Journal of Techniques, ISSN: 2708-8383, Vol. 7, No. 1, 2025, Pages 37-47
DOI: https://doi.org/10.51173/jt.v7i1.2099

JOURNAL OF TECHNIQUES

Journal homepage: http://journal.mtu.edu.iq

REVIEW ARTICLE - ENGINEERING (MISCELLANEOUS)

Identification of Vehicle Logos in Deep Learning: A Comprehensive Survey

Mustafa Noaman Kadhim[1*], Ammar Hussein Mutlag[1], Dalal Abdulmohsin Hammood[1], Nurulisma Binti Hj. Ismail[2]

[1]Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq

[2]Faculty of Electronic Engineering & Technology (FKTEN), University Malaysia Perlis (UniMAP) 02600 Arau, Perlis, Malaysia

[*] Corresponding author E-mail: bbc0080@mtu.edu.iq

Article Info.

Article history:

Received
30 October 2023

Accepted
12 January 2024

Publishing
31 March 2025

Abstract

The identification of vehicle logos in videos and images can be considered a crucial undertaking in several applications, such as traffic surveillance systems. The accelerated progress of deep learning has resulted in an increasing need within the computer vision field for the development of efficient, robust, and outstanding services across several domains, such as the recognition and classification of automobile emblems. This survey begins with an exploration of the escalating significance of logos and the associated challenges to their detection. The core problem addressed revolves around the necessity for robust methodologies capable of accurately identifying logos in diverse scenarios. The objective of our study is to conduct a comprehensive examination of existing deep learning strategies for logo detection, unveil their real-world applications, and contribute insights into future challenges and directions in this domain. Our survey uncovers valuable insights into publicly available datasets, showcasing their diversity and relevance in evaluating logo detection algorithms. An in-depth analysis of deep learning strategies follows, elucidating their strengths and limitations and providing a nuanced understanding of their performance metrics. The survey concludes by delineating anticipated challenges and proposing future directions, thereby presenting a roadmap for researchers and practitioners seeking to advance logo detection using deep learning techniques.

Publisher: Middle Technical University

Keywords: Vehicle Logo Detection; Deep Learning; Small Object Detection; Convolutional Neural Networks; Yolo.

1. Introduction

The recognition of vehicle logos has significant importance in the analysis of vehicle behavior. It serves as a valuable source of supplemental information for vehicle identification, a crucial area of study within the field of autonomous systems. Over recent years, the use of surveillance information systems has increased, which has accelerated the development of vision-based automobile recognition methods. This technology has emerged as a prominent area of study within the domain of automated systems. Vehicle logo recognition is a significant technology in the realm of intelligent transportation systems, akin to license plate recognition.

Vehicle identification in robotic systems may be enhanced by the inclusion of vehicle logo recognition, which offers additional and complementary information [1, 2]. To effectively address car-related criminal activities, a growing number of academics have dedicated their efforts to developing efficient systems for vehicle logo identification. The prevailing techniques include a two-step process, namely the extraction of potential regions for car logos and subsequent logo recognition. Nevertheless, the current vehicle logo recognition techniques still face challenges when it comes to detecting diminutive logos and accurately identifying logos in intricate environmental conditions. Hence, the identification of diminutive objects poses a key obstacle in the field of computer vision. Nevertheless, logo recognition under challenging environmental conditions remains a challenge for the current vehicle logo recognition approaches. Therefore, a significant challenge in computer vision is the recognition of tiny objects. Modern detectors often excel at detecting big items, but their detection accuracy for tiny objects is frequently poor [3].

Classical algorithms provide several tailored components for training a comprehensible and functional detector. Conventional features such as edges, invariant moments, and feature points are often used in many applications. Nevertheless, detectors with specifically tailored attributes are limited in their ability to effectively identify automobile logos under diverse and demanding environmental circumstances. These variables include low light settings, logo tilting, and adverse weather conditions. Deep learning methods for object identification have been the prevailing approach in computer vision tasks in recent years. Even though convolutional neural networks are used for the identification of vehicles [4, 5], vehicle model recognition [6, 7], license plate recognition [8], compression artefact reduction [9], object detection [10], object tracking [11, 12], very few studies have made contributions to vehicle logo recognition. Therefore, it is imperative to acknowledge the exceptional performance of convolutional neural networks (CNNs) in vehicle logo recognition applications. Several studies [13-15] have enhanced their network performance using strategies such as expanding network depth or developing optimized architectures.

Nomenclature & Symbols			
CNN	Convolutional Neural Network	TP	True Positive
AP	Average Precision	TN	True Negative
mAP	Mean Average Precision	FP	False Positive
IoU	Intersection Over Union	FN	False Negative

The realm of vehicle logo detection confronts multifaceted challenges rooted in the real-world dynamics of varying logo sizes and diverse contextual backgrounds. The diminutive size of logos on vehicles often leads to difficulties in their identification, particularly when they are overshadowed by other elements in the visual scene. Moreover, the diverse backgrounds against which logos must be discerned introduce complexities in segmentation and recognition, further complicating the accurate identification of logos. Complexities in segmentation and recognition, further complicating the accurate identification of logos. Existing methodologies, while showcasing advancements, may encounter limitations when dealing with these intricacies. Therefore, a critical examination of these challenges becomes imperative to advance the field and devise robust solutions capable of handling the complexities inherent in vehicle logo detection scenarios.

Our survey paper significantly contributes by addressing a notable research gap in the field of vehicle logo identification, specifically within deep learning applications. Despite the widespread use of deep learning in this area, a comprehensive assessment has been lacking. Our study uniquely focuses on recent advancements in deep learning methodologies tailored for vehicle logo identification. The distinctiveness of our contribution lies in a thorough examination and critical discourse on the current state of research in vehicle logo identification, encompassing datasets and evaluation metrics. Additionally, we meticulously investigate prospective research obstacles, pinpointing unresolved challenges in vehicle logo detection. Our objective is to provide a unique viewpoint that enhances understanding of deep learning-based vehicle logo identification and encourages further investigation into unresolved issues. By outlining prospective research obstacles and identifying future avenues, our survey accelerates progress in the broader area of vehicle logo research, serving as a guiding resource for researchers and inspiring advancements in this field.

The subsequent sections of this work are structured in the following manner: In the second section, an extensive examination and categorization of the existing literature on vehicle logo detection is conducted. In the third section, we examine the datasets used for public vehicle logo detection. In the fourth section, we discuss the performance evaluation metrics. In the fifth section, we will examine the results and discuss them. The conclusion of the research is offered in the final section.

2. Previous Work

With a focus on research done in the previous four years, this portion of the paper examines current advancements in the field of vehicle logo detection and categorization. The recent works can be organized according to the one- and two-stage object detection for vehicle logo detection and classification as follows:

2.1. One-step algorithms

Single-stage object detection algorithms represent a pivotal advancement in computer vision, streamlining the complex task of identifying and localizing objects within an image in a single pass. Unlike two-stage methods that involve region proposal and subsequent classification, single-stage algorithms excel in efficiency by combining these steps into a unified process. This streamlined approach significantly reduces computational overhead, making them well-suited for real-time applications. The approach proposed by Yin et al. [16] involves using YOLOv2 for logo recognition. The proposed technique encompasses the integration of automated testing methods across many levels, the fusing of channels at numerous levels, and the use of separable convolution algorithms. The suggested methodology for vehicle identification has several advantages when compared to the standard technique that depends on manual feature extraction by humans. The benefits included within this particular setting are self-directed learning skills and the capacity to directly input visual representations. Moreover, it facilitates the placement and identification of automotive emblems. The experimental findings indicate that the model has remarkable stability when exposed to low-resolution circumstances, fluctuations in lighting, rotational transformations, and interference from noise. Furthermore, the model demonstrates exceptional levels of accuracy, recall, and real-time performance. The recall rates observed after the completion of training were found to be 99.7%, indicating a notable level of accuracy in the identification of pertinent circumstances. The mean average precision (mAP) was determined to be 99% in this study.

Shuo Yang et al. [17] introduced a comprehensive dataset, named 'VLD-30', specifically designed for addressing the vehicle logo identification challenge. Vehicle logo detection is extensively employed in the field of Intelligent Transport Systems, particularly in applications such as vehicle monitoring. Regarding the object identification method in deep learning, the inclusion of a high-quality dataset has the potential to enhance its resilience. The dataset exhibits a notable degree of dependability due to the inclusion of comprehensive analyses on several aspects. To validate the performance of the dataset, common target identification algorithms like Faster-RCNN and YOLO achieved mAP of 87.5% and 85.3%, respectively. Linghua Zhou et al. [18] introduced a novel methodology for the recognition of automobile logos in the presence of motion blur. This approach combines the techniques of VL-YOLO and Filter-DeblurGAN. The Filter-DeblurGAN model incorporates a decision-making process that assesses the level of blurriness in an image to decide whether deblurring is necessary. Additionally, it can restore clarity to photographs of varying resolutions. The Filter-DeblurGAN algorithm addresses the limitation of DeblurGAN by including a judgment process and mitigating the issue of excessive resolution degradation. The deployed model achieved a mAP score of 98.1% when assessed on the LOGO-17 dataset. The research findings show that the suggested technique outperforms currently used approaches in recognizing objects inside a motion-blurred environment with a considerable degree of accuracy.

Xiaoli Jiang et al. [19] presented a more effective method for identifying car logos based on YOLOv4, aiming to address the issue of poor recognition rates resulting from tiny objects of several kinds and a complex backdrop around vehicle logos. To include more superficial information, a superficial output layer was introduced to modify the neck architecture of the initial model. The integration of surface-level spatial data with in-depth semantic data mitigated the degradation of fine-grained characteristics in the identification of automobile logos. To enhance the rate at which tiny object features are reused, the integration of the CSPDenseNet module into the Darknet53 framework was implemented. In comparison to the initial model applied to the VLD-45 dataset, the enhanced vehicle logo recognition model exhibited a 5.72% improvement in mean average precision (with intersection over union ranging from 0.5 to 0.95) and a 5.58% increase in recall.

Li Song et al. [20] used the YOLO-T model and made use of the correlation inside the car space structure to develop an innovative approach for vehicle logo detection. The proposed approach incorporates several fields of reception and establishes a detection framework that operates at various scales and is well-suited for visual landmark identification tasks. They employed a method of properly identifying and extracting the region of interest relevant to the automobile logo by taking advantage of the spatial correlation between the car logo and the lights to decrease the influence of background interference. The research results demonstrate that the approach we have presented attains a notable detection accuracy of 98.5% in terms of mAP, surpassing the performance of current car logo identification techniques.

Xiao Ke and Pengqiang Du [21] proposed three data augmentation procedures in their study, including tiny frame segmentation, Gaussian distribution segmentation, and cross-sliding segmentation. These strategies aim to enrich the dataset, enlarge the logo region, and improve the variety of logo positions. The experimental findings show that these strategies exhibit superior performance in terms of feature representation and overall enhancement compared to standard approaches. The F1 score of the suggested technique inside the YOLO framework is determined to be 77.65%, accompanied by a precision value of 92.95%. Conversely, within the Faster R-CNN framework, the F1 score is observed to be 77.99%. The findings of this study demonstrate the efficacy of the suggested methodologies in accurately detecting and identifying car logos within complex visual environments. Junxing Zhang et al. [22] introduced a methodology known as the multi-scale vehicle logo detector, which is built upon the principles of the single-shot multi-box detector (SSD). This approach achieves superior outcomes compared to existing detection techniques through the manipulation of preset box characteristics, modification of pre-training strategies, and adjustment of network architecture. The empirical results presented support the assertion that the proposed technique provides improved performance in the area of multi-scale automotive logo identification. The identification of car emblems with a wide range of sizes has a high level of clarity, resulting in a significant improvement in detection accuracy when compared to other conventional methods. The SVLD technique demonstrates a 3.1% enhancement compared to traditional approaches. Furthermore, it achieves 84.8% of Map [23].

Shuo Yang et al. [24] suggested a tweak to the YOLOv3 model to attain a trade-off between accuracy and speed while detecting vehicle logos in intricate environments. Additionally, they developed a novel dataset called VLD-30 specifically tailored for this purpose. In the VLD-30 dataset, the suggested technique produced a mAP of 89.9%. The experimental findings provide evidence that the suggested data-training strategy is beneficial and that the improved YOLOv3 algorithm is proficient in swiftly and accurately detecting vehicle logos in intricate environments. Shuo Yang et al. [25] introduced a novel dataset named VLD-45 that encompasses a multi-class vehicle logo detection (VLD) task. The dataset comprises a collection of 45,000 photos, whereby each image contains 50,359 unique items that may be classified into 45 separate categories. This research offers new perspectives on the difficulties related to the identification of small-scale items and the recognition of logos. The VLD100K-61 dataset's vehicle logos were identified and classified using the YOLOv5s-IoAv model, which was proposed by Xiaohui Shi et al. [23]. To enhance the precision of car logo recognition, a recommended approach for enhancing the regression of bounding boxes uses an intersection over average (IoAverage) loss. The model achieved a mAP0.5 score of 99.2%. However, its performance is mediocre across several conditions, such as nighttime reflections of headlights, pictures with multiple targets, and nighttime parking.

2.2. Two-step algorithms

Two-stage object detection algorithms represent a foundational approach in computer vision, designed to meticulously identify and localize objects within images. This method bifurcates the detection process into distinct stages—initial region proposal followed by subsequent classification. While potentially more computationally intensive compared to single-stage methods, two-stage algorithms often excel in accuracy and precision. The initial stage involves proposing potential regions of interest, and the subsequent stage precisely classifies and refines these proposals, offering a robust solution for intricate object recognition tasks. Junxing Zhang et al. [26] presented three deep convolutional network models (VLD-C, VLD-B, and VLD-A) for the job of detecting vehicle logos. Additionally, the authors proposed the use of a lighter network architecture known as Separable-VLD., which enables real-time car logo identification on embedded devices or CPUs via the use of deep separable convolution. The experiment demonstrates that the model can significantly enhance the accuracy of car logo detection compared with the other methods[27]. Zhongjie Huang et al. [28] VGG-16 and ResNet-50, two different convolutional neural networks, were integrated into the Faster-RCNN model. Following that, a curated dataset including 4000 images of vehicles was assembled, spanning a wide range of viewpoints, backgrounds, and resolutions, with a special focus on eight unique automobile emblems. The employment of Faster-RCNN methods yields a remarkable mean average precision outcome of 94.33%. The aforementioned results indicate that these techniques show potential for accurately identifying vehicle logos on-road surveillance vehicles and demonstrate a noteworthy degree of resilience.

Wanglong Lu et al. [27] presented a new architecture for deep network learning that ensures category consistency and improves the accuracy of VLR. Their suggested model is a convolutional neural network (CNN) that aims to extract characteristics related to car logos. This model considers both low-level and high-level components that are present inside an image. Additionally, this research introduces a unique module for learning category-consistent masks. This module enhances the framework's ability to prioritize areas that are consistent with the target category without the need for license plate identification. Comprehensive empirical assessments and comparisons done on the XMU and HFUT-VL1 datasets show that the recommended method is both possible and better. Yongtao Yu et al. [29] developed a deep convolutional network cascade for recognizing car logos from front and back views of autos. An area suggestion network and a convolutional capsule network make up this two-step processing method. By creating a collection of area suggestions, the region suggestion network is in charge of identifying suitable vehicle logo areas in the input image. The recommended framework had recognition rates of 99.4%, 98.1%, and 98.7%, respectively, for overall performance, detection rates, and overall performance. The suggested framework was practical, efficient, and durable in handling various vehicle logo circumstances. It also accurately detected and recognized vehicle logos.

Ruikang Liu et al. [30] developed a VLR technique using an upgraded matching approach for tiny objects, an SSFPD network, and a limited area. The Faster R-CNN algorithm is used to extract an area that is restricted in size and contains the logos of vehicles. This study proposes an improved matching technique that utilizes limited area segmentation. The objective is to enhance the contribution of minuscule entities to the process of acquiring features when training a network. The objective of using the reduced ResNeXt architecture is to increase the precision of recognition by enhancing the classification accuracy of the network. This is done while still keeping more subtle information to facilitate the identification of small vehicle logos. The results of comprehensive trials have shown that the approach described in this study outperforms previous methods in the identification of tiny vehicle logos. Moreover, it is deemed more suitable for implementation in complicated contexts.

This paper conducts a comprehensive exploration of recent advancements in logo detection, with a focus on deep learning-based solutions. Table 1 accompanies this discussion, providing an in-depth review of previous studies, analyzing existing deep-learning strategies for logo detection, and shedding light on the inherent strengths and weaknesses of each approach.

Table 1. State of the Art in vehicle logo detection

Ref/year	Approach	Metric	Dataset	Advantages	Limitation
[16]/2020	improved YOLOv2	The model attained a recall rate of 99.7%, an average accuracy of 99% in terms of mean Average Precision (mAP)and exhibited a test rate of around 21.3 frames per second.	PASCAL VOC.	The method has the capability of autonomous learning and feature extraction. It is capable of concurrently identifying and classifying targets, exhibiting superior accuracy, recall, and real-time performance.	The enhanced use of image optimization techniques has resulted in heightened network complexity, therefore leading to an extended duration for training.
[17]/2020	YOLOv2 (DarkNet19) and Faster-RCNN(VGG16)	The Faster-RCNN (VGG16) and YOLOv2 (DarkNet19) models exhibit average overlap rates of 81% and 76%, respectively.	VLD-30	A recently introduced dataset has shown notable advancements in the field of tiny item recognition. Additionally, there is promising potential for the development of VLD.	Other unresolved issues need attention in the future, such as the diverse range of contents found in vehicle logos.
[18]/2020	Filter-DeblurGAN and VL-YOLO	The model that was put out attained a mean average precision (mAP) score of 98.1% when evaluated on the LOGO-17 dataset.	LOGO-17	In the presence of motion blur, the suggested strategy outperforms current ones and achieves high detection accuracy.	The suggested methodology is deemed unsuitable for real-time automobile logo detection since it exhibits an elevated level of complexity.
[19]/2022	improved YOLOv4	The experimental findings showed the mean accuracy across every group in the VLD-45 is 62.94%, exhibiting a notable improvement of 5.72% compared to the initial model.	VLD-45	A new strategy was introduced that utilizes a convolutional transformer block to mitigate the impact of intricate backdrops on the recognition of car logos.	The use of a deformable convolution inside the enhancement procedure has led to a decrease in the rate of detection.
[20]/2023	YOLO-T	The model achieved a mean average accuracy (mAP) score of 98.5% when it was assessed on the LOGO-17 dataset.	LOGO-17	The methodology demonstrates a notable level of precision in detecting small-sized car logos, effectively addressing the issue of background interference.	The YOLO-T network employs a hybrid pyramid network topology that combines both top-down and bottom-up approaches, resulting in heightened complexity and increased computational requirements.
[21]/2020	FasterR-CNN and YOLO	The F1, precision (P), and recall (R) values of our technique implemented within the YOLO framework are 77.65%, 92.95%, and 66.67%, respectively. Whereas the faster R-CNN framework has shown notable results. Specifically, we have attained an F1 score of 77.99%, a precision (P) value of 93.58%, and a recall (R) value of 66.85%.	BDCI	To optimize the speed of recognition and strengthen the resilience of vehicle logo detection and identification in difficult scenarios.	The efficacy of Faster R-CNN in terms of improvement is somewhat less pronounced compared to YOLO.
[22]/2021	SSD	The VLD-45 dataset attained a mean average accuracy (mAP) of 84.81%. Furthermore, the speed of detection for the processing of an individual image is documented at 0.32 seconds.	VLD-45	This approach has a high level of reliability and exhibits the ability to adapt well to the identification of objects in complex and demanding scenarios.	The VLD-45 dataset comprises logos of reduced scale, with a limited size. The suggested approach still results in false detections.

Continue Table 1. State of the Art in vehicle logo detection

[23]/2023	YOLOV5s	In the VLD100K-61, the suggested model obtained 99.2% of mAP0.5.	VLD100 K-61	The use of IoU Average loss performance has many key benefits. Firstly, it enhances the accuracy of the bounding box. Secondly, it enables the attainment of greater confidence levels. Thirdly, it facilitates the correction of misclassifications. Fourthly, it allows for the addition of missing bounding boxes. Lastly, it aids in the removal of overlapping bounding boxes.	The model performs moderately in a variety of scenarios, including the reflection of headlights at night, multi-target images, and parking during the night.
[24]/2019	Modify YOLOv3	The proposed model attained a mAP score of 89.9% on the VLD-30 dataset.	VLD-30	The modified YOLOv3 model proves to be successful in achieving both speed and accuracy in the recognition of vehicle logos in complicated scenarios.	Poor detection accuracy in complicated vehicle logos.
[25]/2021	Faster R-CNN, YOLOV3, SSD, RetinaNet, YOLOV4 and RefineDet	The Faster R-CNN, YOLOV3, SSD, RetinaNet, YOLOV4, and RefineDet models demonstrated mean Average Precision (mAP) accuracies of 82.8%, 79.6%, 83.3%, 82.3%, 84.7%, and 81.2% respectively.	VLD-45	The new dataset has substantial research potential in the domain of tiny object identification. The primary objective of this research is to establish the performance of six detectors when applied to the given dataset.	The presented dataset presents many obstacles, including small-sized objects, shape distortion, poor contrast, and other factors.
[26]/2021	Faster R-CNN and YOLO	The YOLO+VLD-B model attained a mAP of 79.5%, whereas the F-RCNN+VLD-C model obtained a mAP of 87.4%.	VLD-30	A lightweight model was created to minimize the number of parameters, thereby improving the accuracy of detection. The implementation of a lightweight network can effectively address the challenge of achieving a trade-off between speed and accuracy in the detection process.	The accuracy of detecting tiny vehicle logos is quite low, and there are obstacles to achieving real-time identification of vehicle logos on embedded devices and central processing units (CPUs).
[27]/2021	CNN	The proposed methodology yielded a classification accuracy of 99.56% on the HFUT-VL1 dataset and a perfect accuracy of 100.0% on the XMU dataset.	HFUT-VL1 and XMU	The proposed framework has the potential to enhance the performance of vehicle logo recognition in both frontal photos of cars and vehicle logo images.	The approach used in the tough recognition tasks with complex imaging settings is not tested.
[28]/2019	Faster-RCNN	The Faster R-CNN model had a mAP of 94.33% when evaluated on the custom dataset.	Own dataset.	Showed that approaches based on Faster-RCNN have strong robustness and may be utilized to identify vehicle emblems of vehicles employed for traffic monitoring.	The dataset used in this study was restricted in size.
[29]/2019	Cascaded Deep Convolutional Network.	The recognition rate, overall performance, and detection rate of the suggested framework were 99.4%, 98.1%, and 98.7%, respectively.	Own dataset.	This study introduces a cascaded deep convolutional network that enables the direct recognition of car emblems, eliminating the need for reliance on the presence of license plates.	It is not appropriate for real-time car logo detection and recognition.

Continue Table 1. State of the Art in vehicle logo detection

[30]/2019	Faster R-CNN and SSFPD	For the Common Vehicle Logo Dataset and another publicly available dataset, the suggested technique outperformed the current methods, achieving accuracy of 93.79% and 99.52%, respectively.	CVLD	This study proposes a technique for reliably extracting the candidate area of a logo by segmenting the vehicle head and car tail in a limited zone.	The current network architecture is not suitable for real-time vehicle logo detection.

3. Benchmark Datasets

This section gives a general overview of the vehicle datasets that are often used for vehicle logo recognition and categorization. Vision-based systems have difficulties when creating a huge dataset under a variety of environmental circumstances, such as changing illumination and weather. VLD-45 Benchmark Dataset: the VLD-45 dataset [25] dataset specifically designed for vehicle logo identification and recognition. This dataset has a total of 45 categories, including 45,000 distinct pictures and a total of 50,359 individual objects. The maximum limit for picture dimensions is 7359 pixels in width and 4422 pixels in height, while the lower limit is set at 610 pixels in width and 378 pixels in height. The VLD-45 dataset encompasses a diverse range of automobiles, including a majority of the prevalent vehicle manufacturers found in the contemporary market. The collection includes several research issues, including but not limited to tiny item detection, poor contrast, backdrop interference, form distortion, and other relevant issues. By conducting a thorough analysis of the VLD-45 dataset, it emerged that many images included not only annotations of the logo found on the car itself but also annotations of the brand positioning in the backdrop of the automobile. The dataset has considerable scientific significance within the domain of small-scale object identification challenges.

LOGO-17 Benchmark Dataset: the LOGO-17 dataset [18] The dataset LOGO-17 comprises a collection of 18,089 images, each depicting one of 17 distinct categories of car logos. The visual representations used in LOGO-17 were derived from a diverse array of circumstances. In several approaches, the relative positioning of the licence plate and the automobile brand is often used as a rudimentary means of determining the approximate location of the automobile brand. Nevertheless, this approach proves to be laborious and ineffective in instances where the licence plate has been detached. In addition to LOGO-17, we also took into account the unique scenario of licence plate shortages or eliminations. Hence, the LOGO-17 dataset may be considered a typical dataset. VLD100K-61 Benchmark Dataset: the VLD100K-61 dataset [23] comprises a collection of images sourced from the Institute of Static Transportation Research at Xi'an University of Architecture and Technology. The size of the dataset is 36.78 gigabytes. The dataset comprises a comprehensive collection of 100,041 RGB images from 61 distinct manufacturers. The identification of these 61 distinct automobile emblems can accurately classify more than 99 percent of cars within the geographical boundaries of China. The dataset exhibits an average image size of 1262 x 725 pixels.

VL-10 Benchmark Dataset: the VL-10 dataset [31] focuses on cars and includes instances where brands are either clearly visible or somewhat obscured owing to the different angles often seen in surveillance environments. The logos used in this study were obtained through self-collection from a range of local and online sources. These sources included numerous vehicle sale websites that provide publicly accessible photos. The logos are classified into ten distinct vehicle classes, namely Faw, Hino, Nissan, Daihatsu, Mitsubishi, Hyundai, Kia, Honda, Suzuki, and Toyota. The training and validation sets were formed by selecting a total of 500 and 50 images per class, respectively. The process of data augmentation was thereafter conducted by introducing blur and noise to every individual picture. Consequently, the number of photos per class was adjusted to 1500, with 150 allocated for the validation set and 150 for the training set.

HFUT-VL3 Benchmark Dataset: the HFUT-VL3 dataset [32] comprises a collection of 6,000 images that have been acquired from roadway monitoring systems in China. The photographs of the vehicles were taken in many weather circumstances, including instances of snowfall, rainfall, and dense fog, as well as under varying lighting levels, encompassing both night-time and daytime settings. Hence, the logos of vehicles stored in the database are subject to the effects of factors such as diminished light, blurred imagery, and other forms of noise. In addition, it should be noted that the car brands shown in the images constitute a rather minute fraction of the overall visual composition. The aforementioned variables together contribute to the challenging nature of the HFUT-VL3 dataset for visual language understanding and description tasks. There are a total of 54 distinct kinds of vehicle brands. For training, a training set consisting of 200 images for each brand was used. Similarly, a test set including 100 images for each brand was employed.

CVLD Benchmark Dataset: the CVLD dataset [30] has an overall of 14,950 images, involving several instances of suboptimal outdoor image conditions. This dataset contains a categorization of car logos into 13 distinct classifications. The logos in question exhibit a variety of resolutions, spanning from 10 × 10 pixels to 150 × 150 pixels. It is worth noting that the bulk of these logos possess resolutions below 50 x 50 pixels. A total of 13,000 images were used for training, while an additional 1950 images were designated for testing. Each producer in the study used a dataset consisting of 1,000 images for training purposes and an additional 150 images for testing purposes. The CVLD_weather test set has a total of 920 images depicting adverse weather conditions such as rain, fog, and snow. The CVLD_night test set has a total of 665 nocturnal images. The CVLD_tilt test dataset has a total of 750 images, each exhibiting horizontal tilts ranging from 15 to 45 degrees and vertical tilts ranging from 15 to 45 degrees.

Vehicle-logo images Benchmark Dataset: the vehicle-logo images dataset [33] comprises a collection of 4000 automobile images involving eight distinct vehicle logos: BMW, Toyota, Audi, Buick, Hyundai, Honda, Volkswagen, and Benz. Partitioning a dataset consisting of 500 images, each belonging to one of eight distinct kinds, into two separate sets: a set for training and a set for testing. This partitioning is to be done by a ratio of 8:2, where the set for training will include 80% of the images and the set for testing will contain the remaining 20%. Fig. 1 illustrates the total number of images included in each dataset. Table 2 presents an overview of the distinctive attributes about the various data sets throughout 2018–2023. Furthermore, it should be noted that all the pictures within the dataset have been normalized to a standardized size of 1000 x 600 pixels.

Table 2. Characteristics of different data sets from the years 2018–2023

Ref	Year	Dataset	Total number of images (in thousand)	Image Size	Number of classes
[33]	2019	Vehicle-logo images	4	1000 × 600 pixels	8
[18]	2020	LOGO-17	18,089	N/A	17
[23]	2023	VLD100K-61	100,041	1262 × 725 pixels	61
[31]	2022	VL-10	16,500	N/A	10
[30]	2019	CLVD	14,950	From 10 × 10 to 150 ×150 pixels	13
[32]	2018	HFUT-VL3	6	From 64 × 64 to 64 × 96 pixels	54
[25]	2021	VLD-45	45	From 610 × 378 to 7359 ×4422 pixels	45

4. Evaluation Metrics

The evaluation of the object recognition algorithm is conducted using measures known as mean average precision (mAP) and average precision (AP). The AP metric is derived by the use of many other measurements, including recall, intersection over union (IoU), precision, false negative, true positive, and false positive. These metrics together contribute to the calculation of AP and mAP, as shown in Fig. 1.

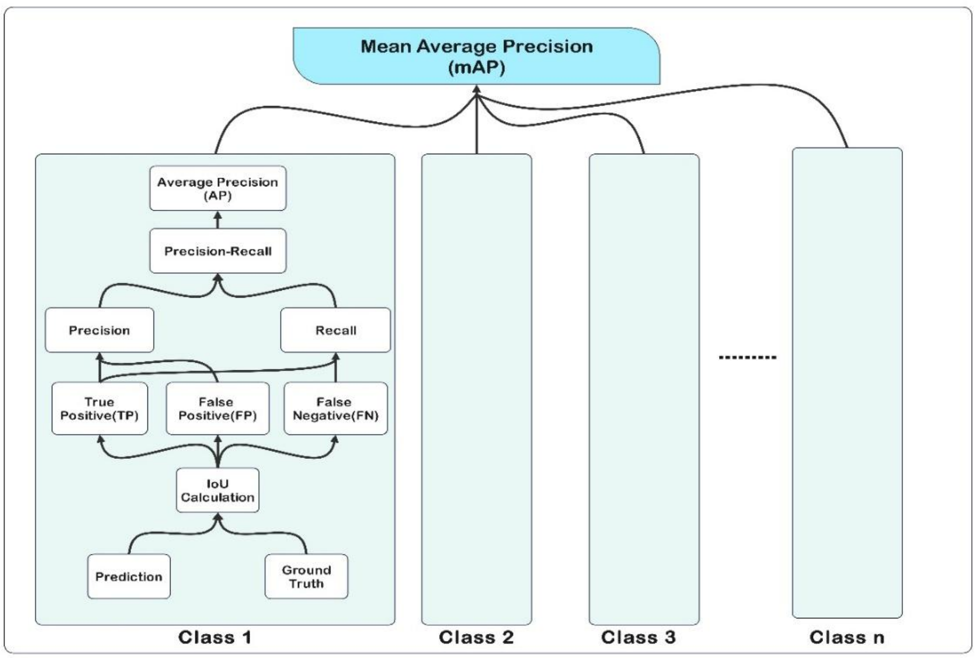

Fig. 1. Calculate mean average precision

4.1. Intersection over union

The intersection over union criterion is a way of calculating the extent of intersection between a pair of bounding boxes, which are the bounding box of the ground truth and the bounding box of the projected. The number in question is bounded inclusively between 0 and 1. If the two bounding boxes exhibit total overlap, the prediction is deemed flawless, resulting in an IoU value of 1. Conversely, when the two bounding boxes do not intersect, the IoU value is 0. As shown in equation (1), the IoU is measured by dividing the area of two bounding boxes' intersection via the region of their union [34, 35].

$$IoU = \frac{Ground\ Truth\ bounding\ box \cap Predicted\ bounding\ box}{Ground\ Truth\ bounding\ box \cup Predicted\ bounding\ box} \quad (1)$$

4.2. True positive and false positive and false negative

The metrics are calculated by considering the threshold value, IoU, and class labels that are applied to both the predicted and actual bounding boxes. The term "true positive" (TP) represents situations when positive samples are correctly identified as car logos. The term "true negative" (TN) describes situations when the positive samples, namely car logos, are correctly identified as not being there. A false positive (FP) represents situations when samples that do not contain car logos are incorrectly identified as containing vehicle logos. A false negative (FN) refers to instances when the positive samples, specifically those depicting vehicle logos, are not correctly identified as such [36].

4.3. Precision and recall

The precision and recall parameters are calculated for each labeled class based on the false negatives, false positives, and true positives [37]. The evaluation of the suggested method's performance is conducted using the parameters recall and precision, which are computed according to equations (2) and (3).

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

4.4. Mean average precision and average precision

The average precision is defined as the integral of the two-dimensional curve formed by precision and recall [38]. The average precision metric has a positive correlation with both precision and recall, indicating that high values of accuracy and recall contribute to high average precision, whereas low values of either precision or recall result in low average precision. The average precision scale is a numerical continuum that spans from 0 to 1. Equation (4) shows the calculation of AP.

$$AP = \int_0^1 p(r)dr \quad (4)$$

The parameter often used to assess the precision of vehicle logo detection algorithms is the mean average precision. The mAP improves the precision-recall data [39, 40]. A greater value of the mean average precision value signifies an enhanced degree of accuracy in the prediction, as shown by the following equation (5).

$$mAP = \frac{1}{N}\sum_{N}^{j=1} APj \quad (5)$$

5. Results and Discussion

There are two distinct categories of object detection: Two-step object detection algorithms, such as Faster R-CNN and its variations, use a two-step process consisting of proposal generation and subsequent object classification and localization. This approach aims to achieve a trade-off between accuracy and computational efficiency. In contrast, one-step algorithms like YOLO and SSD provide direct predictions of object properties, enabling real-time inference. However, this approach may come at the expense of reduced accuracy. The accuracy results of the one-step algorithms applied to various datasets are shown in Fig. 2. The accuracy results achieved by using the two-step algorithms are shown in Fig. 3. The accuracy of the results is greatly influenced by the data set. The amount of precision achieved is directly proportional to the clarity of the data set, the intensity of the illumination, and the optimal angle of sight.

The choice between one-step and two-step algorithms in object detection hinges on the specific demands of the task at hand. One-step algorithms, exemplified by YOLO and SSD, excel in real-time applications where rapid processing and inference times are paramount. These algorithms, by directly predicting object properties in a single pass, offer a significant advantage in scenarios that require swift responses, such as video surveillance, autonomous vehicles, and live-stream analysis. On the other hand, two-step algorithms like Faster R-CNN prioritize accuracy and flexibility, making them well-suited for situations where precision and adaptability to diverse datasets are critical. These algorithms, by separating the process into region proposal and subsequent classification, often achieve higher accuracy rates but may be associated with increased computational demands. Crucially, the decision-making process for selecting the most suitable object identification method should involve a thorough evaluation by researchers and practitioners. Understanding the specific needs of the application, considering the trade-offs between speed and accuracy, and accounting for the characteristics of the dataset are essential steps in this evaluation. For instance, in applications like traffic surveillance or medical imaging, where accuracy is paramount, two-step algorithms may be favoured despite potential computational overhead.

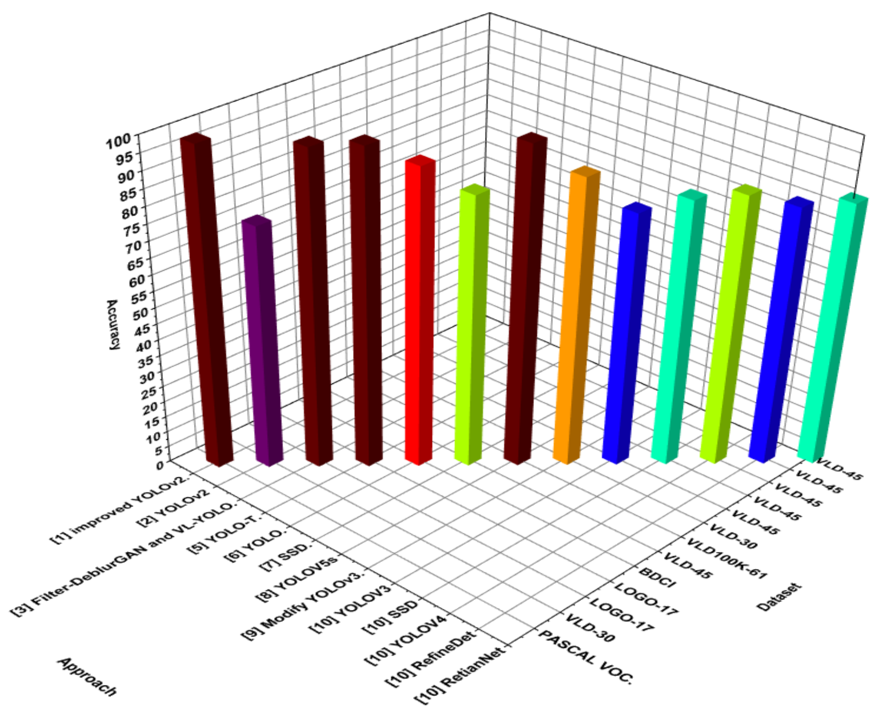

Fig. 2. The value of accuracy attained by the use of diverse one-step algorithms on different datasets

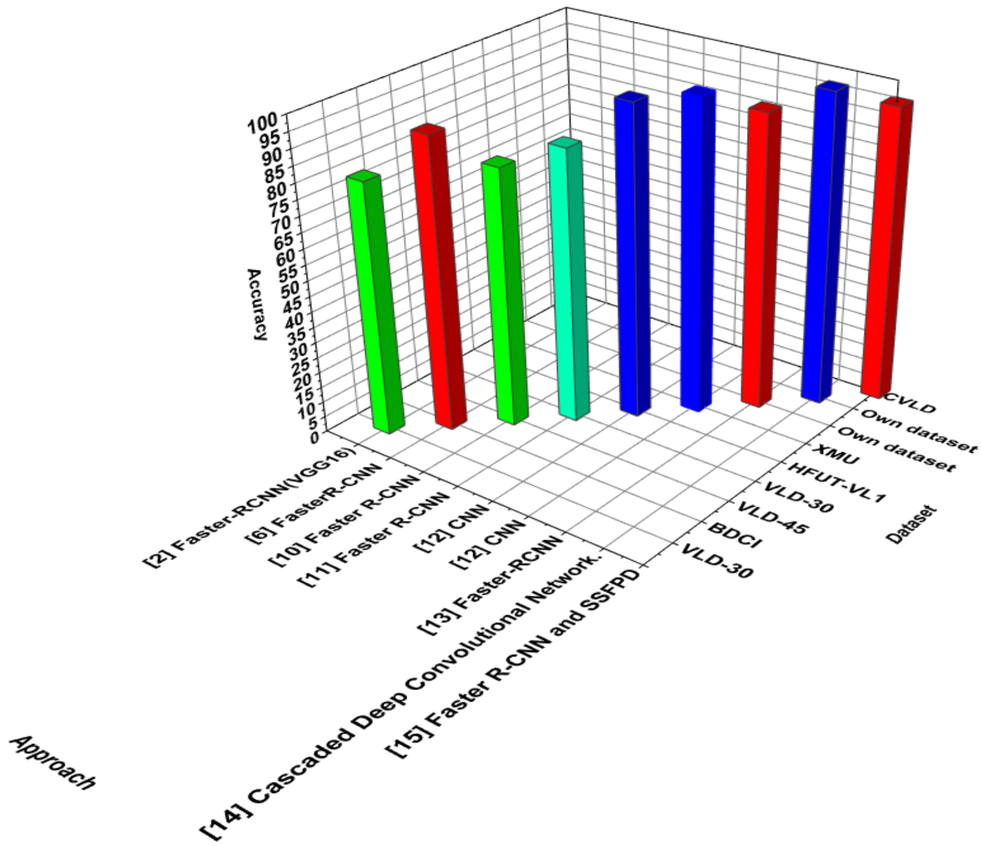

Fig. 3. The value of accuracy attained by the use of diverse two-step algorithms on different datasets

Moreover, the dynamic nature of object detection tasks requires a nuanced approach. Hybrid approaches that integrate the strengths of both one-step and two-step algorithms are gaining attention. These approaches aim to strike a balance between real-time processing and high accuracy, catering to applications that demand both speed and precision. As the field evolves, ongoing research and advancements will likely contribute to more sophisticated algorithms that can cater to a broader range of applications and offer versatile solutions for varied requirements. In conclusion, careful consideration of algorithmic characteristics and task-specific needs is imperative for selecting the most effective object detection approach in diverse and dynamic real-world scenarios.

Recently, there has been a greater focus on logo identification because of its many applications. However, comprehensive and reliable logo identification remains challenging in real-world scenarios and may provide significant obstacles to advancement due to the unique features of logo imagery. We try to summarise them as follows:

- Small dimensions: In contrast to generic objects, logos often possess a diminutive size, which might present challenges in differentiating them from their surroundings, particularly intricate backgrounds.
- Dynamic Environments and Motion Blur: In real-world scenarios, vehicles are often in motion, leading to dynamic environments and potential motion blur in images. Detecting logos under these conditions becomes challenging, as traditional algorithms may struggle to accurately identify and localize logos in images affected by motion blur. Developing methods that are resilient to dynamic environments is essential for practical applications such as traffic surveillance.
- Diversity in Logo Designs and Styles: Vehicle logos exhibit a wide range of designs, styles, and colour variations across different automotive brands. This diversity poses a challenge for detection algorithms, as they need to generalize effectively across varied visual characteristics. The need for algorithms to be adaptable to the distinctive features of different logos contributes to the complexity of the vehicle logo detection task.

6. Conclusion

This paper provides a comprehensive examination of the significant advancements, accomplishments, and limitations related to the use of deep learning methods in the recognition and classification of vehicle logos. This study investigates the efficacy of using deep learning methodologies in the detection and categorization of vehicle logos. The paper examines benchmark datasets, various assessments of performance indicators, and a diverse array of experiments and research undertaken within the domain of vehicle logo identification and classification. The primary goal of this study is to thoroughly investigate deep learning techniques and assess their efficacy in the domain of vehicle logo identification and classification. The identified challenges, ranging from varied scales and perspectives to real-world disturbances and diversity in logo designs, present compelling avenues for future exploration. To address these challenges, forthcoming works could focus on the development of scale-invariant techniques, algorithms resilient to real-world disturbances, adaptive logo recognition models capable of handling diverse designs, and lightweight logo detection solutions for improved computational efficiency. Additionally, proposed solutions involve the exploration of hybrid approaches that integrate the strengths of one-step and two-step algorithms, leverage transfer learning for logo recognition, and employ semantic segmentation for precise logo localization. These future directions aim to overcome current challenges and contribute to the continual advancement of deep learning methodologies in the domain of vehicle logo identification and classification, providing valuable insights and recommendations for researchers and practitioners seeking to enhance the efficacy of logo detection in diverse and dynamic real-world scenarios.

Acknowledgment

The authors thank the Electrical Engineering Technical College, Middle Technical University, Baghdad, Iraq, for their essential support in facilitating the project's advancement.

References

[1] L.-C. Chen, J.-W. Hsieh, Y. Yan, and D.-Y. Chen, "Vehicle make and model recognition using sparse representation and symmetrical SURFs," Pattern Recognition, vol. 48, no. 6, pp. 1979–1998, Jun. 2015, doi: https://doi.org/10.1016/j.patcog.2014.12.018.
[2] A. Boukerche, A. J. Siddiqui, and A. Mammeri, "Automated Vehicle Detection and Classification: Models, Methods, and Techniques," ACM Comput. Surv., vol. 50, no. 5, pp. 1–39, Sep. 2018, doi: https://doi.org/10.1145/3107614.
[3] H. Zhang, K. Wang, Y. Tian, C. Gou, and F.-Y. Wang, "MFR-CNN: Incorporating Multi-Scale Features and Global Information for Traffic Object Detection," IEEE Trans. Veh. Technol., vol. 67, no. 9, pp. 8019–8030, Sep. 2018, doi: https://doi.org/10.1109/TVT.2018.2843394.
[4] B. Zhang et al., "Latent Constrained Correlation Filter," IEEE Trans. on Image Process., vol. 27, no. 3, pp. 1038–1048, Mar. 2018, doi: https://doi.org/10.1109/TIP.2017.2775060.
[5] W. Min, M. Fan, X. Guo, and Q. Han, "A New Approach to Track Multiple Vehicles With the Combination of Robust Detection and Two Classifiers," IEEE Trans. Intell. Transport. Syst., vol. 19, no. 1, pp. 174–186, Jan. 2018, doi: https://doi.org/10.1109/TITS.2017.2756989.
[6] F. C. Soon, H. Y. Khaw, J. H. Chuah, and J. Kanesan, "PCANet-Based Convolutional Neural Network Architecture for a Vehicle Model Recognition System," IEEE Trans. Intell. Transport. Syst., vol. 20, no. 2, pp. 749–759, Feb. 2019, doi: https://doi.org/10.1109/TITS.2018.2833620.
[7] L. Lu and H. Huang, "A Hierarchical Scheme for Vehicle Make and Model Recognition From Frontal Images of Vehicles," IEEE Trans. Intell. Transport. Syst., vol. 20, no. 5, pp. 1774–1786, May. 2019, doi: https://doi.org/10.1109/TITS.2018.2835471.
[8] W. Min, X. Li, Q. Wang, Z. Qing-Peng, and Y. Liao, "New approach to vehicle license plate location based on new model YOLO-L and plate pre-identification," Iet Image Processing, vol. 13, no. 7, pp. 1041–1049, May. 2019, https://doi.org/10.1049/iet-ipr.2018.6449.
[9] B. Zhang et al., "One-Two-One Networks for Compression Artifacts Reduction in Remote Sensing," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 145, pp. 184–196, Nov. 2018, doi: https://doi.org/10.1016/j.isprsjprs.2018.01.003.
[10] N. N. Ali, A. Hameed, A. G. Perera, and A. Al_Naji, "Custom YOLO Object Detection Model for COVID-19 Diagnosis," Journal of Techniques, vol. 5, no. 3, pp. 92–100, Sep. 2023. doi: https://doi.org/10.51173/jt.v5i3.1174.
[11] B. Zhang, A. Perina, Z. Li, V. Murino, J. Liu, and R. Ji, "Bounding Multiple Gaussians Uncertainty with Application to Object Tracking," International Journal of Computer Vision, vol. 118, no. 3, pp. 364–379, Jul. 2016, doi: https://doi.org/10.1007/s11263-016-0880-y.
[12] A. A. Kareem, D. A. Hammood, R. A. Khamees, and N. B. Hj. Ismail, "Object Tracking with the Drone: Systems Analysis," Journal of Techniques, vol. 5, no. 2, pp. 89–94, Jun. 2023, doi: https://doi.org/10.51173/jt.v5i2.755.
[13] X. Zhang, J. Zou, K. He and J. Sun, "Accelerating Very Deep Convolutional Networks for Classification and Detection," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 38, no. 10, pp. 1943-1955, Oct. 2016, doi: https://doi.org/10.1109/TPAMI.2015.2502579.
[14] S. Wu, S. Zhong, and Y. Liu, "Deep residual learning for image steganalysis," Multimedia Tools and Applications, vol. 77, no. 9, pp. 10437–10453, May. 2018, doi: https://doi.org/10.1007/s11042-017-4440-4.
[15] S. Luan, C. Chen, B. Zhang, J. Han, and J. Liu, "Gabor convolutional networks," IEEE Transactions on Image Processing, vol. 27, no. 9, pp. 4357-4366, Sep. 2018, doi: https://doi.org/10.1109/TIP.2018.2835143.
[16] K. Yin, S. Hou, Y. Li, C. Li, and G. Yin, "A Real-Time Vehicle Logo Detection Method Based on Improved YOLOv2," Wireless Algorithms, Systems, and Applications, vol. 12384, pp. 666–677, Sep. 2020, doi: https://doi.org/10.1007/978-3-030-59016-1_55.
[17] S. Yang, C. Bo, J. Zhang, M. Wang, and L. Chen, "A New Dataset for Vehicle Logo Detection," Cognitive Internet of Things: Frameworks, Tools and Applications, vol. 810, pp. 171–177, Feb. 2020, doi: https://doi.org/10.1007/978-3-030-04946-1_17.
[18] L. Zhou, W. Min, D. Lin, Q. Han, and R. Liu, "Detecting motion blurred vehicle logo in IoV using filter-DeblurGAN and VL-YOLO," IEEE Transactions on Vehicular Technology, vol. 69, no. 4, pp. 3604–3614, 2020, doi: https://doi.org/10.1109/TVT.2020.2969427.
[19] X. Jiang, K. Sun, L. Ma, Z. Qu, and C. Ren, "Vehicle Logo Detection Method Based on Improved YOLOv4," Electronics, vol. 11, no. 20, pp. 3400, Oct. 2022, doi: https://doi.org/10.3390/electronics11203400.
[20] L. Song, W. Min, L. Zhou, Q. Wang, and H. Zhao, "Vehicle Logo Recognition Using Spatial Structure Correlation and YOLO-T," Sensors, vol. 23, no. 9, pp. 4313, Apr. 2023, doi: https://doi.org/10.3390/s23094313.
[21] X. Ke and P. Du, "Vehicle Logo Recognition with Small Sample Problem in Complex Scene Based on Data Augmentation," Mathematical Problems in Engineering, vol. 2020, pp. 6591873, Jul. 2020, doi: https://doi.org/10.1155/2020/6591873.
[22] J. Zhang, L. Chen, C. Bo, and S. Yang, "Multi-Scale Vehicle Logo Detector," Mobile Networks and Applications, vol. 26, no. 1, pp. 67–76, Feb. 2021, doi: https://doi.org/10.1007/s11036-020-01722-0.
[23] X. Shi, S. Ma, Y. Shen, Y. Yang, and Z. Tan, "Vehicle logo detection using an IoAverage loss on dataset VLD100K-61," EURASIP Journal on Image and Video Processing, vol. 2023, no. 1, pp. 4, Apr. 2023, doi: https://doi.org/10.1186/s13640-023-00604-1.
[24] S. Yang, J. Zhang, C. Bo, M. Wang, and L. Chen, "Fast vehicle logo detection in complex scenes," Optics & Laser Technology, vol. 110, pp. 196–201, Feb. 2019, doi: https://doi.org/10.1016/j.optlastec.2018.08.007.
[25] S. Yang, C. Bo, J. Zhang, P. Gao, Y. Li, and S. Serikawa, "VLD-45: A Big Dataset for Vehicle Logo Recognition and Detection," IEEE Transactions on Intelligent Transportation Systems, vol. 23, no. 12, pp. 25567–25573, Dec. 2022, doi: https://doi.org/10.1109/TITS.2021.3062113.
[26] J. Zhang, S. Yang, C. Bo, and Z. Zhang, "Vehicle logo detection based on deep convolutional networks," Computers & Electrical Engineering, vol. 90, pp. 107004, Mar. 2021, doi: https://doi.org/10.1016/j.compeleceng.2021.107004.
[27] W. Lu, H. Zhao, Q. He, H. Huang, and X. Jin, "Category-consistent deep network learning for accurate vehicle logo recognition,"

Neurocomputing, vol. 463, pp. 623–636, Nov. 2021, doi: https://doi.org/10.1016/j.neucom.2021.08.030.
[28] Z. Huang, M. Fu, K. Ni, H. Sun, and S. Sun, "Recognition of Vehicle-Logo Based on Faster-RCNN," Signal and Information Processing, Networking and Computers, vol. 494, pp. 75–83, Nov. 2019, doi: https://doi.org/10.1007/978-981-13-1733-0_10.
[29] Y. Yu, H. Guan, D. Li, and C. Yu, "A Cascaded Deep Convolutional Network for Vehicle Logo Recognition From Frontal and Rear Images of Vehicles," IEEE Transactions on Intelligent Transportation Systems, vol. 22, no. 2, pp. 758–771, Feb. 2021, doi: https://doi.org/10.1109/TITS.2019.2956082.
[30] R. Liu, Q. Han, W. Min, L. Zhou, and J. Xu, "Vehicle Logo Recognition Based on Enhanced Matching for Small Objects, Constrained Region and SSFPD Network," Sensors, vol. 19, no. 20, pp. 4528, Oct. 2019, doi: https://doi.org/10.3390/s19204528.
[31] Z. Sultan, M. U. Farooq, and R. H. Raza, "Improved Vehicle Logo Detection and Recognition for Complex Traffic Environments Using Deep Learning Based Unwarping of Extracted Logo Regions in Varying Angles," Digital Interaction and Machine Intelligence, vol. 710, pp. 12–25, Jul. 2022, doi: https://doi.org/10.1007/978-3-031-37649-8_2.
[32] Y. Yu, J. Wang, J. Lu, Y. Xie, and Z. Nie, "Vehicle logo recognition based on overlapping enhanced patterns of oriented edge magnitudes," Computers & Electrical Engineering, vol. 71, pp. 273–283, Oct. 2018, doi: https://doi.org/10.1016/j.compeleceng.2018.07.045.
[33] C. Cao et al., "An Improved Faster R-CNN for Small Object Detection," IEEE Access, vol. 7, pp. 106838–106846, Aug. 2019, doi: https://doi.org/10.1109/ACCESS.2019.2932731.
[34] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, Jun. 2017, doi: https://doi.org/10.1109/TPAMI.2016.2577031.
[35] M. Maheswari, M. S. Josephine, and V. Jeyabalaraja, "Customized deep neural network model for autonomous and efficient surveillance of wildlife in national parks," Computers and Electrical Engineering, vol. 100, pp. 107913, May. 2022, doi: https://doi.org/10.1016/j.compeleceng.2022.107913.
[36] M. A. Berwo et al., "Deep Learning Techniques for Vehicle Detection and Classification from Images/Videos: A Survey," Sensors, vol. 23, no. 10, pp. 4832, May. 2023, doi: https://doi.org/10.3390/s23104832.
[37] S.-H. Park, S.-B. Yu, J.-A. Kim, and H. Yoon, "An All-in-One Vehicle Type and License Plate Recognition System Using YOLOv4," Sensors, vol. 22, no. 3, pp. 921, Jan. 2022, doi: https://doi.org/10.3390/s22030921.
[38] A. Taheri Tajar, A. Ramazani, and M. Mansoorizadeh, "A lightweight Tiny-YOLOv3 vehicle detection approach," Journal of Real-Time Image Processing, vol. 18, no. 6, pp. 2389–2401, Dec. 2021, doi: https://doi.org/10.1007/s11554-021-01131-w.
[39] S. Sahel, M. Alsahafi, M. Alghamdi, and T. Alsubait, "Logo Detection Using Deep Learning with Pretrained CNN Models", Eng. Technol. Appl. Sci. Res., vol. 11, no. 1, pp. 6724–6729, Feb. 2021, doi: https://doi.org/10.48084/etasr.3919.
[40] M. Ahmed, K. A. Hashmi, A. Pagani, M. Liwicki, D. Stricker, and M. Z. Afzal, "Survey and Performance Analysis of Deep Learning Based Object Detection in Challenging Environments," Sensors, vol. 21, no. 15, pp. 5116, Jul. 2021, doi: https://doi.org/10.3390/s21155116.