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Research Article

A Comprehensive Review of Deep Learning and Machine Learning Techniques for Real-Time Car Detection and Wrong-Way Vehicle Tracking

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ABSTRACT

This research focuses on the advancements in car detection techniques, particularly targeting wrong-way driving vehicles, using deep learning and machine learning methodologies. In recent years, numerous techniques have been proposed to address vehicle detection in real-time scenarios, leveraging algorithms such as YOLO (You Only Look Once) and centroid tracking to detect vehicles in various traffic situations. Additionally, methods involving UAV imagery, infrared imaging, and frame differencing approaches have enhanced the capabilities of real-time vehicle detection systems. Despite achieving significant milestones in accuracy and efficiency, existing methods still face limitations, such as high false-positive rates, imbalanced datasets, and challenges in complex environments like poor lighting and diverse road conditions. This study provides a comprehensive review of recent car detection approaches, comparing various algorithms including YOLO variants, CTAD, CNN, and DLMTD, and evaluating their strengths and limitations. A critical analysis of these methods reveals areas for improvement, particularly in terms of enhancing robustness, optimizing real-time response, and expanding detection capabilities to accommodate complex traffic patterns. The findings underscore the potential of hybrid approaches that combine object detection, tracking, and feature extraction techniques to achieve higher accuracy and adaptability in real-time applications. The study concludes by proposing a framework that addresses the observed limitations, suggesting pathways for future research in developing efficient, AI-powered car detection systems tailored for real-world applications.

1. INTRODUCTION

Various techniques have been proposed and applied as a way to facilitate the achievement of cars' detection regardless of the different equipment and programs used. Furthermore, some attempts were limited by the research approaches; others were based on the application ones, while the rest were emitted from the integration between the research and the application leading to a hybrid system as an acquisition of all the essential simulation and applicable demonstration reflecting the reality instantaneously on real time. The following will show some of the most applied and used methodologies in the domain of car detection and path tracking; focusing on the wrong-driving cars as a way to ignore the possible faults and illegal issues. Moreover, the limitations of these methods will be presented followed with a confined comparison between them and ending with a brief conclusion.

2. RELATED WORKS

In this section, we will present the most related literature to our main topic which is oriented towards deep learning and object detection focusing on car/vehicle detection. The concentration will be on the main used algorithm/s for each approach.

2.1. Automatic Wrong Way Vehicle Detection System from On-Road Surveillance Camera Footage

The system which was applied in [17] is focusing on an automatic detection system for wrong way detection and it is based on three main steps, which are confined in the following procedure:

1. Vehicles' detection using YOLO algorithm
2. Tracking each vehicle in the interested specified region making use of the centroid tracking algorithm
3. Detecting the wrong way driving vehicles

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The following four parts summarize the whole implementation of the proposed system:

a. Every vehicle in the video frame is detected using the YOLO object detection algorithm with the generation of a bounded box for each detected vehicle.

b. The bounded boxes are fed to the centroid based moving object tracking algorithm

c. The algorithm tracks each vehicle independently in a specified ROI.

d. The vehicle's direction is determined by calculating its centroid's height in each frame, thus detecting whether it's moving in the wrong direction or not.

Figure 1 shows the centroid tracking algorithm described in such mechanism.

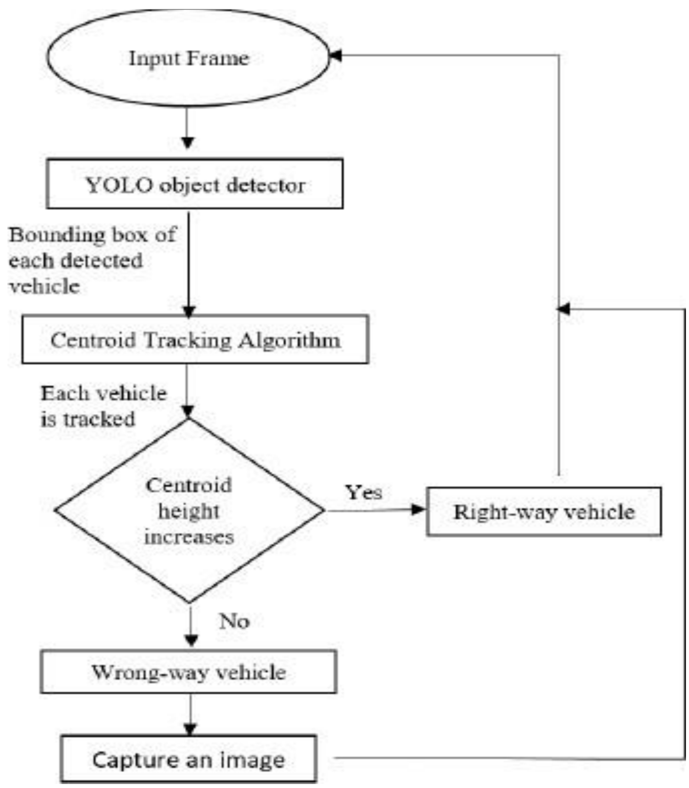

Fig. 1. A flowchart of the whole intended system using centroid tracking algorithm.

To sum up the previous; if the vehicle is noticed that it's steering towards the wrong way, the system will capture an image of it. The main aspects in this work is the virtual region of interest, this means tracking the cars in a specified region of the video frame. Then vehicle tracking using the centroid tracking algorithm is applied and takes the bounding boxes generated by YOLO as input. The algorithm will be updated and the old objects will be given new centroid to track each vehicle separately. Finally, there will be detection of the wrong-way car in which the identification number is used to compute and store the heights from the top of the frames dealing with the tracked cars' centroids.

2.2. Car Detection Using YOLO Algorithm

In the work presented in [18], YOLO algorithm is used to detect the illegal cars using single neural network algorithm to full image followed by dividing the last into regions and predicting bounding boxes and regions' probabilities according to figure 2.

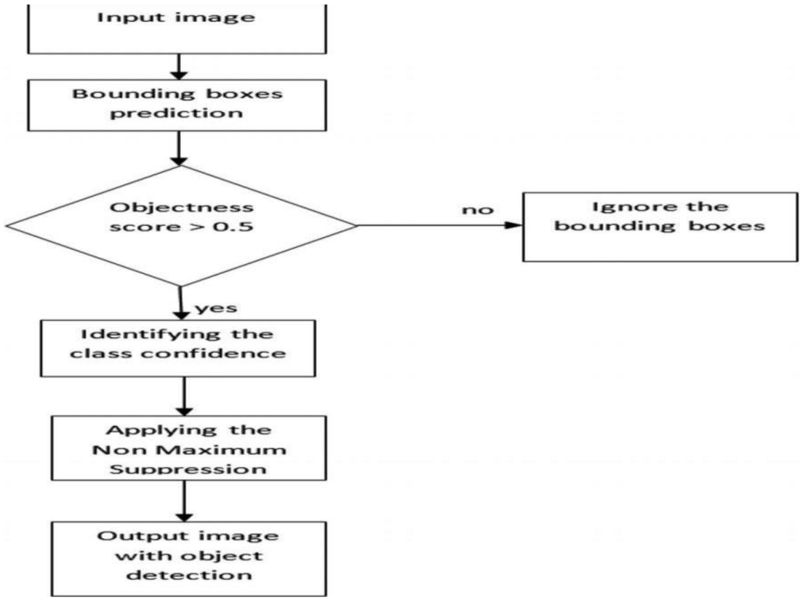

Fig. 2. A flowchart shedding light on the object detection scenario levels

In this implementation, YOLO v3 neural network was applied, containing 106 layers [21]. After extraction an image from the video, it's then taken as an input, returning tensor as output, representing the coordinates and the positions of the predicted bounding boxes which should occupy objects. Objects' detection is done on 3 distinct layers with an approximate input dimensions:$13x13, 26x26$, and $52x52$ [21]. Furthermore; output sensors have same widths and heights like their inputs, but the depth is different and can be defined according to the following:

$$Depth = (4 + 1 + class\ probabilities) * 3 \qquad (1)$$

The essential stages followed in such are:

- Applying neural network to the full image
- Dividing the image into regions
- Bounding boxes prediction and region's probabilities
- YOLO framework takes the entire image in a single instance and predicts the bounding box coordinates class probabilities for these boxes.

During the training process of the network, it becomes able to know about the environment of the object and the complete scenario, the way which facilitates the network in giving better proficiency with a précised results. The breakdown of the image into the grid cells is special in the YOLO algorithm, unlike the other methodologies. In addition to the previous, the input is split into $S * S$ cells' grid where every grid cell can predict 3 bounding boxes. Figure 3 clarifies more the previous illustration.

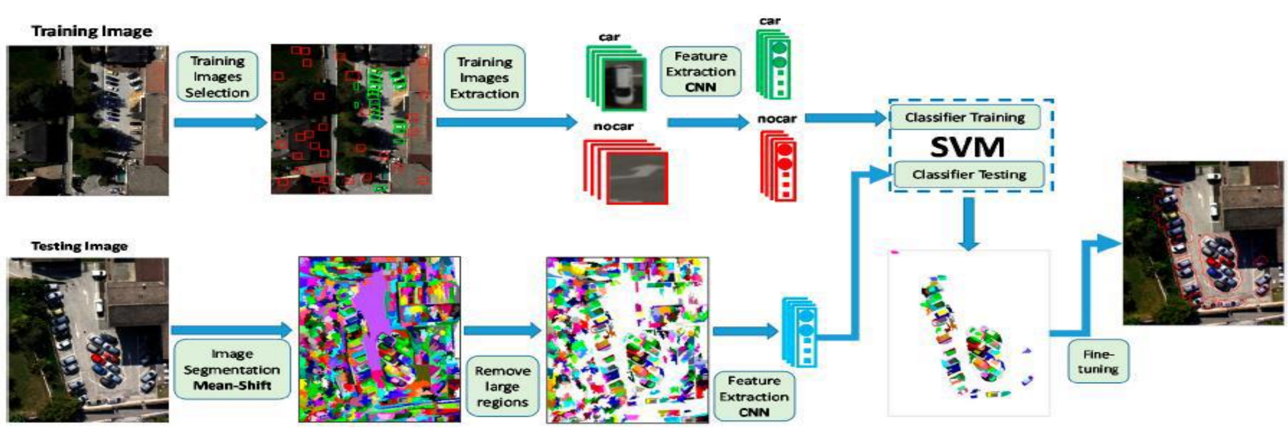

Fig. 3. The bounding boxes for the grid cells divided by YOLO

In this methodology, the YOLO algorithm processed in real-time, an input video stream from the dashboard camera with a frame resolution (1920 × 1080 px). Figure 2.4 shows the input image to be processed by YOLO algorithm before shedding light on the output one (figure 5) [21].

Fig. 4. Input image before operating the YOLO algorithm

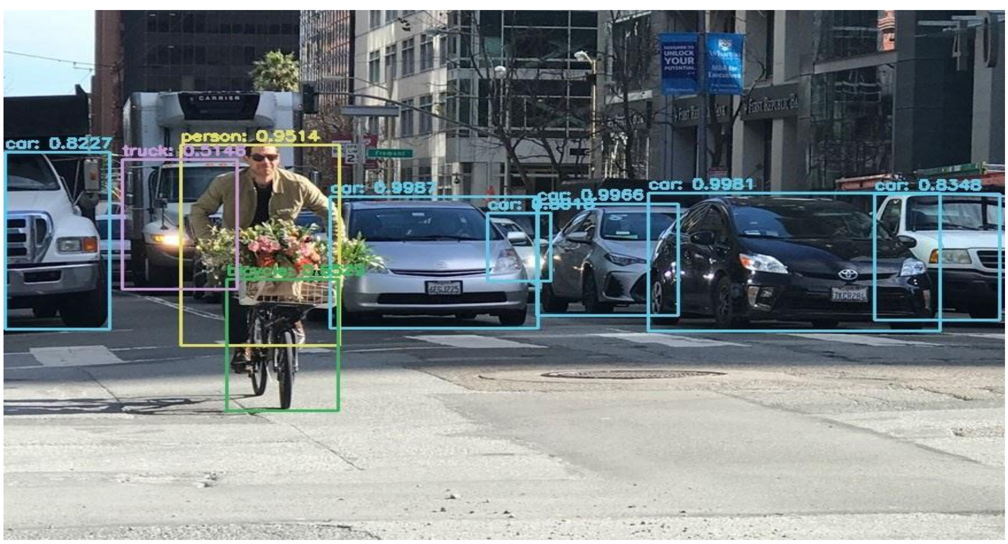

Fig. 5. The output image processed by YOLO algorithm

2.3. Deep Learning Approach for Car Detection in UAV Imagery

One of the common techniques applied before as a way in cars' detection is making use of the UAV imagery; the stages below summarize this approach.

A- Input image segmentation into small homogenous regions as a way for car's detection localization

B- Each region is extracted by a window around it before mining the highly descriptive characteristics from these windows by deep learning

C- SVM classification for the various regions

D- Smoothing the detected regions and filling holes by morphological dilation which are confined in a fine-tuning mechanism [22]

The flowchart presented in figure 2.6 shows the main technique' stages that are done to accomplish such work.

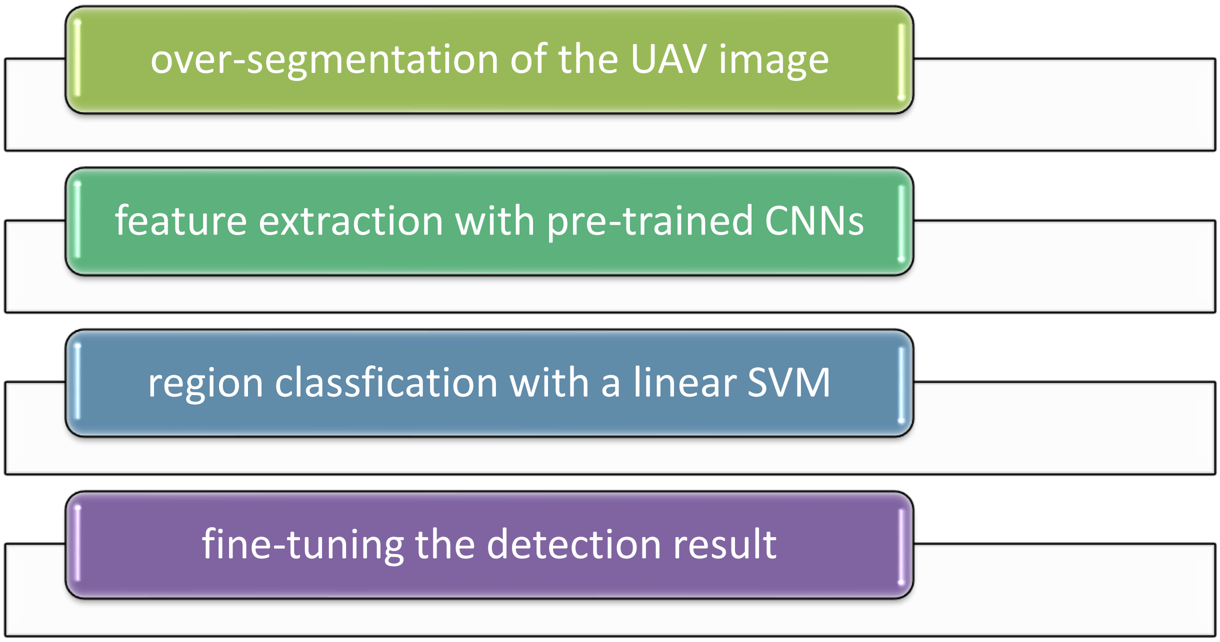

Fig. 6. The procedure of the DL approach for car detection.

Knowing that the process uses a deep CNN system which is pre-trained on big auxiliary data (as an extraction tool feature), and merged with a linear SVM classifier to differentiate between the regions whether there is car or not.

Moreover; in the segmentation process, the application of computer vision methods are highly required due to the wide-range of its methods which are alternated between graph-based segmentation and the gradient-ascent- based segmentation. The table below illustrates some of the most popular examples of the algorithms used in both methods.

In this mechanism, and due to need of the robustness of space-analysis, that can be very significant in the requirements of discontinuity preservation, clustering, tracking, seeking, and the numerous segmentation barriers; the mean-shift algorithm thus used due to its ability to solve such obstructions going along the work. Although such algorithm can't segment very huge resolution images, but it can be applied apart to a smaller regions after fixing the larger ones and divide them into tiny parts.

Add to that; and after segmentation, the pre-trained CNNS with the extraction of the features will be applied, so that the regions of the image are fed to into these CNNs after their identification by mean-shift algorithm and resizing them to be of the 244 × 244 pixels (as implemented in this project), before the occupation of 4096 features dimension as shown in figure 7 [22], knowing that VGG16 CNN which is a 16-layer network is used as the descriptor of the feature for image training and validating.

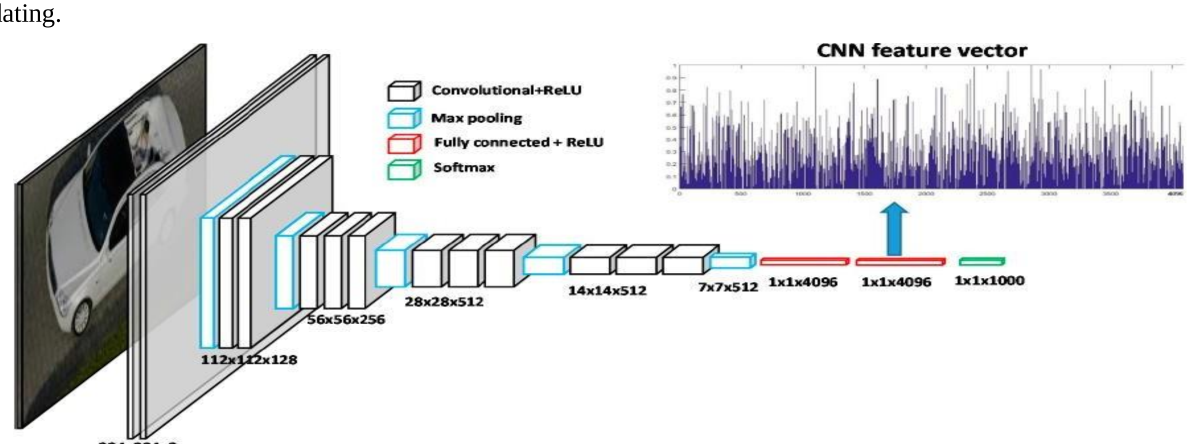

Fig. 7. Feature extraction with pre-trained RCNNs

Furthermore; a linear SVM is used for region classification as highlighted before, in which there will be a complete survey for all the images to check the formation of a car. Note that, the feature descriptor with the SVM classifier deducts the presence or absence of the car. Finally; after discovering the map occupying all the regions that are categorized as cars, fine-tuning for the results takes place in order to clean-up the map.

2.4. Car Detection Using Machine Learning Techniques

This methodology proposed by [23] is a sum up of different hardware and software peripherals. Such tools, equipment, programs, and softwares presented in this technique are briefed in the following:

- Python: An ancient programming language which is applied to various platforms, such as: GUI, mathematics, GNU-Radio, mobile development, web programming, etc. On the other hand; certain libraries are used dealing with this programming language, for example, Numpy which is an open source library, is essential to calculation's operations, matrices, and arrays. Also, Matplotlib, which is a plotting library, enables the data to be more visualized and understandable; and facilitates in extracting the features of colors [24].
- Jupyter notebook: By referring to [25] can be defined as a web application, deals with several issues such as: plaintexts, visualizations, modifying live codes, machine learning, numerical simulation, etc.
- PC: For training and testing the whole implementation, taking into account the suitable specifications concerning the RAMs, processor, graphics…

During the process of implementation, a software pipeline is to be written as way to detect the cars in the video frame, which can be executed according to the chronology below:

a. HOG feature extraction on training images with the use of a linear SVM classifier

b. Sliding-window mechanism used for images' searching

c. Apply and run the pipeline on a streaming video

d. Bounding box estimation for the detected cars

- Color Histogram: It's confined as graphical representation of the image pixels' number in a limited range regardless if luminance or colorful. In brief; the comparison of the images' intensities and colors' range they occupy is one of the main missions that can be attained by the valor histogram as a way to detect whether the image is related to car or not [26].
- Histogram of oriented gradients (HoG): It's a description feature that extracts the meaningful and useful information of the desired image and getting rid of the insignificant meaning [27]. Add to that; the histograms which show the distribution of the oriented or steered gradients (directions of gradients) use such task as an essential feature in the implementation process.
- Classifiers: Two types of classifiers are used in this methodology:

1. SVMs: classification learning techniques, and used for regression and outliers detection [28]. Linear SVC is one of this type which have been applied in this implementation.
2. Decision Tree: a machine learning algorithm which is used for data classification.

- Sliding window: As we know; it's a rectangular region with specified dimensions of fixed width and height that slides along with the image. Add to that; image classification is applied to the region of the window to find if the object within the latter is of our interest or no. On the other hand; sampling by hog sub is one of the very interesting efficient criteria concerning the attempts of sliding window, due to its ability in reducing time for calculation while searching for HOG features, the way which leads to a rate of a high throughput [29].

Figure 8, shows the sliding windows related to the cars viewed taking in consideration the refined sliding windows also.

Fig. 8. Sliding window with the refined sliding windows

2.5. Car's Detection with Infrared Images in Road Traffic Using YOLO

The implementation of such work developed in [30] is based on developing a tracking algorithm that can detect the illegal cars which interrupt the laws of transportation in general by making use of IR image sequence. The design of the framework depends primarily on a correlation filter for the tracking system and deep learning for the detection process. Thus we will have a hybrid tracking and detection system (CTAD). Moreover; tracking has been approached by the facilities given by LCT which was approved after taken into account numerous number of IR sequences of image, and the detection is achieved by YOLO. The following flowchart in which there is a pseudo code chronology as shown in figure 2.9 gives a summary about the operating work of the CTAD technique.

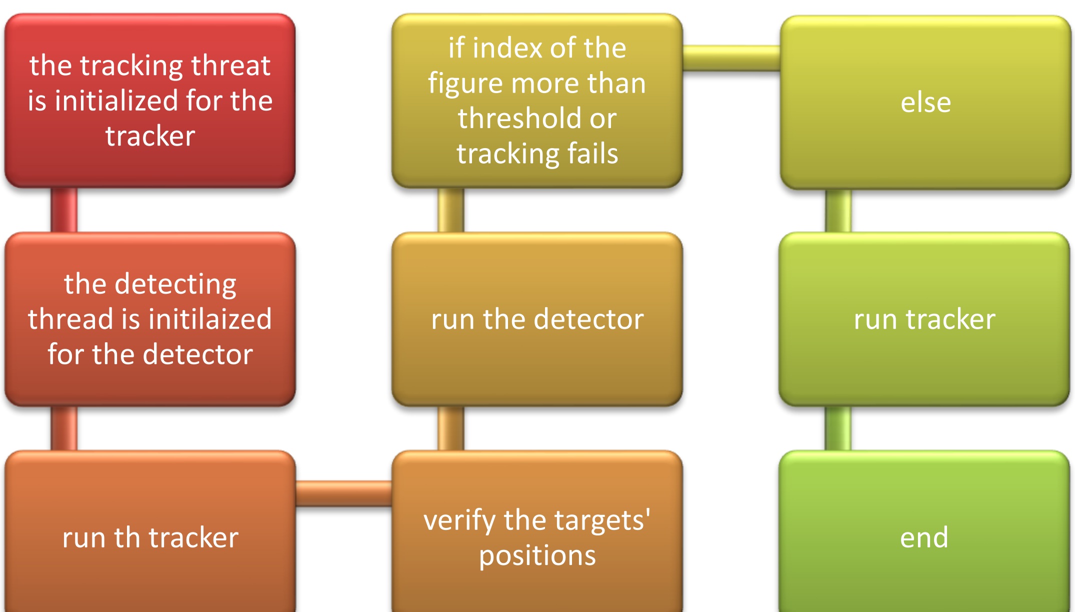

Fig. 9. A flowchart showing the pseudo-code of the used CTAD technique

2.6. The K-mean ++ Clustering Algorithm Technique

Dealing with the car detection or object detection in the intelligent transport system (ITS); beyond the YOLO (v2,v3,…) and the CTAD algorithm, there is an essential related technique: Kmean++ Clustering Algorithm (KCA), which is used in [31] in which the bounded boxes are responsible for training dataset, and six anchor boxes with alternating sizes are responsible for the object identification in the targeted image. YOLOv2 distance function is used instead of the Euclidean distance for the process of boxes' separation. On the other hand; the evaluation metric IOU is applied according to the following equation:

$$(box, centroid) = 1 - (box, centroid) \qquad (2)$$

Add to that; and in order to find the width and the height of the bounding boxes, normalization calculations are used. Moreover; and for the satisfaction of the car`s detection or object detection in general, a design of network should be achieved, in which there will be two steps:

1- The multi-layer feature fusion: to detect the vehicles in traffic images

2- Removing the repeated convolution layers in the high layers

2.7. Deep Learning Multi-Target Detection (DLMTD)

It's a multi-vehicle detection algorithm as presented in [32], where the ImageNet is the basic source for training model, in which there is tuning, adjustment, and calibration for the parameters according to the features of the car (vehicle) and the results of the training process. DLMTD also make use of YOLOv2 (concerning most of the previously related methodologies) as a distinguishable algorithm to separate between the background and the target, adding to this the specification of real-time prediction. On the other hand; the CNN method (more details about it will be in the next section) is acquired in the DLMTD process as a source for the ignorance of the complex and vague preprocessing that in need for images.

2.8. Infrared Using Convolutional Neural Network (CNN)

An aerial IR image that depends on CNN is one of numerous approaches that seek for ground vehicles' detection [33]. An IR dataset is required for the evaluation of IR technique.

To sum up; and after shedding light on some of the literature review concerning the related projects to object detection in public and vehicle (car) detection particularly, and after highlighting the specification of each method with the deductions and results that it occupies, a

small comparison for the last four techniques (CTAD, KCA, DLMTD, and CNN) is shown in table 2.1 according to the results' discussion achieved in previous implementations taking in consideration the different used algorithms in [34].

TABLE I. COMPARISON BETWEEN THE FEATURES OF SOME VEHICLE DETECTION ALGORITHMS

	CTAD	KCA	DLMTD	CNN
Tracking	LCT	Kmean++	CNN	**CNN**
Detection	YOLOv3	YOLOv2	YOLOv2	**Label toolbox**
Error correction	**Uses regression models**	**Multi-layer feature fusion**	**Intersect over union**	**Suppression**

On the other hand; the same techniques are differentiated from each other concerning other features dealing with the evaluation of speed, thus the frames per second (FPS) and the detection's accuracy (precision). Table 2.2 as deduced from [34] explains more the previous by real obtained values.

TABLE II. A COMPARISON BETWEEN THE DIFFERENT ALGORITHMS

	CTAD	KCA	DLMTD	CNN
FPS	18.1	17.8	19.8	**17.48**
Precision (%)	**81.1**	**94.78**	**97.567**	**94.61**

A deduction can be picked up from the above table, states that CTAD efficiency can be enhanced by applying all the techniques to the IR images that were used.

2.9. Motion Vehicle Detection and Segmentation Approaches

The recognition of the changeable regions related to a moving object in a certain image sequence captured at various intervals is considered one of the computer vision main pillars and tasks at the same time. Some applications related to this specialty are: video surveillance, medical treatment, remote and under-water sensing, infrastructure, etc. The dynamic/motion vehicle detection is divided into three basic approaches: background subtraction method, feature based methods, and frame differencing and motion based methods [35].

- Background subtraction method: This technique can be defined as the extracting of the input image (moving foreground objects) from static image (stored background image) [36]. Then the moving objects extracted previously are obtained as the threshold of image differencing
- Gaussian Probability distribution model dealing with every pixel in the image is an essential task in such method, where there is an update for each pixel value in the new image series [36]. Moreover; for each pixel (x, y) in the image is belonged to be a part of the moving objects or background, depending on the equation below:

$$(x, y) - (x, y) < (C\ x\ Std\ (x, y)) \qquad (3)$$

where $I(x, y)$ is the intensity of the pixel, C is a constant, $Mean(x, y)$ is the mean, and

$Std\ (x, y)$ is the standard deviation.

Some related approaches to this aspect depend on adaptive background approximation, followed by the image's division into tiny overlapped blocks, then principal component analysis (PCA) as a statistical technique is done as a way to predict the two histograms related to the candidate vehicles [37]. Furthermore; a support vector machine (SVM) is applied to classify the different parts of the vehicle [38]. Add to that; extraction the size features from previously gathered information depending on the distance between the front and rear tires taking in consideration the underneath shadow of the vehicles.

- Feature based methods: This process takes into account the sub-features such as the edges, corners, layers... of the vehicle; such process makes use of labeled training data, Haar wavelet method, and support vector machine classifier [39] to attain the classification goal. Also the sub-region technique takes place in this aspect as a source to recognize non-occluded and partially occluded cars (vehicles) [40]. Independent component analysis (ICA) coefficient vector is applied for the components of high frequency [41]; adding to this the PCA weight vector, in which both vectors are resulted by sub-regions.

Moreover; the configuration process of a local-feature point with the use of computer graphics (CG) is used for vehicle classification, in which the Eigen-window attempt proposed in [42] is applied due to its non-complexity in tracking the car or any other vehicle even when it's steered or directed towards a different path rather than the ordinary one. In addition to the previous; the CG model supports the collection of real images of all the desired and targeted vehicles [43].

2.10. Frame differencing and motion based methods

The frame differencing is defined as the subtraction of two subsequent frames in a series of image to segment the moving object from the image of the background frame [44]. On the other hand; motion segmentation is the isolation of the moving objects through pixels' analysis depending on the motion's direction and speed from the motion scene image sequence background [45]. Many techniques can be related to this method mainly in the issue of real-time vehicle detection such as the multi-modal temporal panorama (MTP) used in the proposed technique in [46] which depends on using a monitoring system which is usually hybrid (audio and video). Add to that; and dealing with the traffic surveillance system, night-time traffic supervision is applied by using the image segmentation and pattern analysis mechanism as implemented in [47]; the way which leads to the identification of the headlights and the taillights of the vehicles. Finally; a technique where the threshold of a multi-level histogram is used as presented in [48] to extract and get the required bright objects from a road view in which darkness or night-time is occurred.

2.11. Multiple YOLO-Based Target Detectors and Trackers for ADAS in Edge Devices

In this method proposed by [49] there is a combination of YOLO_R-CSP detector DeepSORT tracker. The following steps confine the whole work in this research.

- BDD 100K data was chosen due to its greater diversity in the representation of various situation.
- Regrouping of classes with the mitigation of FN detection

- Sub-Sampling of the dataset into a smaller dataset composed of 10000 images, by using the original dataset validation set
- A balanced sub-sampled data was employed to train YOLOv8 variants (YOLOv5, YOLOv4, YOLOR, YOLOv7 and YOLOv8) to enhance model performance and reduce the risk of over-fitting
- Analysis of confusion matrices was conducted
- he models trained on the BDD 100 K were implemented and deployed with the trackers utilizing Deep Stream
- The object detectors combined with the trackers were tested in an urban driving tracking datasets.

3. LIMITATIONS OF THE PREVIOUS APPROACHES

After highlighting the main approaches related to the desired research focusing in object detection with the technology of DL, we can deduce that most of these techniques have been attained their aim, but still, although there are some pros but there are some significant limitations and disadvantages that should be eliminated or avoided as much as possible in order to reach the satisfied outcomes.

In other words, and illustrating the previous, in the real-time wrong-way vehicle detection-based technique which is based on YOLO and centroid tracking, the following limitations are detected:

- Concerning the centroid tracking algorithms, the centroids of the object must lie close together between subsequent frames.
- The identification number might be switched due to overlap of one object to another

On the other hand, and with the proposed approach dealing with the effective method of vehicle detection using DL, the following drawbacks are notified:

- Use of data is not well-balanced
- Cause the network to pay more attention to the characteristics of the targeted category
- Reduces the detection effect of other categories
- Needs more kinds of algorithms for vehicle detection

Add to that, in the car detection using YOLO algorithm mechanism, the main shortcomings recognized are summarized according to the following:

- Not efficient accuracy
- Needs more training and diverse datasets that cover different weather and lighting conditions
- Needs to be in fusion with other sensor’s readings

Furthermore, in the work proposed according to [49] which is focused on the interpretation of multiple YOLO-based target detectors and trackers for ADAS in edge devices, the following limitations are noticed:

- Complex road markings such as the models difficulty in segmenting the driving area when a speed lump was introduced or when multiple lane markings appeared, leading to confusion
- Differences between training data and interference data, then exhibiting slight differentmarkings
- Need for more comprehensive and diverse datasets that represent various distinct environments

Finalizing with the DL approach for car detection in UAV imagery, some drawbacks are discovered such as:

- High false positive rate
- Lack of “detection by parts” technique
- Lack of how to detect each car separately to increase the accuracy when counting the cars

The following Table (3) summarizes the limitations of the different recent approaches.

TABLE III. THE LIMITATIONS OF THE PREVIOUS STUDIES

Name of the method's article	Limitations
A Real –Time Wrong-Way Vehicle Detections Based on YOLO and Centroid Tracking	- Geometry of centroids (far away from each others) - ID switching (avoid overlapping)
An Effective Approach of Vehicle Detection Using DL	- Imbalance data use - reduces effect of detection due to categories unknown criteria
Car Detection Using YOLO Algorithm	- Inaccuracy in results - Low rate of training and datasets
Comparative Analysis of Multiple YOLO-Based Target Detectors and Trackers for ADAS in Edge Devices	- Complex road markings - Lack of comprehensive and diverse datasets
DL Approach for Car Detection in UAV Imagery	High false positive readings
Vehicle Detection and Tracking Using ML Techniques	- Inaccurate detection and tracking - Datasets distribution is not organized
Roadside LiDAR Vehicle Detection and Tracking Using Range and Intensity Background Subtraction	- Low performance of suitable detection rate - Low interfere/ occlusion

4 . COMPARISON BETWEEN THE RELATED WORK TECHNIQUES

In addition to the previous methodologies and the attempts that have been achieved concerning the domain of object detection and tracking with a particular privacy for the car's detection field, there are also numerous techniques that deal with this field; some are very similar to those in which we shed light previously and the others come in less priority regarding the scientific significance efficiency. Table 4 confines a comparison between the main previous related woks.

TABLE IV. A COMPARISON BETWEEN THE RECENT RELATED WORKS.

Technique number	Author/s	Algorithm/s	Results' notifications
[1]	Zillur Rahman, Amit Mazumder Ami and Muhammad Ahsan Ullah	YOLO and Centroid tracking	Very high accuracy /quickness of YOLO than any object detector algorithm
[2]	Ajinkya Marode, Akash Ambadkar, Aniket Kale and Tilak Mangrudkar	YOLO	Real-time response requiredfor ADAS development/ provision of a solid base for the object detection moduleas a part of the ADAS
[3]	Sehyun Tak, Jong-Deok Lee, Jeongheon Song, and Sunghoon Kim	YOLOv4	Reducing the search space/extraction of high descriptive features/ no need for big training data
[4]	Chirag Rawari	YOLOv5	Automatic vehicle's detection and tracking either in static or varying manner
[5]	Dr. Benila, Karan Kumar, Karthikraja, and Kavimukilan	SSD and YOLO	Computational simplicity/real-time tracking enhancement/high accuracy
[6]	Tianya Zhang and Peter J. Jin	YOLOv8	Mitigation of redundant background Points(90%)/increase the data acquisition efficiency/ better expandability/sophisticatednetwork design and GPU tosupport the operation/ flexiblemaintenance .
[7]	Nastaran Yaghoobi Ershadi, JoseÂ Manuel MeneÂndez, David JimeÂnez	YOLOv4	Remove perspectivewithout any harmful effect on thereal information/more accurate compared to thestate-of-the-art methods
[8]	B.W. Balkhnade, Rohit Chaurasia, Pallavi Dhumal and Kirti Gupta	Open CV and HAAR Cascade Classifier	Preprocessing the aerial images for noise removal before the detection phase

5. CONCLUSION

After showing the main previous approaches in the domain of object detection and mainly the vehicle's or car's recognition with the use of various algorithms and mechanisms dealing with the illegal cars or the wrong-way vehicles as shown in figure 2.10 , followed by a brief comparison between them, we deduce that even though there are some advantages but still there are adequate number of limitations and drawbacks. In other words, our targeted mission is to make use of these pros and enhance it to attain the best possible efficiency and accuracy while eliminating the disadvantages. The latter hopefully will be achieved by following our proposed methodology which will be explained and described in the next chapter.

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Conflicts of Interest

The author declares no conflict of interest in relation to the research presented in the paper.

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