

Deep Learning System for Automatic License Plate Detection and Recognition

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Abstract—the detection and recognition of a vehicle License Plate (LP) is a key technique in most of the applications related to vehicle movement. Moreover, it is a quite popular and active research topic in the field of image processing. Different methods, techniques and algorithms have been developed to detect and recognize LPs. Nevertheless, due to the LP characteristics that vary from one country to another in terms of numbering system, colors, language of characters, fonts and size. Further investigations are still needed in this field in order to make the detection and recognition process very efficient. Although this domain has been covered by a lot of researchers, various existing systems operate under well-defined and controlled conditions. For example, some frameworks require complicated hardware to make good quality images or capture images from vehicles with very slow speed. For this reason the detection and recognition of LPs in different conditions and under several climatic variations remains always difficult to realize with good results. For that, we present in this paper an automatic system for LP detection and recognition based on deep learning approach, which is divided into three parts: detection, segmentation, and character recognition. To detect an LP, many pretreatment steps should be made before applying the first Convolution Neural Network (CNN) model for the classification of plates / non-plates. Subsequently, we apply a few pre-processing steps to segment the LP and finally to recognize all the characters in upper case format (A-Z) and digits (0-9), using a second CNN model with 37 classes. The performance of the suggested system is tested on two datasets which contain images under various conditions, such as poor picture quality, image perspective distortion, bright day, night and complex environment. A great percentage of the results show the accuracy of the suggested system.

Keywords— LP detection; LP recognition; segmentation; deep learning; CNN; Tensorflow

I. INTRODUCTION

Vehicles are widely used in all areas of production as well as in our daily lives. Therefore, the vehicle License Plate (LP) number is an efficient way to identify vehicles, which is unique for each vehicle. With the rapidly increasing number of vehicles, traffic violations appear more frequently in public traffic, such as fraud tolls in highways or parking, speeding, theft of cars, etc. Therefore, it is necessary to identify the LPs of vehicles for safety. The extracted information from an LP can be used for several purposes, like access and flow control, monitoring border crossings and highway toll stations, searching for suspicious vehicles or even fighting crime, etc.

This makes the automatic LP detection and recognition crucial and inevitable in the system of LP extraction. There are two separate processes: LP detection and LP recognition. Different algorithms, system and techniques have been worked out and applied to both of them. Moreover, the previously image processing developed concepts of or other concepts are applied in order to get more accuracy. However, there is still room for improvement. Although some studies have been performed on LP detection and recognition, this research work is different from the previous ones due to a number of reasons. Nevertheless, in major researches, a neural network or a deep learning system is used only in the detection or recognition process. The novelty of this work is that our system uses a few pre-processing steps to classify LPs / non LPs utilizing a first Convolution Neural Network (CNN) model for LP detection, and to classify and recognize the characters and digits from an LP using a second CNN. This paper is organized as follows. Section 2 presents the literature review for LP detection and recognition. The proposed system is mentioned in section 3. In section 4 we provide the evaluation and experimental results. Finally, section 5 includes the conclusions of this study, the limitations and future work.

II. RELATED WORK

A. LP detection

The different systems proposed in LP detection are based on different properties. Some techniques use simple rules based on deterministic methods, detection contours, morphological operations and statistical analyses, while others opt for learning and classification systems. Belongie and al. [1] used shape descriptors, called "context shapes", who described the distribution of the rest of the forms relative to a given point on the contour. Seeking the correspondence between two forms was then equivalent to finding the point on the other form that had a "shape context" similar to each point on a shape. Parallel to this, Carmichael et al. [2] showed the variation of the context shapes in order to differentiate between the form and the content. Another approach utilized morphological operations on gray-scale images [3]. On the other hand, the authors of [4,5] combined a contour detector with morphological operations to search the rectangles that were considered a candidate LP. Moreover, Kim and al. [6] proposed a method based on the extraction of the contour to localize an LP on images taken in low light conditions. In [7],

the authors put forward a method for the detection of the LP of a vehicle image with a complex background. They used the histogram equalization to find the threshold in order to improve the quality of the image that contained the LP.

Furthermore, the LP color can be different and few regions may have specific colors. For that reason, some authors have used a color-based approach to extract LPs by localizing their colors in the image. The authors in [8] and [9] checked a test image using a color-model classifier. In addition, the authors in [10] segmented color images by way of a shift algorithm into candidate regions. The latter were then classified as with or without an LP. It was clear that a combination of features of edge density, aspect ratio and rectangularity were exploited in determining these candidate regions. In the goal of addressing the effect of illumination variations (in other words addressing the problem of illumination variation in relation to the color-based method), the authors put forward in [11] a fuzzy logic method in order to recognize LP colors. The LP extraction utilizing color information could detect inclined and deformed LPs. On the other hand, this method would be very sensitive to some different illumination alterations and would suffer from false positives, mainly in case the other parts of testing images had similar colors of LPs.

The color based approach has various benefits such as detecting inclined and deformed LPs, but it is sensitive for multiple illumination environments. However, this appears to be ineffective when the plate has different colors and patterns. For that, a texture-based method is applied to detect the desired regions according to their pixel intensity distribution in LPs. For example, the Support Vector Machines (SVMs) were used by [4] to analyze the color properties of the LP texture. The color values of the raw pixels that made up the color texture model were attributed directly to the SVMs. Then the LP zones were identified by applying the CAMShift algorithm (continuously adaptive mean shift algorithm) on the results of the analysis of the texture color. In [12], the authors opted for an intensity saliency map in the target of segmenting out the characters on an LP. After that, they applied a sliding window on such characters so that they could compute some features related to saliency in order to detect LPs. The writers of the work in [13] modified an LP detection algorithm from a face detection one, by means of an adaptive boosting on Harr-like features. In addition, the authors in [14] developed a sliding concentric window algorithm for the purpose of detecting an LP on the basis of an image-texture local-irregularity property. The writers in [15] used a method based on the Wavelet Transform (WT) to extract license plates. There were four sub-bands in the WT. This color-based method is efficient and robust against color variation and LP size and can detect any deformed LP.

Yet, it is limited in complex and illumination conditions. Other research studies are found in the literature about the LP detection using character-based approaches. If these methods find characters in LPs, their region will be extracted. Maximally Stable Extremal Regions (MSERs) were basically utilized by [16] and [17] in the aim of obtaining a set of character regions as well as non-character ones, which were removed with a heuristic filter. Added to that, the authors in [18] and [19] first recognized the character region through the

identification of character width as well as through the difference between an image character region and its background. After that, they extracted the LP by finding in the plate region the inter-character distance.

Other approaches have been suggested, which represent a combination of two or more methods, named hybrid approaches. The authors in [20] combined color and texture features through the application of fuzzy rules to extract the some color as well as the texture feature. Besides that, Lim et al. [21] proposed a combination of the MSER method and the sift-based unigram classifier.

Recently Wang et al. [22] used the edge-based approach and the Back Propagation Neural Network. In [23], the authors put forward an efficient and robust classifier to ultimately localize the exact position of the LP in the image. The writers in [24] proposed a method for localizing the LP region in the captured image while extracting a set of candidate regions using a weak sparse network classifiers. They also filtered them utilizing a CNN classifier.

B. Character segmentation

The second step in LP detection and recognition systems is the character segmentation stage approaches and techniques have been applied to detect the region character in a plate license image. To detect the candidate region of an LP, the authors in [20] used the image segmentation method, called the sliding window. Anagnostopoulos et al [14] suggested an approach based on fuzzy logic for segmentation and CNN discrete time for LP characteristics extraction. The method based on connected components was utilized for character segmentation [25]. The most commonly used character segmentation algorithms were the projection application [26] (there were two types of projections: horizontal and vertical), the mathematical morphology [27], the contours [28], the local and adaptive threshold [29] and the histogram treatment [30].

C. Character recognition

The last step in the LP detection and recognition system is the character recognition process. Different methods for character recognition, such as raw data, extracted feature and neural networks, have been defined in the literature. Indeed, the authors of [31] performed template matching after resizing the extracted characters similarly. We can mention some similarity measuring techniques like the Hamming, Hausdorff and the Mahalanob distance. In [32], the writer generated a feature vector by horizontally and vertically projecting a binary character. After feature extraction, a lot of classifiers could be utilized for character recognition, like the HMM [33], the SVM [34] and the ANN [35]. Two types of classification schemes were integrated by some researchers: a "parallel" mixture of various classifiers [36] or multi-stage classification schemes [37]. The authors in [38], trained a three-layer CNN model by means of an unsupervised learning algorithm for character recognition. As a matter of fact, a two-way text/non-text CNN classifier was utilized to detect texts. On the other hand, another character CNN classifier sensitive to 62 characters was employed to recognize words. This classifier was combined with the Viterbi-style algorithm as well as the beam search technique. The writers in [39] developed a 4-layer CNN to spot texts in natural scenes. Jain et al. [40] used a

CNN model with a spatial transformer network to detect and recognize characters in videos scenes.

III. PROPOSED SYSTEM

In this section, we will propose an overview of the system for LP detection and recognition. This system is divided into three sub categories: (i) LP detection, (ii) character segmentation and (iii) character recognition (see Fig. 1).

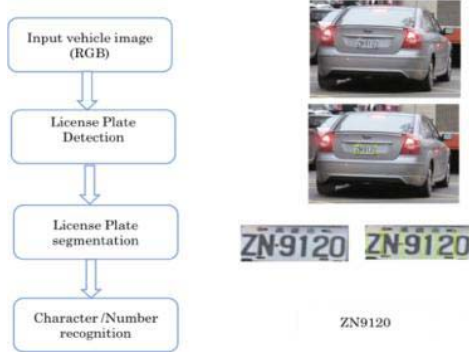


Fig. 1. System Flow-chart

A. License plate detection

To have an effective system of plate detection from an image of a vehicle, we consider the different plate variations such that its position changes in direction and scale as well as in lighting or background. Our algorithm of LP detection is divided into pre-processing and CNN classifier steps, presented in Fig. 2.

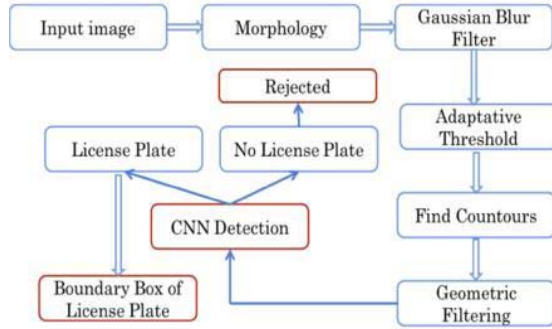


Fig. 2. Flowchart of LP detection

a) Convert RGB to HSV image

First, the user of our system introduces an image in an RGB format. Second, the system converts the image to HSV (Hue, Saturation and Value) and will define a type of color space. The hue (H) represents the color type and saturation (S) is the vibrancy of the color. Its value ranges from 0 to 255 and the value (V) represents the brightness of the color. It ranges from 0 to 255, with 0 is dark and 255 is bright.

b) Morphology filtering to contrast maximization

To maximize the contrast of our image with the purpose of extracting small elements and details of the picture, so we will apply morphological operations such as the top hat transform. There are two types of top hat transform: white and black. The white top hat is the difference between the input image and the

opening one and the black top hat is the difference between the closing image and the input one (1, 2). The top white transform is defined by: $T_w(f) = f - f \odot b$ (1), where f is the gray-scale image, \odot is the opening operation, and b is the gray-scale structuring element. The top black transform is defined by $T_b(f) = f \bullet b - f$ (2), where \bullet is the closing operation. To get a picture with the maximum contrast, we must add up the gray-scale image to the image of white top hat transform result. After that, the resulting image is subtracted from the image transform black top hat.

c) Gaussian blur filter

After maximizing contrast to a gray scale image and improving the results of further processing on the image, we apply a Gaussian blur filter to remove details and noise from this image using a 5×5 kernel. This is required in order to ameliorate the results of further processing image.

d) Adaptive threshold

Since the images are taken in different circumstances, lighting conditions and areas, we will apply an adaptive thresholding to eliminate unimportant regions in the image. Our algorithm calculates two values: the threshold value of the neighbourhood area whose size is 19 and the weighted sum of neighbourhood values where the weights are a Gaussian window is 9.

e) Finding all contours

After removing and eliminating unimportant regions in the image, we will seek and find a curve joining all continuous points having the same color or intensity. To find all contours, we use the hierarchy technique to create a full family hierarchy list, but we do not need all points of boundary. For this, and since our LP is rectangular, we require only 4 points, so we apply the simple contour approximation method.

f) Geometric filtering

After the previously implemented steps, it is necessary that the system should meet a set of constraints in the size and shape of the boundary box to extract a Region Of Interest (ROI) in an RGB image. Therefore, some geometric filtering rules will be applied to improve the precision LP detection by very large and very small objects. Hence, very large and very small aspect ratios are rejected. The used filter rules are: width, height and ratio.

g) CNN license plate detection

In this stage, we extract the possible various boundary boxes that can be considered as LP. But to decide whether an LP from several boundary boxes is correct, we integrate the deep learning architecture represented by the CNN model to filter and distinguish between LPs and non LPs. Our CNN model is implemented with tensorflow framework which composed of four layers: two convolutional layers for feature extraction and two fully connected layers.

First of all, we resize all images to 100×36 in gray level, as an input of our model. The first convolution layer C1 consists of 16 feature maps calculated using a 5×5 filter kernel for the image. The layer C1 provides 96×32 feature maps. At the level of the first subsampling layer S2, we have 16 maps of

characteristics of size 48×16 obtained by sub-sampling based on a maxpooling using a 2×2 kernel of the output of the layer C1. For the second convolution layer C3, there are 32 feature maps calculated using a 5×5 filter kernel on the output of the layer S2. It produces 44×12 feature maps. At the second subsampling S4, we have 32 characteristic maps of size 5×5 , calculated by sub-sampling based on the maxpool using a 2×2 kernel on the output of the layer C3, which produces 22×6 feature maps. Thus, we get a first fully connected layer that contains 4224 of features. To reduce overfitting our model, we apply a dropout, which is a regularization technique, with a ratio equal to 0.5. Finally, we obtain the second fully connected layer that produces 2 neurons, which are values of softmax whose output is 2 classes.

h) Boundary box of license plate

The result of the final step in the process of detection will be given by our classifier if the prediction is positive and greater than 0.7, which is the minimum threshold of the score obtained by the classifier. In fact, this boundary box is considered as a positive LP, and as a result, a boundary box will be drawn on the image that shows the LP. However, if it is less than 0.7, it will be considered a non-LP.

B. Characters segmentation

The character segmentation is a very important phase to facilitate the recognition process. In fact, it consists in extracting the numbers from the image of the LP. Several factors make this stage complex, such as the numbering system, the colors, the style (background), the low blur resolution, the noise and the plate rotation. To deal with these complexities, a new process is developed to segment the characters in an effective way. Therefore, the segmentation process is divided into several steps (see Fig. 3).

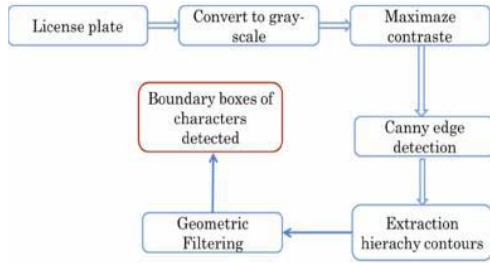


Fig.3 . Flowchart of LP segmentation

After detecting the LP, the segmentation steps begin with the conversion of the plate image derived from the RGB to a gray scale image. Then it maximizes the contrast to improve and clarify better the image. After that, an image edge detection is applied using the canny technique in an automatic way. Auto-canny is a function that requires two arguments: a single-channel image and an argument sigma used to make changes in the thresholding rates determined by means of simple statistics. Consequently, the average pixel intensities in the image are calculated. Next, this average value is taken to build a lower thresholds and an upper one. Both are controlled based on the sigma argument. In our case, after several tests, 0.20 is chosen as a sigma value. Finally, once the upper and lower thresholds are obtained, the canny edge detector is then

applied. In addition, we apply the same contour extraction technique hierarchically in the previous section. Afterwards, a few geometric operations are performed to minimize a boundary box so as to improve the accuracy of the segmentation process.

C. Character recognition

The final stage in our system is the character recognition. There are currently a lot of techniques applied to the character and number recognition, such as the syntactic, the statistical and neural networks. In our system, to recognize the characters on an LP, the Tensorflow framework will be reused to classify the characters with a second CNN model with 37 classes. For training, 36 entry classes (10 classes of digits (0 to 9) and 26 upper case characters (A..Z)) and another non-character class are considered. The configuration of the CNN model is presented in Table I

TABLE I. CONFIGURATION OF CNN MODEL FOR CHARACTER RECOGNITION

| Layer Type | Parameters |
|-----------------|---|
| Sofmax | #37 classes |
| Fully connected | #37. neurons |
| Dropout | 0.5 |
| Relu | |
| Fully connected | #1024 neurons |
| Maxpooling | P :2 x 2 , stride :2 |
| ReLU | |
| Convolution | #filtres 256 kernel :3 x3 , stride :1 |
| ReLU | |
| Convolution | #filtres 128 kernel :3 x3 , stride :1 |
| Maxpooling | P :2 x 2 , stride :2 |
| ReLU | |
| Convolution | #filtres : 64 kernel :3 x3 , stride :1 |
| Maxpooling | P :2 x 2 , stride :2 |
| ReLU | |
| Convolution | #filtres : 32, kernel :5x5, stride :1, p :0 |
| Input | 32 x 32 gray-scale image |

Our second CNN model contains four convolutional layers and two fully connected layers for 37 classes. The input image is resized to 32×32 in gray-scale. We firstly utilize a 5×5 kernel and we secondly modify it by 3×3 . The subsampling is based on maxpooling using a 2×2 kernel, except the fourth convolution layer, which respects the same output size of the third convolution layers but we modify the number of features maps. The dropout is involved within a set of fully connected layers having a 0.5 in the aim of preventing overfitting. Finally, we follow this softmax layer to predicate every class probabilities. Besides, we used our CNN model to eliminate a false positives element.

IV. EXPERIMENT RESULTS AND EVALUATION

In this section, a set of data are used to carry out the various tests of LP detection and character recognition as well as the experimental results of our proposed system for each phase.

A. Datasets

To obtain the best training results for a CNN model, a dataset must be either large for positive classes (LPs and characters) or negative ones (non-LP and non-characters). For this, we adopt two dataset types: the first dataset is for LPs / non LPs and the second one is for characters and non characters. The LP dataset is around 2.400 images cropped from a few public LP dataset, from the Caltech dataset [41] and the AOLP dataset [42]. Regarding non-LPs, we crop 4.150 images from this dataset and we use other datasets like the Microsoft Research Cambridge Object Recognition Image database [43]. To increase the dataset size we use the technique of data augmentation by exploiting transformation, rotation, Gaussian blurring and random lighting. After applying this technique, we obtain for each class 21.600 and 37.350 images. All these images are resized to 100 x 36. For the second training character recognition dataset, we exploit two other datasets to extract character and the non-character images, which are ICDAR 2003 [44] and Chars74 [45]. Furthermore, we crop the characters ourselves from the LP Caltech and AOLP datasets to the order of 72.000 characters in an uppercase format and digits and 20.000 non characters, where all these images are resized to 32 x 32. Again, we apply data augmentation to expand the dataset size, so we get 288.000 character images and 80.000 non-character ones.

To test our approach, we use two datasets. The Caltech dataset (1999) comprises 126 image sets with a 896x592 resolution. In fact, we have color and real world images. The second benchmark dataset is the AOLP. The latter contains exactly 2,049 images which are divided to three categories: Road Patrol (RP), Law Enforcement (LE) and Access Control (AC). The images are captured in different weather and illumination conditions.

B. Results

The experiments is conducted on an Intel PC Core i7 CPU 2 GHz, 8 GB of RAM and ubuntu LTS 16 the operating system. Our proposed system is implemented with python, opencv 3.1 and a TensorFlow framework.

a) LP Detection result

The process of LP detection is illustrated in Fig. 4 which shows the various steps of the LP detection, and the results of the accuracy rate are given in Table II and Table III with a comparison to other methods.



Fig.4.Process of different steps of LP

The proposed system of LP detection is evaluated in terms of precision, recall and f-score rate. The first evaluation criterion is precision. The latter one is defined as the number of LPs, which are rightly and divided by means of a total number of detected regions. After that, the second evaluation criterion is the recall which defined as a number of correctly detected LPs divided by the total number of ground-truth and finally is F-score rate is given in equation (3) :

$$F - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (3)$$

The detection results of experimentation for the Caltech cars dataset is provided in Table II and for the AOLP dataset in Table III.

TABLE II. Comparison of LP results by different approaches on Caltech cars dataset (%)

| Method | Precision(%) | Recall (%) | F-score (%) |
|------------------|--------------|--------------|--------------|
| Lim & Tay [21] | 83.73 | 90.47 | 86.97 |
| Zhou et al. [46] | 95.50 | 84.80 | 89.83 |
| Our method | 93.80 | 91.30 | 92.01 |

We observe in the specific Caltech dataset that our method based on deep learning, especially one CNN model for LP detection, has a higher precision (93.80%) and recall (91.30%) compared to the method of Lim & Tay [21], who utilized the character-based methods. However, for comparing with method of Zhou and al. [46], our system is performant in recall only. On the AOLP benchmark dataset and with the same evaluation criterion, our solution produces a higher precision for each dataset category: 92.6 % for AC, 93.5 % for LE and 92.9 % for RP but for recall rate, the method of Hsu et al. [42] is better only for LE sub category by 95%.

TABLE III. Comparison of LP results by different approaches on AOLP cars (P=Precision %, R=Recall %)

| Method \ Subset | AC | | LE | | RP | |
|-----------------|-------------|-------------|-------------|-----------|-------------|-------------|
| | P | R | P | R | P | R |
| Hsu et al. [42] | 91 | 96 | 91 | 95 | 91 | 94 |
| Our method | 92.6 | 96.8 | 93.5 | 93.3 | 92.9 | 96.2 |

b) Recognition result

The experiment of character recognition is presented through the example in Fig. 5.



Fig. 5. Examples of LP recognition

The performance of our recognition system of the characters is measured by character recognition accuracy. The latter consist in the number of correctly recognized characters divided by the total number of ground-truth characters. The experiment result of character recognition is evaluated with two dataset (see Table IV).

TABLE IV. Comparison of LP results by different approaches on AOLP Cars dataset

| Subset Method | Accuracy rate (%) | | | |
|----------------------|-------------------|------|------|------|
| | Caltech | AC | LE | RP |
| Jia et al. [35] | - | 90 | 86 | 90 |
| Christos et al. [14] | - | 92 | 86 | 91 |
| Hsu et al. [42] | - | 95 | 93 | 94 |
| Our method | 94.8 | 96.2 | 95.4 | 95.1 |

The character recognition accuracy rate of our methods compared with the work in [35], [14] and [42] shows higher accuracy. Nevertheless, our CNN model provides a better result compared to the Artificial Neural Network and Probabilistic Neural Network architectures. Thus, the robustness of our architecture is due to the high reliability and efficiency of the CNN architecture.

c) Discussion

The CNN is used in several research areas such as image and text detection / recognition, speech recognition, computer vision, deepDream etc. We have exploited the high performance and effectiveness of the CNN and the TensorFlow framework to detect and recognize LP vehicles, which improves our system reliability. Most importantly, it provides our experimentation with high rates of accuracy in character recognition in the Caltech and the AOLP datasets. Nevertheless, in LP detection, we have obtained a highly accuracy rate in one evaluation criterion, either in precision or in recall. The experiment results for LP detection in the recall and f-score accuracy rate conducted on the Caltech dataset have given a high rate: 93.8% and 91.3 % respectively. On the other hand, we have observed some failure in the precision rate compared with Zhou et al. [46]. On the AOLP dataset benchmark, the experiment results have given highly precision in the three sub-sets. Moreover, the recall rate has been a failure only in LE sub-sets because this category of dataset contains two vehicles and consequently two LPs. For this, our system fails in a few cases contains multiple LPs which are a bad inclination or a brightness/darkness lighting condition.

For character recognition, we have tested our system with two datasets, and the experiment results for the Caltech dataset have given 94.8 %, but on the AOLP dataset in the three sub-sets they given 96.2 % in the AC, 95.4% in the LE and 95.1 % in the RP. For both phases, we have used different datasets to get the maximum number of images for training our model; and to have a better result, we have utilized the data augmentation techniques such as the Gaussian blur, the rotation with multiple degrees, the transformation, etc. We have noticed that there are some failings in our systems which emerge from several factors like high inclinations, illegibility of the plate, a multiples LPs in image and under-bad climatic conditions.

V. CONCLUSION AND FUTURE WORK

Several studies have been conducted on LP detection and recognition. In fact, various researchers have developed several methods and techniques for the application of this process. However, all the techniques have their own advantages and disadvantages. Moreover, each country has its own system of numbering the LP, background, size, colors and language of characters. Although some studies have been conducted on LP detection and recognition, this research is different from previous work studies because we have used a deep learning architecture represented by a CNN model in both LP detection and recognition. To ensure the proper functioning of our detection and recognition system, a few steps of pre-processing the image to be tested have been applied. These steps include a few morphological operations, adaptive thresholding, fine contours, geometric filtering, etc. The detection process of the LP started on the pre-processed image, and the detected objects is classified into two types: "plate" and "no plate". This classification has led to the TensorFlow CNN model, once they are trained. In addition, some steps of pre-processing segmentation are applied before being used another time in the CNN model for character recognition. Besides, to improve the system, future work will focus on the accuracy rate of improvement in the detection and recognition plaques with various constraints mentioned above. In addition, we will try to develop our real-time system using new technologies (smartphone, tablet, etc.) so that we can exploit it in a mobile environment.

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