License Plate Detection using Cascaded Classifier with Two-Phase Training and Testing

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***Abstract*—License plate recognition (LPR) is a core infrastructure of most intelligent transport systems (ITS). Plate detection is the first and the most important step for license plate recognition. In this paper, several schemes are proposed based on cascade classifier to detect multi-plates in an image. Here, a two-phase testing approach is suggested to improve the efficiency of the system in tackling false alarm and improving the detection precision. Besides, a two-phase training with feedback is proposed by collecting negative data feedback to improve the training of the cascade classifier. Finally, a combined approach is also proposed by merging the two-phase testing and the two-phase training with feedback schemes. To analyze the efficiency of the proposed approaches, the experiments are conducted on the real-world images with the plates in different environments as well as the plates in two different languages with various size, complexity, illumination, multiple plates at front/rear of cars. The results show that the proposed schemes can improve the performance of the plate detection system.**

***Index Terms*—Cascade Classifier; Classification; License Plate Recognition; Plate Detection; Two-Phase Train/Test.**

I. INTRODUCTION

Nowadays, Intelligent Transport system (ITS) has a main role in traffic management to improve safety and mobility of people's life. A key element of ITSs is the automatic license plate recognition subsystem, which is employed in many applications such as electronic payment systems (tax payment, toll payment, parking fee payment) [1], detection of stolen vehicles, vehicle-based authentication [2], monitoring traffic systems [3], vehicle tracking [4], vehicle speed estimation [5, 6] and etc.

A smart plate recognition system operates at three main stages; plate detection, character segmentation and character recognition. The first and foremost important stage is the plate detection or plate localization. This step, in comparison with other steps, meets different challenges including collecting insufficient proper data, low image resolution, varying light volumes, and complicacy of image in the jammed traffic, multiple plate images and negative effects of vehicle distance on assessing the size of the plate.

A very oft-used method in plate detection is connected to component technique and morphological functions. In [7] and [8], a Sobel edge detector followed by binarization, morphological operation and connect component is utilized to find plates in Egypt and Libya, respectively. In 2017, Luvizon et al. [5] employed a similar method to find plates for vehicle speed estimation. Hough transform is also used in combination with the edge detection to detect vertical and horizontal edges of plate rectangle [4]. In 2016, Sahar Tabrizi et al. [9] used Prewitt edge detection with dilation and connected component to detect plates. The plate characters are recognized using K-nearest neighbor (KNN) and support vector machine (SVM) classifiers. In 2018, Wasif et al. [10] introduced the segmentation technique for the detection of plate area. In this technique, the plates are detected with the movement of a window on an image followed by using morphological functions of erosion and dilation. The disadvantages of the connected-component-based methods, which usually use edge detection, are that they are very sensitive to illumination changes, they produce many false alarms in complex environments, and they can hardly be applied on complex images. These methods usually examine certain geometrical features, such as proportion of length to the width of the candidate area, and the size of the area to reduce the number of false alarms.

Another common technique for the detection of plate area is color-based methods. Y. Yang et al. [11] used the color of plate background area along the characters with its texture to identify the plate regions. In 2014, Amir Hossein Ashtari et al. [12] introduced an optimized color-based method to detect plates for Persian vehicles. Through this method, the shared color on the plates (the blue rectangle on the left of the plate) was used to identify the plate area. In 2017, Asif et al. [13] introduced a technique for detecting multinational plates. In this technique, the backlight of the vehicle with red color is detected to eliminate the background. It is then followed by calculating horizontal edges through the Heuristic Energy Map, then through histogram. The area which has a higher density will be selected as the plate. The main drawback is that the technique can only find single plates and it has inefficiency in finding front plates. The general problem of color-based methods is their unreliability because the color of plates is prone to be confused with other objects, especially in complex environment. It is also very sensitive to illuminate change and may produce many false alarms. Besides, it is unusable to detect non-color plates.

Matas and Zimmermann [14] detects character-like regions using a neural network to find car plates. The combination of wavelet transform and neural network is also used for plate detection [15, 16]. Recently, deep neural networks have shown a good performance for object detection in images [17, 18]. This network is also utilized to detect plates in image. In 2019, Li et al. [19] developed a plate detection and recognition system using convolutional neural network (CNN) trained over 460000 images. One of the main challenges in deep neural networks is collecting and labeling a massive number of training data, which is very time consuming and expensive. In some researches, pre-trained networks on large dataset are utilized in combination with transfer learning to fine-tune the parameters of the network using smaller dataset. For example, YOLO object detection neural network [20, 21] is employed for Brazilian license plate recognition [22, 23]. The deep network models have some hyperparameters whose values need to be fixed before training. Tuning of these parameters is more of an art than a science incurring extensive trial- and- error experiments [1]. Besides, deep networks have high computational complexity and they are usually implemented on GPU platforms at an expensive cost [24].

In recent years, one of object detection algorithms achieve a good performance on image object detection is Viola and Jounes [25] cascade classifier. This method has been successfully applied on different object detection such as face detection [25], pedestrian detection [26, 27], character detection and recognition [28, 29] and vehicle detection [30, 31, 32]. This technique can be used on both color and gray images, and enjoys high accuracy and speed. Elbamby et al. [33] utilized a pre-processing function to extract candidate plate regions, and then, they used a LBP-based cascade classifiers to detect Egyptian license plates. In 2017, Rokonuzzaman et al. [3] proposed a plate detection system by training two cascade classifiers. The first classifier is employed to find the rear part of the cars and the second one is used to find the plate region. The proposed method can only be used to find plates located at the rear of the car. In [34], the candidate region is extracted using Sobel edge detector and the proposed edge filter and then an SVM cascaded classifier is trained to identify the true plates from the candidate regions.

In this paper, we adopt the cascade classifier to develop a multi-plate detection system in different environments with various complexity, illumination, and multiple plates at front/rear of cars with different size. First, a cascaded classifier with its classical training and testing is built for plate detection. The preliminary results of the work have been presented in a conference paper [35]. Second, a two-phase testing trend is suggested to increase the detection precision and reduce false alarm rate. Third, with regard to the effect of negative data in the training of the cascade classifier, a two-phase training with feedback is suggested by collecting negative data feedback and providing more efficient training samples for the classifier. Finally, the two later schemes are merged together to benefit from their opportunities. The results evaluated on real-world plates in English as well as Persian plates in different conditions show the effectiveness of the proposed schemes.

The rest of the paper is organized as follows: Section II briefly reviews the cascade classifier. The proposed approaches are explained in Section III. The experimental results and discussion is provided in Section IV. Finally, the conclusion and future work are given at the last section.

II. A Review Of The Cascade Classifier

The cascade classifier, introduced by Viola and Jones [25], combines several classifiers in series to detect an object in an image with high speed and precision. In this method, according to Adaboost algorithm [36], several classifiers are combined in series so that one classifier output will feed into the next classifier in the cascade. The earlier classifiers try to eliminate the background areas, and the higher classifiers in the cascade try to find the candidate's objects.

The training of the cascade classifier requires many positive samples (candidate objects) and negative samples (non-candidate objects). To obtain the features, Haar features with kernels, shown in Figure 1 are extracted. Every feature is obtained through the subtraction of sum of all pixels located on the white kernel region from the sum of pixels located on the black kernel region.

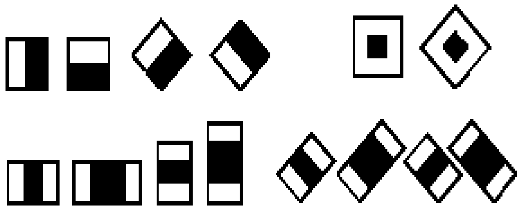


Figure 1: Some feature extraction kernels of cascade classifier

III. The Proposed Algorithm

Here, cascade classifier is employed to build an efficient system for plate detection. In this way, four approaches (named LPD1, LPD2, LPD3 and LPD4) were anticipated to gain the most efficient result. Here, LPD is the abbreviation of License Plate Detection. First, in LPD1, the cascade classifier is used in its classical training and testing procedures. Then, a two-phase testing approach and a two-phase training method to get feedback from negative samples are proposed in LPD2 and LPD3, respectively. Finally, the idea of LPD2 and LPD3 are combined and LPD4 is suggested for plate detection. In the following sections, the LPD methods will be described in more detail.

A. LPD1 Approach

Recently, the cascade classifier has been successfully used in detecting faces, eyes, human and other objects in images [37, 38, 26]. At the first stage, positive image (image with plate) and negative images (images without plate) were collected. Then proper features as explained in section 2 were obtained. Finally, a cascade classifier was trained for detecting plates on the images, as shown in Figure 2. The results of this approach, called LDP1 indicated many false alarms on the image. Besides, the detected area was inaccurate, which encompassed a larger part of the plate area. Two sample results of LPD1 are shown in Figure 3(a).

B. LPD2 Approach

In order to reduce the false alarms and improve the detection accuracy, a two-phase testing approach was employed in LPD2. Here, an image was primitively put in the model to detect the earlier plate candidates. Next, each candidate area was put again in the model as a separate image to extract more precise plate region and reduce the spurious candidates. The output samples of LPD2 are shown in Figure 3(b). As it can be seen, using the same trained model, LPD2 approach has resulted in an improvement over LPD1.

C. LPD3 Approach

LPD2 improves false alarms and detection precision of LPD1. However, analysis of the results showed that there are still some false alarms in the detections, which is unsatisfactory. Several experiments on the cascade classifier method has shown that providing more negative data can enhance the efficiency of the cascade classifier and can decrease the false alarm rates. In LPD3, a two-phase training approach was proposed by getting feedback from the classifier and increasing the negative training samples. To do so, all training samples were given to the classifier, then the false detected areas was obtained as separate images. These images were added to the trained data as negative samples and the classifier was re-trained with the new training data. To provide more negative images, each negative image was also rotated 90*, -90* and 180* degrees and added to the training data. Two sample results of LPD3 are shown in Figure 3 (c).

D. LPD4 Approach

The LPD3 approach generates fewer false alarms and detects the plate area more precisely in comparison with LPD1. Analyzing the general results indicated that in some images, LPD2 was better than LPD3, but in some other images, it was the reverse, and LPD3 had a better performance. According to this observation, it could be expected that a combination of the two approaches, LPD2 and LPD3, could complement one another and would yield a better result. So, a final approach (LPD4) was offered by combining the earlier approaches.

LPD4 benefits from the two-phase training and two-phase testing to detect plates. Figure 4 shows the two-phase training steps. Similar to LPD3, the classifier was firstly trained using the primitive training data, and then the model was re-trained by getting feedback from the false positive result.

At the test step, a two-phase testing approach was performed similar to LPD2 shown in Figure 5. For this, an image was given to the classifier to detect the earlier candidate areas. Next, each candidate was given as a separate image to the classifier again. So, the false candidate area was be eliminated and the plate detection precision increased. The output result for LPD4 approach is shown in Figure 3(d). As can be seen, the false candidate area was removed and the plate area was accurately detected in this approach.

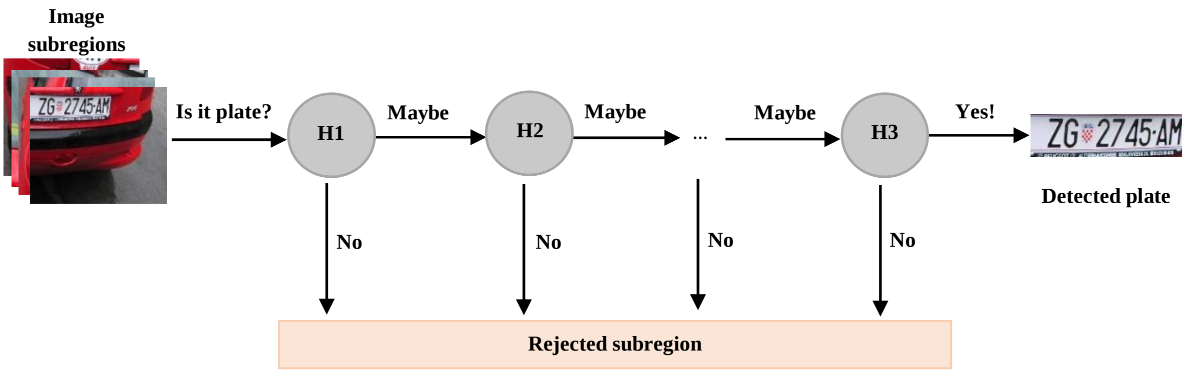


Figure 2: A cascade of N classifiers for plate detection

(a) LPD1 (b) LPD2 (c) LPD3 (d) LPD4

Figure 3: Output samples of four approaches LPD1, LPD2, LPD3 and LPD4

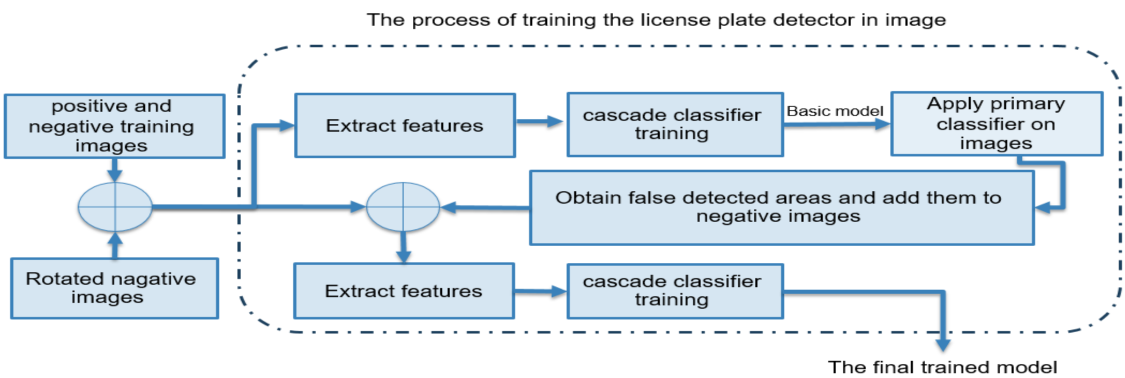


Figure 4: The training steps of the license plate detector

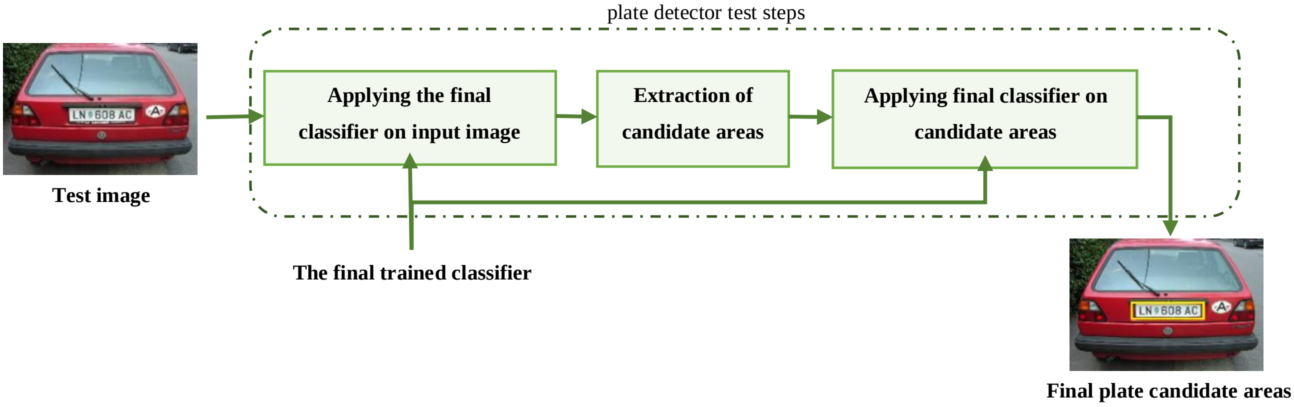


Figure 5: The test steps of the license plate detector

IV. Results and Evaluation of the Suggested Approach

In this section, first, the images used for the training and testing of the suggested approaches are described. Then, the qualitative and quantitative methods are compared with the previous methods. To assess the performance of the proposed approaches, we evaluated the methods not only with plates in different environments but also the plates in two different languages with various types.

A. *Providing Training and Testing Images*

Due to the lack of an adequate benchmark dataset, a publicly available dataset[1] in combination with our collected images were used to evaluate the proposed approaches. The data contains various images in different lights and distance positions of the vehicles in the image, including one or several plates from the front and back sides of the vehicles. The 70% of the data were used as training samples and the remaining 30%, which were not used for training, were randomly used for testing and evaluating the system.

For the training data, images contain one or more plates were used as positive samples. To increase the negative images, the plate areas in the positive images were eliminated and they were used as the negative samples. In addition, all negative images were rotated by 90*, -90* and 180*, and then were added to the negative samples. To increase the efficiency of the functions, negative images were reckoned as twice as the positive images. Figure 6 represents some positive images, including color and gray, front and back, day and night, sloping and straight plate positions, busy environments and etc. Figure 7 shows some negative images in various conditions.

B. *Comparison with Previous Methods*

In order to evaluate the performance of the proposed method, it was qualitatively compared with Ashtari [12], Asif [13], Tabrizi [9], Chowdhury [10], Yuan [34] and Rokonuzzaman [3]. Then, the approches were also quantitatively compared with Ashtari [12] and Asif [13] plate detection methods.

i. *Qualitative Comparison*

The qualitative comparison between the suggested approaches and the other mentioned previous methods are shown in Table 1. As shown in this table, Ashtari's [12] and Asif's [13] methods, which are based on color, and Tabrizi's [9] and Chowdhury's [10] methods, which use edge morphological functions show high sensitivity to light fluctuations in the image. This is because color and edge features within plate regions are not discriminative, with respect to those of other objects, especially in the scene with illumination change and complex environment. The Yuan's [34] method utilized cascade SVM classifier to identify the plate regions. This method has also high sensitive to illumination change because it finds the primitive plate candidates via edge structures. Rokonuzzaman [3] utilizes two cascade classifiers to find the rear light of the vehicle and then find the plate region. It cannot be applied on the front plate.

Intuitively, our approach is more suitable in busy environments because it tries to learn the pattern of the plate regions, including the edge patterns via a combination of cascade classifiers. For this, it can achieve less sensitivity to scene changes (e.g. illumination, high edge, etc.) and it can be less sensitive to the plate condition in the image (e.g. plate location, color, size and multiple plates).

(a) Image at night with flash

(b) Close-up color image of the rear view

(c) Close-up gray image of the front view

(d) Image with shadow in plate

[1]The LPR Dataset available on: http://www.medialab.ntua.gr/research/LPRdatabase/

(d) Busy environment image of the rear view

(e) Far image with sloping and straight plate

(f) Image at night

(g) Environment with many edges and multiple plates

Figure 6: Several samples of positive images containing plates

(a) Examples of positive images where plates are removed by black area

(b) Examples of negative images without a plate

Figure 7: Several samples of Negative Image

ii. Quantitative Comparison

Four proposed approaches of LPD1, LPD2, LPD3 and LPD4 were quantitatively compared together and with Ashtari's [12] and Tabrizi's [9] methods. To evaluate the results of the methods, recall rate, precision, f-score, and false positive rate were employed and calculated respectively as:

$$\text{Recall} = \frac{\text{true positive}}{\text{true positive} + \text{false negative}} \tag{1}$$

$$\text{Precision} = \frac{\text{true positive}}{\text{true positive} + \text{false positive}} \tag{2}$$

$$\text{fscore} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

$$\text{false positive rate} = \frac{\text{false positive detected areas}}{\text{all images}} \tag{4}$$

To have a better evaluation of the results, we used plates in two different languages in various conditions. Figure 8 visualizes several results of the methods. Here, Ashtari's [12] method, which uses blue region on the left edge of plates, is not helpful to detect plates with other color styles. In comparison with the suggested approaches, Ashtari's [12] method, which utilizes color feature and Tabrizi's [9] method, which works based on edge detection, suffer from higher false detection rate and low detection precision. In Figure 8 (c), LPD3 and LPD4 provides less false alarm rate and more accurate Localization.

To have a better analysis, the methods were quantitatively evaluated on three scenarios:

- Scenario 1: In this scenario, the proposed approaches were trained and tested on English plates.
- Scenario 2: In this scenario, the proposed approaches were trained and tested on Persian plates.
- Scenario 3: Finally, in Scenario 3, the two datasets were merged together and the models were trained and tested on the overall image plates.

Table 2 shows the number of train and test images used for each scenario. For each scenario, the parameters of the cascade classifier (false alarm rate (FAR) and the number of classifiers (NoC)) were tuned via cross validation. Figure 9 and Table 3 show the numerical results, including the average false positive rate, recall rate, precision rate and f-score criteria for each method on each scenario. The parameters of the cascade classifier, i.e., false alarm rate (FAR) and the number of classifiers (NoC), were tuned via cross-validation; and the best configuration of the parameters were determined for each scenario in Figure 9.

As the figures show, and it was anticipated, the use of color for plate detection (Ashtari's [12] method) included both high false alarm rate (FAR) and low recall rate in comparison with the other methods. This is because in outdoor environment, objects with the same color of the plate region and the light reflection might produce many false alarms. The recall rate of this method is also low because the color characteristic is very sensitive to the illumination change along a day. Furthermore, this method is limited to be applied on plates with different color styles. Tabrizi's [9] method which finds plate based on edge detection achieves suitable recall rate because there are notable edges in plate regions. The FAR of this method is also high because the edge feature within the plate regions is not discriminative with respect to the other edges, especially in complex environments. Besides, the precision is less than the other methods because the unwanted edges add extra area to the plate region (for example, see the third row in Figure 8). The proposed LPD approaches create lower FAR than [9] and [12]; specifically, LPD2, LPD3 and LPD4 provide lower FAR than the LPD, which used cascade classifier with classical training and testing.

In Scenario 1, (Figure 9(a)) and Scenario 2 (Figure 9(b)), LPD1 and LPD3 achieve better recall rate than the others and LPD3, which uses training with feedback reaches higher precision rate than LPD1. Both LPD2 and LPD4, which employed two-phase testing improve FAR and precision rate at the cost of a little reduction in recall rate. The results of Scenario 3 (Figure 9 (c)), which is trained using all samples containing two language plates with various shapes are interesting. Here, the two phase testing (LPD2) achieves notably better precision rate, but with lower FAR than training with feedback (LPD3). Accordingly, it seems that LPD2 and LPD3 can complement each other. The results show that the LPD4 which combines LPD2 and LPD3 ideas provide lower false alarm rate, good recall rate and higher precision rate than the others.

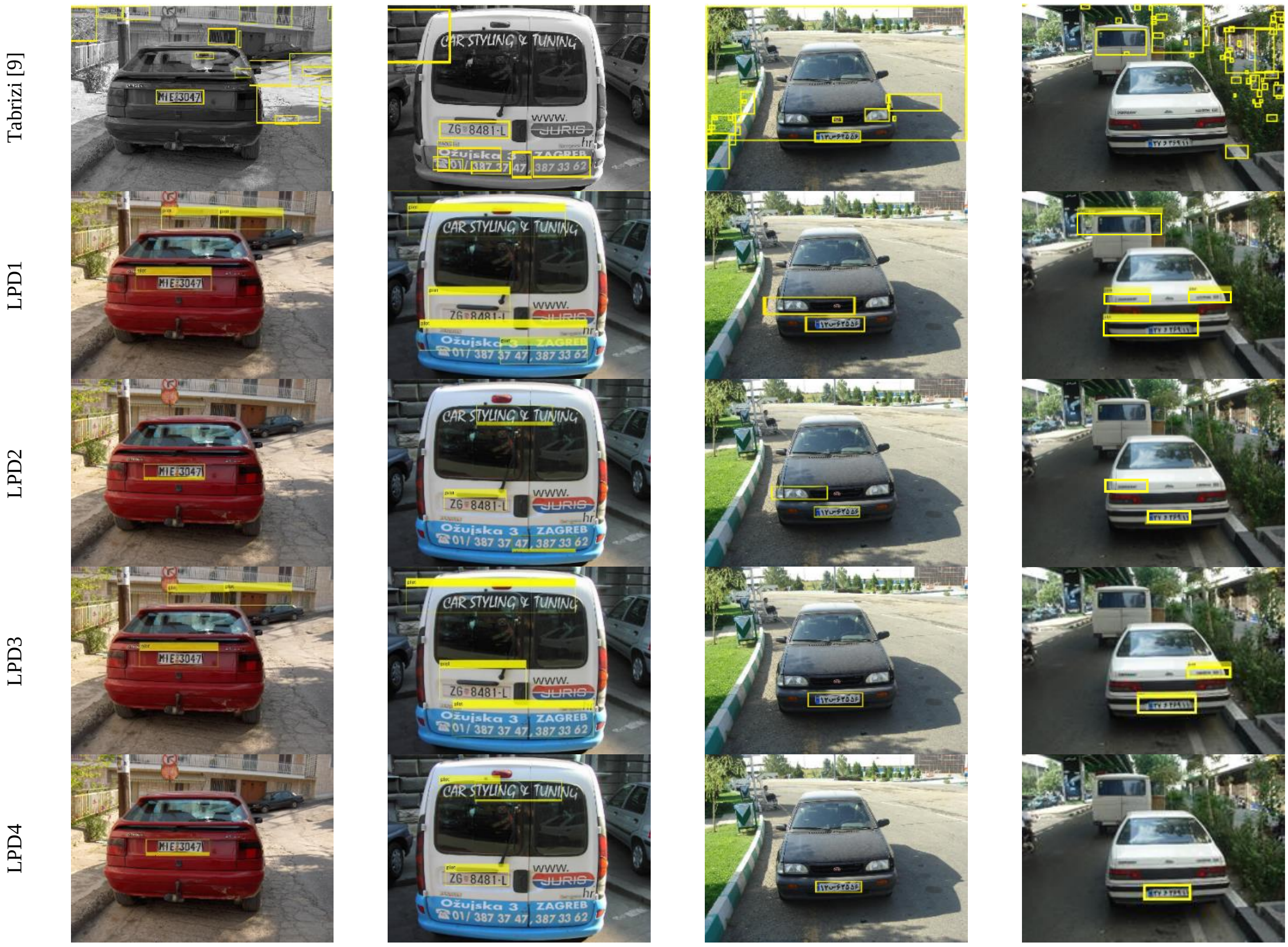
In summary, it can be said that the two-phase testing (used in LPD2 and LPD4) achieves lower false alarm rate and better precision in the cost of a very little reduction in recall rate. Therefore, if the recall rate is too important for an application, the LPD3 which benefits from training feedback can be a better choice for plate detection. For larger number of plates with various types and shapes, the combination of two-phase training feedback and two-phase testing (LPD4) can improve the overall performance of the plate detector.

Table 1
Qualitative Comparison of the Proposed Approach with Previous Methods

Evaluation Criteria / Methods	Sensitivity To Night And Day (Low / Medium / High)	Sensitivity To Light Fluctuations (Low / Medium / High)	Sensitivity To Plate Size (Low / Medium / High)	Limitations On The Rear Or Front Of The Vehicle (Yes / No)	Performance On Busy Environment (Weak / Medium / Good)	Dependency On A Specific Area Of The Car Or Plate
Suggested Approaches	Low	Low	Low	No	Good	Non
Ashtari [12]	High	High	Medium	No	Weak	The blue rectangle on the left of the plate
Asif [13]	Medium	High	Medium	Yes	Weak	Car red tail lights
Tabrizi [9]	Medium	High	High	No	Weak	Non
Chowdhury [10]	Medium	High	High	No	Weak	Non
Yuan [34]	Medium	High	High	No	Medium	Non
Rokonuzzaman [3]	Medium	Low	Low	Yes	Good	Car red tail lights

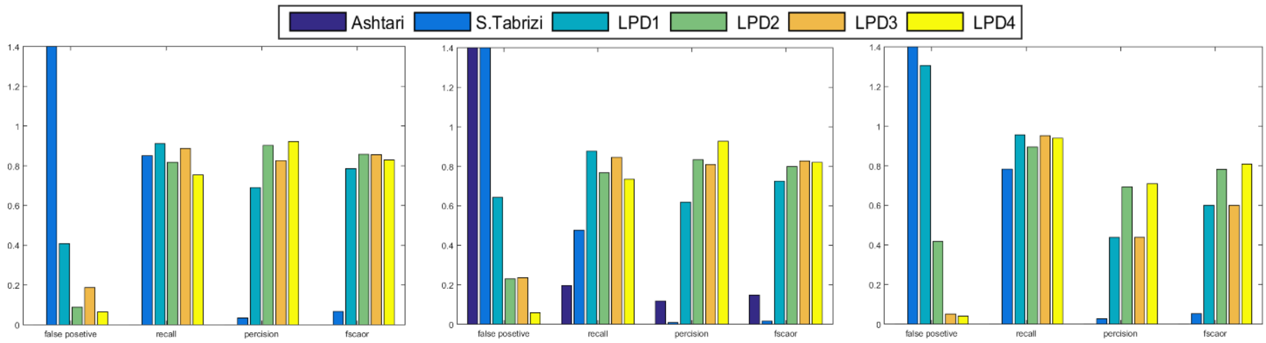
Table 2
Number of Samples Used In Train and Test for Each Scenario

	Scenario 1	Scenario 2	Scenario 3
Train Image	660	755	1313
Test Image	203	246	405



(a) Sample English plate 1 (b) Sample English plate 2 (c) Sample Persian plate 1 (d) Sample Persian plate 2

Figure 8: Results of Ashtari's [12], Tabrizi's [9] methods and our proposed approaches



(a) Scenario 1 (FAR=0.1, NoC=9) (b) Scenario 2 (FAR=0.07, NoC=8) (c)Scenario 3 (FAR=0.1, NoC=9)

Figure 9: The results of the plate detection methods

Table 3
Plate Detection Methods Results

Scenario	Methods	False Positive Rate	Recall	Precision	Fscore
Scenario 1	Ashtari [12]	--	--	--	--
	Tabrizi [9]	41.820	85.040	3.480	6.700
	LPD1	0.400	91.110	69.020	78.550
	LPD2	0.088	81.770	90.200	85.790
	LPD3	0.180	88.720	82.640	85.570
	LPD4	0.060	75.360	92.160	82.950
	Ashtari [12]	1.465	19.630	11.810	14.750

Scenario	Methods	False Positive Rate	Recall	Precision	Fscore
Scenario 2	Tabrizi [9]	57.100	47.630	0.820	1.620
	LPD1	0.646	87.670	61.690	72.420
	LPD2	0.230	76.720	83.300	79.870
	LPD3	0.230	84.540	80.920	82.690
	LPD4	0.050	73.450	92.660	81.940
Scenario 3	Ashtari [12]	0.000	0.000	0.000	0.000
	Tabrizi [9]	48.000	78.330	2.700	5.280
	LPD1	1.300	95.590	43.780	60.050
	LPD2	0.410	89.480	69.380	78.160
	LPD3	0.050	95.150	43.820	60.000
	LPD4	0.040	93.300	70.890	80.790

V. CONCLUSION

In this paper, a license plate detection approach was proposed based on cascade classifier. A two-phase training approach and a two-phase testing approach were suggested to improve the performance of the cascade classifier for plate detection. To examin the efficiency of the proposed approaches, four schems named as LPD1, LPD2, LPD3 and LPD4 were conducted and their results were compared together and with several related approaches. The methods were evaluated on real world color/gray images in different environment with various complexity and illumination in day and night, single/multiple plates at front/rear of cars with different size. The experimental results show that the proposed approaches can effectively improve the overall performance of the plate detection system. In future work, we are going to work on the next step of a license plate recognition system, i.e., plate character segmentation and recognition.

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