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# Vehicle Brand Detection Using Deep Learning Algorithms

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***Abstract:*** The aim of this study is to provide a solution for different applications using an effective and cost-effective method to detect the brand and model of vehicles. A classification method is implemented using deep neural network in the detection of the vehicle brand. We aimed to detect 20 vehicle brands which are covers approximately 96.91% of cars registered in traffic in Turkey. The proposed solution is tested on 1280 various images taken from different angles and obtained from different sources. Faster-RCNN method which is one of deep neural networks is used to brand detection of vehicles in this study. It is observed that Faster-RCNN method performs 67.66% classification accuracy.

***Keywords:*** *Vehicle brand detection, Image Processing, Deep Neural Networks, Tensorflow, Faster-RCNN.*

## 1. Introduction

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 control of the vehicles in the traffic; such as license plate, speed detection, license belt control, brand, model 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 reasons and the most important 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 the brands of vehicles from vehicle images. In the study Faster-RCNN which is the deep neural network method is used.

The paper is divided into five sections. In the following chapter, literature review was given. In the third chapter, data used methods and materials were explained. The conducted applications and their results are presented in Section 4. Finally, the study was concluded by Chapter 5.

## 2. Literature Review

Placzek [1] suggest a method in his study about that vision-based vehicles recognition. The fuzzy description of image segments was used for vehicle recognition from image. This description considers selected geometrical properties and shape coefficients which were determined for reference images segments. 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 [2] were presented a method which uses Convolutional Neural Network (CNN) to vehicle color recognition. CNN was designed to classify images based on shape information. They proved that CNN can also classify based on color distribution.

Saghaei [3] proposed a system for mechanized and automatic recognition of license and number plate. The system could detect license plate number of the vehicles which is passing through specified location without using GPS and RFID. They used localization, orientation, normalization, segmentation and finally optical character recognition for identifying.

Cheand et al. [4] proposed a unified CNN-RNN model to recognize license plate from real-world images. 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.

In study worked by Sochor et al. [5] they proposed an approach which is based on 3D bounding boxes built around the vehicles. 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. [6] presented full system for vehicle detection and

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tracking. Their system works only with 3D lidar information. The system uses CNN for detection. The system was evaluated on the KITTI tracking dataset. The study showed that the performance boost provided by CNN-based vehicle detector over a standard geometric approach.

Sheng and et al. [7] proposed vehicle detection system using neural networks. They presented a method based on CNN. Their method consists of two steps: vehicle area detection and vehicle brand detection. They applied Regions with Convolutional Neural Network features (RCNN), Faster RCNN, AlexNet, Vggnet, GoogLenet and Resnet. They noted that their algorithm obtained 93.32% classification accuracy in the classification of six kinds of vehicle models.

Watkins et al. [8] investigate whether ResNet architectures can outperform more traditional CNN on the task of fine-grained vehicle 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 localization step 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 3.4 percent points. Using both increases accuracy by 3.7% points giving a top-1 accuracy of 96.351% on the Comprehensive Cars dataset. Their method achieves higher accuracy than a range of methods including those that use traditional CNNs. However, their method does not perform quite as well as pre-trained networks that use SWP.

Pan et al. [9] worked on the problem of training data which were collected by Self-driving vehicle vision systems. Since the volume of collected data are too large it impossible to train offline. They use near-to-far labeling strategy by first marking large, close objects in the video. They tracked marked object back in time to induce labels on small distant presentations of these objects.

Soleimani et al. [10] investigated the problem of aerial vehicle recognition. They used a text-guided deep CNN classifier. The inputs are an aerial images and classes. They train and test proposed model on a synthetic dataset and classes consist of the combination of the class types and colors of the vehicles.

In study worked by Nazemi et al. [11], they formulate the vehicle make and model recognition. They used unsupervised feature learning methods. They applied Locality constraint Linear Coding (LLC) method as a fast feature encoder for encoding the input SIFTS features. The proposed method can perform in real environments of different conditions. The applied their method on two datasets: Iranian on-road vehicle dataset and CompuCar dataset. Experimental results showed superiority of the proposed framework over the state-of-the-art methods.

## 3. Material and Method

In this section, the materials and methods used for the study will be discussed.

### 3.1. Method

#### 3.1.1. TensorFlow

TensorFlow is an open source software library. It uses for high performance numerical calculation. Its flexible architecture enables it to work 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].

#### 3.1.2. OpenCV

Open Source Computer Vision Library (OpenCV) is an open source computer vision 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 makes it 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 OpenCL interfaces are being actively developed now. [13].

#### 3.1.3. Faster-RCNN Neural Networks Algorithms

Faster R-CNN algorithm is the object detection system composed of two modules. The first module is a deep fully convolutional network that proposes regions, and the second module is the Fast R-CNN detector that uses the proposed regions. The entire system is a single, unified network for object detection (Fig. 1). In the first module called RPN, an input vehicle image is passed through convectional neural networks layers. A feature network is obtained from this stage. RPN is created using this feature network. Region propositions are made on this network(RPN). Region propositions is resized using RoI pooling. (Fig. 1).

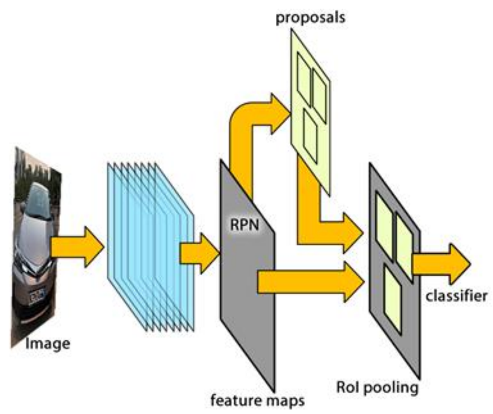



**Fig. 1.** Faster R-CNN architecture [14]

### 3.2. Material

#### 3.2.1. Identify Brands

In this study, a study of Turkish Statistics Institute named “Number of cars registered to traffic by trademarks” [15] dated 2017 is referenced. Statistics of this study for 2016 and 2017 is given in Table 1. Alfa Romeo logo include more complex illustrations than other vehicle logos and it’s 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 others. 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.

As shown in Table 1, the study covers approximately 96.91% of cars registered in traffic.

There are 2 basic parts in the classification training for brand detection. These are the training and testing parts. While creating these parts 1557 images are used in training set, 398 images are used in test set. In order to see the results of the brand detection, 1280 images are used, independent of other images. This set of data is created by taking pictures of the front and back parts of randomly selected vehicles. Pictures are taken at different places and at different times of the day. 3 camera-enabled device including iPhone SE, IPhone 6S and Canon 600D 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 [15]

| | 2016 | 2017 | Rate |
|---|---|---|---|
| Audi | 22.064 | 21.435 | 2.89% |
| BMW | 27.704 | 18.255 | 2.46% |
| Citroen | 16.304 | 15.745 | 2.12% |
| Dacia | 40.723 | 41.236 | 5.56% |
| Fiat | 50.664 | 61.305 | 8.26% |
| Ford | 42.006 | 40.211 | 5.42% |
| Honda | 19.518 | 27.313 | 3.68% |
| Hyundai | 47.996 | 50.060 | 6.75% |
| Kia | 14.668 | 11.501 | 1.55% |
| Mercedes | 34.596 | 29.070 | 3.92% |
| Nissan | 28.161 | 32.217 | 4.34% |
| Opel | 53.194 | 45.646 | 6.15% |
| Peugeot | 24.041 | 27.639 | 3.73% |
| Renault | 102.829 | 118.907 | 16.03% |
| Seat | 20.837 | 15.987 | 2.15% |
| Skoda | 28.153 | 25.110 | 3.38% |
| Toyota | 46.353 | 41.401 | 5.58% |
| Volkswagen | 100.877 | 91.330 | 12.31% |
| Volvo | 4.192 | 4.627 | 0.62% |
| Other | 21.194 | 22.907 | 3.09% |
| **Total** | **746.074** | **741.902** | **100.00%** |

## 4. Applications

In this study, automatic detection of the brands of the vehicles has been tried. This section describes how detection process is carried out.

In determining the vehicle brands; it is aimed to determine the brand logos on the 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 six 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.

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 collected and 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. Labelling of the collected images is also made at this stage. This collecting and labeling are discussed in detail in the pretreatment phase.

**Table 1.** List of images used in the study according to areas of use

| | Total | Train | Test | Evaluate |
|---|---|---|---|---|
| Alfa Romeo | 60 | 48 | 12 | 51 |
| Audi | 83 | 66 | 17 | 87 |
| BMW | 100 | 80 | 20 | 55 |
| Citroen | 126 | 100 | 26 | 53 |
| Dacia New | 92 | 73 | 19 | 50 |
| Dacia Old | 50 | 40 | 10 | 50 |
| Fiat | 90 | 72 | 18 | 51 |
| Ford | 81 | 64 | 17 | 82 |
| Honda | 101 | 81 | 20 | 55 |
| Hyundai | 100 | 79 | 20 | 69 |
| Kia | 96 | 77 | 19 | 52 |
| Mercedes | 103 | 81 | 21 | 55 |
| Nissan | 83 | 66 | 17 | 91 |
| Opel | 97 | 78 | 19 | 128 |
| Peugeot | 100 | 80 | 20 | 33 |
| Renault | 107 | 85 | 22 | 65 |
| Seat | 81 | 65 | 16 | 50 |
| Skoda | 100 | 80 | 20 | 50 |
| Toyota | 99 | 80 | 19 | 50 |
| Volkswagen | 130 | 100 | 30 | 52 |
| Volvo | 80 | 64 | 16 | 51 |
| **Total** | **1957** | **1559** | **398** | **1280** |

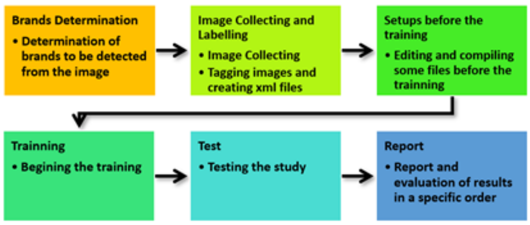



**Fig. 2.** Stages of brand detection study

In Setups before the training stage, some files must be compiled and organized before the training. These files are training configuration file, labelmap file, Test and Train record files. Record files are obtained 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.

### 4.1. The Pretreatment Phase

The pretreatment phase includes steps of images collecting, labeling and pre-training setups.

In the pretreatment phase, an average of approximately 93 images from each brand is collected for the training stage. In total, 1957 images are collected. However, in order to test the study, 1280 images are collected, unlike these images.

As shown in Table 2, a total of 3237 images are collected to use in the study. 80% of images of each brand from collected images for training stage is divided as training, 20% of them is divided as test. Images are labeled at pre-training stage. This labeling is stored in XML files. The full details of these files are also stored in the CVS files. The sample file content is as follows;

filename,width,height,class,xmin,ymin,xmax,ymax
3drot0145.jpg,100,100,volkswagen,3,20,94,81
3drot0146.jpg,100,100,volkswagen,5,19,93,81

alfaromeo.jpg,580,435,alfaromeo,275,294,300,318
alfaromeo2.jpg,580,435,alfaromeo,291,251,319,277

The contents of the file continue this way. In this study, 1557 data are used for training and 398 data are used for testing.

### 4.2. 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. The first module is a deep fully convolutional network that proposes regions, and the second module is the Fast R-CNN detector that uses the proposed regions. The entire system is a single, unified network for object detection (Fig. 1). In the first module called RPN, an input vehicle image is passed through convectional neural networks layers. A feature network is obtained from this stage. RPN is created using this feature network. Region propositions are made on this network(RPN). Region propositions is resized using RoI pooling. Faster RCNN inception v2 is used for feature extractor. First stage iou threshold value is 0,7. First stage objectness loss weight is 1,0. Second stage classification loss weight value is 1.0. Initial learning rate value is 0,0002.

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 6 hours as 55682 steps.
As a result of training, frozen 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 1280 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 Toyota. As shown in the Fig. 3 The program has detected the car as Toyota by %99.

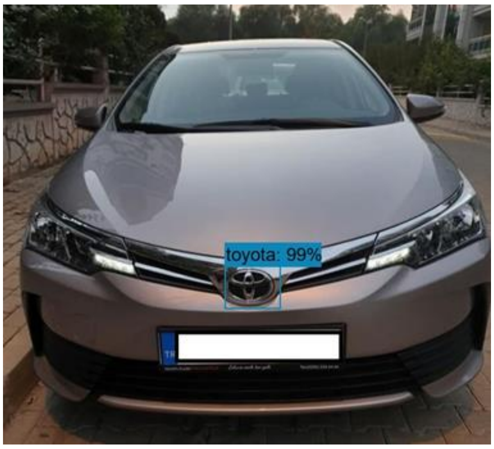



**Fig. 3.** Detection of the vehicle’s brand correctly by the software

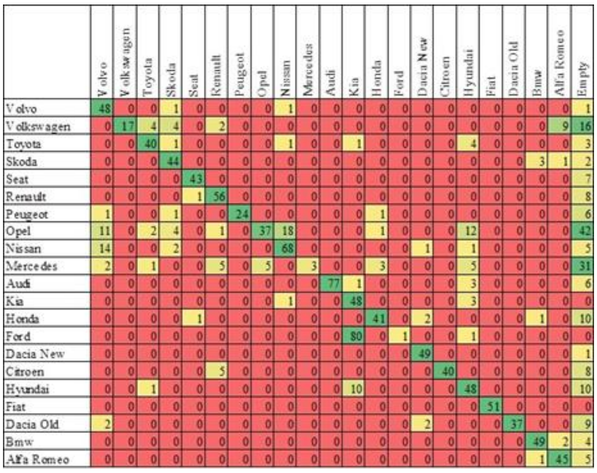
## 5. Conclusion

Faster RCNN 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 maked as true estimate. As 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 | 51 | 48 | 3 | 94.12% |
| Volkswagen | 52 | 17 | 35 | 32.69% |
| Toyota | 50 | 40 | 10 | 80.00% |
| Skoda | 50 | 44 | 6 | 88.00% |
| Seat | 50 | 43 | 7 | 86.00% |
| Renault | 65 | 56 | 9 | 86.15% |
| Peugeot | 33 | 24 | 9 | 72.73% |
| Opel | 128 | 37 | 91 | 28.91% |
| Nissan | 91 | 68 | 23 | 74.73% |
| Mercedes | 55 | 3 | 52 | 5.45% |
| Audi | 87 | 77 | 10 | 88.51% |
| Kia | 52 | 48 | 4 | 92.31% |
| Honda | 55 | 41 | 14 | 74.55% |
| Ford | 82 | 1 | 81 | 1.22% |
| Dacia New | 50 | 49 | 1 | 98.00% |
| Citroen | 53 | 40 | 13 | 75.47% |
| Hyundai | 69 | 48 | 21 | 69.57% |
| Fiat | 51 | 51 | 0 | 100.00% |
| Dacia Old | 50 | 37 | 13 | 74.00% |
| Bmw | 55 | 49 | 6 | 89.09% |
| Alfa Romeo | 51 | 45 | 6 | 88.24% |
| **Grand Total** | **1280** | **866** | **414** | **67.66%** |



| | Volvo | Volkswagen | Toyota | Skoda | Seat | Renault | Peugeot | Opel | Nissan | Mercedes | Audi | Kia | Honda | Ford | Dacia New | Citroen | Hyundai | Fiat | Dacia Old | Bmw | Alfa Romeo | Empty |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Volvo | 48 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Volkswagen | 0 | 17 | 4 | 4 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 9 | 16 |
| Toyota | 0 | 0 | 40 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 4 | 0 | 0 | 0 | 0 | 3 |
| Skoda | 0 | 0 | 0 | 44 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 3 | 1 | 2 |
| Seat | 0 | 0 | 0 | 0 | 43 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7 |
| Renault | 0 | 0 | 0 | 0 | 1 | 56 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 8 |
| Peugeot | 1 | 0 | 0 | 1 | 0 | 0 | 24 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 6 |
| Opel | 11 | 0 | 2 | 4 | 0 | 1 | 0 | 37 | 18 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 12 | 0 | 0 | 0 | 0 | 42 |
| Nissan | 14 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 68 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 5 |
| Mercedes | 2 | 0 | 1 | 0 | 0 | 5 | 0 | 5 | 0 | 3 | 0 | 0 | 3 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 31 |
| Audi | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 77 | 1 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 6 |
| Kia | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 48 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 0 | 0 |
| Honda | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 41 | 0 | 2 | 0 | 0 | 0 | 0 | 1 | 0 | 10 |
| Ford | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 80 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| Dacia New | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 49 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| Citroen | 0 | 0 | 0 | 0 | 0 | 5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 40 | 0 | 0 | 0 | 0 | 0 | 8 |
| Hyundai | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 10 | 0 | 0 | 0 | 0 | 48 | 0 | 0 | 0 | 0 | 10 |
| Fiat | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 51 | 0 | 0 | 0 | 0 |
| Dacia Old | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 37 | 0 | 0 | 9 |
| Bmw | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 49 | 2 | 4 |
| Alfa Romeo | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 45 | 5 |

**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 the overall success rate. For example, the software developed in the study detected correctly the entire brand in the images used in Fiat brand. However, the software didn’t determine Mercedes brand logo or liken different brands in images which including Mercedes brands. In addition, it has detected only 1.22% of the Ford brand correctly. It liken ford brand to kia brand in all ford images except 1 image. Fig. 5 shows the model's inability to distinguish between the Ford brand and the Kia brand. The figures of the Kia brand and the Ford brand are quite similar as shown in Fig. 5. The Shape of both brands is elliptical.


**Fig. 5.** A sample of the model's inability to distinguish between the Ford brand and the Kia brand

As can be seen from the results, the correct detection rate is 67.66% in the brand detection realized using the Fast-RCNN method. However, it is seen that the correct detection rate of 78.58% is achieved if the brands Mercedes and Ford which have extreme values such as 5.45% and 1.22% 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 images used 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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