies the continuous monitoring of specific objects depend on motion.

 DOI : 10.35291/2454-9150.2022.0151

ISSN : 2454-9150 Vol-08, Issue-01, APR 2022

IV. EXISTING SYSTEM

The existing system will detect the vehicle object and also classify what type of vehicle it is by the use of CNN(Convolutional Neural Network). The vehicle object is detected by the object tracking algorithm, according to the recognized vehicle's position the algorithm changes the tracking center point. Then, the localized image like a birds-eye view will be shown on the monitor along with visualized objects of the vehicle. The system will also calculate the distance between the vehicle object and the driving car.

Disadvantages:-

This system uses the feature of satellite image through CNN by using the image of the Satellite as input. Along with SVM, Binary Classification is executed on the basis of input data to detect vehicle-BBox. The bounding box obtained by detection of objects present on images or videos is utilized by this system.

V. COMPARTIVE STUDY

SR NO.	PAPER TITLE	AUTHORNAME	METHOD	ADVANTAGE	DISADVANTAGE
1.	Bird's eye view localization of surrounding vehicles: Longitudinal and lateral distance estimation with partial appearance	E. S. Lee, W. Choi, D. Kum	Stereo vision, geometry, deep learning	detection and tracking of vehicles which are partially visible	
2.	Robust vehicle detection by combining deep features with exemplar classification	L. Cao, Q. Jiang, M. Cheng, C. Wang	DNN	the possibility of exploitation of deep neural features for robust vehicle detection is examined	Due to multiple low resolution images , it is difficult to attain high accuracy
3.	Detection and classification of vehicles for traffic video analytics	A. Arinaldi, J. A. Pradana, A.A .Gurusinga	RCNN	detecting and classifying vehicles detected in videos of traffic.	Sometimes unable to detect fast moving vehicle resulting in less accuracy
4	Online Self- Supervised Multi- Instance Segmentation of Dynamic Objects	A. Bewley, V.Guizilini, F. Ramos, B. Upcroft	unsupervised motion clustering	detect moving objects with no previous knowledge of their visual presence, location, or shape.	Sometime create false alarm while detecting dynamic objects

Table 1 : Comparative study

DOI : 10.35291/2454-9150.2022.0151

International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-08, Issue-01, APR 2022

VI. PROBLEM STATEMENT

To develop a project that uses techniques of machine learning to detect unpredictable accidents under poor CCTV monitoringcircumstances, using various algorithms to detect the object and conventional tracking of object using Faster R-CNN which is most popular deep learning network.

The existing system has some drawbacks,like the system takes out the features using satellite images through CNN algorithm using the image of satellite as an incoming signal and then uses SVM to do binary classification for detecting the vehicle BBox. This system utilizes B Box achieved by detection of objects in images as well as videos.

That system was comparatively slow . So an R-CNN a model of deep learning is used to optimize the system.

VII. PROPOSED SYSTEM

In the proposed system an attempt is made to generate an object detection & tracking system (ODTS) with yolo, that can obtain moving information of target objects with their names by combining the object trackingalgorithm with the deep study-based object detection process.

It is presumed that ODTS has been trained enough to carry out object detection correctlyassigned image frame ODTS senses specific frames of video at Selected interval of time c and gets sets of coordinates, n BBoxs can be detected. BBox t of objects on a frame of the current object at the time t, from the object detection system which is trained.

The corresponding type or class Classt of each detected object BBoxt is simultaneously classified by the object detection module.

Algorithm: R-CNN(Regional Convolution Neural Network), YOLO Model

VIII. ALGORITHM

The general idea of working of proposedsystem algorithm is given as follow:

Step.1: Start

Step.2: Prepare the COCO class labels in which the YOLO model was trained on **Step.3:** Determine class ID along with probability (Confidence)of the current object detected

Step.4: Remove predictions which are weakby checking that the probability of detected object is greater than the minimum probability

If confidence > args["confidence"]:

box = detection[0 to 4] x array([W, H, W, H]) (centerX, centerY, width, height) = box.astype("int")

Where x = (centerX - (width / 2)) and y = (centerY - (height / 2))

Step.5: To suppress weak or overlapping Bboxes, non-maxima suppression is applied **Step.6:**Determine the Bbox coordinates

(x, y) = (boxes[i][0], boxes[i][1])

(w, h) = (boxes[i][2], boxes[i][3]) **Step.7:** read first image file in black andwhite mode and display all the imageproperties

Step.8: read second image file in black and white mode and display all the imageproperties

Step.9: Prepare image for performing hour transform on them

Step.10: create a histogram to analyze about the thresholded image

Step.11:find local maximum peaks in accumulator

for i in range of 1 to accumulator.shape[0]-1for j in range of 1 to accumulator.shape[1]-1 if(accumulator[i][j]>accumulator[i-1][j] and accumulator[i][j]>accumulator[i-1][j+1] and accumulator[i][j]>accumulator[i-1][j-1] and accumulator[i][j]>accumulator[i+1][j] and accumulator[i][j]>accumulator[i+1][j-1] and accumulator[i][j]>accumulator[i+1][j+1] and accumulator[i][j]>accumulator[i][j-1] and accumulator[i][j]>accumulator[i][j+1] and accumulator[i][j]>50):

r_list.append(i) theta_list.append(j)

Step.12: calculate u and v using lucas kanademethod

Step.13: weighted_sum_list = [a x b for a,b inzip(bin_list,value_list)] weighted_angle_value_left = sum(weighted_sum_list)/sum(value_list) max_degree_left = weighted_angle_value_left

Step.14: left_correct = False right_correct = False if(max_degree_left < 0):

Then the vehicle present on the left side of road is assumed to be in accurate direction

left_correct = True else:

Then the vehicle present on the left side of the road is assumed to be in an incorrect direction

if(max_degree_right > 0):

Then the vehicle present on the right side of road is assumed to be in an accurate direction

right_correct = True else:

Then the vehicle present on the right side of road is assumed to be in an incorrect direction

 DOI : 10.35291/2454-9150.2022.0151

ISSN : 2454-9150 Vol-08, Issue-01, APR 2022

Step.15: Exit

IX. MATHEMATICAL MODEL

It is expected that ODTS has been sufficiently trained to correctly detect objects in a given image frame. From the object detection system which is trained, ODTS collects selected frames of video at a predetermined time period c and obtains sets of coordinates, n BBoxes are detected based on objects on the provided image frame at time t. The module of object detection classifies each detected object into theappropriate type or class at the same time.

Depending on detected object data, forpredicting the next position of every object a module for object tracking is introduced, it allocates a distinctive ID number to every object detected. The value of n differs from the number of tracked BBox u. If the previously tracked BBox is zero, then the number of detected objects equals the number of the tracking BBox. For instance, in time c+t, if the value of u is zero, then the value of u' is equal to the value n'. Particularly, the current tracking Bounding Box is taken from the identified objects per class, when previously tracked BBox doesn't exist. An object tracking algorithm called theSORT algorithm was introduced for composing this object tracking module, which uses a concept called Intersection Over Union i.e IOU to trace the same object with the same ID number and for predicting the next position of the identified objects it uses Kalman Filter and Hungarian algorithm.

The same operations are followed on the fresh images at time step t+c to obtain and c by the same object detection module as at time t. The IOU of all feasible pairs of anticipated locations, at time t, and detected object positions, at time t+c, is then calculated. The pair of entities with the greatest IOU value will be presumed to be thesame object with the same ID. And any entitythat does not have an object pair with an IOUvalue greater than 0.3 will be deemed asvanished from the selected area.

Similarly, at t+c, any entity with no object pair with an IOU value greater than 0.3 will be regarded as recently appeared in the RoI. A new ID number will be assigned to the freshly emerged entity, which will avoid overlapping with the existing ID number.

For ID assignment and object tracking, this system uses a SORT algorithm, and for object detection, it uses a faster RCNN learning algorithm. SORT is notable for its ability to track several objects at the speed of100-300 frames per second. Because this system uses the SORT algorithm method to track objects based on IOU values, the object tracking capability was impacted by video frame intervals.

By modifying the detection interval of the object detection network, video frame intervals can minimize the computationamount over time. To test this, objecttracking ability was tested over a frame interval, and it was figured out that the objects could be tracked up to six-frame intervals. Because increasing the frame interval affects object tracking capacity, the video frame interval should be tuned for the number of camera devices connected to a deep-learning server simultaneously.

X. SYSTEM ARCHITECTURE

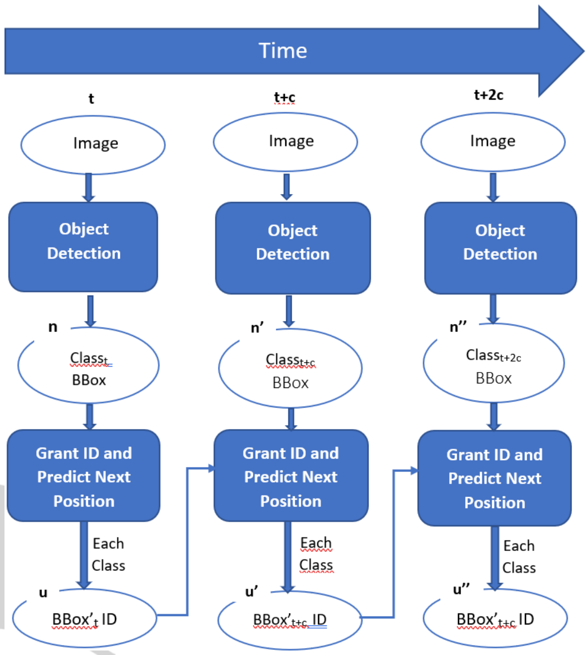


Fig.1: System Architecture

Description:

This system includes CADA, which distinguishes each cycle based on dynamic data from the automobile objects. It was easyto recognize the accidents within the

time span of just 10 seconds after testing with the image representing each accident. Deep learning training, then improved the object detection performance of a dependable Car object, but Person had a low object detectionperformance. However, due to the small quantity of Fire objects, there is a considerable risk of the wrong detection in untrained footage in the event of Fire. However, by simultaneously training objectsthat are not on fire, it is possible to reduce the probability of wrong detections.

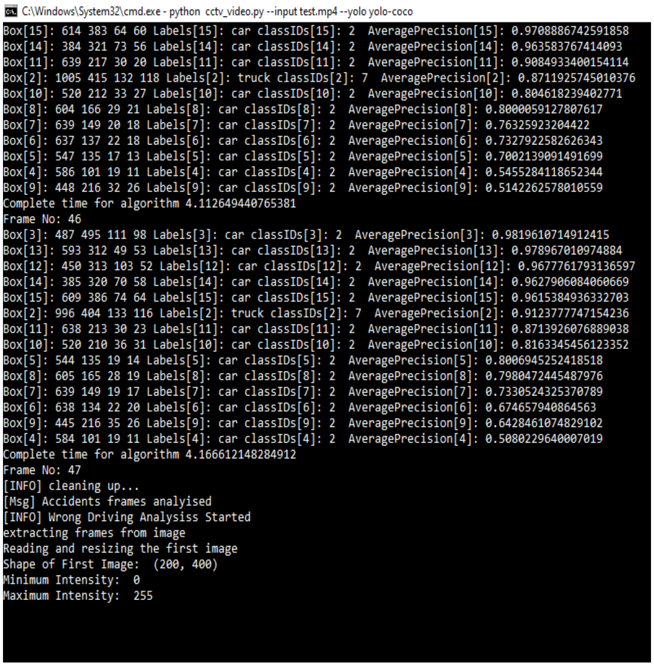
XI. ADVANTAGES

1. A deep learning model of R-CNN was used for training with the yolo object detection model.
2. This object tracking module was built by introducing an object tracking model called yolo.
3. Because of this, the system will detect objects faster.

 DOI : 10.35291/2454-9150.2022.0151

International Journal for Research in Engineering Application & Management (IJREAM)
ISSN : 2454-9150 Vol-08, Issue-01, APR 2022

XII. DESIGN DETAILS



```
C:\Windows\System32\cmd.exe - python  cctv_video.py --input test.mp4 --yolo yolo-coco
Box[15]: 614 383 64 60 Labels[15]: car classIDs[15]: 2  AveragePrecision[15]: 0.9708886742591858
Box[14]: 384 321 73 56 Labels[14]: car classIDs[14]: 2  AveragePrecision[14]: 0.963583767414093
Box[11]: 639 217 30 20 Labels[11]: car classIDs[11]: 2  AveragePrecision[11]: 0.9084933400154114
Box[2]: 1005 415 132 118 Labels[2]: truck classIDs[2]: 7  AveragePrecision[2]: 0.8711925745010376
Box[10]: 520 212 33 27 Labels[10]: car classIDs[10]: 2  AveragePrecision[10]: 0.804618239402771
Box[8]: 604 166 29 21 Labels[8]: car classIDs[8]: 2  AveragePrecision[8]: 0.8000059127807617
Box[7]: 639 149 20 18 Labels[7]: car classIDs[7]: 2  AveragePrecision[7]: 0.76325923204422
Box[6]: 637 137 22 18 Labels[6]: car classIDs[6]: 2  AveragePrecision[6]: 0.7327922582626343
Box[5]: 547 135 17 13 Labels[5]: car classIDs[5]: 2  AveragePrecision[5]: 0.7002139091491699
Box[4]: 586 101 19 11 Labels[4]: car classIDs[4]: 2  AveragePrecision[4]: 0.5455284118652344
Box[9]: 448 216 32 26 Labels[9]: car classIDs[9]: 2  AveragePrecision[9]: 0.5142262578010559
Complete time for algorithm 4.112649440765381
Frame No: 46
Box[3]: 487 495 111 98 Labels[3]: car classIDs[3]: 2  AveragePrecision[3]: 0.9819610714912415
Box[13]: 593 312 49 53 Labels[13]: car classIDs[13]: 2  AveragePrecision[13]: 0.978967010974884
Box[12]: 450 313 103 52 Labels[12]: car classIDs[12]: 2  AveragePrecision[12]: 0.9677761793136597
Box[14]: 385 320 70 58 Labels[14]: car classIDs[14]: 2  AveragePrecision[14]: 0.9627906084060669
Box[15]: 609 386 74 64 Labels[15]: car classIDs[15]: 2  AveragePrecision[15]: 0.9615384936332703
Box[2]: 996 404 133 116 Labels[2]: truck classIDs[2]: 7  AveragePrecision[2]: 0.912377747154236
Box[11]: 638 213 30 23 Labels[11]: car classIDs[11]: 2  AveragePrecision[11]: 0.8713926076889038
Box[10]: 520 210 36 31 Labels[10]: car classIDs[10]: 2  AveragePrecision[10]: 0.8163345456123352
Box[5]: 544 135 19 14 Labels[5]: car classIDs[5]: 2  AveragePrecision[5]: 0.8006945252418518
Box[8]: 605 165 28 19 Labels[8]: car classIDs[8]: 2  AveragePrecision[8]: 0.7980472445487976
Box[7]: 639 149 19 17 Labels[7]: car classIDs[7]: 2  AveragePrecision[7]: 0.7330524325370789
Box[6]: 638 134 22 20 Labels[6]: car classIDs[6]: 2  AveragePrecision[6]: 0.674657940864563
Box[9]: 445 216 35 26 Labels[9]: car classIDs[9]: 2  AveragePrecision[9]: 0.6428461074829102
Box[4]: 584 101 19 11 Labels[4]: car classIDs[4]: 2  AveragePrecision[4]: 0.5080229640007019
Complete time for algorithm 4.166612148284912
Frame No: 47
[INFO] cleaning up...
[Msg] Accidents frames analysed
[INFO] Wrong Driving Analysiss Started
extracting frames from image
Reading and resizing the first image
Shape of First Image:  (200, 400)
Minimum Intensity:  0
Maximum Intensity:  255
```

Figure 1: accident detection

Figure 2: assigning unique ID to all moving objects

XIII. CONCLUSION

Thus,We have tried to implement the paper of Author "Kyu Beom Lee, Hyu Soung Shin", "*An Application Of Deep Learning Algorithm For Automatic Detection Of Unexepected Accidents Under Bad CCTV Monitoring Conditions In Tunnels*", A International Conference of Deep Learning And Machine Learning 2019, IEEE 2019. This research offers a new ODTS method that combines a deep learning-based object recognition network with an object tracking algorithm to acquire and use dynamic information about an object for a certain object class. The object detection performance is critical since SORT, which isutilized in ODTS object tracking, depends mainly on BBox information and does not employ an image. As a result, unless theobject tracking technique is heavily reliant on object recognition performance, continual object detection performance may be unnecessary. And an ODTS-based Tunnel CCTV Accident Detection System was created. Experiments on the training and evaluation of a deep learning object identification network, as well as the detection of a system-wide accident, were carried out. Complete-time for the algorithm is 4.166. Average precision is calculated for every box detected in the frame. A total of 47frames are detected in the algorithm. Average precision ranges from 0.5 to 0. The minimumintensity is 0 and the maximum intensity is 255.

REFERENCES

[1] Kyu Beom Lee, Hyu Soung Shin, "An Application Of Deep Learning Algorithm For Automatic Detection Of Unexepected Accidents Under Bad CCTV Monitoring Conditions In Tunnels", A International Conference of Deep Learning And Machine Learning 2019, IEEE 2019.

[2] E. S. Lee, W. Choi, D. Kum, "Bird's eye view localization of surrounding vehicles :Longitudinal and lateral distance estimation with partial appearance," Robotics and Autonomous Systems, 2019, vol. 112, pp.178-189.

[3] L. Cao, Q. Jiang, M. Cheng, C. Wang, "Robust vehicle detection by combining deep features with exemplar classification," Neurocomputing, 2016, vol. 215, pp. 225- 231.

[4] A. Arinaldi, J. A. Pradana, A. A. Gurusinga, "Detection and classification of vehicles for traffic video analytics," Procedia computer science, 2018, vol. 144, pp. 259- 268.

[5] K. B. Lee, H. S. Shin, D. G. Kim, "Development of a deep-learning based automatic tunnel incident detection system on cctvs," in Proc. Fourth International Symposium on Computational Geomechanics, 2018, pp. 140-141.

[6] S. Ren, K. He, R. Girshick, J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in Proc. Neural Information Processing Systems, 2015, pp. 91-99.

[7] A. Bewley, Z. Zongyuan, L. Ott, F. Ramos, B. Upcroft, "Simple Online and Realtime Tracking," in Proc. IEEEInternational Conference on Image Processing, 2016, pp. 3464-3468.

[8] C. Dicle, M. Sznaier, and O. Camps, "The way they move: Tracking multiple targetswith similar appearance," in International Conference on Computer Vision, 2013.

 DOI : 10.35291/2454-9150.2022.0151