Vehicle license plate detection using morphological operations and deep learning

2022 International Conference of Advanced Technology in Electronic and Electrical Engineering (ICATEEE) | 979-8-3503-4674-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICATEEE57445.2022.10093752

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***Abstract*— Vehicle License Plate Detection (VLPD) is the most critical stage of any vehicle License Plate Recognition (LPR) system because it has a direct impact on its robustness and accuracy. As a result, VLPD remains a difficult task because vehicle license plates (VLP) vary in size, axes, orientation, and may be occluded or have their locations changed. In this paper, we present our framework for an image-based VLPD system based on morphological information and deep learning. To address this issue, we created a new "YellowLP" dataset with 1050 images of unique and different rear VLP numbers. Pecision, recall, and overall accuracy of the morphological results are 98.65%, 97.90%, and 96.61%, respectively, with a detection rate of 97.90%. Deep learning increases the recall and overall accuracy of the proposed approach to 100% and 98.65%, respectively. As an outcome, the proposed method produced acceptable results.**

Keywords*—— License Plate detection, Car number plate, morphological operations, deep learning, artificial intelligence, images database

I. Introduction

The process of removing the license plate from a picture of a vehicle using characteristics such as the boundary, color, or presence of characters is known as number plate localization. In today's world, the number of vehicles on the road is rapidly growing. The identity of these vehicles must be verified for a variety of reasons, including automatic vehicle access control, unattended vehicle parking lots, stolen vehicle detection, traffic law enforcement, restricted zone security surveillance, and statistics collection [1]. It is, however, difficult to manually inspect such a large number of vehicles. Consequently, developing an accurate Automatic Vehicle License Plate Recognition (VLPR) system, that is a critical and important task at the same time to resolve the technical issue. VLPR's goal is to extract the VLP from images that contain vehicles. In general, VLPR techniques have two major phases: locating VLPs and identifying vehicle license numbers. The VLP detection phase is the most significant phase of any VLPR system for removing the unwanted regions and locating the VLP position in images. Indeed, the majority of license plate images captured at specific locations (e.g., the entrance to restricted zones, company and firm portals, the inlet of a parking lot, etc.) have a good quality image due to high acquisition equipment performance, simple background scenes due to a short distance between vehicle and camera, and relatively fixed license plate sizes, making it easy to locate the VLP even for the simplest VLP techniques. This is not the case for images of highways, roads, intersections, and pedestrian-vehicle mixed traffic, which contains a variety of objects with complex and irregular shapes. In the literature, however, only a few methods for VLPD per image with complex background have been proposed. Recent advances in parallel processing allow for faster handling of large amounts of available data and the provision of better solutions to various fields of application through advanced technologies [2]. Deep Learning (DL) techniques have recently proved promising results in speech [3, 4] and vision systems [5, 6, 7], that obviously convenience ALPR systems. Deep Convolutional Neural Networks (CNNs) are, in fact, the most widely used machine learning algorithm for locating vehicles and license plates (LPs) [2]. A typical ALPR system includes vehicle detection, characters location and recognition [8]. Vehicle detection is a facultative phase that can be thought of as preprocessing license plate location. In this work, we present a deep convolutional neural network method for detecting vehicle license plates based on morphological operations.

The following is how the paper is structured. The related work is discussed in the second section. Section III contains the proposed system, which examines characteristics of our database, the ideology behind it and training phase. Section IV describes the testing procedure and the results obtained. Section V reserved for the conclusion and perspective plans.

II. Related Work

One popular research topic is license plate recognition. This is due to the lack of an international standard for capturing and displaying license plates. For example, all vehicles in one country display their license plates in the same format or style. As a result, developed systems perform well when it comes to images of respective countries.

A number of factors influence LPD systems. Some methods employ deterministic rules, edges detection, morphological operations, textures and colors analyses, while others employ machine and deep learning methods.

The color-based approaches have several advantages, including the ability to detect tilted and off-axis LPs; however, these methods are sensitive to light intensity [9]. But it can be useful when the LP has a variety of colors. On the other hand, a pixel-based method is used to locate the coveted areas in LPs based on their pixel intensity distribution [9]. The color of the LP can vary, and some regions may have different colors. As a result, other works have employed a color detection method to extracting LPs by determining the desired colors the LP in images.

In both Algeria and the United Kingdom, a plate's color scheme is fixed and has the same standard, with front plates being white and rear plates being yellow. The license plate is thought to be a pattern with high contrast variations. This trait has been evaluated in the context of image texture detection and can be employed to locate LPs. They have, in fact, proven to be more effective in real-world applications. Texture and edge features of high-density distribution of

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Arabic numbers (Algerian license plate) and Latin letters (British license plate) character are important indicators for distinguishing Algerian and British license plates from other objects. Many algorithms have been presented to fix the License Plate Detection (LPD) task, with attribution to these characteristics, some of which are established in classical computer vision methods and others in machine learning. To locate the license plate region, traditional studies typically used manual methods and conventional computer vision classifiers, along with binarization of images and analysis of gray levels. Their mainstream methods are classified in three classes: based on contour detection, color analysis and based on texture classification. In [10], authors presented a filter based on linear density technique for connecting densely packed regions with edge densities. The sparse regions of each line of the matrix are then removed from the resulted image. Authors in [11] presented a study for detecting Taiwan's license plate using RGB images on complex background images, via the manipulation a color edge localization that can locates different boundaries between various colors. Shouyuan et al. [12] concentrated on LP detection problems in the presence of significant variations in lighting and background. They used a technique for detecting license plates that was based on empirical mode decomposition analysis. However, the computational complexity of the aforementioned traditional techniques remains elevated. They are inapplicable to real-time LPD because the actual effect is disrupted by different outdoor conditions and the long processing time. A color-model classifier was used by [13] to evaluate a test image. A shift algorithm was also used by the [14] to segment color images in labeled areas. Letters were then categorized as either having or not having an LP.

With the rise of deep learning, considerable studies now investigate deep CNN for License plate detection. Advanced object classification networks rely on machine learning has emerged as a major domain of artificial intelligence in the last decade, with versions such as You Only Look Once (YOLO) [15], a series of Single Shot Multi-Box Detector (SSD) [16], and a Faster Region-Convolutional Neural Network (Faster R-CNN) [17]. Image classification methods based on CNNs are also used to validate detected vehicle license plates due to their high performance for classification problems.

Faster R-CNN-based network was proposed by Li et al. [18]. To detect the region of the prospective LP and extract the significant data maps, the region of interest pooling layer employs a region suggestion network. The objects of prospective LPs are then fed into the network's final part, which computes the likelihood that it is an LP. In [19], authors presented multi directions YOLO based on CNN framework for LPD. Most previous works use commonly used backbones for feature extraction, such as DarkNet, ResNet version (18, 34, 50, 101, 152), VGG, and DenseNet.

The ResNet [20] structure is based on a model of pyramidal cells in the cerebral cortex and employs jump connections, or shortcuts, to overshoot some layers. Standard ResNet frames are created with a double- or triple-layer jump that includes nonlinearities (ReLU) and batch normalization in between.

In this paper, we proposed a method for detecting vehicle license plates that combines the Sobel filter, connected component, and morphological operations for extracting plate features with a simple deep learning architecture. This latter improves license plate detection accuracy by distinguishing vehicle license plates in images from non-vehicle license plates, without consuming processor resources; therefore, it is qualified to be employed in real time systems.

III. The Proposed Method

The aim of our work is to reach a system for detecting vehicle license plates, in natural scenes that does not consume much time and processors. Figure 1 shows a flow chart of the proposed method for detecting vehicle license plate numbers.

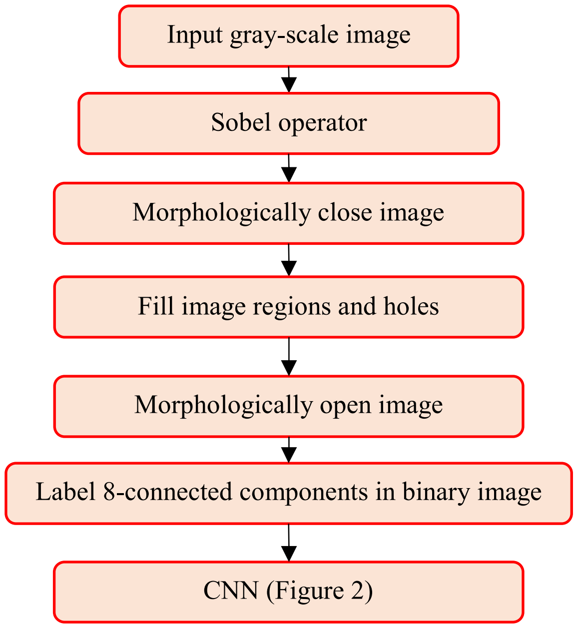

Fig. 1. Main stages of the proposed morphological operations approach

Our proposed method is grouped into two major phases: vehicle license plate detection, followed by the addition of a CNN module to determine whether the detected vehicle license plate number is true or false.

A. *License plate number detection*

The RGB image is converted into grayscale. Besides that, the RGB picture is difficult to segment. As a result, the captured pictures are converted from color level into grayscale images to provide a primary image. This conversion is required to reduce an image's complexity. Morphological operations for extracting plate features is utilized to trait images based on shapes by adjusting the shape and size of a structuring element [21]. It can be considered as a vast array of machine vision operations that process images based on shapes. However, we firstly perform edge detection on the grayscale image using the Sobel method, which find the convergent absolute gradient proportion at all point in an image. When an image is converted to a binary image, the components with an area smaller than an x parameter are removed. Morphological operations can be thought of as transformations with a structuring element that adjusts its shape locally to the image structures and thus has robust filtering efficiencies. The resulting binary image is a subset of a connected compact set that is also scale and rotation invariant; this technique is time and processor intensive.

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B. Deep learning as a process of validation

We use deep learning as a validation process to eliminate the incorrect detection results. Image CNN-based classification techniques are also used to validate detected vehicle license plates due to their high performance for classification problems.

We propose our CNN architect model, which is based on traditional CNN architecture. Our architecture, as shown in figure 2, is tailored to perform vehicle license plate validation on the output of morphological operations. We use a four-layer convolutional neural network with an increasing number of filters and a small filter size.

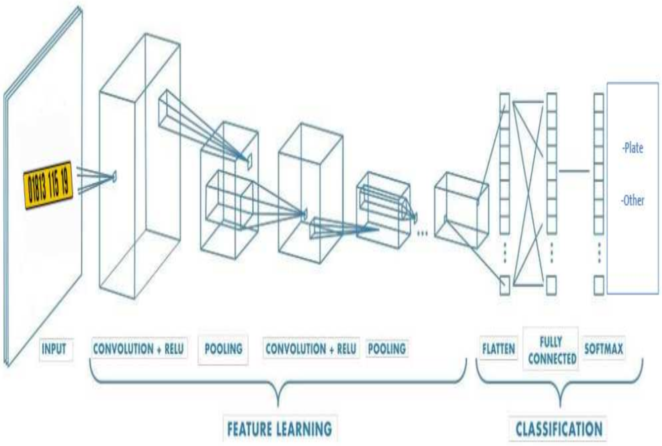

Fig. 2. The CNN model architecture implemented in the case study

In a two-dimensional convolutional layer, sliding convolutional filters are applied to two-dimensional inputs. The layer wraps the image through displacing the filters over the image horizontal and vertical directions, then calculating the results of weights, and finally combining a bias coefficient. Every convolution layer is attached in a rectified linear activation function and a Maximum pool layer. Non-linearity is introduced by rectified linear activation function, and noise removal is aided by maximum pooling.

The first convolution layer conv 1 uses three 3×3 kernels to filter three 224×224 input images. Because the producer of this convolution is over on three channels, three feature maps will be extracted using three kernels and the image is given padding.

C. Database

To apply the proposed method, we created a vehicle license plate number database called "YellowLP," which contains 1050 natural scene color level vehicle images collected under various conditions of size, orientation, color, complex background, contrast, resolution, and ambient illumination.

Figure 3 depicts some image examples from our database. This database contains 600 images of Algerian vehicles and 450 images of UK vehicles, all with yellow license plates and photographed from the rear. The YellowLP database is adequate for license plate detection and recognition research, streetcar surveillance, LPR for mobile applications, access car control in private zones, image car detection, recognition, and classification.

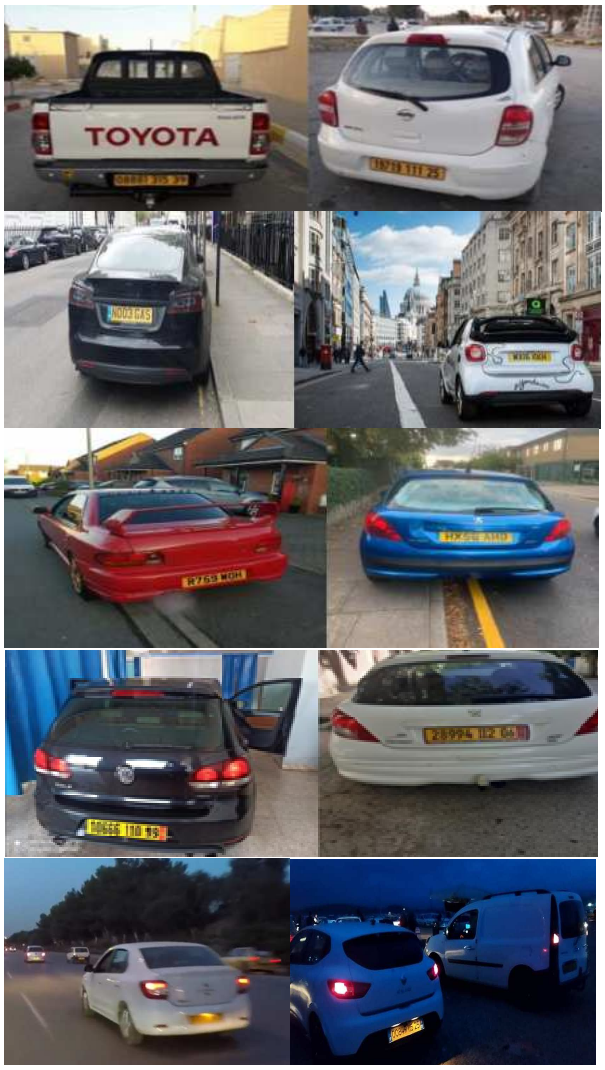

Fig. 3. Examples of images from our database

Figure 4 shows some samples from the baza_slika database [22]. The currently available database contains 510 vehicle images; most are Croatian, Taken under different angle and lighting conditions.

The database is divided in a 3:7 ratio, so 70% of the database assigned for training and the remainder is for testing. Furthermore, because we labeled another non-plate database image (see figure 5), the system gives us two output options: plate or non-plate.

Fig. 4. Example of images from our non-plate database.

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Fig. 5. Some examples from the baza_slika database.

D. The simulation environment

An Intel Core I7-7700 CPU running at 2.80GHz and 2.81GHz with an NVIDIA Quadro M1200 GPU was used for training data.

The input license plate image size is 224×224×3, and the primary learning parameters used in this article's experiment are:

- Initial learning rate = 0.001.
- Factor influencing the decrease in learning rate=0.2.
- The number of epochs required to reduce the learning rate =5.
- The maximum number of epochs allowed =600.
- Size of mini-batch =64.
- learning Rate Drop Factor: 0.3
- learning Rate Drop Period: 7

Figure 6 depicts the proposed CNN architecture's accuracy during the learning process.

The accuracy visualization graph shows that accuracy increased dramatically during the first three epochs, and as we can see from figure 6, we achieved a 100 percent accuracy rate.

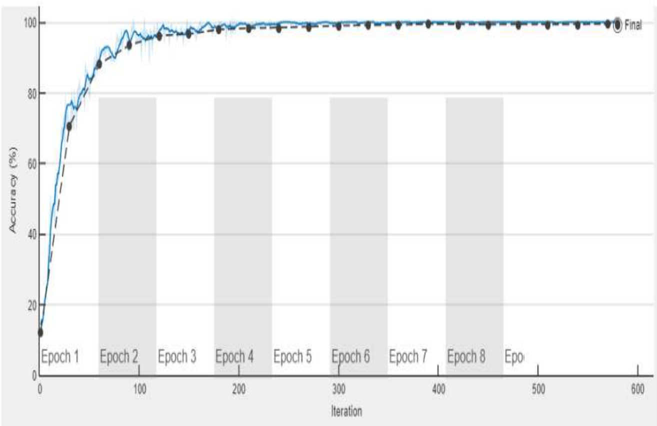

Fig. 6. Accuracy of the proposed CNN architecture during the learning process

Figure 7 shows the proposed CNN architecture's validation loss during the learning process.

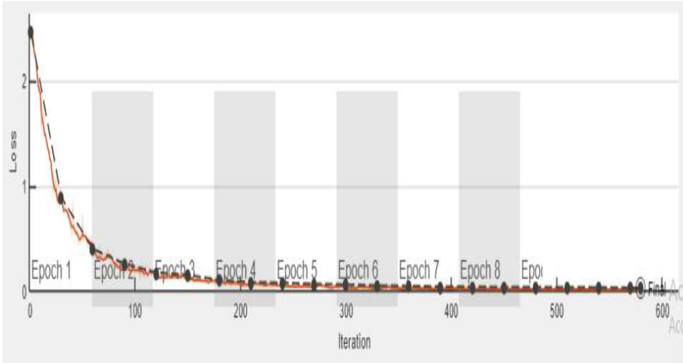

Fig. 7. Validation loss in the proposed CNN architecture's learning process

The validation loss visualization graph shows that during the first 200 iterations, the validation loss drops dramatically and reaches a Loss of nearly 0.

IV. RESULTS OF EXPERIMENTS AND ANALYSIS

In this section, we assess the performance of our proposed license plate detection algorithm. As previously stated, the proposed system's performance was evaluated by running experiments on "YellowLP" database. Figure 7 depicts an example of the process of detecting a vehicle's license plate number, with the result image of each operation shown as: (a) Original image; (b) Sobel operation; (c) morphological close image; (d) morphological open image; (e) detected objects; and (f) detected license plate. As illustrated in Figure 8, the morphological approach can detect other objects than license plates.

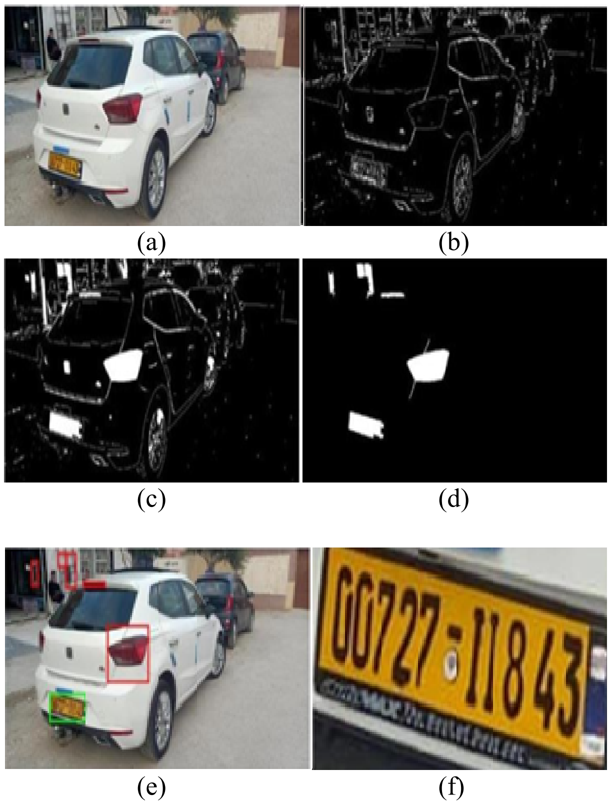

Fig. 8. (a): Original image (b): Sobel opertion (c): morphological close image (d): morphological open image (e): detected objects (f): detected license plate.

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The approach was graded on Precision (Pr), Recall (Re), and Overall Accuracy (OA). These metrics have the following definitions [23]:

$$\text{precision} = \frac{TP}{TP+FP} \quad (1)$$

$$\text{recall} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{OA} = \frac{TP}{TP+FP+FN} \quad (3)$$

As a result, 1014 vehicle license plate numbers were identified as true positives, 14 as false positive and 22 as false negatives. The Pr, Re, and OA of the morphological results are 98.65%, 97.90%, and 96.61%, respectively.

Deep learning is then used as a validation process to eliminate incorrect detection results. Image classification methods based on CNNs are also used to validate detected vehicle license plates due to their high performance for classification problems. Figure 8 and 9 show some examples of how the approach improves morphological results. Table 1 shows that our proposed method capable of distinguishing vehicle license plate and improve the previous outcome.

Fig. 9. Some examples of the proposed approach's outcomes from algerien vehicles.

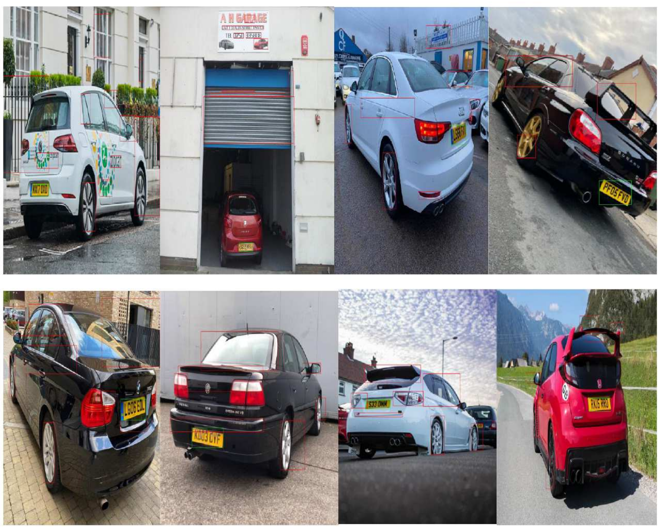

Fig. 10. Some examples of the proposed approach's outcomes from UK vehicles.

TABLE I. CORRECT DETECTION RATE USING OUR APPROACH APPLIED TO YELLOWP DATABASE.

	Detection rate (%)
Algerian Vehicle License Plate	**98,00**
United Kingdom Vehicle License Plate	**97,90**
YellowLP database (all images)	**97,77**
baza_slika database	**98,48**

Fig. 11. Some examples outcomes from the baza_slika database.

TABLE II. COMPARISON OF LICENSE PLATE DETECTION RESULTS BY DIFFERENT METHODS.

	Detection rate (%)
Yu [24]	**92,00**
Al-Ghaili et al. [25]	**91,4**
Silva et al. [26]	**78,00**
Laroca [27]	**98,33**
This work	**98,48**

The recall and overall accuracy of the proposed approach increase to 100% and 98.65%, respectively. As a result, the proposed approach yielded satisfactory results and the average execution time of one image is 0.48 second. As can be seen from Table 2, the experimental results presented on the license plate detection systems suggest that the proposed approaches can be effectively employed to achieve high performance system.

V. CONCLUSION

We presented a method for detecting vehicle license plates based on morphological operations and deep learning. CNN was trained to validate only true detected vehicle license plate numbers images and ignore any false detection images obtained during the preceding stage, ensuring that only the appropriate vehicle license plate numbers are provided in later phases (characters segmentation and recognition). To overcome this limitation, we created a new "YellowLP" dataset containing 1050 images of distinct rear vehicle license plate numbers. The morphological results' precision, recall, and overall accuracy are 98.65 percent, 97.90 percent, and 96.61 percent, respectively, with a detection rate of 97.90 percent. Deep learning raises the proposed approach's recall and overall accuracy to 100 percent and 98.65 percent, respectively. As a result, the proposed technique gives satisfactory results. In the future, we hope to create another database containing front vehicle license plate numbers, develop our optical character recognition (OCR) system, and finally design a complete real time vehicle license plate detection and recognition algorithm.

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