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# A novel approach for vehicle identification based on image registration and deep learning

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Vehicle classification;
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Smart augmentation;
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**Abstract.** Fine-grained vehicle type recognition using on-road cameras is among interesting topics in machine vision. It has several challenges like inter-class similarity, different viewing angles, and different lighting and weather conditions. This paper presents a novel approach for vehicle classification based on a novel augmentation method and deep learning. In the proposed smart augmentation, the vehicle images of each class are registered on the reference vehicles of all other classes and then added to the training set of that class. In this way, we will have a lot of new images which are very similar to both reference and target classes. This helps the Convolutional Neural Network (CNN) model to handle inter-class similarities very well. In the test phase, the input image is registered on every reference image in parallel and applied to the model. Finally, the winner is determined by summing up the provided scores of all models. The targeted data augmentation along with the proposed classification strategy has high recognition power and is capable of providing high accuracy using small CNNs or any other classification method without the need for large datasets. The proposed method achieved a recognition rate of 99.8% with only 150 K parameters.



## 1. Introduction

Exact vehicle type identification has attracted the attention of Intelligent Transportation System (ITS) scientists as a challenging issue. Currently, most monitoring systems employ license plate numbers to identify different vehicles. Due to different environmental conditions and damage of license plates, the Automatic Number Plate Recognition (ANPR) system may fail in recognizing the numbers. Therefore, vehicle type identification might help the police identify suspicious vehicles. Vehicle identification has various other applications; for instance, statistics on the number and types of vehicles might provide good information about traffic congestion (for traffic control) and frequency of

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vehicles (for car dealers and car accessories dealers) [1,2].

Various methods are presented for vehicle type identification, which obtain good accuracy on their datasets. These methods try to identify the accurate vehicle type by measuring the vehicle's apparent similarity with each class. The similarity of some parts of the vehicles to each other (for example, the similarity of the front window, logo, and lamps) is a major source of errors in these algorithms. According to the studies, some of these identify vehicle type considering images taken from the front of the vehicle and close to it. While the monitoring cameras are usually a few meters above the road, the captured image is from the top view, reducing the image quality, challenging the identification, and increasing the error in practice [3–8].

This paper aims to present a method to prevent the destructive effects of vehicles' similarity on identification accuracy. A novel approach is proposed for vehicle classification for the first time. First, some vehicles are selected as the reference for each class. Then, in the training process, each class's samples are registered on all reference vehicles and used as a training set for the Convolutional Neural Network (CNN). Registration generates new data and increases the inter-class similarity, and thus the network tries to extract better distinctive features. In the test phase, the input vehicle image is registered on all reference vehicles, and the registered images are applied independently to the CNNs (all networks are the same), and the total votes of these networks determine the vehicle class. To evaluate the proposed method on real-world data, a set of vehicles is captured from the roads (at the same orientation and height as the road cameras).

The rest of this paper is organized as follows. Section 2 reviews the relevant methods. Section 3 describes the proposed method. Section 4 presents the experimental results. Finally, the paper is concluded in Section 5.

## 2. Literature review

Studies on vehicle type identification are classified into two classes, DNN-based methods and methods based on traditional feature extraction and classification [9,10]. These studies are reviewed in the following.

### *2.1. Methods based on DNNs*

In [3], it is mentioned that if the camera used for providing training data is different from the camera used to provide test images, the error percentage of the methods increases. To reduce the dependency on the training data camera, this method employs web data providing images of high quality for each vehicle. The neural network used in this study has an architecture similar to ALEXNET architecture, which is comprised of five Conv layers, three pool layers, and three fully-connected layers. To detect the vehicle in the images, faster Region-based Convolutional Neural Networks (RCNN) is used [11], which is used to detect objects and requires a large set for training.

Yang et al. [12] have collected a large dataset for identifying the exact vehicle type and have presented a method using a CNN, which can identify the vehicles from different views. A similar work was conducted by Gholamalinejad and Khosravi [13] which prepared a dataset of Iranian vehicles. Yu et al. [14] employ two CNNs; the first network is used for vehicle detection, and the second is used to identify the vehicle type.

Sochor et al. [15] have presented a method that does not require the cameras to be above the vehicles and can use the cameras located in their normal position (roadside). The data used in this method is about 21000 images provided from an angle similar to that of the roadside camera. In this method, a 3D box is constituted considering the vanishing points. The vehicle's unpacked image is obtained considering this box and applied to the CNN to enhance the result. The method presented in [16] is almost similar to [15]. The database collected in [16] is comprised of 116000 images obtained from the monitoring camera.

Huang et al. [17] determine the vehicle type via high and low-frequency information. To this end, the input image is divided into high and low-frequency parts using Gaussian filters. Then, each part is applied to fully connected and VGG [18] networks in two different paths. Ultimately, the exact type of vehicle is determined by combining the results of these two paths.

Liu et al. [19] present an anchor-free architecture that contains two subnetworks. the first subnetwork called the Corner Affinity Field Network (CAFNet) utilizes stacked Hourglass networks to detect each vehicle as a pair of corners. and the second subnetwork, named TBox Keypoint Network (TKNet), determines the TBOX of each vehicle that is detected by CAFNet.

Meng et al. [20] introduce a method for vehicle re-identification. In this method, a Parsing-based View-aware Embedding Network (PVEN) is defined for the accurate identification of the vehicle. In this method, the vehicle is decomposed into four parts, namely top, sides, front, and back, and feature vectors are obtained for each part. Moreover, a general feature vector is determined for the vehicle using the CNN, and re-identification is performed with the help of all these obtained feature vectors. It is mentioned in [21,22] that vehicle re-identification is challenging due to the large intra-class variances and small inter-class variances. In [22], weakly supervised data augmentation is used to deal with the problem of insufficient data.

### *2.2. Methods based on feature extraction and applying to the classifier*

Hsieh et al. [23] first extracted the Scale Invariant Feature Transform (SIFT) points for the whole image because the front images of the vehicles are symmetric; then, they detected all symmetric objects of the image by examining all symmetric points of all objects of the image and extracted the vehicle through applying some processes. In this method, after detecting the vehicle, the obtained image is graded, and Histogram of Oriented Gradients (HOG) and Speeded Up Robust Features (SURF) features are used and applied to Support Vector Machines (SVM) to identify the exact vehicle type. In this method, 2048 images are used for training, and 4090 images are used for the test.

Biglari et al. [1,24] present a part-based method that tries to find the discriminating parts for each vehicle sub-group. In [1], they mention that using CNN neural networks requires heavy computations, large memory, and time. Thus, HOG features are utilized to describe each part, and SVM-based methods are used for classification. In this method, after vehicle detection in each image, it is applied to an algorithm to determine its type, and the score of each vehicle is calculated. If its score is lower than a threshold, it is considered an unknown vehicle. The database of this method is comprised of 5991 vehicle images. This obtained a good result (97% accuracy) using a small amount of data.

Madden and Munroe [25] have used the distance between the vehicles' front lamps and the center of the vehicle image as a feature vector for vehicle type identification. In [26], the prominence (saliency) and shape of the rear lamps and registration plate have been used for identification to counteract the light limitation at night. In this method, SVM, K-Nearest Neighbors (KNN), and decision trees have been used for classification.

Sarfaraz and Khan [27] present a probabilistic method based on patches that automatically learns a set of patches for the vehicles' classes in the training phase. Then, in the test phase, it determines the vehicle's class considering the patches' similarity with the training model. In [28], which is the authors' previous work, the vehicle's class has been determined using the bag of words along with the dimensions of the vehicles.

Experiments show that the accuracy of the methods presented in group A is higher than the accuracy of the group B methods. However, deep network methods have a major drawback, which is that they require a large amount of data to achieve high accuracy. To solve this problem, the proposed method uses a light-weight CNN in addition to an image registration technique to reach high accuracy with low data.

## 3. The proposed method

Figure 1 shows the proposed recognition process. As can be seen, the test and training procedures are different from the conventional procedures of recognition algorithms. Here, the purpose is to demonstrate this mechanism's efficiency; thus, a simple CNN is used. Details are described in the following.

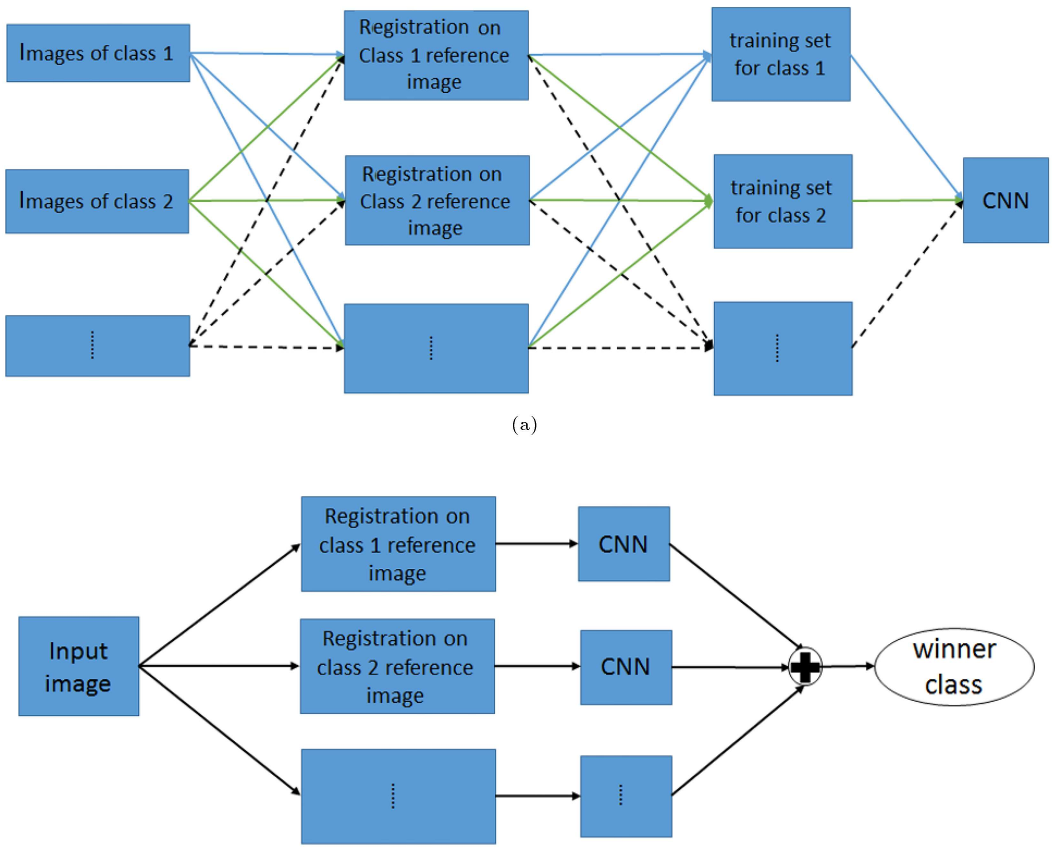
### *3.1. Train phase*

Figure 1(a) shows the training procedure of the proposed mechanism. According to this figure, in the training step, all vehicle images of the training set are registered on the reference image of other classes to construct training sets for each class. Thus, if there are $M$ training images in each class and we have $N$ classes, then $M^*N$ training images are constructed for each class. After constructing the training sets, these sets are applied to a light-weight CNN.

Figure 2 shows the probabilistic process of the training step. The symbol $\nearrow$ in this figure indicates an increase and $\searrow$ indicates a decrease. Various types of vehicles, including Peugeot, Pride, and other groups, are visually similar and may be misclassified. Using the proposed method which is like a smart augmentation process, we overcome this problem. In the training step, for example, the Pride 131 images are registered on the reference image of the Peugeot 405, Samand, Pride 132, and other classes. Then they are added to the set of Pride 131 images. The above process is repeated for all classes until all training sets are constructed. Finally, all sets are applied to the CNN. Registering images of each class on the reference images of the same class reduces the intra-class distance and increases accuracy. Also, registering on the reference image of other classes reduces the inter-class distance (overlap of probability density functions of the classes increases) and reduces the classification accuracy. It is dictated to the deep network (considering the high capability of these networks) to use the features that result in a higher distinction between the classes and reduce the PDF overlap. Certainly, this is not satisfied completely, but the network test procedure is organized in such a way that the algorithm error is decreased significantly.

Registration has the advantage of increasing the number of training data. The images selected as the reference for each class should be clear and taken from the front or behind view of the vehicle (one reference image is selected for each class). The image Figure 3(a) represents some of the reference images and the images Figure 3(b) and (c) represent some vehicle images and their registered version.

Images of the first row in Figure 4 show two Peugeot vehicles. As can be seen, these two vehicles are different in terms of imaging angle and appearance.




(a)

(b)

**Figure 1.** Proposed recognition mechanism (a) train process and (b) test process.

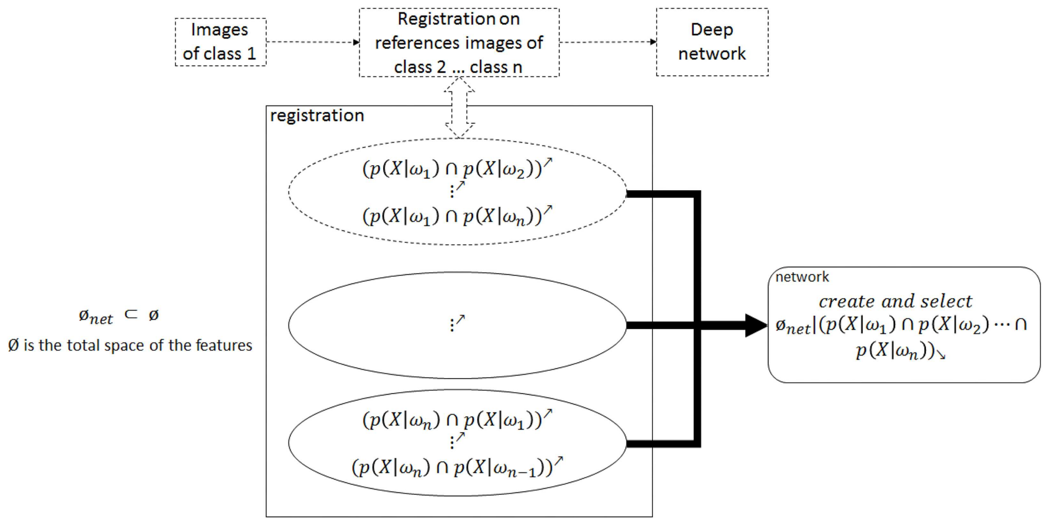



**Figure 2.** Probabilistic process of the training step.

The purpose is to register the black vehicle Figure 4(a) on the white vehicle Figure 4(b). Figure 4(c) is before registration, and Figure 4(d) is after registration. The green parts represent the reference vehicle, and the pink parts represent the target vehicle considered for registration. A comparison of the images of the second row shows that image Figure 4(b) is more compatible than Figure 4(c).

### *3.2. Test phase*

The test procedure of the proposed method is shown in Figure 1(b). In this procedure, the input image

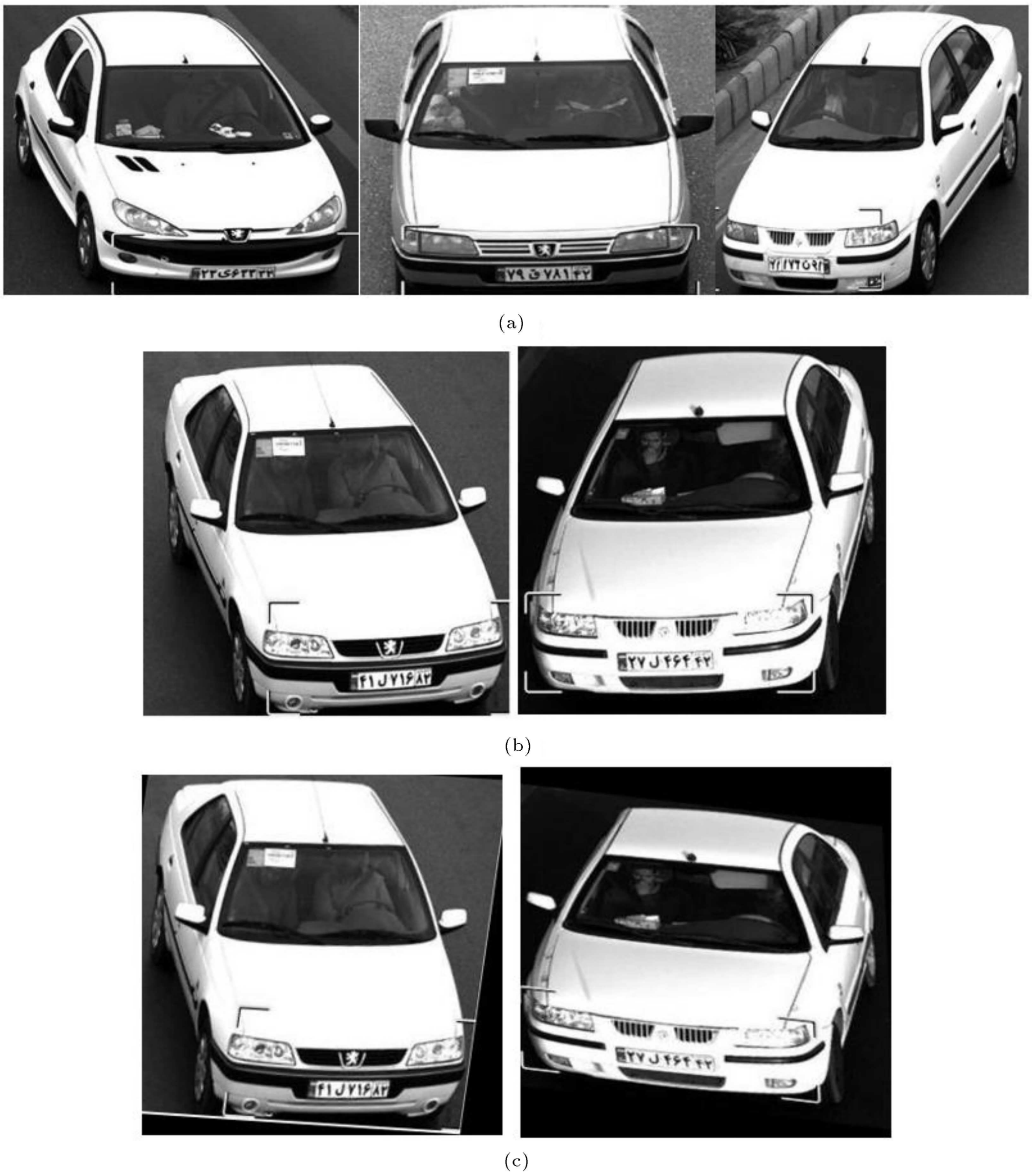



**Figure 3.** Representing several reference and registered vehicles of (a) Reference images; (b) Passing vehicles; and (c) The registered version of images (b).

is first registered on the reference images, which are the same in the test and training phases. Then, the obtained images are applied to the CNNs (all networks are the same and are trained on training data). The CNN's output is a scalar score vector, where each of its elements corresponds to one of the classes. The total of the elements is equal to 1, and the greatest element is the winning class. Finally, the output vector of all these CNNs is summed, and the winning class is determined considering the final vector.

Figure 5 shows the test procedure and relationships. For example, if image X is a member of the $x$th class, the network has learned to announce the $x$th class as the winning class (not certainly) after registering it on each class's reference vehicle.

Figure 6 shows an example of the input image and the registered samples. Here, six vehicles including Pride 131, Pride 132, Peugeot 206, Peugeot 405, Peugeot Pars, and Samand, which are very similar in terms of appearance, have been used to demonstrate efficiency.

Table 1 shows the neural network's output score for the input image of Figure 6 without using the proposed mechanism and registration. According to this figure, the input image is associated with Pride 131, but considering the camera's distance and orientation and the similarity of Pride 131 and Pride 132, the network has assigned the maximum score to Pride 132 incorrectly.

In Table 2, the results of the proposed mechanism

(a) (b)

(c) (d)

**Figure 4.** Registration of two vehicles: (a) Moving image, (b) fixed image, (c) matching differences before registration, and (d) matching differences after registration.

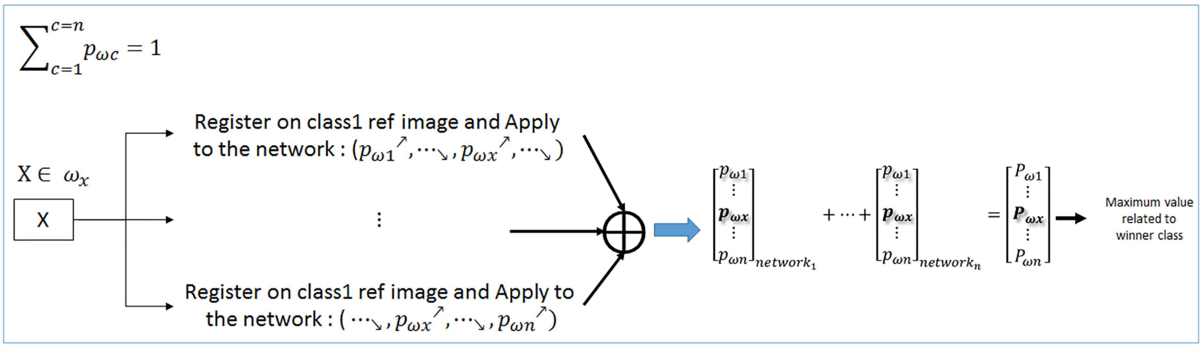



**Figure 5.** Probabilistic process of the testing phase.

**Table 1.** Type recognition of the passing vehicle by simple CNN.

| Type | Peugeot 206 | Peugeot 405 | Peugeot Pars | Pride 131 | Pride 132 | Samand |
|---|---|---|---|---|---|---|
| Score | 0 | 0 | 0 | 0.0131 | 0.9869 | 0 |

for Pride 131 recognition have been presented. As can be seen, after registration and summation of the scores, class 131 has won.

## 4. Results

The database used to test the proposed method is comprised of 7000 images, where 3500 images are from the front view and 3500 images are from the rear view. In this dataset, the camera is a few meters above the road level, and its orientation is similar to the monitoring cameras. Some of the images were taken by the police, and some others were obtained through extracting one or two images for each vehicle

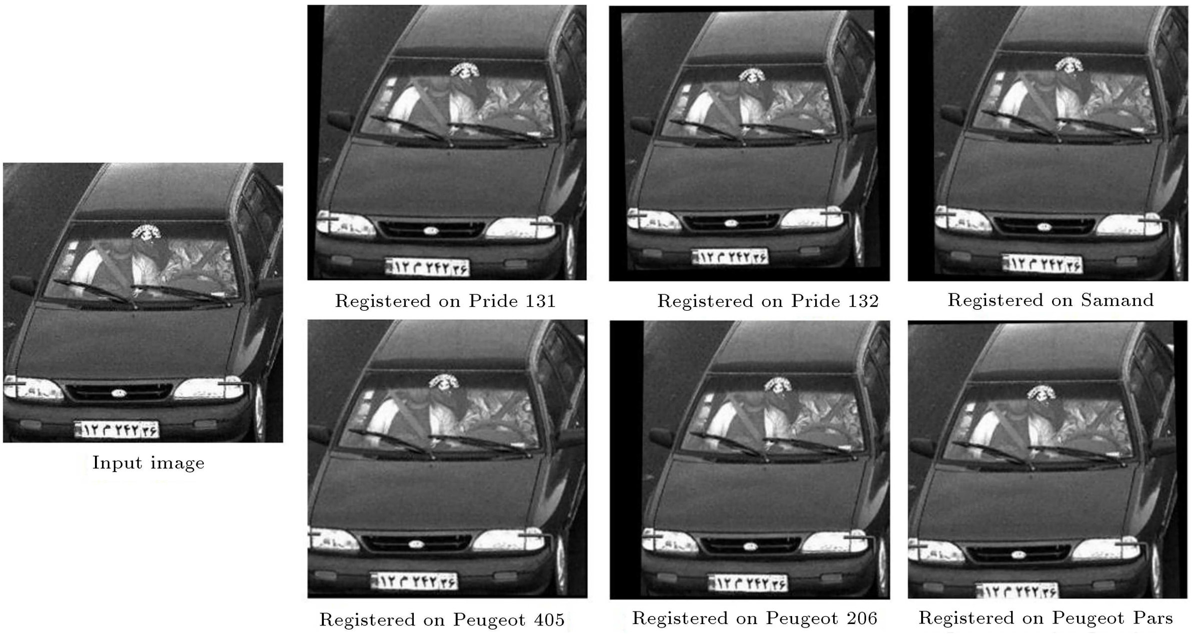



**Figure 6.** Input image and its registered samples.

**Table 2.** Type recognition of the passing vehicle by the proposed mechanism.

| | **Peugeot 206** | **Peugeot 405** | **Peugeot Pars** | **Pride 131** | **Pride 132** | **Samand** |
|---|---|---|---|---|---|---|
| Score of registering on the Peugeot 206 reference image | 0 | 0 | 0.0005 | **0.6489** | 0.3417 | 0.0089 |
| Score of registering on the Peugeot 405 reference image | 0 | 0 | 0 | 0.0001 | **0.9992** | 0.0007 |
| Score of registering on the Peugeot Pars reference image | 0.0087 | 0 | 0 | 0.2272 | 0.2634 | **0.5007** |
| Score of registering on the Pride 131 reference image | 0 | 0 | 0.0032 | **0.6394** | 0.3401 | 0.0173 |
| Score of registering on the Pride 132 reference image | 0 | 0 | 0 | **0.7877** | 0.2133 | 0 |
| Score of registering on the Samand reference image | 0 | 0 | 0 | **0.9044** | 0.0956 | 0 |
| Total Scores | 0.0087 | 0 | 0.0037 | **3.2076** | 2.2524 | 0.5275 |

from non-sequential frames of road videos. The images include many vehicle groups, but most of these images are related to the 12 popular classes which have more frequency in Iran. Figure 7 shows several images of the dataset.

Table 3 shows the mean accuracy of CNN, CNN+ Data Augmentation, and the proposed method. As can be seen, Augmentation does not affect accuracy significantly, and the proposed method has improved accuracy by 6.8% compared to the CNN, indicating the significant success of this method.

Table 4 shows a comparison between the proposed

**Figure 7.** Some images from the provided dataset.

**Table 3.** Comparing with CNN classifiers.

| Method | Accuracy |
|---|---|
| CNN | 93 |
| CNN + Augmentation | 94.1 |
| Proposed method | 99.8 |

method and several famous networks for the provided dataset. The VGGNet [18], MobileNet_V1 [29] and EfficientNet_B0 [30] networks listed in the table are popular networks that are commonly used for comparison. The proposed structure is a lightweight network with three layers and a few parameters that does not require strong hardware. However, this method can be used to improve the accuracy of every other network as well. As shown in Table 4, despite the very low parameters of the proposed structure, it has the same response as other networks.

The third column of Table 4 compares the speed of different methods on NVIDIA MX 150 GPU (2G RAM). We used the method presented by Nagy et al. [31] as the image registration technique. This method processes each frame in less than 1 ms on the aforementioned GPU. In addition, our designed network reaches 2 ms for each frame. Hence, according to Figure 1(b), if we have 12 classes, the total duration of the proposed method is around 36 ms (this time consists of input image registration on reference images and imposing the image to the network).

## 5. Conclusion

Identifying vehicle type is an important and useful problem in the field of machine vision. The new method presented by this paper has different training and testing procedures compared to other methods. In the testing step of this method, smart augmentation is performed for each class using registration, and the class data are increased and applied to a small Convolutional Neural Network (CNN). In the testing step, the vehicle type is accurately determined using targeted registration and application to identical CNNs.

The use of smart augmentation and a small CNN eliminates the need for a large training dataset. Furthermore, the realistic dataset extraction, small CNN size, and parallelism of the proposed structure make operational implementation possible on low-cost boards, such as NVIDIA Jetson, in the future.

## Conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

**Table 4.** Comparison between methods.

| Method | Average accuracy | Number of params | Process time |
|---|---|---|---|
| VGG16Net [18] | 99.7 | $\simeq$ 14 M | $\simeq$ 90 ms |
| MobileNet_V1 [29] | 99.4 | $\simeq$ 2.2 M | **$\simeq$ 16 ms** |
| EfficientNet_B0 [30] | 100 | $\simeq$ 4 M | $\simeq$ 37 ms |
| Proposed method | **99.8** | $\simeq$ 150 K | $\simeq$ 36 ms |

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## Biographies

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