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AN APPLICATION OF A DEEP LEARNING SYSTEM FOR AUTOMATED IDENTIFICATION OF UNFORESEEN INCIDENTS IN TUNNELS UNDER POOR CCTV SURVEILLANCE CIRCUMSTANCES

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ABSTRACT:

Object Detection and Tracking System (ODTS) will be introduced and applied in this project along with the well-known deep learning network Faster Regional Convolution Neural Network (Faster R-CNN) for Object Detection and Conventional Object Tracking algorithm for automatic detection and analysis of unexpected events on CCTVs in tunnels, which are probable to include (1) Wrong-Way Driving (WWD), (2) Stop, (3) Person out of vehicle in tunnel, (4) Fire. The Bounding Box (BBox) results from Object Detection are obtained by ODTS using a video frame in time as an input. To identify each moving and detected object, a unique ID number is then assigned by comparing the BBox results of the current and previous video frames. This technique makes it feasible to follow a moving item in real time, something that is typically not achievable with other object detection frameworks. A collection of event photos in tunnels was used to train a deep learning model in ODTS, which resulted in Average Precision (AP) values for the target objects Car, Person, and Fire of 0.8479, 0.7161, and 0.9085, respectively. The Tunnel CCTV Accident Detection System was then evaluated using four accident recordings that included each accident, based on a trained deep learning model. As a result, the system has a 10-second detection time for all incidents. The most crucial aspect is that, as the training dataset grows in size, the detection ability of ODTS might be automatically improved without any changes to the programme codes.

Keywords : Average precision, CCTV, ODTS, CNN

[1] INTRODUCTION

Finding the size and location of target items in still photos or moving movies has been made possible with the help of object detection technologies. Applications for self-driving cars, CCTV security systems, cancer diagnosis, etc. have all become more prevalent. Another aspect of image processing that may be accomplished is object tracking, which involves tracking the locations of specified objects over time and performing unique identification. However, in order to track objects, it is first essential to establish object class and location in a static picture that has been provided. Therefore, it can be claimed that the effectiveness of the object detection used should have a significant impact on the outcomes of object tracking.This object tracking technology has been effectively applied to a variety of tasks, including the tracking of a targeted pedestrian and a moving vehicle, accident monitoring in traffic cameras, monitoring of local crime and security concerns, etc.

This research conducts a case study in the realm of traffic control about the analysis and management of traffic conditions by automated object detection. These summaries are provided. A self-driving car's on-road vehicle detecting system reportedly has been created. This system recognises a moving item and categorises the type of moving object using a convolutional neural network (CNN). By adjusting the tracking centre point in accordance with the location of the detected vehicle object on the picture, the vehicle object tracking algorithm tracks the vehicle object. The system then computes the distance between the driving automobile and the visualised vehicle items, and the monitor displays a localised image from the perspective of a bird with the visualised vehicle objects. This system procedure makes it possible to see the location of a vehicle object objectively, aiding the self-driving system. As a consequence, it can pinpoint the vehicle object at the camera within 1.5 m of vertical and 0.4 m of horizontal tolerance. Another deep learning-based detection system that combines CNN and Support Vector Machine (SVM) was created in for the purpose of remotely monitoring moving cars on highways or city streets.This system uses the satellite picture as an input value to CNN to extract the feature, and then uses SVM to conduct binary classification to find the vehicle BBox. Additionally, Arinaldi, Pradana, and Gurusinga created a method to calculate vehicle speed, categorise vehicle types, and assess traffic volume. This system makes use of BBox, which was discovered through object identification in films or photos. The system's applied method was contrasted with the speedier RCNN and Gaussian Mixture Model SVM. The position and kind of the vehicle appear to have been more precisely detected by the quicker R-CNN at that point. In other words, it may be argued that the algorithm-based object detection system is inferior to the deep learning-based method.As a conclusion, this paper's development scenarios all use object information and demonstrate exceptional deep learning performance. However, they were all challenging to provide the discovered items distinctive IDs and follow them by maintaining the same ID throughout time.

In order to create an object detection and tracking system (ODTS) that can monitor moving information about the target objects, object tracking algorithm and deep learning-based object identification method are combined in this study. In the part that follows, the complete ODTS processes will be thoroughly explained. Additionally, the tunnel accident detection system inside the ODTS framework will be taken into account. This technique is used to track a certain local area on CCTV and find accidents or unexpected occurrences that happen to moving objects.

A simplified version of a tracking-by-detection framework for the multiple objects tracking (MOT) issue, in which bounding boxes are used to represent objects that are identified every frame. This work is primarily focused towards online tracking, where only detections from the past and the current frame are supplied to the tracker, in contrast to numerous batch-based tracking systems. Additionally, efficiency is heavily stressed to enable real-time monitoring and to encourage wider use in applications like pedestrian tracking for autonomous cars. The goal of the MOT issue, which can be seen as a data association problem, is to link detections across different frames of a video sequence. Trackers mimic the motion and look of objects using a variety of techniques to help with the data association process of objects in the scene.

This paper's methodology was inspired by findings made on a freshly created visual MOT benchmark. Firstly, there is a comeback of mature data association approaches such Multiple Hypothesis Tracking

(MHT) and Joint Probabilistic Data Association (JPDA) which hold several of the top spots in the MOT benchmark. Second, the top-ranked tracker is the only one that does not employ the Aggregate Channel Filter (ACF) detector, indicating that the other trackers may be hindered by poor detection quality. Additionally, it appears that there is a significant trade-off between accuracy and speed, since the majority of accurate trackers have a pace that is too sluggish for real-time applications. This paper examines how straightforward MOT can be and how effective it can be, given the prevalence of conventional data association techniques among the top online and batch trackers as well as the usage of various detections by the top tracker. Following Occam's Razor, tracking just uses the bounding box location and size for both motion estimate and data association, ignoring appearance characteristics past the detection component. Additionally, problems with short-term and long-term occlusion are disregarded since they happen seldom and because treating them explicitly adds unneeded complexity to the tracking system.

We contend that adding complexity in the form of item re-identification places a major burden on the tracking system and may prevent real-time applications from using it. Contrary to many suggested visual trackers that include a plethora of components to manage different edge situations and detection mistakes, this design philosophy focuses on the user's experience. Instead, the emphasis of this study is on addressing typical frame-to-frame relationships in an effective and dependable manner. We take use of recent developments in visual object identification to directly address the detection problem rather than attempting to be resilient to detection failures. This is shown by contrasting the conventional ACF pedestrian detector with a more modern CNN-based detector. Additionally, the tracking problem's movement estimation and data association components are handled by two conventional yet highly effective methods, the Kalman filter and the Hungarian method, respectively. In this paper, this approach is only applied to tracking pedestrians in different environments, but due to the flexibility of CNN based detectors, it naturally can be generalised to other object classes. This simple and elegant formulation of tracking facilitates both efficiency and reliability for online tracking. The main contributions of this paper are:

• In the context of MOT, we make use of the effectiveness of CNN-based detection.

• On the basis of a recent MOT benchmark, a practical tracking technique based on the Kalman filter and the Hungarian algorithm is provided.

• To provide a standard procedure for research experimentation and adoption in collision avoidance applications, code will be made publicly available.

Multiple Hypothesis Tracking (MHT) or Joint Probabilistic Data Association (JPDA) filters have traditionally been used to solve MOT, delaying critical judgments when there is considerable uncertainty regarding the object assignments. These methods are problematic for real-time applications in extremely dynamic contexts because their combinatorial complexity grows exponentially with the number of monitored objects. Rezatofighi et al. have reviewed the JPDA formulation in visual MOT with the aim of addressing the combinatorial complexity issue with an effective approximation of the JPDA by taking use of current advancements in solving integer algorithms.Similar to this, Kim et al. pruned the MHT graph to obtain cutting-edge performance by using an appearance model for each target. These techniques are inappropriate for online tracking since they continue to slow down decision-making. Many online tracking techniques seek to create global or individual object-specific appearance models using online learning. Motion is frequently used in addition to appearance models to help link detections to tracklets. Globally optimum solutions, like the Hungarian method, can be utilised when simply taking into account one-to-one correspondences modelled as bipartite graph matching. The Geiger et al. technique employs the Hungarian algorithm in two steps. Tracklets are first created by linking detections across neighbouring frames where the affinity matrix is built by combining both geometry and appearance cues. Using both geometry and visual cues, the tracklets are then connected to one another to repair broken trajectories brought on by occlusion. This strategy can only be used for batch computing because of the two-step association mechanism. Our strategy is modelled by the tracking element of, but we reduce the connection to a single step using the outlined fundamental signals.

[2] LITERATURE SURVEY

Driving environments must be perceived through on-road vehicle detection, and localising the identified vehicle aids in risk assessment and accident avoidance. The approach for partially visible vehicle localisation has not been investigated, and there are few studies on vehicle detection with partial visibility. This research uses stereo vision and geometry to present a novel framework for vehicle recognition and localisation with incomplete appearance. To create a v-disparity map, the stereo camera's original pictures must first be processed. With information of potential vehicle locations on the picture, vehicle candidates are produced following object detection using v-disparity. Vehicle detection is finished by deep learning-based verification.A new partially visible vehicle tracking method is introduced for each identified vehicle. This method finds the vehicle edge on the ground, also known as the grounded edge, in order to monitor partially visible cars. It then chooses a basis of comparison for Kalman filter tracking. In order to show the longitudinal and lateral positions of the vehicle, a rectangular box is lastly created on the bird's eye view. The suggested system successfully detects and tracks vehicles that are only partially visible. The datasets from an urban environment and a highway are utilised to evaluate the localization performance and yield less than 1.5 m of longitudinal error and 0.4 m of lateral error as standard deviation.

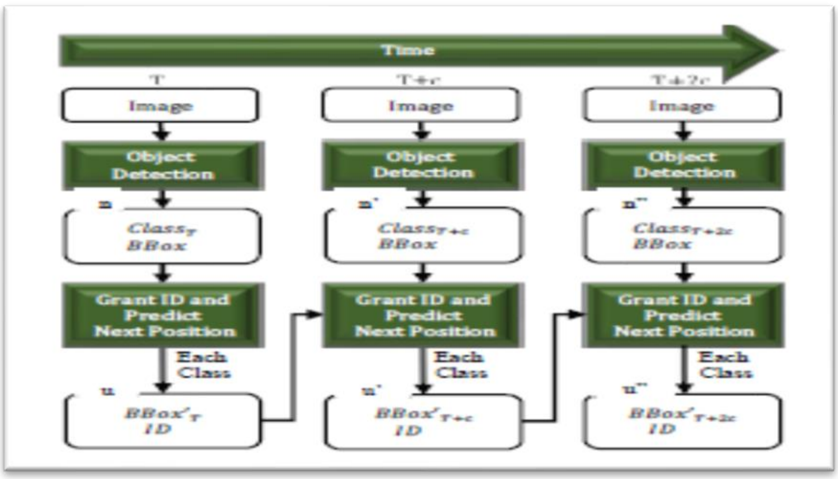
Vehicle identification in satellite imagery is a relatively new study area with a variety of applications in both military and commercial systems. It still remains an unresolved subject, nevertheless, mostly because of the intricate variations in imaging settings, changes in object intra-class, and low resolution. In this research, we explore the potential for utilising deep neural features for reliable vehicle recognition in light of the significant advancements in deep learning for feature representation. Additionally, a new classification approach is required to explicitly address the intra-class changes along with the exponential expansion in data amount. In this study, we offer a system for detecting vehicles that integrates feature learning from Deep Convolutional Neural Networks (DNN) with Exemplar-SVMs (E-SVMS), to accomplish effective vehicle recognition in satellite photos, a strong instance classifier is needed. To learn discriminative picture features in particular, we use DNN, which has a large learning capacity. In our experience, the use of DNN has resulted in a considerable speed gain when compared to a series of manually created features. Additionally, we use an E-SVMs-based robust classifier, which can be thought of as an instance-specific metric learning method, to further increase the classification robustness. We further demonstrate that the combination of both techniques may profit from each other to jointly increase the detection accuracy and efficacy by performing comprehensive tests with comparisons to a series of state-of-the-art and alternative works.

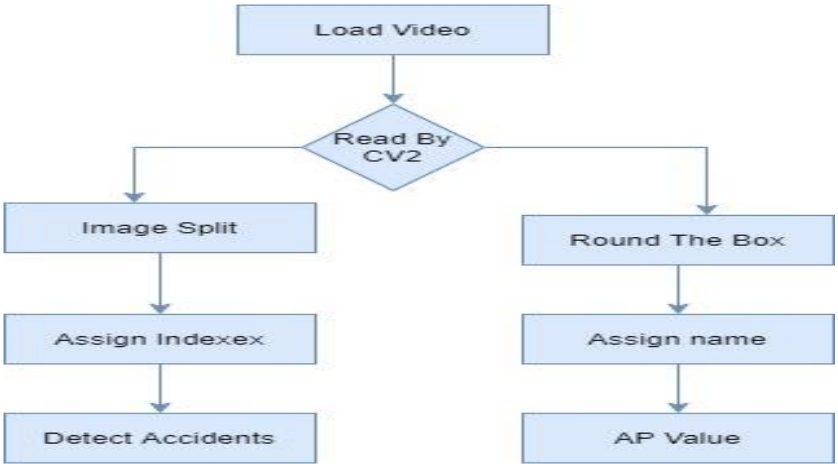
We describe a computer vision-based method for traffic video analysis. The technology is built to automatically compile crucial data that will be used by regulators and policymakers. These statistics include lane usage tracking, vehicle type categorization, vehicle speed calculation from video, and vehicle count. The identification and categorization of automobiles in traffic recordings is the basis of such a system. For this, we develop two models: a MoG + SVM system and a Faster RCNN-based system. Faster RCNN is a newly well-liked deep learning architecture for object recognition in pictures.In our studies, we demonstrate that Faster RCNN beats MoG in the identification of moving objects under static, overlapping, or low-light settings. For the purpose of categorising vehicle kinds based on looks, faster RCNN beats SVM.

K. B. Lee, H. S. Shin, D. G. Kim et.al _Object Detection and Tracking System (ODTS) will be proposed and applied for automatic detection and monitoring of unforeseen events on CCTVs in tunnels, which are likely to include (1) Wrong-Way Driving (WWD), (2) Stop, (3) Person out of vehicle in tunnel, and (4) Fire. Faster Regional Convolution Neural Network (Faster R-CNN) for Object Detection and Conventional Object Tracking algorithm will also be introduced and applied. To acquire Bounding Box (BBox) results via Item Detection, ODTS receives a video frame in time as an input. It then compares the BBoxs of the current and prior video frames to assign a unique ID number to each moving and identified object.This technique makes it feasible to follow a moving item in real time, something that is typically not achievable with other object detection frameworks. A collection of event photos in tunnels was used to train a deep learning model in ODTS, which resulted in Average Precision (AP) values for the target objects Car, Person, and Fire of 0.8479, 0.7161, and 0.9085, respectively. The Tunnel CCTV Accident Detection System was then evaluated using four accident recordings that included each accident, based on a trained deep learning model. As a result, the system has a 10-second detection time for all incidents. The most crucial aspect is that, as the training dataset grows in size, the detection ability of ODTS might be automatically improved without any changes to the programme codes.

A. Bewley, V. Guizilini, F. Ramos, and B. Upcroft et. Al**.** provides a technique for the continuous segmentation of moving objects without any prior information of the object's appearance utilising just a vehicle mounted monocular camera. By adding an unsupervised motion clustering phase, previous work in online static/dynamic segmentation is expanded to recognise multiple instances of dynamic objects. Within a self-supervised framework, a multi-class classifier is then updated using these clusters. Our system is able to recognise live objects without any prior information of their visual appearance, shape, or position, in contrast to existing tracking-by-detection based approaches. The classifier is also used to transmit labels of the same item from earlier frames, making it easier to monitor moving objects continuously. The performance of segmenting numerous instances of items is measured using a novel multi-instance labelled dataset, recall and false alarm measures, and the suggested system.

[3] SYSTEM ARCHITECTURE





[4] IMPLEMENTATION

4.1 MODULES DESCRIPTION:

i) User: The cctv videos are user-loadable. The user must provide -input to begin the project (Video file path). The open cv class VideoCapture(0) designates the system's primary camera, whereas VideoCapture(1) designates the system's secondary camera. Without a camera, we may import a previously recorded ideo file into the system thanks to the VideoCapture(Videfile path) command. The Yolo object detection system, which is based on RCNN principles, must then be loaded by the user. This yolo module is used to recognise and label the things in each frame. It can identify individuals, objects, flames, etc.…

ii) Object Detection and Tracking:

Classifiers or localizers are repurposed by prior detection systems to carry out detection. They use the model to analyse a picture at various sizes and places. Detections are areas of the image's bounding box with high scores. To the entire picture, we apply a regional convolution neural network. The picture is divided into regions by this network, which also forecasts coordinates and probabilities for each region. The projected probabilities are used to weight these bounding boxes. Compared to classifier-based systems, our model provides a number of benefits. When testing, it considers the entire image, allowing the global context of the image to influence its predictions.

iii) RCNN(Regional Convolution Neural Network):

R-CNN models first choose a number of suggested areas from an image (anchor boxes are one form of selection method, for instance), and then label the categories and bounding boxes of those selected regions (e.g., offsets). Following that, they undertake forward computation using a CNN to extract characteristics from each suggested location. Then, we forecast the categories and bounding boxes of each suggested region using its attributes. Then, based on the information about the identified items, a dependent object tracking module is started to give each of the detected objects a special ID number, IDt, and anticipate each object's subsequent location, BBOX. Tracking BBox u has a different number than tracking BBox n. However, if the previous tracked BBox was zero, the number of trackingBBoxes was equal to the number of the detected objects.

iv) **Average Precision:**

The training dataset's AP values for the target items to be detected show that cars represent the largest object class and have the highest AP values of all the classes. In other words, it was anticipated that the Car's deep running object recognition performance would be quite trustworthy. On the other hand, because Person object has a long, tiny shape and is modest in size, AP for Person object has a relatively low value. The AP of the Fire object was high, but due to the small number of training items, erroneous detection for the object could be quite likely. Nevertheless, training in deep learning, which also covers No Fire objects, could minimise false detection Fire event in training.

4.2 Sample Screenshots

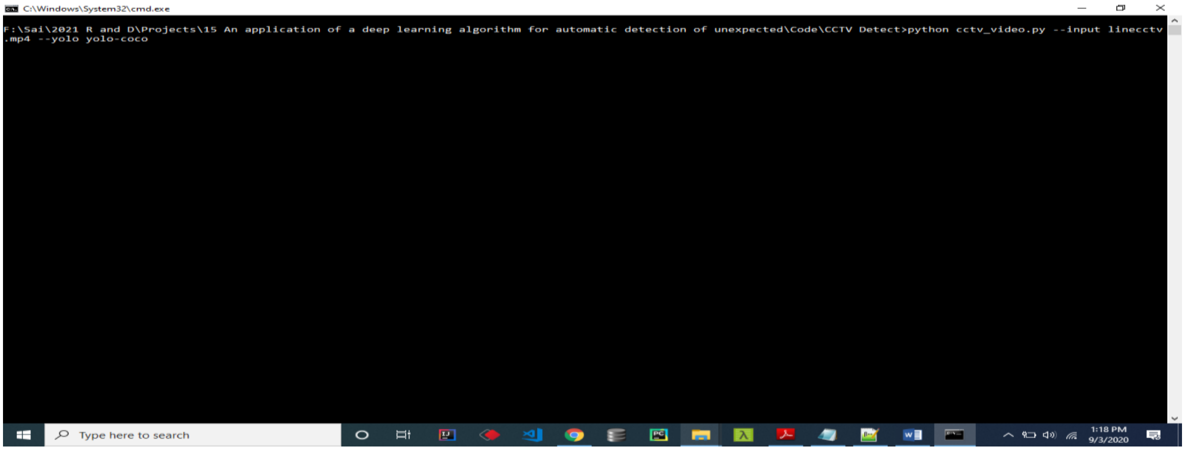


Fig. 1 Starting project

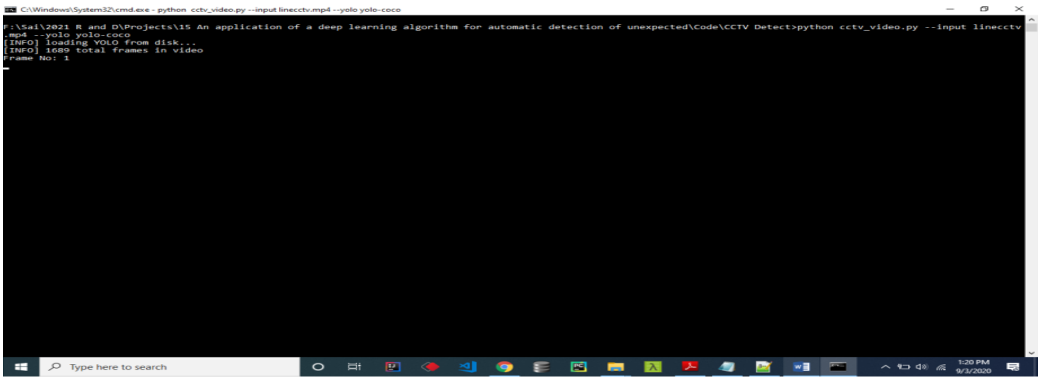


Fig. 2 Loading Training Model

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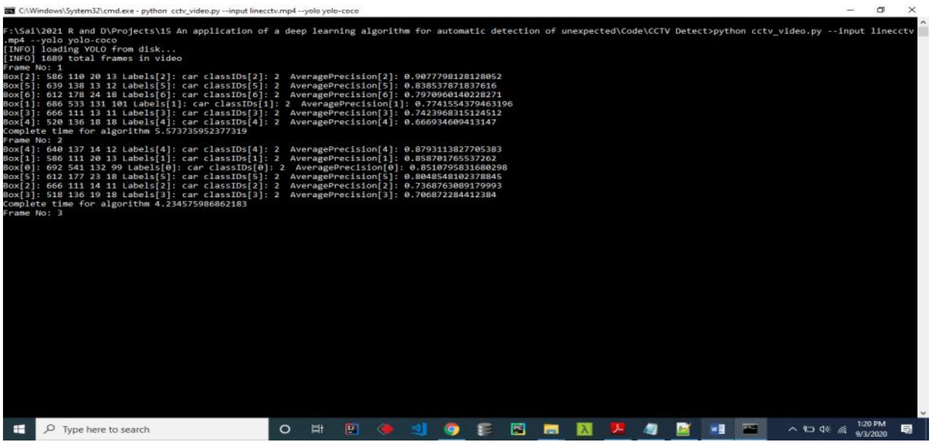

Fig. 3 Video separated as frames

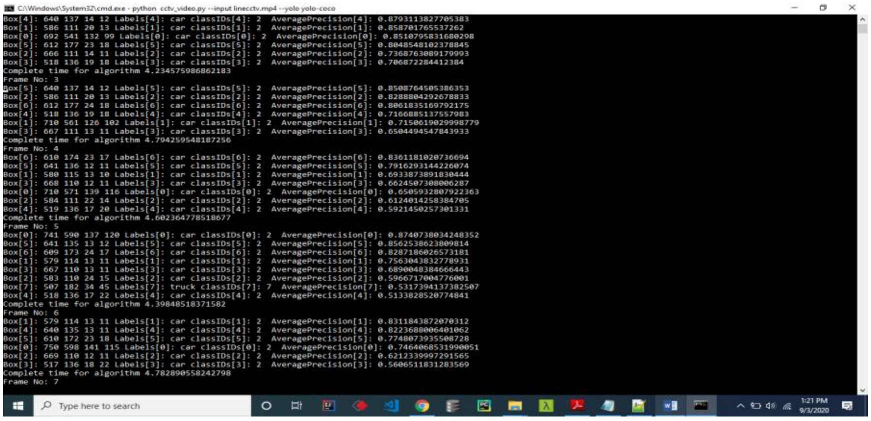

Fig. 4 Staring each frames

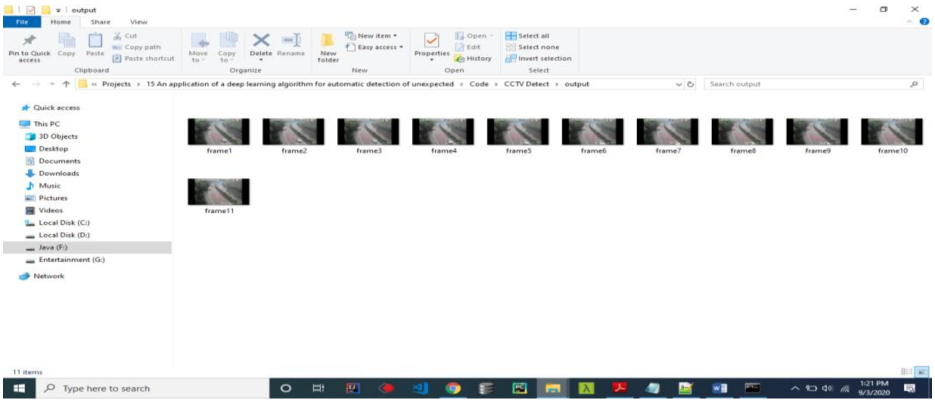

Fig. 5 Output frames

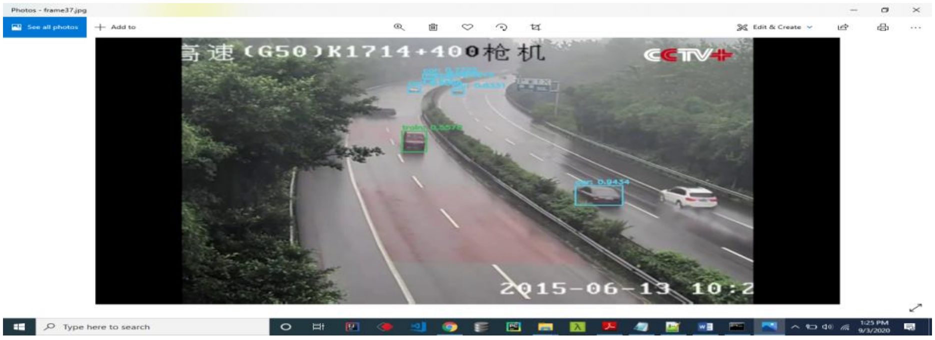

Fig. 6 Object Detection

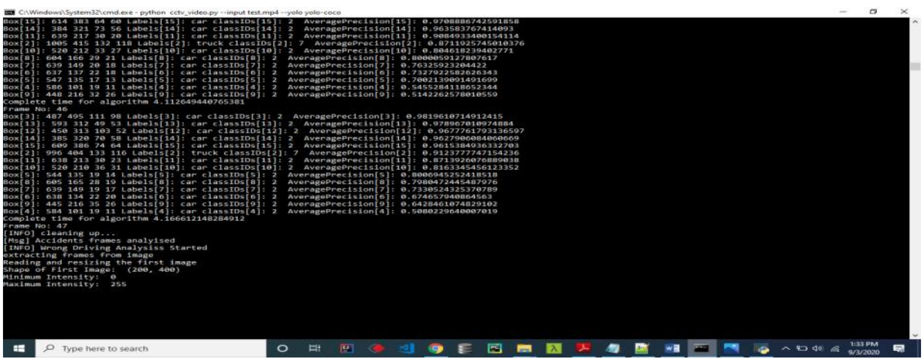

Fig. 7 Preprocess done

Fig. 8 First Image Compare

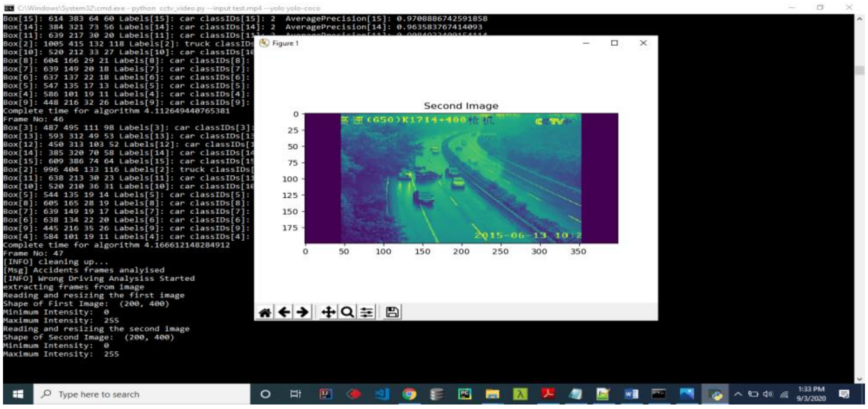

Fig. 9 Second Image Compare

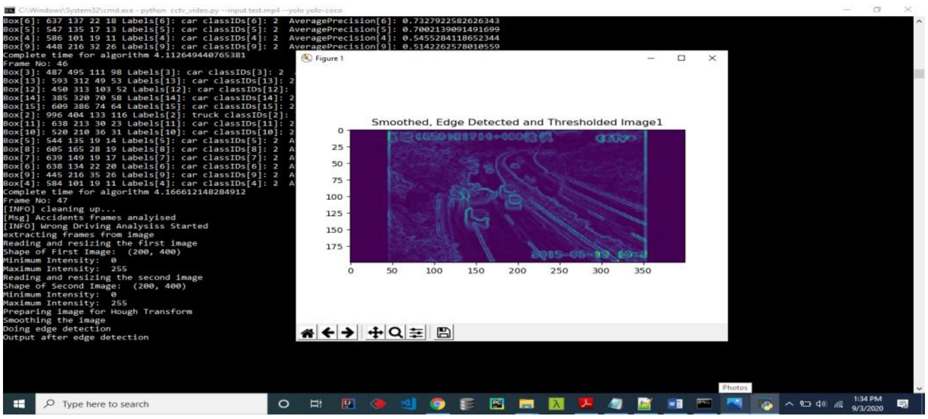

Fig. 10 Smooth Detection

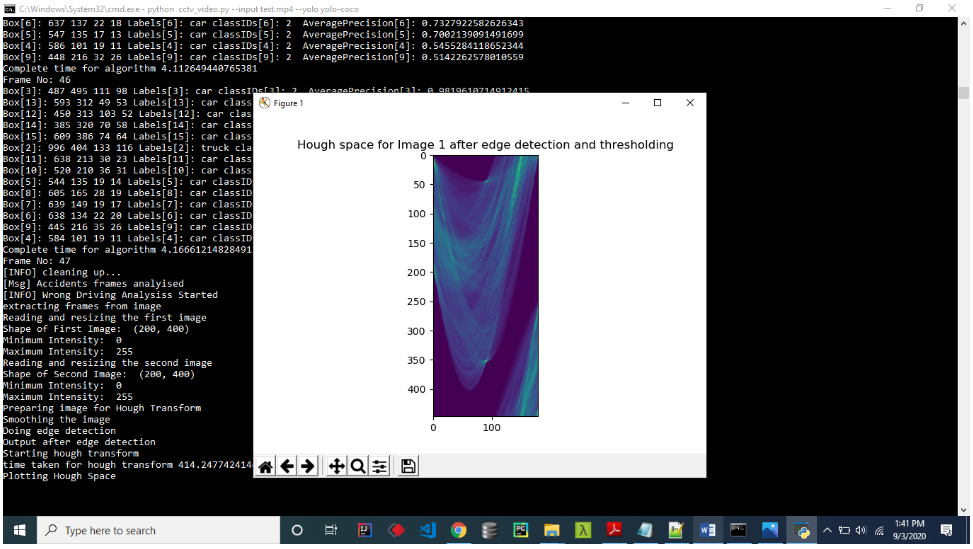

Fig. 11 Space Count

Fig. 12 Making Video

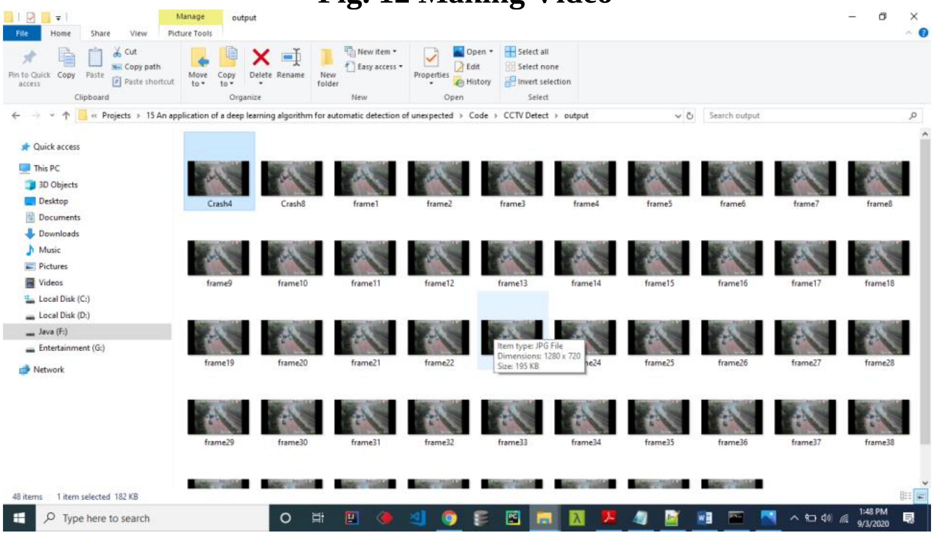

Fig. 13 Crash Detected

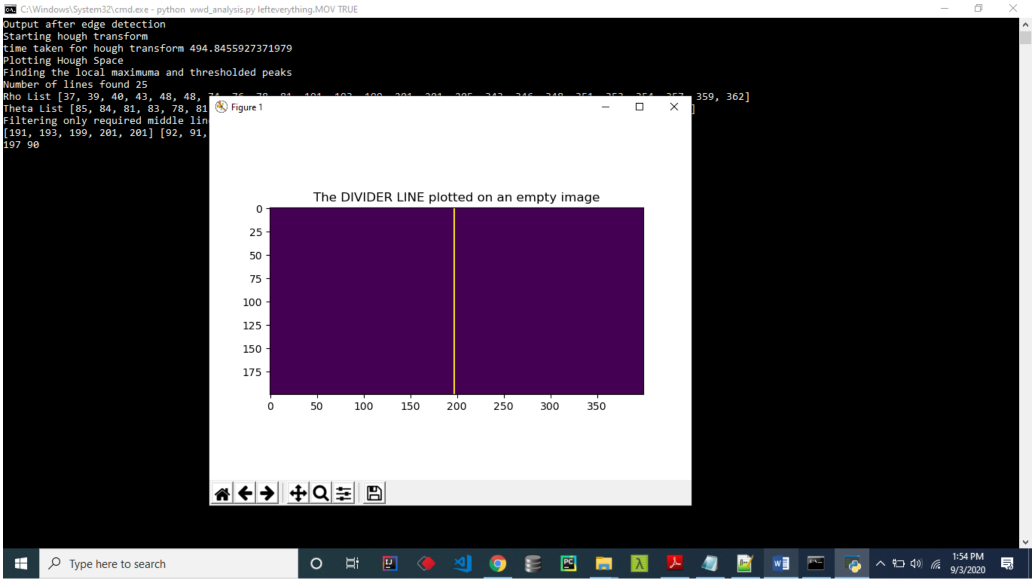

Fig. 14 Identifying driving line

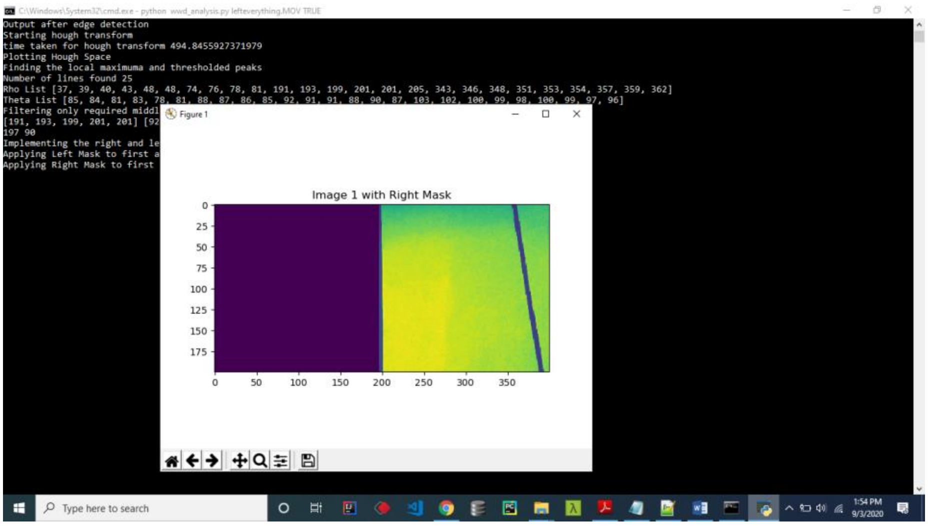

Fig. 15 Image with left mask

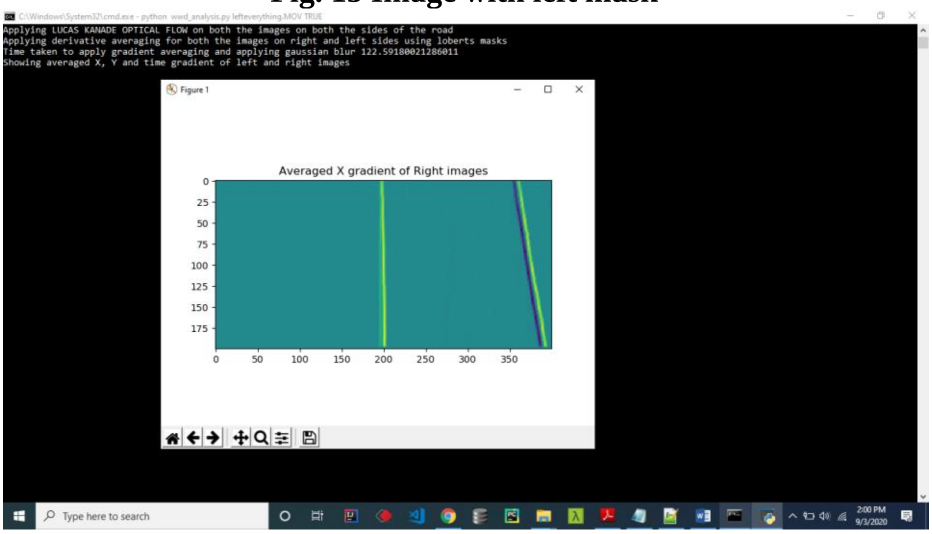

Fig. 16 Average Gradient Image

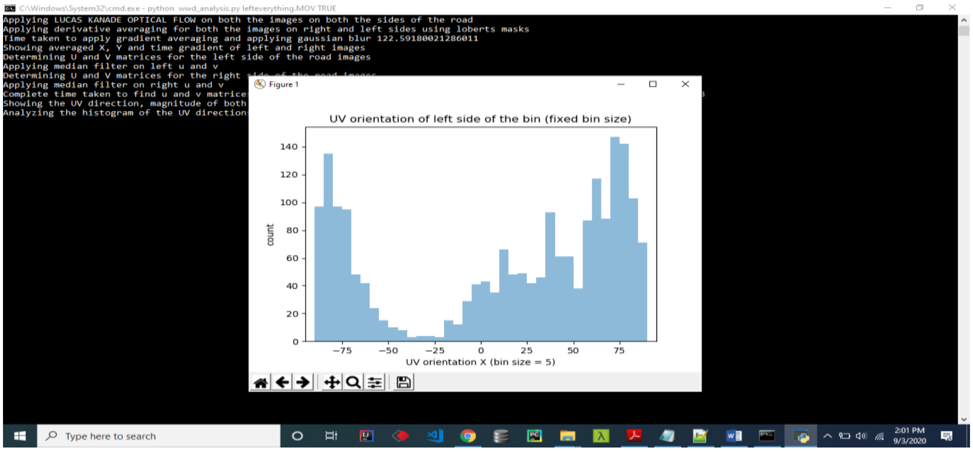

Fig. 17 UV orientation

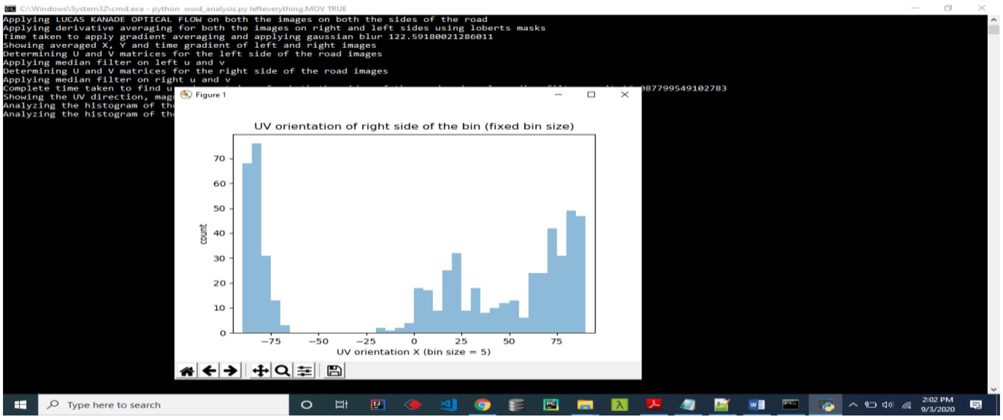

Fig. 18 UV orientation

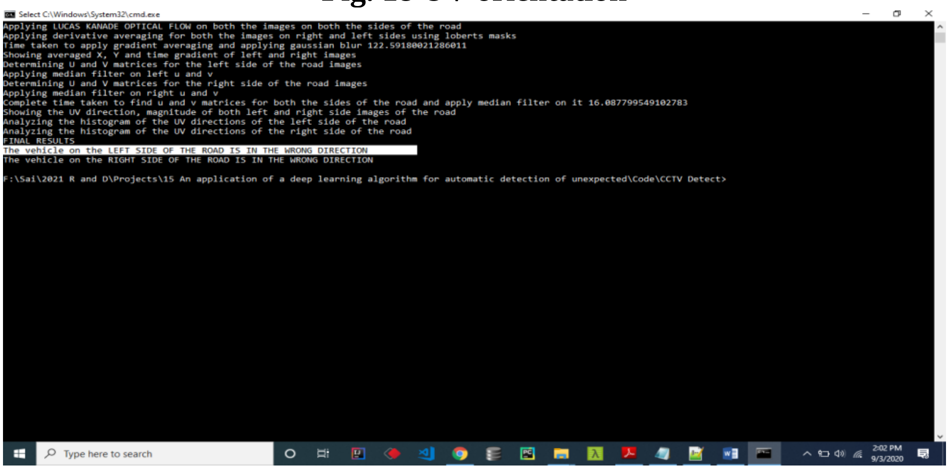

Fig. 19 Detect Vehicle Direction

[5] CONCLUSION

This research suggests a new method for ODTS that combines an object detection network powered by deep learning with an object tracking algorithm. It demonstrates how dynamic object information for a particular object class may be gathered and used. On the other hand, the performance of object detection is crucial since SORT, which is utilised in ODTS object tracking, only takes data from BBox and does not employ an image. Therefore, unless the object tracking technique is significantly reliant on object identification performance, continuous object detection performance may not be as necessary. Additionally, an ODTS-based Tunnel CCTV Accident Detection System was created. The experiments on deep learning object identification network training and assessment as well as system-wide accident detection were carried out.It was feasible to identify the incidents within 10 seconds after testing with the picture that contained each incident. However, deep learning training guaranteed the object recognition performance of a trustworthy Car object, but Person displayed comparatively poor object detection performance. Due to the scarcity of Fire objects in the untrained movies, there is a significant likelihood of erroneous detection in the event of Fire. Nonetheless, by simultaneously training objects that are No Fire, it is feasible to decrease the incidence of erroneous detections. Securing the Fire image afterwards should enhance the deep learning object detection network's performance in detecting fire objects. Although the ODTS may be used as an example of a Tunnel CCTV Accident Detection System, it can also be utilised in other industries that need to track the dynamic movement of a particular item, such as estimating vehicle speed or tracking unlawful parking. Securing diverse photos as well as Fire and Person objects is required to improve the system's dependability. In addition, the system's dependability might be increased by application and ongoing monitoring of the tunnel management site.

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