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Vehicle Brand Live Detection Using YOLOv8 and Deep Learning Algorithms

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Abstract

Car brand detection is important task it is used to provide a solution for all applications using a new method. To detect the car brand and model of vehicles using opencv, yolov8 and TensorFlow methodology.it is also used to detect the live object from video camera when we capture image by camera the image is divided into number of part using segmentation algorithm. aim of paper is study different software by effective method to detect car brand and vehicle model. for this operation we need to use deep Learning neural network for vehicle brand detection the aimed to detect 30 vehicle brands which are covers approximately 3266 of cars registered in traffic office the proposed solution is tested on 1833 various images taken from different angles and obtained from different sources opencv and yolov8 method which is one of deep neural networks is used to brand detection of vehicles in this study it is observed that yolov8 method performs 97.70 classification accuracy.

Keywords: Image Processing, Vehicle brand detection, Deep Neural Networks, OpenCV, YOLOv8, Image matching, TensorFlow.

1. Introduction

Most of the vehicle logo detection algorithms, the logo is very difficult task to find the brand from live video camera, and the detection is roughly to be complete in bad any environment. Even though the recognition accuracy of convolution neural network (CNN) is very high, it also needs a large number of samples [1].

ANY vision-based intelligent transport systems for detecting, tracking, or recognizing vehicles in image sequences have been cited in the literature. Vehicle-type classify- function is a task that has been adequately addressed [2]–[7]. However, compared with vehicle-type classification, vehicle manufacturer recognition (VMR) is an area with fewer published systems and methods. The majority of the approaches concerning VMR described in the literature focus on scale-invariant feature trans- using (SIFT) and image matching, using vehicle images detection algorithm, segmented the license plate area using SIFTs algorithm introduced by Lowe [8] Image matching is a fundamental problem in computer vision that takes place in many image processing applications in a variety of fields, including image retrieval for security enforce- ment and robot navigation. A common approach is to locate characteristic image features (or keypoints) from the images and compare them through descriptors of these features.

At present, Computer and Electronic technologies trying to find solutions for problems of many areas. One of them is security. There is a lot of problems in security for the technology. One of these problems is traffic safety. The vehicles control in the traffic; such as speed detection, license belt control, license plate, model, brand, or many different license information control is very important for both traffic safety and the city and also in the terms of region security. One of the functions required in traffic is detection of brands and models of vehicles. There are several reasons for this control. One of the most important reasons is traffic safety. Some of the different types of vehicles in traffic may be forbidden from using some points and roads. For example; a control point is created. The properties of the vehicles passing through the control point are detected. According to the detected features, the passage of the vehicle can be prevented in advance. One of these reasons is the validity of the vehicles. In other words,the brand and model of the vehicle are detected through license plate and the actual brand and model may not match. Similarly, the more common one may be the discrepancy between the actual color of the vehicle and the registered color of the vehicle. Especially for stolen vehicles or illegal situations, it becomes easier to encounter such events more frequently. Many purpose or problems may occur and vary according to the demands and needs of institutions and organizations. In order to minimize such problems, the aim of this study is to detect the brand of vehicles by image processing methods.

In this study, it is tried to develop an algorithm that determines thebrands of vehicles from vehicle images. In the study Faster-RCNN which is the deep neural network method is used.

2. Literature Review

Placzek [2] recommend a method for his study which is vision-based vehicles brand detection. For image segments from vehicle brand detection they use fuzzy description. This method used for geometrical properties and segment object from image. The proposed method was applied using reasoning system with fuzzy rules. An extension of the algorithm with set of fuzzy rules was provided classification of vehicles in traffic scenes. The author noted that, this method is suitable for application in video sensors for road traffic control and surveillance systems.

In study by Rachmadi and Purnama [3] were presented a method which uses Convolutional Neural Network (CNN) to vehicle color recognition. CNN was designed to classify images based on shape information. in this study they use CNN algorithm for classify the color images.

Saghaei [4] proposed a system for mechanized and automatic recognition of license and number plate. without using GPS and RFID system detect number plate of the vehicles from specified location. they used segmentation, localization, orientation, normalization and they implement optical character detection for identifying.

Cheand et al. [5] In this study they use CNN-RNN model to detect license plate from real-world images which is capture by video camera. They used CNN for feature extraction and Recurrent Neural Network (RNN) for sequencing. They noted that based on experimental results the CNN-RNN architecture performed significantly better.

Sochor et al. [6] In this study they used 3D bounding boxes algorithm for vehicles brand and license plate detection. They used 3D bounding box to normalize the image viewpoint by “unpacking” the image into a plane. They also proposed to randomly alter the color of the image and add a rectangle with random noise to a random position in the image during the training of CNN. They made a number of experiments and showed that their method significantly improves CNN classification accuracy. Vaquero et al. [7] presented full system for vehicle detection and tracking. Their system works only with 3D lidar information. The system uses CNN for detection. The system was evaluated on the KITTI tracking dataset. They use CNN-based vehicle brand detector for geometric approach.

Sheng and et al. [8] proposed vehicle detection system using neuralnetworks. They proposed a method based on CNN algorithm. Their methodconsists of two steps: vehicle area detection and vehicle brand detection. They applied Faster RCNN, AlexNet, Vggnet, GoogLenet and Resnet for Regions with Convolutional Neural Network features (RCNN). They noted that their algorithm obtained 93.32% classification accuracy in the classification of six kinds ofvehicle models.

Watkins et al. [9] investigate whether ResNet architectures can outperform more traditional CNN on the task of fine-grainedvehicle classification. They train and test ResNet-18, ResNet-34 and ResNet-50 on the Comprehensive Cars dataset without pre- training on other datasets. They then modify the networks to use Spatially Weighted Pooling (SWP). Finally, they add a localizationstep before the classification process, using a network based on ResNet-50. They find that using SWP and localization both improve classification accuracy of ResNet50. SWP increases accuracy by 1.5% points and localization increases accuracy by 3.4percent points. This algorithm increases accuracy by 3.7% points giving a top-1 accuracy of 96.351% on the Complete Cars dataset. Their method achieves higher accuracy than a range of methods including those that use traditional CNNs. However, theirmethod does not perform quite as well as pre-trained networks thatuse SWP. Pan et al. [10], in this study they generate its own dataset using self-driving vehicle systems for to solve problem of training data. but collected date is very large it is impossible to process offline training data. they use near-to-far labeling method for to detect object from video clip. They segment selected object from video. Soleimani et al. [11] they proposed aerial vehicle detection algorithm. they used deep CNN classifier for classification. The give input are aerial images and different classes. They detect class of the vehicle and vehicle color using this classifier. Nazemi et al. [12], In this study they find the model of vehicle for that purpose they uses unsupervised feature learning methods for model detection. They use SIFTS algorithm for features extraction and these features are given to LLC algorithm for object detection. these methods are applied on Iranian on-road vehicle dataset and CompuCar dataset.

3. Different Method

Following are the methods which is used for vehicle brand detection.

3.1 YOLOv8 Method

YOLO is a single-shot algorithm that usually classifies an object from video camera using bounding box and extract the object from video camera images it uses neural network, so many techniques are available for live video camera object recognition, these are YOLO, Faster R-CNN and SSD. every technique has its advantages and limitations. While Faster R-CNN very useful for accuracy, but it has some disadvantages in real-time scenarios, so in this paper uses YOLOv8 and deplaning algorithm.

Vehicles brand recognition is very necessary traffic signal detection. machines should identify the object from frame or screen for detection. in the privacies study so many vehicles brand detection algorithms are developed. know days YOLOv8 algorithm are very

successful used for object detection. it provides so many facility or features for vehicles brand detection.
In this study we use three object detection methodology which is used for vehicle brand detection algorithm: SSD, Faster R-CNN, and YOLOv8.

3.2 TensorFlow

TensorFlow is an open source library used in python which is used for object detection. It is used to detect high performance numerical values. This method is used on various platforms (CPUs, GPUs, TPUs). Enables easy calculation from desktop computers to server clusters, mobile devices to edge devices. It is a software library originally developed by researchers and engineers from the Google brain team within Google's AI organization, using a flexible numerical computation core that comes with a strong support for machine learning and deep learning and in many other scientific areas. This library, which is preferred by the companies around the world,is also easy to use for developers who are new to deep learning [12].

3.3 OpenCV

OpenCV stands for Open Source Computer Vision Library and machine learning software library. OpenCV provides a common infrastructure for computer vision applications and accelerates the use of machine perception in the commercial products. OpenCV is BSD-licensed product, it makesit easy for businesses to use and modify the code.

It has Python, C++, Java and MATLAB interfaces and supports Linux, Windows, Mac OS and Android. A full-featured CUDA and OpenCV interfaces are being actively developed now. [14].

3.4 Faster-RCNN Neural Networks Algorithms

Faster Region-based Convolutional Neural Network (Faster R-CNN) algorithm is used for deep learning object recognition. It is calculated by R-CNN and Fast R-CNN it is frameworks which is extension of Fast R-CNN. It is used for region proposal network for generate region proposals. The RPN is used for image is divide in number of layers these layers are used for detection. Faster R-CNN methods are used for object detection. It is presented by two module deep learning and Fast R-CNN. This method is used for object detection which is displayed in (Fig 1). First input he image in NN layers. It extracts the features and detect the object.

3.5 Identify Brands

In this study, a study of Turkish Statistics Institute named “Number of cars registered to traffic by trademarks” [16] dated 2018 is referenced. Statistics of this study for 2017 and 2018 is given in Table 1. Alfa Romeo logo include more complex illustrations than other vehicle logos and its shapes is similar to some included round shaped brand logos such as BMW, Skoda, Volkswagen. The produced software in this study should detect round shaped and complex brand logos between each other’s. Therefore, in addition to the 19 most registered vehicle brands at Table 1, Alfa Romeo brand is also included in the study. The Besides both the old logo and the new logo of the Dacia brand are studied. In total, 20 different brands and 21 different classes are studied. Number of cars registered to traffic by brands and the ratio of the brands of registered cars in 2017 to the total number are showed in Table 1.

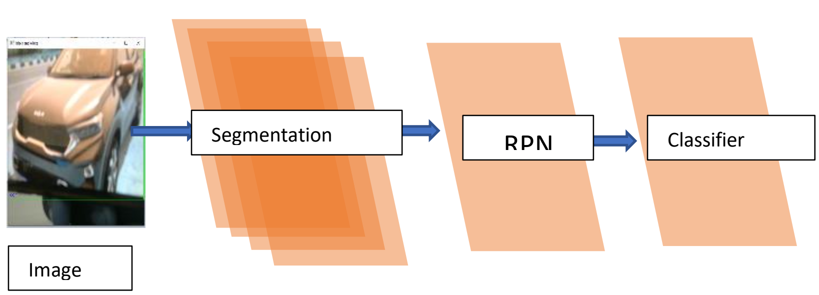

Fig. 1. Faster R-CNN architecture

As shown in Table 1, the study covers approximately 97.70% of cars registered in traffic. Brand detection and classification we should use two basic part these are testing and training parts. While creating these parts 1563 images are used in training set, 270 images are used in testing set. These techniques are used for to label the collected images. This collecting and labeling are discussed in detail in the pretreatment phase.

In order to see the results of the brand detection, 1563 images are used, independent of other images. This set of data is created by taking pictures of the front and back parts of randomlyselected vehicles. Pictures are taken at different places and at different times of the day. 3 camera-enabled device including mobile phone and Canon camera are used for the taken pictures by the authors. The numbers used in the study according to the brand, train, test and general test parameters is given in Table 2.

Table 1. Number of cars registered to traffic by trademarks

	2017	2018
Audi	22.06	21.43
BMW	27.70	18.25
Citroen	16.30	15.74
Dacia	40.72	41.23
Fiat	50.66	61.30
Ford	42.00	40.21
Honda	19.51	27.31
Hyundai	47.99	50.06
Kia	14.66	11.50
Mercedes	34.59	29.07
Nissan	28.16	32.21
Opel	53.19	45.64
Peugeot	24.04	27.63
Renault	102.82	118.90
Seat	20.83	15.98
Skoda	28.15	25.11
Toyota	46.35	41.40
Volkswagen	100.87	97.66
Volvo	4.19	4.627
Other	21.19	22.90
Total	**746.07**	**741.90**

Table 2. List of images used in the study according to areas of use

	Total	Train	Test
Alfa Romeo	70	61	9
Audi	84	82	2
BMW	86	75	11
Citroen	95	90	5
Dacia New	92	52	40
Dacia Old	60	50	10
Fiat	90	51	39
Ford	81	80	1
Honda	85	80	5
Hyundai	89	86	3
Kia	96	53	43
Mercedes	90	85	5
Nissan	84	82	2
Opel	98	88	10
Peugeot	96	90	6
Renault	85	75	10
Seat	81	51	30
Skoda	91	90	1
Toyota	97	92	5
Volkswagen	98	90	8
Volvo	85	60	25
Total	**1833**	**1563**	**270**

4. Applications

In this study, automatic detection of the brands of the live vehicles hasbeen tried. This section describes how detection process is carriedout.

In determining the vehicle brands; it is aimed to determine the brand using logo which is present on vehicles. When the logos are detected, it is ensured that the first brand logos are trained with artificial neural network methods. After the training stage, the trained model is used in the program. The program is tested on the material prepared for the determination of the results. Obtained results is tabled and reported. The study consists of seven stages. Fig. 2 shows these stages. In the process of identifying the brands, it is determined which brands the application will detect and which ones will be ignored. In this stage, the data is based on "Number of cars registered to traffic by trademarks" from 2017 TurkStat [18]. Therefore, it is aimed to determine the brand of approximately 96.9% of the cars in traffic.

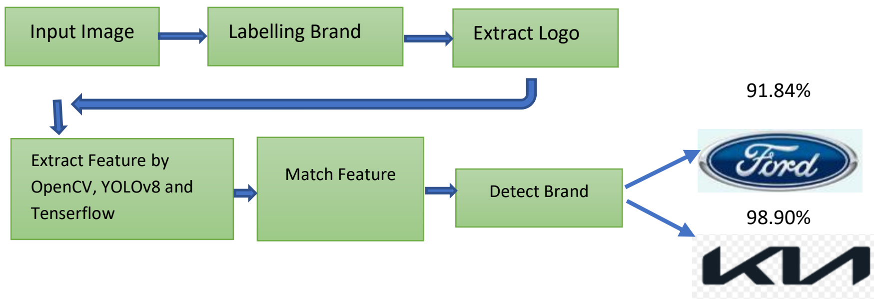

Fig. 2. Stages of brand detection study

In addition to the first 19 car brands in Table 2, the brand, Alfa Romeo, is also included in the study. However, since the Dacia brand's logo changed in 2010, separate images have been collectedand classified as the old and new logo of the brand. Thus 20 brand logo and 21 classes are planned in total. Images are collected at the image collecting and labelling stage.

In Setups before the training stage, some files must be compiled and organized before the training. These files are training configuration file, label map file, Test and Train record files. Record files are collected from csv files. These assemblies and arrangements are created at this stage.

At the training stage, the model is trained. At the test stage the training model is tested on test data. Obtained results at the testing stage are documented and regulated at the report stage.

3.5 The Process Phase

The Process phase includes steps of images collecting, labeling and pre-training setups. In the process phase, an average of approximately 270 images fromeach brand is collected for the training stage. In total, 1833 images are collected. However, in order to test the study, 1563 images are collected, unlike these images. As shown in Table 2, a total of 1833 images are collected to use inthe study. 80% of images of each brand from collected images fortraining stage is divided as training, 20% of them is divided as test. Images are labeled at pre-training stage. The contents of the file continue this way. In this study, 1566 dataare used for training and 270 data are used for testing.

3.6 Application stage

The application stage includes phase of training, testing and reporting. At the training phase, training is started based on Faster RCNN method. Faster R-CNN algorithm is the object detection system composed of two modules. In this study two module are used for feature extraction and object detection these are deep learning and YOLOv8 algorithm we also use Fast C-NN detector for extracting regions. This system are used for object detection which is shown in Fir-1. In the first step vehicle image is passed to RPN using convectional neural network. feature network is used for creating RPN. Region are selected using RPN network. ROI is used for resize the Region of vehicle. Faster R-CNN algorithm are used for feature extraction. First stage iou threshold value is 0.8. First stage object loss weight is 1,0. Second stage classification loss weight value is 1.0. Initial learning rate value is 0,0003.

A computer which has a Nvdia GeForce GTX 1080 gpu are used in this stage at the training phase. Training is performed on the GPU.

The training times of the model, trained on computer, lasted approximately 5 hours as 54612 steps. In this algorithm when we training images the ford and kia model is obtained. The frozen model which is obtained from the training is used in the software at the test phase. It is tested on 1563 images which are reserved for testing. In the report phase, the result which is obtained during the test phase is recorded in the tables. Fig. 3 shows detection of the brand of the vehicle on a single image by the software. The vehicle's brand is Kia. As shown in the Fig. 3 The program has detected the car as Kia by 97.70%.

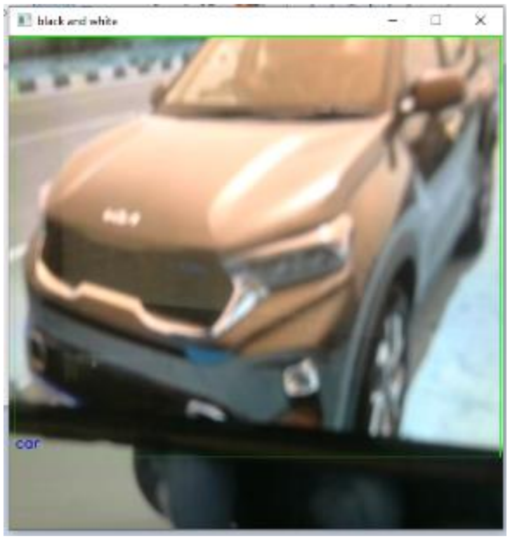

Fig. 3. Detection of the vehicle's brand correctly by the software

Conclusion

Faster RCNN and YOLOv8 method is used to detection of brand. Different versions of the faster RCNN method have been developed. In this study, "ResNet 50" version is used. The model developed at the end of the training is tested on test datas. The obtained results are shown in the summary table (Table 3) and the confusion matrix (Fig. 4).

In Table 3, there are areas such as the name of the vehicle brand, the number of car brands, the number of correct estimates, the number of false estimates, the accuracy and the error rate. In cases where the logo of the brand cannot be detected, detected incorrectly or detected outside the region where the logo is located are marked as false estimate. In cases the correct position of the brand logo is detected correctly on the area where the logo is located are marked as true estimate. this can be seen from Table 3 and Fig. 4 brands have reached their correct ratio of 90% and above and they have not reached even 10% in 2 brands. In the detection of brands, which brand is found in the picture and which brand has detected by software are transferred to the confusion table in Fig. 4.

Table 3. The results obtained in the detection of vehicle brand with Faster-RCNN

	Number of Images	Number of Correct Estimates	Number of False Estimates	Accuracy
Volvo	70	61	9	56.67
Volkswagen	84	82	2	98.77
Toyota	86	75	11	94.12
Skoda	95	90	5	96.63
Seat	92	52	40	55.21
Renault	60	50	10	94.44
Peugeot	90	51	39	97.62
Opel	81	80	1	89.80
Nissan	85	80	5	93.75
Mercedes	89	86	3	88.24
Audi	96	53	43	62.96
Kia	90	85	5	98.90
Honda	84	82	2	94.85
Ford	98	88	10	91.84
Dacia New	96	90	6	70.59
Citroen	85	75	10	56.67
Hyundai	81	51	30	98.77
Fiat	91	90	1	94.12
Dacia Old	97	92	5	96.63
Bmw	98	90	8	55.21
Alfa Romeo	85	60	25	94.44
Grand Total	1833	1563	270	97.70

	Volvo	Volkswag	Toyota	Skoda	Seat	Renault	Peugeot	Opel	Nissan	Mercedes	Audi	Kia	Honda	Ford	Dacia New	Citroen	Hyundai	Fiat	Dacia Old	Bmw	Alfa	Accuracy
Volvo	57	1	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	57
Volkswagen	0	99	4	4	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	99
Toyota	0	0	94	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	94
Skoda	0	0	0	97	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97
Seat	0	0	0	0	55	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55
Renault	0	0	0	0	1	94	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94
Peugeot	1	0	0	1	0	0	98	0	0	0	0	0	0	0	12	0	0	0	0	0	0	98
Opel	11	0	2	4	0	1	0	90	0	0	0	0	0	0	1	0	0	0	0	0	0	90
Nissan	14	0	0	2	0	0	0	0	94	0	0	0	0	1	5	0	0	0	0	0	0	94
Mercedes	2	0	1	0	0	5	0	0	0	88	0	0	0	0	3	0	0	0	0	0	0	88
Audi	0	0	0	0	0	0	0	5	0	0	63	0	0	0	0	0	0	0	0	0	0	63
Kia	0	0	0	0	0	0	0	0	1	0	0	99	0	0	1	0	0	0	0	0	0	99
Honda	0	0	0	0	1	0	0	0	0	0	0	0	95	0	0	0	0	0	0	0	0	95
Ford	0	0	0	0	0	0	0	0	0	0	0	0	0	92	0	0	0	0	0	0	0	92
Dacia New	0	0	0	0	0	0	0	0	0	0	0	0	0	0	71	0	0	0	0	0	0	71
Citroen	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	57	0	0	0	0	0	57
Hyundai	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	99	0	0	0	0	99
Fiat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94	0	0	0	94
Dacia Old	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	97	0	0	97
Bmw	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	55	2	55
Alfa Romeo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	94	94
Accuracy	57	99	94	97	55	94	98	90	94	88	63	99	95	92	71	57	99	94	97	55	94	97.70

Fig. 4. Brand detection confusion matrix

When Fig. 4 is examined, it is seen that which brands are more successful. As seen in Table 4, the success rate of some brands is very high and the success rate of some brands is very low. These brands, which have a very low success rate, have also reduced theoverall success rate. For example, the software developed in the study detected correctly the entire brand in the images used in Fiatbrand. However, the software didn't determine Mercedes brand logo or liken different brands in images which including Mercedesbrands. In addition, it has detected only 1.22% of the Ford brand correctly. It likens ford brand to kia brand in all ford images except1 image. Fig. 5 shows the model's inability to distinguish betweenthe Ford brand and the Kia brand. The figures of the Kia brand andthe Ford brand are quite similar as shown in Fig. 5. The Shape of both brands is elliptical.

Fig. 5.A sample comparison between the Ford and the Kia brand

Fig. 5. A sample comparison between the Fordbrand and the Kia brand as can be seen from the results, the correct detection rate is 97.70% in the brand detection realized using the Fast-RCNN and YOLOv8 method. However, it is seen that the correct detection rate of 97.70% is achieved if the brands Mercedes and Ford which have extreme values such 2.30% correct rate are not taken into consideration in brand detection. A better model can be obtained instead of the model obtained in the study by increasing the imagesused in the training of brands and using images where the brand logo appears clearer. Better results can be achieved if image processing applications such as edge detection and blur are first performed when running the software on an image.

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