A

Research Paper

On

Real time traffic monitoring system using deep learning

Submitted in partial fulfilment of the requirements

For the award of the degree of

Bachelor of Technology

in

Computer Science and Engineering

by

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Abstract

Deep learning-based classification and detection algorithms have emerged as a powerful tool for vehicle detection in intelligent transportation systems. The limitations of the number of high-quality labeled training samples makes the single vehicle detection methods incapable of accomplishing acceptable accuracy in road vehicle detection. This paper presents detection and classification of vehicles on publicly available datasets by utilizing the YOLO-v5 architecture. This paper’s findings utilize the concept of transfer learning through fine tuning the weights of the pre-trained YOLO-v5 architecture. To employ the concept of transfer learning, extensive data sets of images and videos of the congested traffic patterns were collected by the authors. These datasets were made more comprehensive by pointing various attributes, for instance high- and low-density traffic patterns, occlusions, and different weather circumstances. All of these gathered datasets were manually annotated. Ultimately, the improved YOLO-v5 structure becomes accustomed to any difficult traffic patterns. By fine-tuning the pre-trained network through our datasets, our proposed YOLO-v5 has exceeded several other traditional vehicle detection methods in terms of detection accuracy and execution time. Detailed simulations performed on the PKU, COCO, and DAWN datasets demonstrate the effectiveness of the proposed method in various challenging situations.

Keywords: machine learning; object detection; vehicle detection

1. Introduction

The Human Vision System (HVS) reliably and accurately performs complex tasks, such as being able to detect and recognize and identify diverse range of objects with little conscious attention. With the recent developments in the Computer Vision (CV) and Machine Learning (ML), and with the availability of capabilities, such as massive data sets, faster GPUs, and better algorithms, it has now become possible for computers to detect, recognize, and classify several items in an image or video with high accuracy [1]. The aim of vehicle detection and classification is to locate vehicles in either images or videos [2]. Efficiency of vehicle localization is a critical step in traffic monitoring or surveillance. Figure 1 shows several detected vehicles from Pakistani traffic images that are achieved using the machine learning algorithms. Therefore, autonomous vehicle detection methods must exactly detect traffic objects, such as cars, vehicles, or police vans or bikes in real-time to gain good control and make right decisions for the public safety [3].

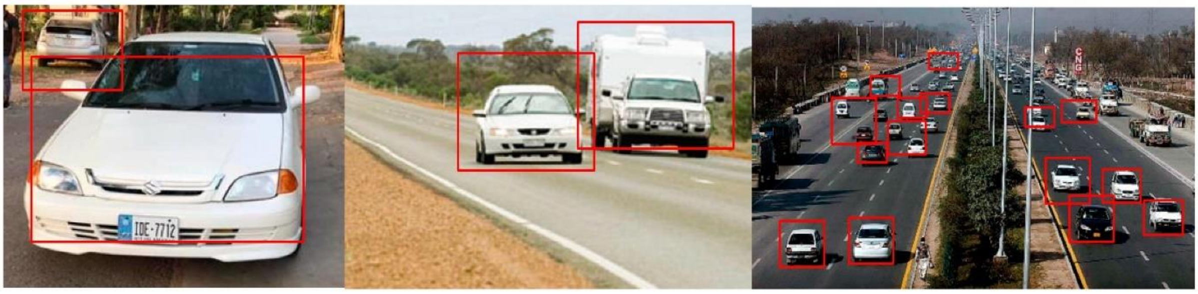


Figure 1. Vehicle detection examples from Pakistani traffic.

With the development of the DNNs, automatic vehicle detection has made substantial progress in recent years, for instance, in Autonomous Driving Systems (ADS) and driver support systems in the context of concerns about traffic congestion and driving safety [4].

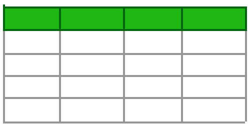
To develop intelligent and autonomous systems, for instance, self-directed driving, surveillance, detecting objects, or tracking, vehicle localization is a crucial problem [5]. Automatic driving is a new high technology invention that relies on the ability to only find vehicles [6]. In the metropolitan areas, frequent incidents happen regarding traffic breaches, vehicle mishaps, and thefts that are recorded through the CCTV cameras. Traffic surveillance system detector should be fast, accurate, and reliable enough to detect vehicles in real-time. In the areas of traffic managing systems or surveillance technology, there have been numerous advancements. Two essential conditions are normally considered to rate vehicle detectors, which are its real-time detection ability and whether it has a high detection accuracy of the traffic objects under adverse weather conditions.

In this work, we target the detection and classification of vehicles in images using deep learning to explore the feasibility of YOLO based methods. The YOLO family of algorithms is first-order object detection method, which uses an anchor box to integrate various objects localization. Up to now, five versions of YOLO family of algorithms have been released. The YOLOv3 is a milestone in the performance and speed of the YOLO family of algorithms. Our motivation to choose the YOLOv5 detection model is due to its smaller architecture and much fast detection ability than the previous generations of its model families. Recently, researchers in various research domains have enhanced the original YOLOv5 model based on the characteristics of their detection targets, which makes the YOLOv5 algorithm an excellent choice in vehicle detection domain. Our main contributions in this work are listed below.

- We propose a modified version of the YOLO algorithm to achieve vehicle detection in real time. Earlier-developed works have been trained on massive datasets, but still need to be fine-tuned for use in congested traffic environments. However, we augment these datasets with our gathered datasets. We compare the efficiency of our trained version with several recent state-of-the-art methods.
- We detect and classify vehicles in images that are captured in various traffic scenes. We perform detailed study on the PKU, COCO, and DAWN datasets. To achieve higher accuracy on images from our local traffic patterns, we gathered an extensive dataset and applied transfer learning to the YOLOv5. The input to a system is a real-time image, and the output is a bounding box corresponding to all objects in the image, along with the class of object in each box.
- In addition, we employ a transfer learning approach to utilize the knowledge embedded in our local datasets. We believe that the ITS based applications require rapid and precise vehicle identification and classification. It is a challenging task to detect different vehicles abruptly and precisely due to short gaps between vehicles on the road and interference aspects of pictures or video frames containing vehicle images. Therefore, we are optimistic that our developed method provides a good insight into locating vehicles in congested traffic environments.

This paper is organized as follows. Section 2 discusses few recent related works. Section 3 describes in detail the proposed method. Simulation results and discussions are presented in Section 4. Finally, Section 5 concludes the paper and hints towards future research directions. For readers' smooth understanding, Table 1 lists the nomenclature that is used extensively in this paper.

Table 1. Nomenclature.



2. Related Work

Vehicle detection has gained considerable attention in the research community in the past two decades. In this section, we briefly discuss the recent advances in the vehicle detection domain. For readers' fair understanding, we categorize the literature into two streams as illustrated below.

2.1. Conventional Methods

This section quickly lists a few of the latest conventional vehicle detection approaches. In [6], the developed method detects vehicles in airborne images. In this work, the vehicle localization is attained through the Gaussian Mixture Model (GMM) and background subtraction representations. In [7], an ensemble-based method is developed for various image descriptors, which illustrate the distributions of gradients, color models, and textures. This work reports good results in high resolution aerial images. In [8], a new methodology through the application of the GMM is developed to detect dissimilar complex structures, for example, objects in residential, agricultural, and industrial zones. This work also reflects spectral and spatial constraints. An efficient, GMM-based image segmentation method is utilized in [9]. This method is capable of detecting the frontal view of different vehicles. To locate the vehicles' driving area, lanes are spotted through the application of the Canny edge detector along with Hough transform. To further enhance the efficiency of proposed method, this work uses the HOG features, colors, and the Harr-features of vehicles, and trains the SVM classifier. In [10], the SVM is trained through multi-feature fusion that results in reduced vehicle detection time. In [11], vehicle detection is achieved through integration of the SIFT with the SVM. To further improve classification ability, an integration of pyramids pooling, sliding windows, and NMS is done that substantially enhances the vehicle detection outputs, which are obtained therein.

2.2. YOLO-Based Methods

In [12] a vision-based object detection and recognition framework for autonomous driving was proposed with particular emphasis on: (i) an optimized model based on the structure of YOLOv4 was presented to detect 10 types of objects; (ii) a fine-tuned part affinity fields approach was developed; (iii) eXplainable Artificial Intelligence (XAI) was integrated to assist the approximations in the risk evaluation phase; (iv) an intricate self-driving dataset was developed, which included several different subsets for each relevant task; and (v) an end-to-end system with a high-accuracy model was discussed.

The overall parameters of enhanced YOLOv4 are reduced by 74%, which meets the real-time capacity. Moreover, when evaluated with other methods, the detection precision of the enhanced YOLOv4 improved by 2.6%. In [13], a novel and efficient detector named YOLO-ACN is developed, which is inspired by the high detection accuracy and speed of YOLOv3. This technique is improved by the addition of an attention mechanism, a CIoU (complete intersection over union) loss function, Soft-NMS, and depth wise separable convolution. In this method, initially, the attention mechanism is built in the channel and spatial dimensions in each residual block focus on small targets. Later, CIoU loss is adopted to achieve accurate bounding box regression. Besides, to filter out a more accurate BBox and avoid deleting occluded objects in dense images, the CIoU is applied in the Soft-NMS, and the Gaussian model in the Soft-NMS is employed to suppress the surrounding BBox. Finally, to improve the detection speed, standard convolution is replaced by depth wise separable convolution. Meanwhile, a hard-swish activation function is utilized in deeper layers.

3. Proposed Method

In this section, we describe our proposed method in detail. As discussed below, we divide our developed method into the following interconnected steps along with a brief description. Figure 2 shows the flow of the proposed method. In addition, Algorithm 1 shows more details of our developed method.

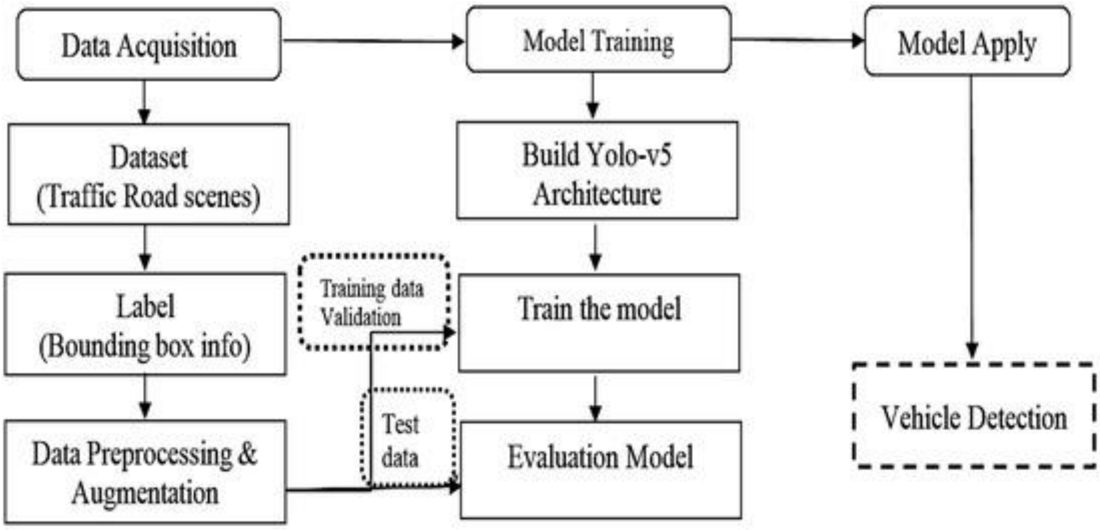
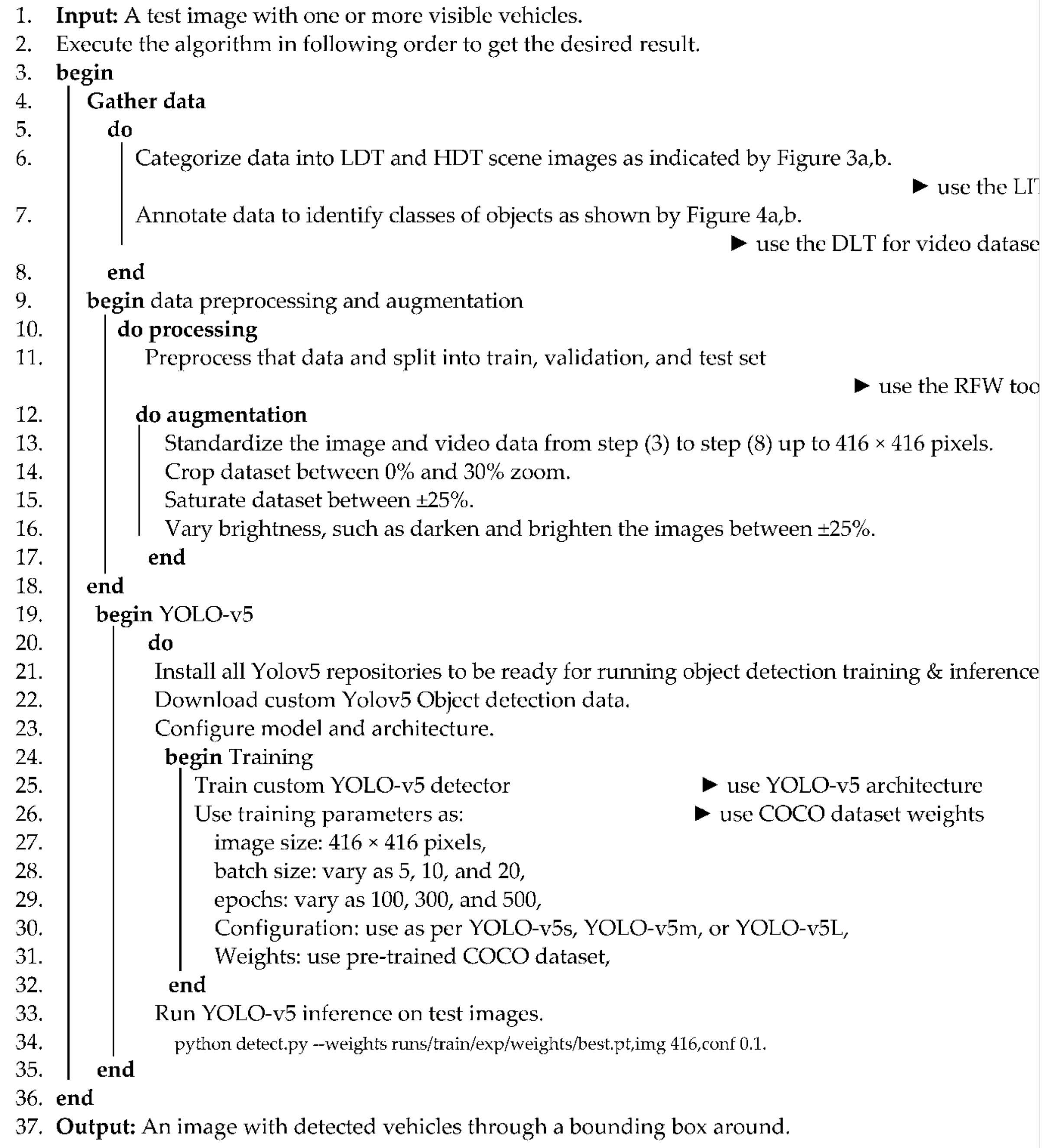


Figure 2. Flow of the proposed method.

To test our method, we gather our own dataset from challenging Pakistani traffic environments. This dataset was collected over a period of two months in different cities of Pakistan. As shown in Figure 2 that the gathered data is preprocessed and augmented. Later it is trained by our model. Meanwhile, the YOLO-v5 model is built and trained. Our collected data is from an unknown distribution in Pakistani traffic. Therefore, it is now tested on the YOLO-v5 model. After the YOLO-v5 is applied, we then investigate and analyse our detector. To aid readers' understanding, below we describe the steps and details of our developed method.

Algorithm 1: Pseudo code of the proposed vehicle detection algorithm



```
1.  Input: A test image with one or more visible vehicles.
2.  Execute the algorithm in following order to get the desired result.
3.  begin
4.  | Gather data
5.  |   do
6.  |   | Categorize data into LDT and HDT scene images as indicated by Figure 3a,b.
    |   |                                                                   ► use the LT
7.  |   | Annotate data to identify classes of objects as shown by Figure 4a,b.
    |   |                                                   ► use the DLT for video datase
8.  |   end
9.  | begin data preprocessing and augmentation
10. |   | do processing
11. |   |    Preprocess that data and split into train, validation, and test set
    |   |                                                            ► use the RFW too
12. |   |   do augmentation
13. |   |   | Standardize the image and video data from step (3) to step (8) up to 416 × 416 pixels.
14. |   |   | Crop dataset between 0% and 30% zoom.
15. |   |   | Saturate dataset between ±25%.
16. |   |   | Vary brightness, such as darken and brighten the images between ±25%.
17. |   |   end
18. | end
19. |  begin YOLO-v5
20. |  |   do
21. |  |   Install all Yolov5 repositories to be ready for running object detection training & inference
22. |  |   Download custom Yolov5 Object detection data.
23. |  |   Configure model and architecture.
24. |  |    begin Training
25. |  |    | Train custom YOLO-v5 detector              ► use YOLO-v5 architecture
26. |  |    | Use training parameters as:               ► use COCO dataset weights
27. |  |    |   image size: 416 × 416 pixels,
28. |  |    |   batch size: vary as 5, 10, and 20,
29. |  |    |   epochs: vary as 100, 300, and 500,
30. |  |    |   Configuration: use as per YOLO-v5s, YOLO-v5m, or YOLO-v5L,
31. |  |    |   Weights: use pre-trained COCO dataset,
32. |  |    end
33. |  |   Run YOLO-v5 inference on test images.
34. |  |     python detect.py --weights runs/train/exp/weights/best.pt,img 416,conf 0.1.
35. |  end
36. end
37. Output: An image with detected vehicles through a bounding box around.
```

3.1. Data Acquisition

To begin with the proposed algorithm, we initially acquire data. First we deal with different conditions on highways. For example, we come across the multi-class objects, such as different types of vehicles, motor bikes, and pedestrians on the roads. Similarly, we also faced severe and crucial challenges, such as massive traffic jams and overlapped vehicles. Therefore, to systematically acquire the data as shown in line (6) of Algorithm 1, we collected the dataset under two different situations, which are (i) High Density Traffic (HDT) scenes that contains multiple objects in an image and

(ii) the Low-Density Traffic (LDT) scene that contains only one class per image, with zero overlaps. For improved training, the images of the LDT and the HDT dataset are placed separately.

The LDT Scenes: This dataset was gathered from daily real-time traffic places, for example open parking lots, less crowded roads, and places with fewer crowds. The objective of assembling this dataset is to separately train the model on each class. We collected a total of 600 images from three classes, which are cars, motor cycles, and pedestrians. Example images of the few of the LDT images are shown in Figure 3a.

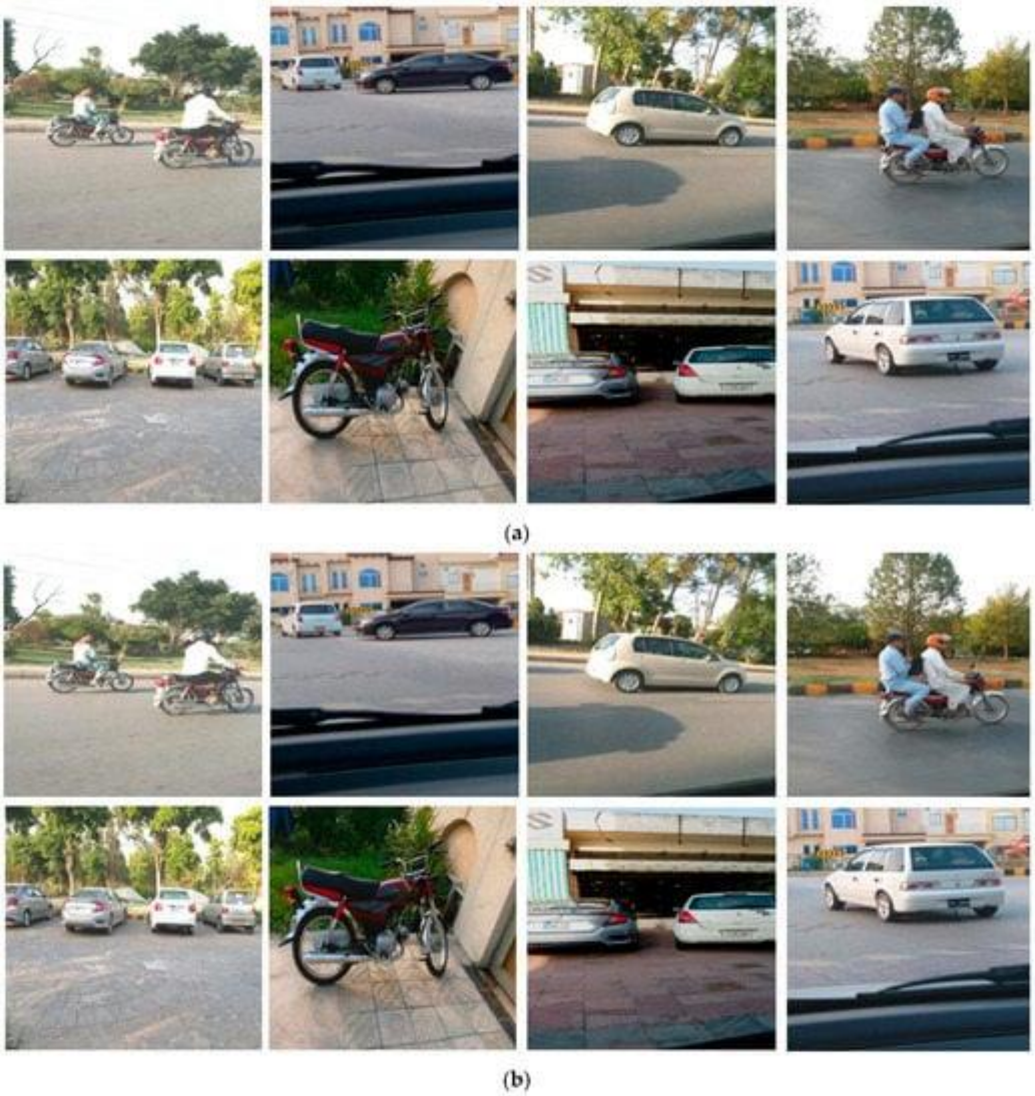


Figure 3. Sample images of our collected dataset: (**a**) Low density traffic scenes and (**b**) High density traffic scenes.

The HDT Scenes: This dataset was collected in congested places, for example public parking lots, big shopping malls, main highways, and places near main traffic sign boards. We gathered a total of 1800 images of the aforementioned classes. We also collected this dataset by thinking about crucial factors, for instance varying illumination, partial/full/long term occlusions, along with collections of objects regardless of size, scale, shape, or appearance. A few such sample images are shown in Figure 3b. The statistics of both the low- and high-density dataset along with each class annotations are described in Table 2.

Table 2. Summary of our collected dataset images.

Video Dataset: Along with the images, we also gathered a video dataset from the different locations of main highways, such as crossway bridges. A few of the sample images of our collected video dataset are shown in Figure 4a. It can be seen that our collected dataset has different types of vehicles that appear in the image. Moreover, the vehicles' resolution also varies. Collecting such a diverse dataset helps us to develop a robust, reliable, and accurate vehicle detection method, which we believe can be used in any real-time application.

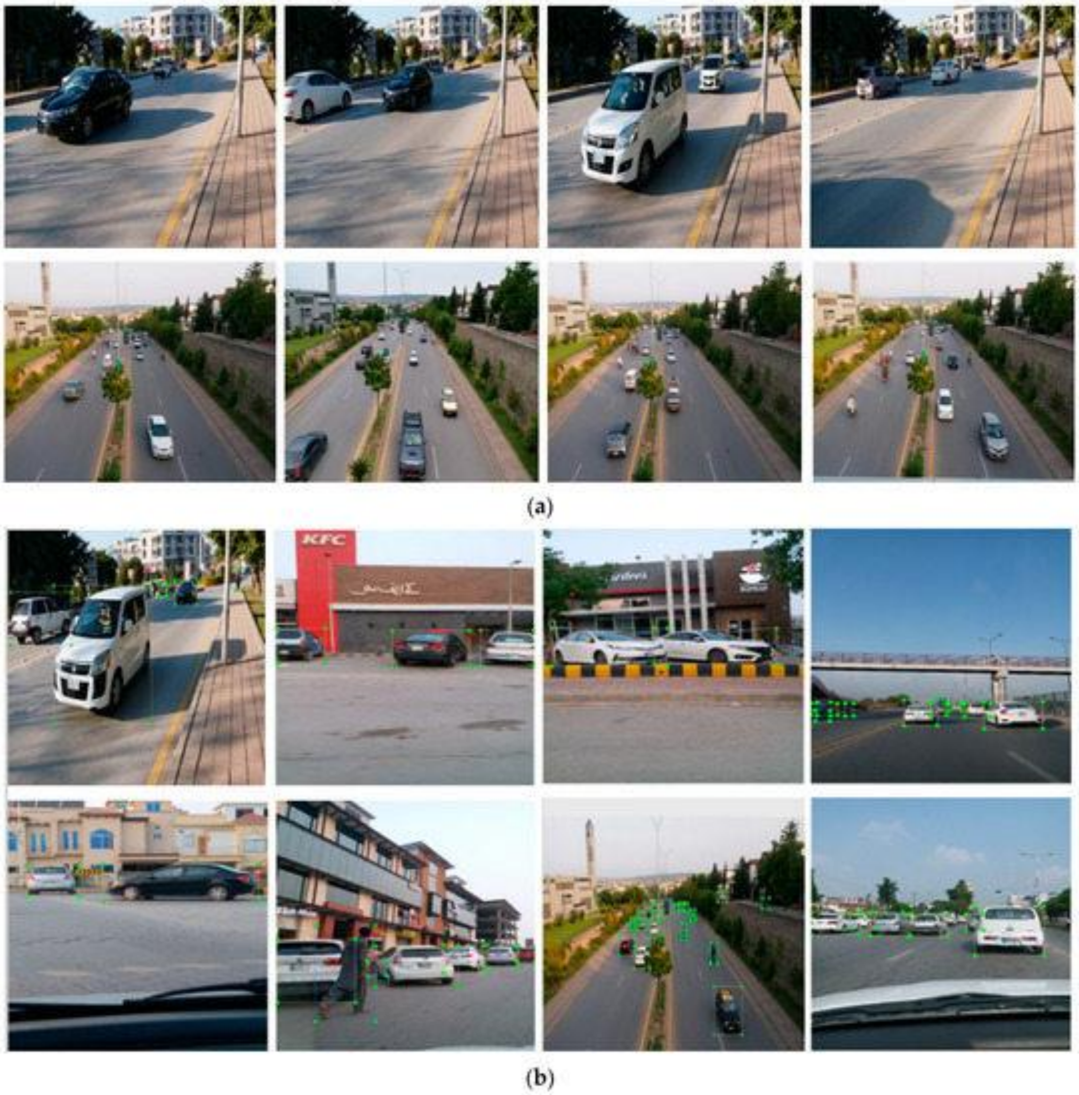


Figure 4. Sample images of our collected dataset: (**a**) video dataset and (**b**) annotated images.

3.2. Data Annotation

It is the proper procedure to label the classes of the datasets to achieve reliable vehicle detection in later stages. This data annotation is an important step for good training of the CNN model so as to get promising results.

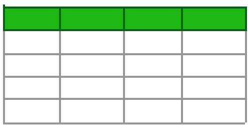
As shown in line (7) of Algorithm 1, we have used Label Image Tool (https://github.com/heartexlabs/labelImg (accessed on 12 January 2023)) (LIT) to label and annotate the image dataset. To use the LIT tool, we upload the image dataset to the LIT, which reads the images. Later, we manually assign a bounding box for each object present in the image as shown in Figure 4b. It is evident that for the HDT category, there are several bounding boxes on a single image. However, for the LDT scenes, there are fewer bounding boxes. These bounding boxes specify the label of the respective class, such as vehicle or motorbike. Every object present in the image is manually labeled, which is indicated by bounding boxes. The overall dataset is then divided into three classes, which are cars, motorcycles, and pedestrians. Readers are referred to the LIT link, which is provided at the bottom of this page, which offers detail about the LIT usage.

For the video dataset, the annotation is some way bit extensive. To do it quickly, we used Dark Label Tool (https://github.com/darkpgmr/DarkLabel (accessed on 12 January 2023)) (DLT) as it consumes less time as compared to the LIT module. The DLT automatically divides the uploaded video dataset into frames, for instance frames of 10 s into 360 frames. These frames are now interpolated, in which the first frame draws a bounding box around an object, and the last frame draws the bounding box around the same object. Hence, all the objects in between the 10 s have been annotated and labelled according to the specified classes. Readers are referred to the DLT link, which is provided at the bottom of this page, which detail about the DLT usage, along with more facilities provided therein.

3.3. Data Augmentation

To increase the data features to obtain better results, data preprocessing is the building block of deep learning-based algorithms. We know that real world datasets might be contaminated with noise. Many times, these datasets are inconsistent, or some things may be missing. Sometimes, uneven and unbalanced classes appear. As can be seen in lines (9) to (18) of Algorithm-1, data preprocessing and augmentation is analyzed. As shown in Table 3, we preprocessed our dataset in distinct steps. One is to get the same size of each image of the HDT, the LDT, and video datasets. We make the dataset of 416 × 416 pixels resolution of each image and video. Then the dataset is split into train, test, and validation set. To split the dataset, we used the RoboFlow (https://public.roboflow.com/ (accessed on 12 January 2023)) (RFW) tool as described below.

Table 3. Dataset statistics after augmentation.



The RFW: this tool hosts free public computer vision datasets in many popular formats. The RFW provides a streamlined workflow to identify edges of various objects in several iterations. With each iteration, the detection models become smarter and more accurate. We used the RFW tool to fragment the entire dataset into train, validation, and test sets. In this study, we keep the split ratio as 7:2:1 that is the image dataset of both categories and the video dataset has been divided into 70% train, 20% validation, and 10% test sets. Training a model on small number of images could result in overfitting [26]. Moreover, it also results in poor generalization despite the fact that the training results are good enough. However, the testing accuracy drops down and the model classifies the samples into one class. In short, the training accuracy is high, but the validation accuracy drops down. To overcome this issue, data augmentation is used, which modifies the data using different techniques and increase the samples of the dataset. Through empirical analysis, we applied the following augmentation techniques on our collected dataset.

3.4. The YOLO-v5

The YOLO-v5 is one of the latest models to obtain reliable object detection in the YOLO family [26]. YOLO-v5 has four more types, which are, YOLO-v5s, YOLO-v5m, YOLO-v5l, and YOLO-v5×. All of these types differ in size and inference time. The size ranges between 14MB to 168MB. The YOLO-v5 surpasses other conventional object detection procedures mostly in terms of detection accuracy. Moreover, the YOLO-v5 is computationally faster in comparison to its companion YOLO family-based algorithms. As shown in Algorithm 1, the YOLO-v5 is used in this study from lines (19)–(35). There are three main architectural blocks in the YOLO-v5 as discussed below [26].

Backbone: In the YOLO-v5, the Cross Stage Partial (CSP) networks are used as a backbone to extract important features from the given input image. Figure 5 lists the details of the backbone modules that are embedded therein.

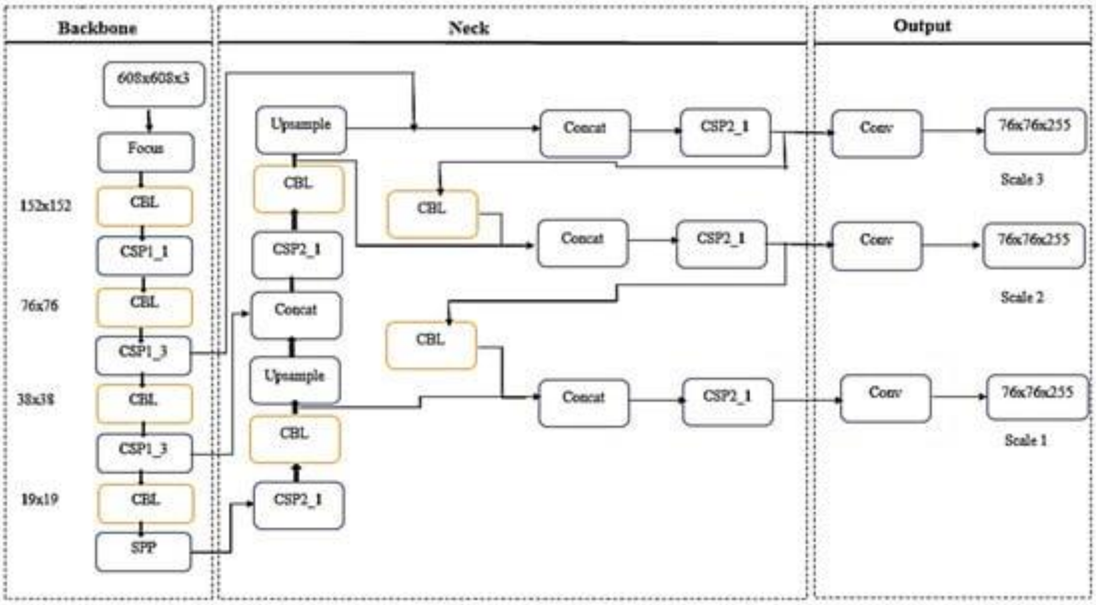


Figure 5. YOLOv5 schematics used in our work.

Neck: The feature pyramid is constructed with the PAN for features accumulation. The features are then passed to head. Figure 5 lists the details of the Neck module along with the necessary details, which are implanted therein.

Head: In this block, the predictions are generated with the help of anchor boxes that ultimately achieves object detection. YOLOv-5 is made more intelligent through a transfer learning mechanism, which is shown in Figure 6, in which an input dataset is processed by the convolutional layers. That in return feeds to the FC layer. Later, our test datasets are processed by pretrained network that yields the final output through the FC layers.

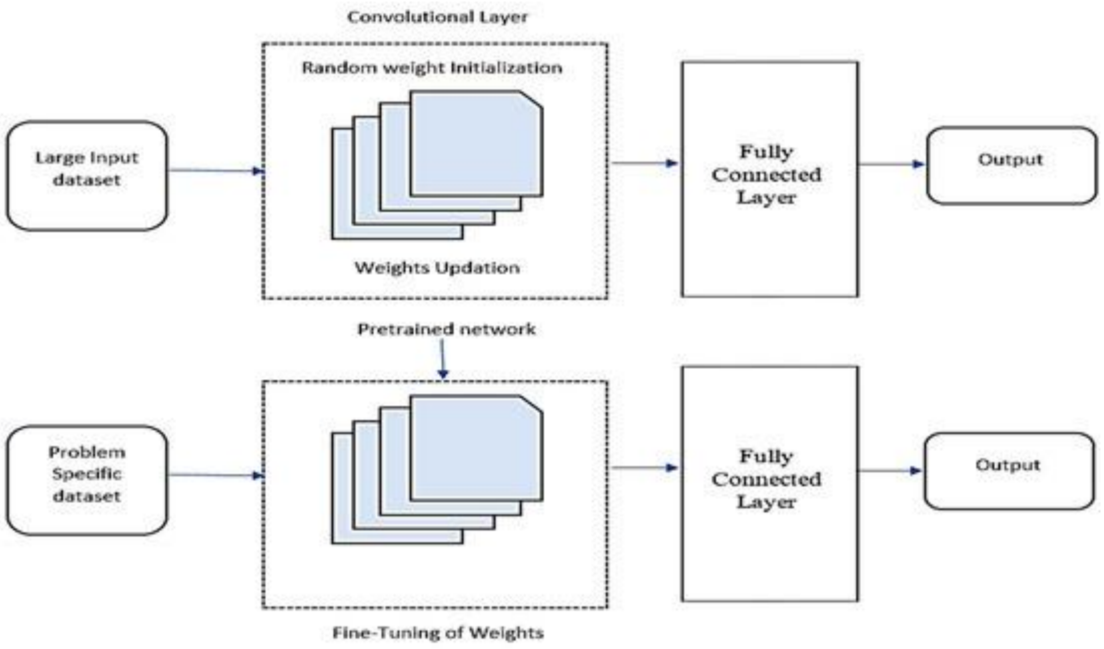


Figure 6. Employed transfer learning in the YOLOv5 architecture.

3.5. Training Strategy

After the data is acquired and processed along with annotations, training and validation datasets are passed to the YOLO-v5s algorithm. For training, we select different parameters, such as batch size, epochs, and image resolution. Training path, testing, and validation dataset are given to the algorithm. We notice that if we train our model from scratch, then we have to initialize it with some random weights. Therefore, we used pre-trained COCO weights for our model training as it saves a considerable amount of time and makes computations easy. Using pre-trained YOLO-v5 model, we get the best weights after transfer learning. Moreover, we used default layers and anchors, as we are utilizing the initial weights of the COCO dataset. We also employed the COCO dataset as a benchmark to train our custom dataset. Furthermore, we have also varied the batch sizes as 5, 10, and 20. We have also changed the epochs to 100, 300, and 500. In this study, the values of confidence $\in[0.4\sim0.6]$∈[0.4~0.6]. After the training phase is done, we use the best weights to detect objects on the dataset. Lastly, we obtain the values of predicted labels and the test images with the bounding boxes with confidence values. The collected dataset and the trained model along with the manuscript will be made publicly available (**http://research.cuiatd.edu.pk/secure/ResearchGroups/comsatsresearchgroups.aspx** (accessed on 12 January 2023)). In the next section, we present and discuss the simulation results in detail.

3.6. Evaluation Criteria

The following criteria are used to measure the robustness of our developed vehicle detection method:

⍰⍰⍰⍰⍰⍰⍰⍰⍰⍰=⍰⍰⍰⍰ ⍰⍰⍰⍰⍰⍰⍰⍰⍰ ⍰⍰⍰⍰⍰⍰⍰⍰⍰⍰⍰ ⍰⍰⍰⍰⍰⍰⍰⍰⍰ ⍰⍰⍰⍰⍰⍰⍰⍰⍰⍰⍰⍰����������=
���� ��������� ����������� ��������� ������������

(1)

⍰⍰⍰⍰⍰⍰⍰=⍰⍰⍰⍰ ⍰⍰⍰⍰⍰⍰⍰⍰⍰ ⍰⍰⍰⍰⍰⍰⍰⍰⍰⍰⍰ ⍰⍰⍰⍰⍰⍰�������=���� �������� ���
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(2)

Similarly, mean Average Precision (*mAP*), the average value of Precision, is also computed for the value of Recall over 0 to 1. The mAP is usually applied in object detection algorithms and is shown mathematically below.

⍰⍰⍰=∫10⍰(⍰)⍰⍰���=∫01�(�)��

(3)

4. Simulation Results

This section presents the detailed simulation results. Extensive experiments are carried out on Google Colaboratory (Colab) platform. The Google Colab provides Intel Xeon CPU with a clock speed of 2.3 GHz and up to 16 GB of RAM. Moreover, the Google Colab also provides NVIDIA K80 or T4 GPU. We use Python V3.6 as a simulation tool for different vehicle datasets as described in subsequent sections. To investigate the performance of vehicle detection methods on different datasets, we select 14 state-of-the-art vehicle detector evaluations and comparisons with the proposed method in terms of accuracy and execution time. All of the compared approaches have been trained on the same training data from each of the PKU, COCO, and DAWN datasets.

4.1. Analysis on the PKU Dataset

The PKU dataset is a collection of diverse vehicle images that are captured under diverse conditions [27]. As shown in Table 4, that this dataset contains a total of 3977 diverse vehicle images. The developers of the PKU dataset divided the vehicles into five distinct and different categories, which they refer as G1, G2, G3, G4, and G5. Out of 3977 vehicle images, the PKU dataset also contains a total of 4263 visible license plates whose pixel resolution varies from 20~62 pixels, which are captured therein. Figure 7 shows a few of the vehicle detection results of our proposed YOLO-based method on all of the five categories of the PKU dataset. As can be seen in the first three rows of Figure 7, for the G1~G3 categories, the proposed method locates all the vehicles in the input images. For the G4 category as shown by the fourth row in the Figure 7, it is obvious that the proposed method is able to locate vehicles that just expose their front bonnet. Moreover, the PKU–G4 category also contains extreme reflective glare. It is always very challenging for any detection algorithm to perform accurately under such circumstances. However, as can be seen, the proposed method handles the aforesaid scenario effectively.

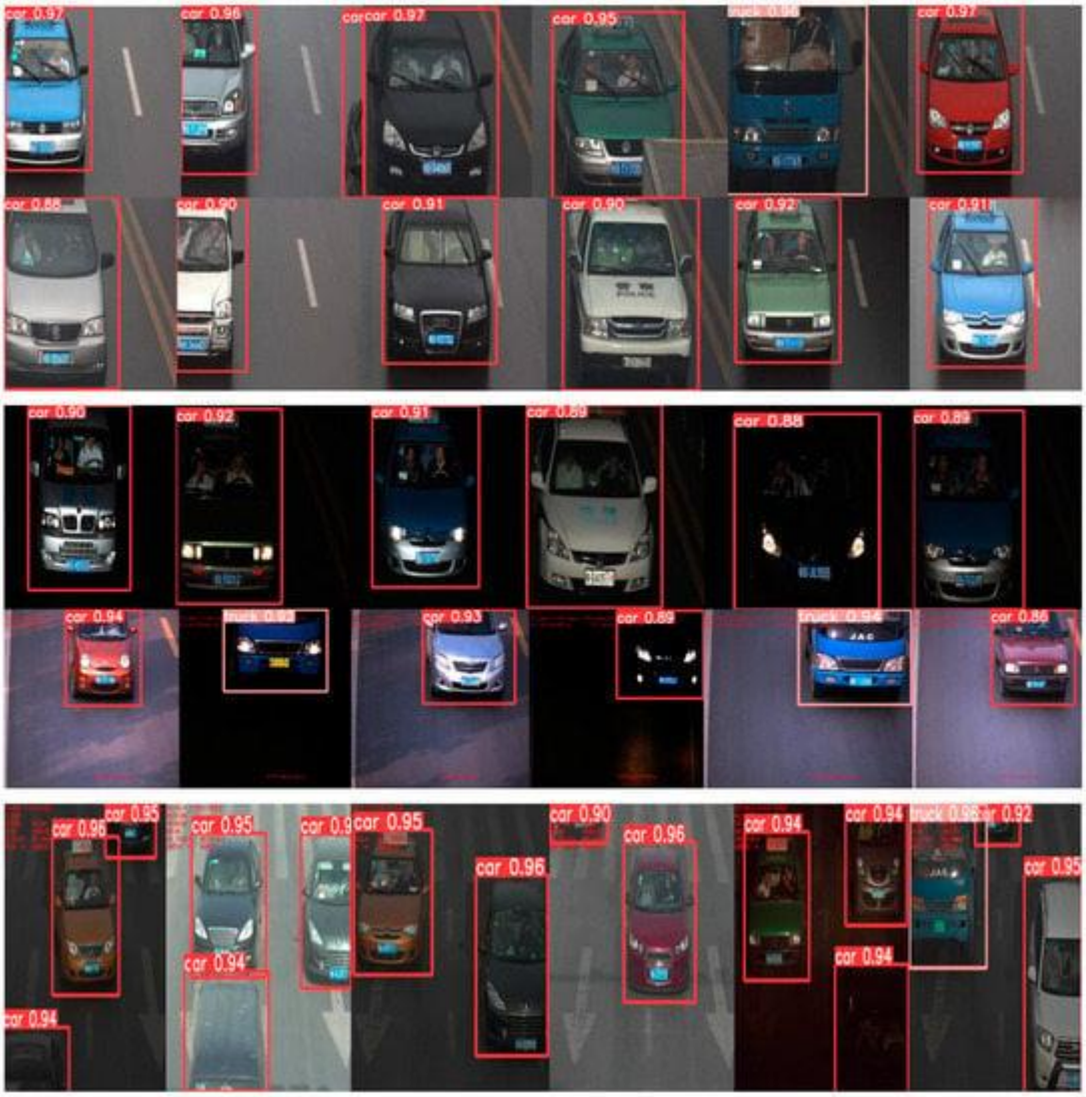

Figure 7. Vehicle detection results on the PKU dataset from G1 to G5 categories

Table 4. The PKU dataset description.

Moreover, the proposed method also performs well on the G5 category, which contains multiple vehicles per image. It can be seen that for different view angles along with the partially occluded vehicles, the proposed method performs well and in most of the instances detects all such vehicles. Figure 7 also reveals that the PKU-G3, G4, and G5 pose a challenge to any detection algorithm due to the fact that the illuminations change abruptly. A few of the images shown in the 3rd, 4th, and 5th rows in Figure 7 have a background that is dark black, or in which the head lights of the vehicles are turned on. In such cases, the proposed method performs well and up to task by locating all the vehicles that appear therein.

Table 5 lists the comparison of the proposed method on the PKU dataset with fourteen other methods. Since we collected most of the data from Pakistani cities, for a fair comparison we tested the methods reported in [28,29,30,31] and [33,34,35,36,37,38,39,40,41,42] on the whole PKU dataset along with our developed method. Table 5 lists the detailed results with important observations.

Table 5. Vehicle detection comparison (%) on PKU dataset.

- From Table 5, it is evident that all the compared methods except [33,35,36,37,41] and [42] yield 100% detection accuracy on the PKU–G1~G3 categories.
- On the G4 category, the proposed method ranks 3rd among all the compared fourteen methods in terms of detection accuracy. On the other hand, on the G5 category, our developed method outperforms all the compared methods. The PKU G5 is a challenging category due to fact it contains multiple vehicles per image and also contains several disguising crosswalks that pose a threat to any vehicle detection algorithm.
- From Table 5, we also observe that for G1, G2, and G3 categories, the methods developed in [28,29,30,38,40] produce 100% vehicle detection result. Our proposed method yields 99.94% vehicle detection accuracy on the G1 category and 100% for the G2 and G3 categories. Therefore, we observe that methods shown in Table 5 have solved the challenge of vehicle detection on these three categories as most of them yield at least 99% accurate vehicle detection.
- Overall, on the PKU dataset, the proposed method ranks 1st at achieving vehicle detection in terms of the mAP as listed in Table 5. The method by [40] ranks 2nd by yielding 99.86% accurate vehicle detection accuracy. The works developed in [30,31] also yield slightly over 99.75% vehicle detection accuracy. In addition, the methods shown in Table 5 report over 97% detection accuracy, which we believe is encouraging in solving real-world traffic problems.
- To best of our knowledge, we observe that vehicle detection challenge is almost solved on the PKU dataset. However, we observe that non-uniform illuminations or high glare at the night could still affect vehicle detection accuracy. Similarly, the researchers who aim to solve the other object detection problems, such as license plate detection or recognition, may need to perform additional preprocessing or postprocessing to achieve reliable detection results.

4.2. Analysis on the COCO Dataset

The COCO dataset is designed to detect and segment various objects that occur in their natural context [32]. As shown in Table 3, the COCO dataset contains various object images, which have been gathered from complex everyday scenes and contains common objects in their natural context. Moreover, objects in this dataset are labeled using per-instance segmentations to aid in precise object localization. Overall, the COCO dataset contains images of 91 object types with a total of two and a half million labeled instances in 328,000 images. Recently, the COCO dataset received extensive attention from researchers investigating various categories of detection including diverse vehicle shapes. Figure 8 shows the vehicle detection results of our proposed method on the COCO

dataset. Clearly, Figure 5 depicts the performance of the proposed vehicle detection algorithm on various challenging images of the COCO dataset.

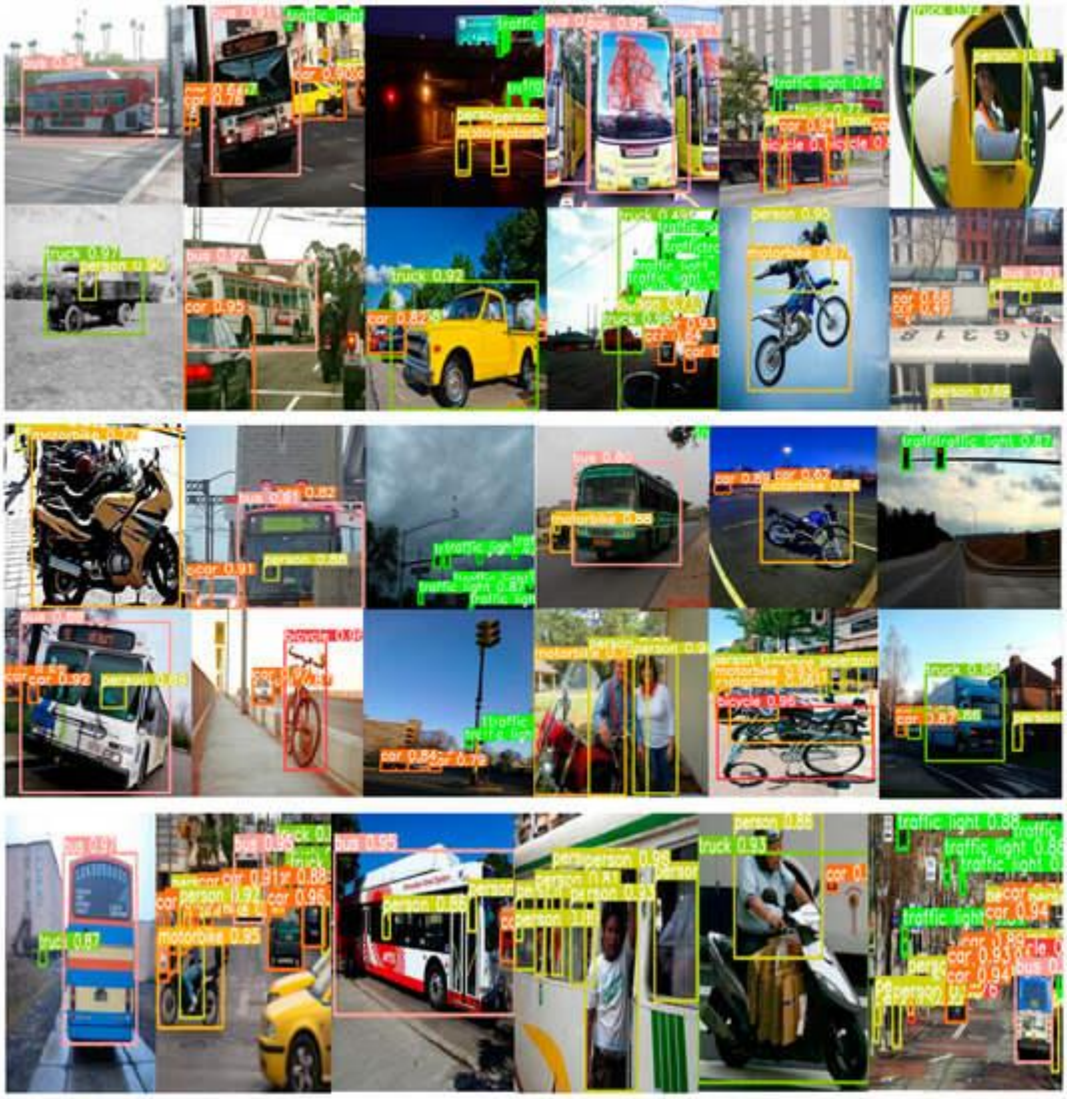

Figure 8. Vehicle detection results on the COCO dataset.

In most of the instances and under huge illumination variations, almost all of the different vehicles are accurately detected by the proposed methodology. We used other objects, such as motorcycles and persons during this phase. Therefore, those are also accurately located in various images in Figure 8. A few such instances can be seen in the 1st image of the 2nd and 3rd rows, respectively. Similarly, the 6th image in the bottom row of Figure 8 also depicts the object detection phenomenon. To further validate the superiority of the proposed method, a comparison with fourteen other methods is listed in Table 6 with some important observations.

Table 6. Vehicle detection accuracy comparison on the COCO dataset.

As can be seen for various image resolutions that range from 512 × 512 to 800 × 800 pixels, the proposed method ranks 1st among all the compared methods and reports the highest mAP value of 52.31%. The work reported in [42] ranks 2nd and yields a 50.40% mAp value followed by [41] with a 49.80% mAP value. Our analysis reveals that the work developed in [35,36] are also an encouraging solution for detecting various objects in the challenging COCO dataset.

- On the COCO dataset, the work reported in [31] yields the lowest (27.89%) mAp value followed by [33], whose method yields a mAP value of 29.10%. Moreover, in the current study, work discussed in [40], which uses the ResNet as a backbone, yields a mAP value of 31.80%, which in the context of current study falls on the lower side.
- The crux of this dataset is that the proposed method effectively and reliably detects miscellaneous objects that include vehicles of varying shapes, including motorbikes and jeeps. Furthermore, the proposed method also effectively handles big buses. A few such samples are also in the 1st and 3rd columns of Figure 8.

4.3. Analysis on the DAWN Dataset

The DAWN dataset is designed to investigate the performance of recent vehicle detection methods on a broad range of natural images including adverse weather conditions. The DAWN dataset contains 1000 image of significant variation in terms of vehicle size and category along with pose variation, non-uniform illumination, position, and occlusion from real traffic environments. Additionally, it exhibits a systematic variation for traffic scenes, for instance, bad winter weather, heavy snow, sleet rain, sand, and dust storms. Figure 9 shows detailed results on fog, sand, rain, and snow situations with important observations.

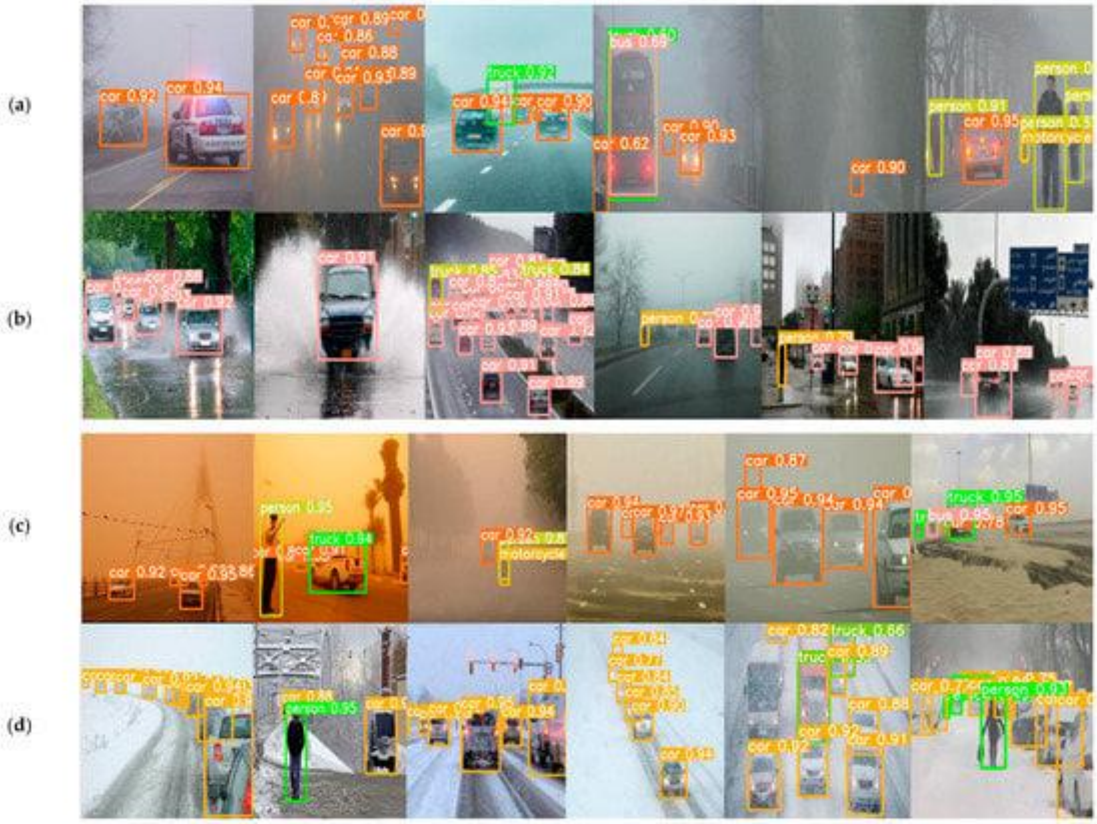

Figure 9. Vehicle detection results on the DAWN dataset row-wise: (**a**) fog; (**b**) rain; (**c**) sand; and (**d**) snow

- For the snow category as seen in top row of Figure 9, it is obvious that many

- times the vehicles are partially visible due to adverse weather conditions, such as fog that is normally experienced in severe winters in areas of various parts of the world. However, our developed method handles all such situations except the 2nd last image of front row in Figure 9, where it is obvious that the vehicle is not visible to the human eye as well.
- For a considerably rainy day as seen in second row of Figure 9, the proposed method accurately locates multiple vehicles that appear therein. In this case, the image scene variations, such as shown in the 2nd and 4th images of the second row in Figure 9 indicates that the proposed method is unaffected by such changes in the image scene. Similarly, the skyscrapers in the vehicle’s background as shown in the 5th image of the 2nd row in Figure 9 also do not affect the detection ability of our developed method.
- For a sand situation as indicated in the third row of Figure 9, the proposed method detects all vehicles that appear there in such challenging conditions. In such situations, visibility is normally very low, which poses threats to most of the machine learning algorithms. Particularly, the first two images in the 3rd row of Figure 9 have intra-class scene variations, i.e., both are images effected by sand storms and yet appear differently to the human eye. Even in such cases, our developed method performs well and detects most of the instances that appear in such condition. The 3rd image in this row is quite challenging for human observers as well. However, as indicated there, our developed method handles such situations by successfully locating the vehicles that appear in such scene images.
- The bottom row in Figure 9 is a case when the scene is dominated by snow. In this case, surprisingly, the image appears neat and clean and thus results in a visually pleasing image due to the massive amount of snow which is present in the image. In this case, our developed method accurately detects and labels all the vehicles that appear therein. Particularly, the 3rd image in this row also reveals a red light along with the snow. Yet in this case, the proposed method performs well and successfully locates all the vehicles. Moreover, the last image in this row shows a few vehicles that overlap and result in partial occlusion. However, our developed method performs well in this case as well.

In Table 7, we compare our method with the works already described in Table 5 and Table 6, respectively. A few of the observations from Table 7 are listed below.

Table 7. The mAP (%) comparison on DAWN dataset.

- As can be seen in Table 7, for the fog scenario the work developed in [40] ranks 1st among 14 compared methods by yielding a 29.68% mAP value. Our developed method ranks 2nd out of all compared methods in fog situation and yields a 29.66% mAP value. In the fog situation, the work developed in [38] yields the lowest mAP value (16.50%) followed by [29] whose method yields a mAP value of 24%.
- For the rain scenario on the DAWN dataset, our proposed method and the work developed in [31] yield the highest mAP value of 41.21%. In this category, the work in [34] ranks 2nd and yields an encouraging result of a 41.10% mAP value. For the aforesaid category, results yielded by [36,37] are also encouraging. For images that are affected by rain, the work in [38] delivers the lowest mAP value of 14.08%.
- For the snow conditions on the DAWN dataset, the work developed in [37] ranks

1st among all compared methods and slightly outperforms the proposed method by yielding a mAP value of 43.02%. For this category, our developed method yields a mAP value of 43.01%. It is important to state here that for this situation, the works in [31,33,36,37] yield almost similar results.

- For the sand condition, our method ranks 1st and outperforms all compared methods by yielding a 24.13% mAP value. On this situation, the works in [28,34,35] yield similar mAP values. For the sand situation, the work in [38] yields the lowest mAP value (10.69%).

4.4. Computational Complexity

We evaluate the computational complexity in terms of the time consumed to yield the vehicle detected output image. While evaluating the computational complexity of the methods listed in Figure 10, we manually vary the test image size from 512 × 512 pixels up to 1600 × 1236 pixels on all the three datasets compared in this study. In addition, all the times shown in Figure 10 are the mean execution time on all the three datasets to process a single image and yield the output image.

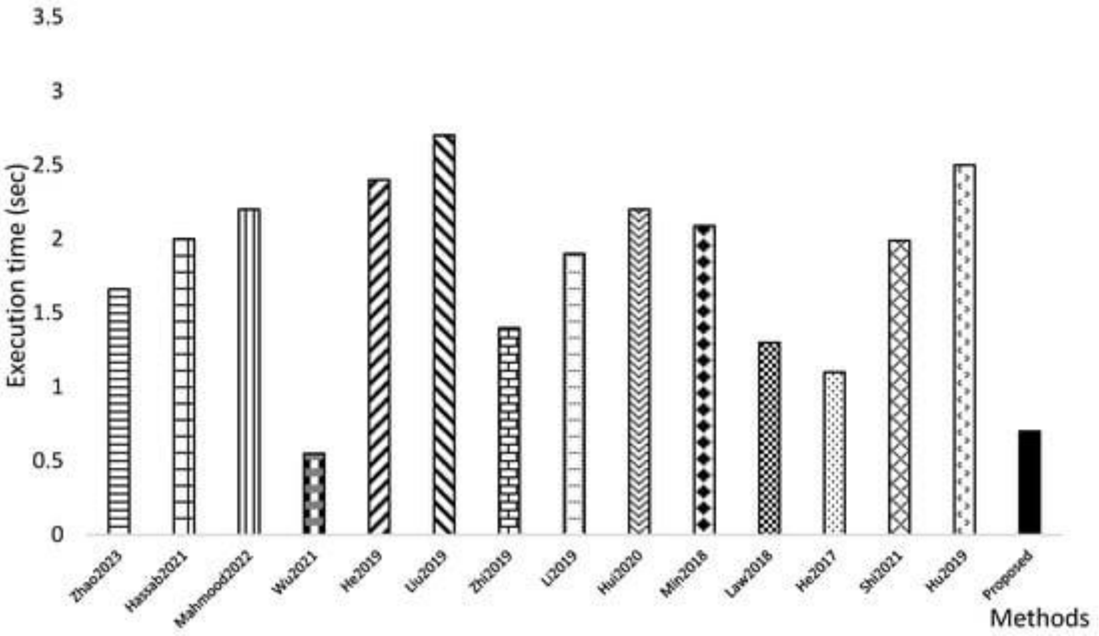

Figure 10. Computational complexity comparison with fourteen other approaches [28,29,30,31,33,34,35,36,37,38,39,40,41,42].

Moreover, in Figure 10, we compare the execution time of 14 state-of-the-art vehicle detection methods with the proposed method. It can be seen that the work of Liu [34] is computationally more expensive than all of the compared methods. Clearly, the proposed method is computationally most economical and consumes slightly more than 0.50 s to yield a vehicle detected output image. Furthermore, the works reported by Wu et al. [31], Law et al. [39], and He et al. [40] consume nearly 1 s to yield the output image with detected vehicles.

4.5. Discussion

Although the analysis presented above familiarizes the readers with the feasibility of our developed method to detect diverse vehicles under diverse range of environments, the discussion below will give further insight to the readers.

- Methods compared in this study are state-of-the-art object detectors. We observed that specific method performs well on a specific dataset but are challenged by other datasets. For instance, the work developed in [28] investigates BIT-Vehicle and UA-DETRAC datasets only. These datasets mostly contain high quality frontal view of the different vehicles with image resolution of 1920 × 1080 to 1600 × 1200 pixels. In contrast, the method proposed in current study explores three different datasets that have variations, such as different road conditions, varying weathers, or complex backgrounds. Moreover, the study presented in this manuscript also explores the detection ability of this method on three standard and publicly available datasets.

- The works discussed in [29,34] mostly focus on KITTI and the DAWN datasets that contain the variations as described earlier. However, we also explore their detection ability on five different classes of the PKU dataset that contain huge road and traffic variations along with our proposed method. This will essentially provide a nice baseline to beginners and researchers to develop their specified tasks.
- The work reported in [30] investigates the generic PKU dataset in its five distinct categories. However, this study further explores the detection capability of [30] on the COCO and the DAWN datasets. Moreover, the detection accuracy of the method proposed in this study provides a fair insight into vehicle detection in various scenarios.
- The method developed in [31] examined the CARLA dataset, which we believe is a limited and relatively small vehicle dataset. The findings presented in this study extend the detection capability of this method to three other datasets. In addition, its detection comparison with the proposed method and several other techniques provides much detailed insight about issues in the vehicle detection domain.
- In [33,37], the PASCAL VOC 2007 dataset is explored only. Moreover, work in [33] also analyzes the subdomain of the COCO dataset to show the detection of trains only. In contrast, this study explores the detection capability of [33] on various vehicle classes of the COCO dataset along with the PKU and DAWN datasets. Moreover, the detailed comparison provided in the earlier sections provides a fair baseline to the research community. Furthermore, the work in [37] explored the PASCAL dataset that already contains annotated images of various objects. This study further expands the detection capability of this method to three different vehicle datasets. Finally, the detailed analysis and comparison provided in earlier section hints towards additional modifications of this algorithm.
- The works in [35,36,39,40] were validated on the MS COCO dataset to detect various objects. The experiments reported in this study extend the detection analysis of the aforementioned approaches to PKU and DAWN datasets as well. Since our method also explores the vehicle detection on these datasets, it will be convenient for researchers and practitioners to choose the appropriate algorithm for their specified applications. Moreover, the work listed in [40] reports the detection of various objects, such as pedestrians, statues, or animals. However, this study reports the detection ability of this algorithm on actual and real-world vehicle images along with several other approaches.
- In [38], the PETS2009 and the changedetection.net 2012 datasets are explored. Results analyzed in their study are mostly standard high quality frontal view images of mono-color cars running on a main highway. In contrast, the analysis presented in this study explores the detection ability this method on different datasets on multiple styles of vehicle and on differently color cars. Moreover, this study also investigates the detection ability of this method on varying illuminations and weathers along with different road conditions.
- The study in [41] analyzed the DLR Munich vehicle and VEDAI datasets. In their study, mostly high-quality aerial vehicle images are analyzed. Few of these are running on roads, while several parked vehicles are shown. However, our study also reports the

- use of this method on actual daily life vehicle images from three publicly available datasets. We are optimistic that detailed analysis and comparisons provided in this manuscript will be handy for the research community to modify any algorithm for their specified tasks.
- Finally, in [42], the KITTI and the LSVH datasets were explored. Results reported in this study are mostly vans, cars, and bus that run on the main highways. However, our study reports the detection ability of this method on varying illuminations, different weathers, and challenging road conditions from three publicly available datasets. We believe that the analysis provided by our developed method and the detailed comparison listed in this manuscript will provide further insight to the research community.

- All of these are useful efforts to solve and automate the vehicle detection problem under varying conditions. For each of the datasets mentioned above, these methods perform well. One of the objectives of the current study was to test and analyze all of the fourteen methods compared in this paper on standard PKU, COCO, and DAWN datasets. The main reason to choose PKU, COCO, and DAWN datasets is that these datasets contain real world and challenging images. For instance, the PKU dataset has five distinct categories that range from normal images to dark night images along with night glare. Similarly, this dataset also contains multiple images that appear in the input along with partial occlusions and different road conditions. Similarly, as mentioned in **Section 4**, the COCO dataset is also a huge dataset and contains a diverse range of objects. Moreover, the DAWN dataset also contains various real-world situation, such as fog, rain, snow, and the sand. An evaluation of fourteen different methods on these three datasets will be a fair guideline for researchers and beginners to develop, implement, or modify any algorithm for their specified applications.
- Out of the datasets that are investigated in this study, we find the DAWN dataset a bit more challenging than the others. The main reason is the inclusion of images in challenging conditions, such as fog, rain, contaminated with sand, or snow. Our study indicates that the sandy images reduce the scene visibility and ultimately reduce the detection accuracy of a detector. The 1st image in the top row in **Figure 11** depicts such conditions in which very low vehicle detection is achieved. Similarly, as shown in the 2nd image of the top row of **Figure 11**, low vehicle detection is observed during a rainy night when the head lights of the vehicle are also turned on. In this case an electricity pole also appears, which results in partial occlusion that ultimately results in reduced object detection.
- We observe that our proposed method still needs to perform well in different situations, such as when the scene is contaminated with the snow storm or blizzard as shown in the 2nd row of **Figure 11**. In such cases, background noise dominates results in low visibility. In this scenario, a Retinex-based image enhancement scheme might be useful. For such a scenario, we suggest that an image dehazing-based enhancement could also be effective. We are optimistic that this proposed solution will essentially enhance the object and image scene, which will later make life easier for any of the vehicle detectors deployed. Ultimately, the application of image enhancement technique will significantly increase the detection ability of object detector.
- For images where snow is dominant, image appears overly white, which also decreases the detection accuracy of state-of-the-art object detection methods. In this case, image contrast correction might produce the desirable results. In many cases, the occlusions on the road also pose a threat to the detector, which ultimately results in false detections. In such cases, an occlusion handling method could also be used to reliably detect any object.
- For all of the aforementioned discussion, **Figure 11** shows a few of the sample images where our developed method struggles. In images shown in **Figure 11**, our method either yields a very low vehicle detection rate or produces false detections. Therefore, future research could also focus on few of the cases as shown in **Figure 11**.

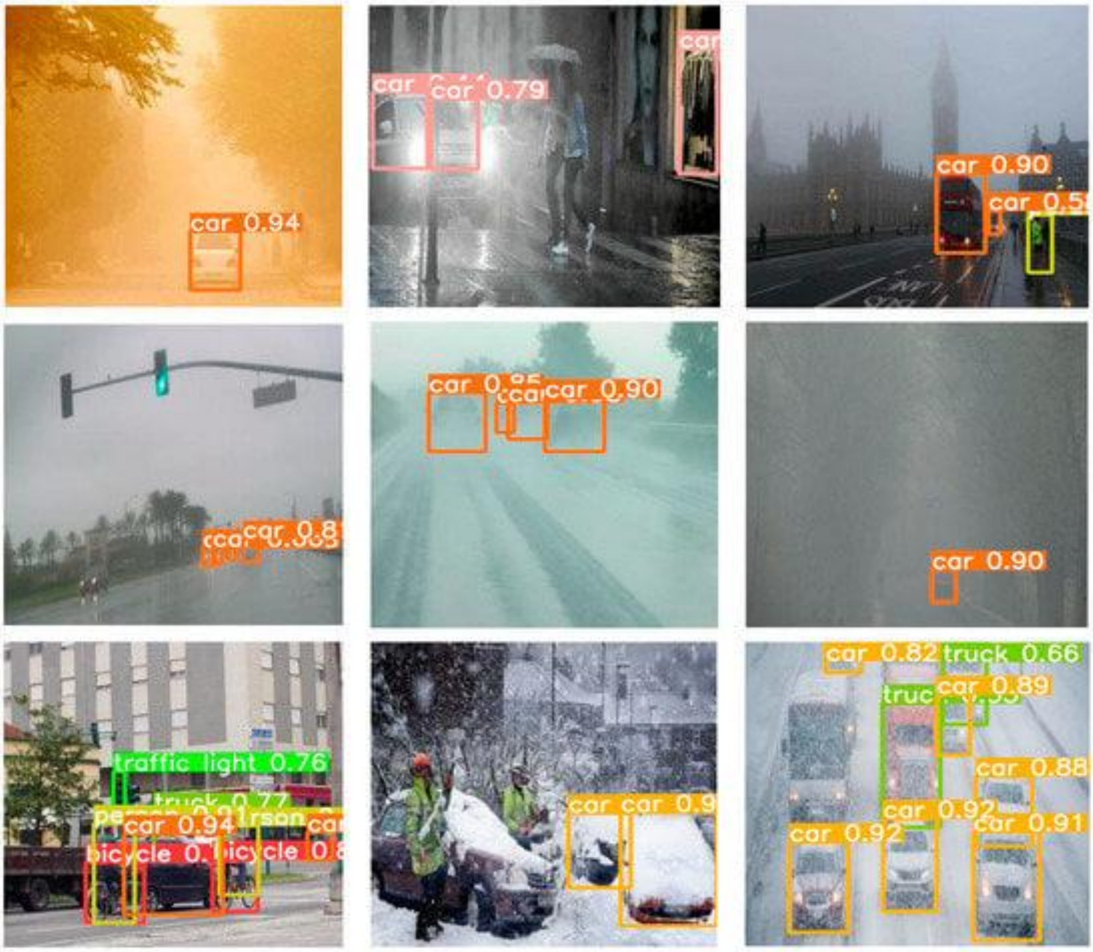

Figure 11. Sample images of low vehicle detection from compared datasets

4.6. Final Remarks

Detailed analysis discussed in this paper indicates that vehicle detection has been an active research field in recent years. From providing early warning signals and monitoring up to exercising control, there are several examples of major research in intelligent vehicle detection. This paper presented a detailed analysis on vehicle detection on three publicly available dataset. For the task of vehicle detection, YOLO-v5-based architecture was used. To make the YOLO-v5-based architecture more intelligent and flexible, a transfer learning methodology was introduced. Detailed analysis indicated that the proposed approach performed well on challenging datasets.

In addition, a detailed comparison of the proposed method was carried with fourteen recent state-of-the-art approaches. We are optimistic that this study will be a fair guideline for beginners and practitioners to modify or use any detector for their desired tasks or applications. Below we list the final summary of developed vehicle detection method on three datasets.

PKU: On this dataset, in the G1 category, the proposed method yielded mAP of 99.94%. In the G2 and G3 categories, the proposed method yielded 100% vehicle detection mAP. In the G4 and G5 categories, the proposed method yielded 99.73% and 99.96% mAP, respectively. Overall, on the PKU

dataset our method yielded 99.92% vehicle detection accuracy. Out of the fourteen compared methods on the PKU dataset, the proposed method ranked 1st among all compared approaches.

COCO: On this dataset, with image resolution of 512 × 512 pixels, the proposed method yielded 52.31% mAP values and ranked 1st among all the compared methods.

DAWN: This dataset contains four prominent sub classes, which are fog, rain, snow, and sand. On images that were affected by fog, our proposed method yielded a mAP value of 29.66% and ranked 3rd out of fourteen compared methods in this category. Meanwhile, for images that contained rain, our developed method produced a mAP value of 41.21% and ranked 1st along with [31] among all compared works. For images that contained snow, our method yielded a 43.01% mAP value and ranked 2nd among all compared works. In this class, the work developed in [37] ranked 1st by yielding a 43.02% mAP value. For images that contained sand, our developed method yielded a 24.13% mAP value and ranked 1st among all methods. In this class, the work developed in [28] also produced a par result by yielding a mAP value of 24.10%.

5. Conclusions

This paper discussed an accurate, fast, and robust vehicle detection method based on the YOLO-v5 architecture. To develop a robust object detection algorithm, transfer learning was performed. The proposed object detection method was tested on three publicly available datasets, which are the PKU, COCO, and DAWN datasets. Simulation results demonstrated that the proposed method is effective at handling various challenging situations, such as night, rainy, and snow conditions. The proposed method significantly elevated the accuracy and operational efficiency. In addition, the detection technique proposed in this research can additionally be relevant to a large number of real time applications. However, the only caveat is that a giant quantity of data is required for training of the detection model. The YOLO-vs-based vehicle detection method discussed in this paper achieved a 99.92% detection accuracy on the PKU dataset and outperformed five methods compared therein. Similarly, on the COCO dataset, the proposed method yielded a superior mean average precision than several methods compared therein. Furthermore, for highly challenging conditions in the DAWN dataset, the proposed method was superior in terms of detection accuracy for fog, rain, snow, and sandy conditions.

In the future, the proposed method can be further investigated to detect the occluded vehicles. Moreover, for moving objects, motion blur could also be investigated. Furthermore, a cloud computing-based domain can be introduced to handle the resources of complex machine learning algorithms. Our algorithm could also be investigated for haze images in which there is very limited visibility and thus vehicles are barely visible to human eye. Moreover, the impact of changes in the network structure of each type of a YOLO model could also be further explored on the datasets explored in this study. Finally, our developed method could be integrated with deep learning methods to further explore the research of vehicle detection, tracking, or recognition.

References

1. Mahmood, Z.; Haneef, O.; Muhammad, N.; Khattak, S. Towards a Fully Automated Car Parking System. *IET Intell. Transp. Syst.* **2018**, *13*, 293–302. [Google Scholar] [CrossRef]

Xiaohong, H.; Chang, J.; Wang, K. Real-time object detection based on YOLO-v2 for tiny vehicle object. *Procedia Comput. Sci.* **2021**, *183*, 61–72. [Google Scholar]

2. Rani, E. LittleYOLO-SPP: A delicate real-time vehicle detection algorithm. *Optik* **2021**, *225*, 165818. [Google Scholar] [CrossRef]
3. Tajar, T.; Ramazani, A.; Mansoorizadeh, M. A lightweight Tiny-YOLOv3 vehicle detection approach. *J. Real-Time Image Process.* **2021**, *18*, 2389–2401. [Google Scholar] [CrossRef]
4. Mahmood, Z.; Bibi, N.; Usman, M.; Khan, U.; Muhammad, N. Mobile Cloud based Framework for Sports Applications. *Multidimens. Syst. Signal Process.* **2019**, *30*, 1991–2019. [Google Scholar] [CrossRef]
5. Hamsa, S.; Panthakkan, A.; Al Mansoori, S.; Alahamed, H. Automatic Vehicle Detection from Aerial Images using Cascaded Support Vector Machine and Gaussian Mixture Model. In Proceedings of the 2018 International Conference on Signal Processing and Information Security (ICSPIS), Dubai, United Arab Emirates, 7–8 November 2018; pp. 1–4. [Google Scholar]
6. Mikaty, M.; Stathaki, T. Detection of Cars in HighResolution Aerial Images of Complex Urban Environments. *IEEE Trans. Geosci. Remote Sens.* **2017**, *55*, 5913–5924. [Google Scholar]
7. Arı, Ç.; Aksoy, S. Detection of Compound Structures Using a Gaussian Mixture Model With Spectral and Spatial Constraints. *IEEE Trans. Geosci. Remote Sens.* **2014**, *52*, 6627–6638. [Google Scholar] [CrossRef]
8. Hbaieb, A.; Rezgui, J.; Chaari, L. Pedestrian Detection for Autonomous Driving within Cooperative Communication System. In Proceedings of the 2019 IEEE Wireless Communications and Networking Conference (WCNC), Marrakesh, Morocco, 15–18 April 2019; pp. 1–6. [Google Scholar]
9. Xiong, L.; Yue, W.; Xu, Q.; Zhu, Z.; Chen, Z. High Speed Front-Vehicle Detection Based on Video Multi-feature Fusion. In Proceedings of the 2020 IEEE 10th International Conference on Electronics Information and Emergency Communication (ICEIEC), Beijing, China, 17–19 July 2020; pp. 348–351. [Google Scholar]
10. Yawen, T.; Jinxu, G. Research on Vehicle Detection Technology Based on SIFT Feature. In Proceedings of the 8th International Conf on Electronics Info. and Emergency Communication (ICEIEC), Beijing, China, 15–17 June 2018; pp. 274–278. [Google Scholar]
11. Li, Y.; Wang, H.; Dang, L.M.; Nguyen, T.N.; Han, D.; Lee, A.; Jang, I.; Moon, H. A Deep Learning-Based Hybrid Framework for Object Detection and Recognition in Autonomous Driving. *IEEE Access* **2020**, *8*, 194228–194239. [Google Scholar] [CrossRef]
12. Li, Y.; Li, S.; Du, H.; Chen, L.; Zhang, D.; Li, Y. YOLO-ACN: Focusing on small target and occluded object detection. *IEEE Access* **2020**, *8*, 227288–227303. [Google Scholar] [CrossRef]
13. Cai, Z.; Vasconcelos, N. Cascade R-CNN: Delving into High Quality Object Detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Salt Lake City, UT, USA, 18–23 June 2018; pp. 6154–6162. [Google Scholar]
14. Wang, C.; Wang, H.; Yu, F.; Xia, W. A High-Precision Fast Smoky Vehicle Detection Method Based on Improved Yolov5 Network. In Proceedings of the 2021 IEEE International Conference on Artificial Intelligence and Industrial Design (AIID), Guangzhou, China, 28–30 May 2021; pp. 255–259. [Google Scholar] [CrossRef]