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Automatic Vehicle License Plate Recognition Using Lightweight Deep Learning Approach

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***Abstract*—Intelligent transportation systems rely heavily on automatic vehicle license plate recognition (AVLPR). This system is required for traffic control, electronic toll collection, and access to parking lots. Due to the complexity and structure of license plate design for each country, especially in Arabic countries, license plate recognition is one of the most difficult recognition problems. Using image processing and deep learning (DL) techniques, the proposed AVLPR system is applied to new Iraqi license plates (LPs). We proposed a Lightweight Convolution Neural Network (LWCNN) in this study. It has four convolutional blocks, each with a batch of Max-pooling and Dropout layers, as well as a Flatten layer and two Dense layers. This architecture is simple, fast, and dependable, with promising classification accuracy that could propel the field forward. The proposed algorithm achieved 98% detection accuracy for the standard new PLs style and 85% training accuracy for digits dataset.**

Keywords— Intelligent Transportation Systems, Lightweight Convolutional Neural Network (LWCNN), Character Recognition, Iraqi License Plate, Image Processing, Automatic Vehicle License Plate Recognition (AVLPR).

I. INTRODUCTION

Vehicles with or without stolen license plates have been involved in a large number of vehicle theft incidents and attacks on public and private government agencies over the years. License plates are used to identify vehicles all over the world, and they can be recognized manually or automatically. [1] Automatic detection is primarily used in security applications such as efficient traffic and access control, as well as the detection of restricted areas or vehicles. Vehicle License Plate Recognition (VLPR) is an artificial intelligence and license plate recognition (LP) application that does not require direct human intervention area [2]. Because each country has its own license plate system and design, developing a common NPR is difficult. The VLPR system's control is determined by the image resolution and the camera used to capture the image. Figure 1 shows samples of Iraqi license plates and in this paper, we focus on the latest version.

Fig. 1. Iraqi license plate examples.

The structure of this article is as follows. The literature review of LP detection research is given in Section II. The suggested license plate detecting mechanism will be discussed in Section III. Finally, the findings and conclusion are covered in parts IV and V, respectively.

II. RELATED WORK

Several Arab countries, like Iraq, Saudi Arabia, and Tunisia, have utilized LP identification, and abundant experiments have been conducted to examine this topic in numerous ways [3]. Omar et al. [4] utilized information from Iraq s northern location to survey Iraqi LPs with a CNN exemplar. They used a dataset and it was gathered 1st, then image processing was utilized to enhance the inequity, followed by segmentation of the license plate and the nation location and metropolis place to categorise. Identification, segmentation, and recognition were all extremely felicitous, with 92.10 %, 94.43 %, and 91.01 %, respectively. To find VLPR in Iranian automobiles, [5] and [6] employed a superior template-matching technique. The formula of this program. Training and testing are the two parts of the processing. while testing is done using the K-fold cross-validation approach. According to the validation procedure, 89 percent of all photos may be correctly recognized. [7] utilized a way to blend SCW (Sliding Concentric Window) tech and structural image processing in order to get the finest outcomes for license plate recognition and captured image extraction. In 2019 [8] presented a survey on license plate identification utilizing public roadside surveillance cameras as said by single-shot multi-box detector (SSD) tech in license plate recognition and utilizing similar tech for recognition and license plate-based recognition. License plate brand. In 2020 [9] utilized YOLOv3 for the LP detection and recognition steps with an accuracy of 95-97 % .basically, the YOLO-based algorithm has been pledging for reuse for LP [10]. Additionally utilizes the CNN segmentation manner to extract options and carry out complete ALPS with parallel CNNs. An accessible license plate information set was utilized in their experimental work and a recognition accuracy of 90.51 % was recorded. In 2017 [11] Deep option extraction and the kernel-based extravagant acquiring engine (ELM) classifier were utilized to evolve a

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novel deep draw for Chinese license plate recognition. The depth option extraction was conducted utilizing a pre-trained CNN exemplar, and the experimental outcomes outperformed other CNNs utilizing Soft max or SVM. [12] Proposed a two-step deep approach for detecting ALP backgrounds. The writers identified the place of the car within a delivered image in the 1st step, and during the 2nd step, The fastest territorial CNN was utilized in conjunction with a hierarchical sampling technique in the 1st step to create numerous regions of candidate license plates. In [13] was the use of NNOCR (Neural Network Optical Character Recognition) in NPR.

III. Proposed Method Of License Plate Detection

The mechanism for recognizing license plates is described in this section. An image of the car taken by an image capture equipment serves as the system's input, while the license number's editable form serves as the output. Figure 2 displays the flowchart for the suggested system. Which consists of the following main steps:

1. Input image captured.

2.Image preprocessing.

a. RGB to grayscale conversion.

b. DE noising by Iterative Bilateral Filtering.

c. Edge detection.

3. License plate extraction with contour tools.

4. Character segmentation.

5. Tag recognition using a Lightweight Convolution Neural Network.

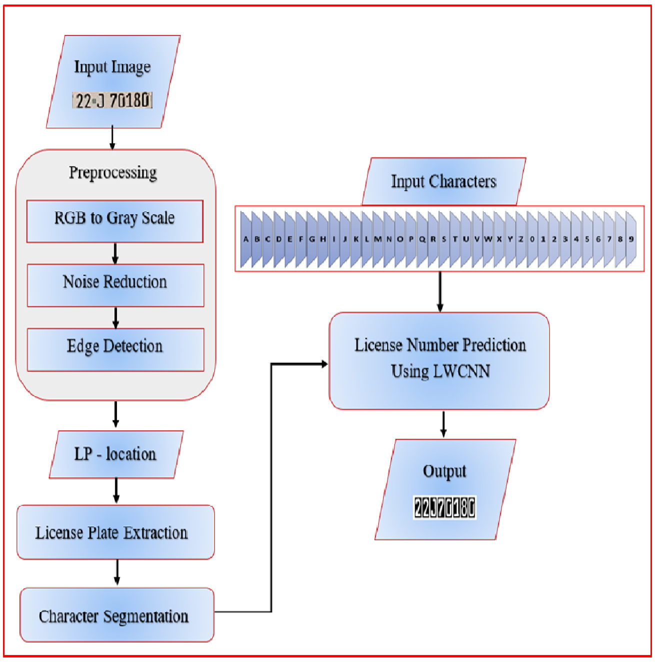

Fig. 2. Proposed method for License Plate Recognition.

A. ACQUIRED INPUT IMAGE

We have two types of datasets in this section:

1. Characters from License Plates.

The dataset used to test our proposed method was obtained from [14]. We anticipate having 8 figures out of 36 figures (A... Z and 0.... 9) On each plate. Each of the 36 figures has a dataset of around 1,000 sample images.

2. Iraqi Driver's License.

We created our own dataset with 306 real-world new Iraqi license plate cars to test the proposed approach. The auto images were created in a variety of lighting and weather conditions, which in our case is taken from an already existing set of images obtained from our smartphone (iPhone X-pro). Figure 3 illustrates samples of new images of Iraqi cars that are available online [15].

Fig. 3. samples of new images of Iraqi cars.

B. IMAGE PRE-PROCESSING

Pre-processing is intended to improve the dataset via enhancing some crucial visual characteristics or suppressing unintentional distortions. This study employed various significant techniques, including (RGB to Gray Scale Conversion, Noise Reduction and Edge Detection).

1. RGB to Gray Scale Conversion

The main purpose of this change is to lower the number of colours as proved in Fig. 3 (a, b).

Fig. 4. (a) Input image (b) Converted to grayscale.

2. Noise Reduction

In this planned manner, we make use of a repetitive bilateral refine for revel removal. It specifies the mechanism for cry reduction in the waiting maintaining edges over other filters.

3. Edge Detection

The task of recognizing the license plate will be easier to complete if the edge detection approach is used first since edges in the binary picture will be more distinct [16].

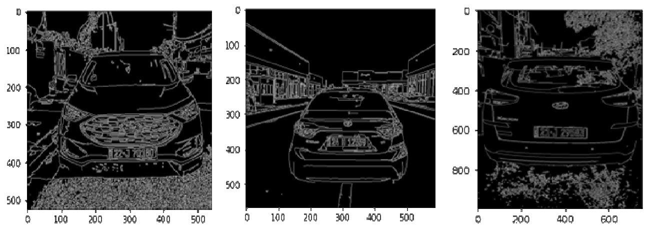

Fig. 5. edge detection using a canny detector.

C. License Plate Extraction

After image processing, the license plate is located by finding all the contours in the input image. The "cv2.findContours" function returns every contour it discovers in the picture. Simply said, a contour is a curve that connects all the continuous points (along the border) and has the same color or intensity. Then, just 10 of the contours are sorted by area. Finally, as illustrated in Figure 4, the location of the license plate is identified.

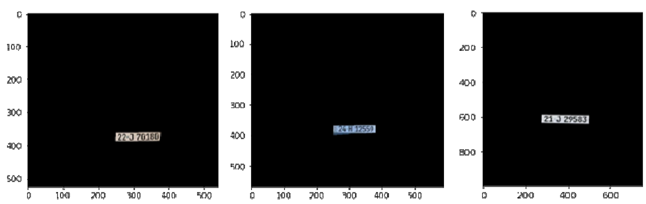

Fig. 6. The results of localizing license plates.

D. Character isolation

The license plate number is directly cut out in RGB format. After that, the grayscale car plate is completely clipped automatically. In the next step, the shape builder is created. By regulating convolution and contrast, the foreground object will be more significant. Finally, the nature of the car's painting type and background area can be changed and filtered. The result in an individual process isolation is proved in Fig. 5.

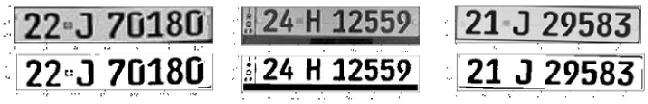

Fig. 7. up number (A). Extracted license plate. Low number (B). Inverted binary image of LP.

E. Character separation

Character separation is done on the double image of the gleaned license plate. Each character/ number has been separately segmented by recommendation of all the contours in the input concept. After finding all the contours we examine them one at a time and calculate the measure of their respective bounding square and draw small four-sided around each integrity as shown in Figure 6(A). For this, we will be performing a few dimensions contrasting by accepting only those rectangles that has a breadth in the range of 0, (length of the picture)/ (number of characters) and distance in the range of (width of the picture)/2, 4*(width of the print)/5. Then extract all the characters as double images as proved in Figure 6(B).

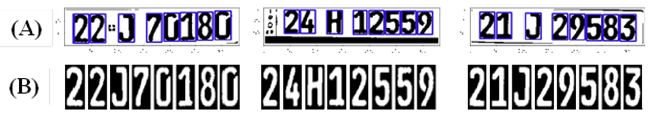

Fig. 8. (A) draw a small rectangular around each character. (B) The binary images of extracted characters.

F. Character Recognition Using LWCNN Model.

The model for deep education a kind of feed-forward interconnected system is a convolutional neural network. Using CNNs to capture adaption invariance, which means that the filter is position-free, can significantly reduce the number of limits. Convolutional, pooling, and completely linked coatings make up the CNN model. These layers complete activity a variety of tasks, containing feature extraction, scope reduction, and categorization. The filter slides over the form of the recommendation during the spiral process of the forward pass and computes the map of incitement, which computes the point-intelligent value of each gain. In this study, we proposed a Lightweight CNN (LWCNN) created to improve act feature extraction and figure recognition with reduced numbers of parameters. The design of the LWCNN is shown in figure 7. As proved in the figure below, it contains four convolutional blocks, each block containing a cluster of Max-pooling and Dropout layers accompanying Flatten layer and two Dense coatings. We used Tensor Flow to train and test our model. Finally, the LWCNN model is fed with the binary images of the number plate characters that were retrieved, and the predicted output is depicted in Fig. 8.

Layer (type)	Output Shape	Param #
conv2d_43 (Conv2D)	(None, 28, 28, 256)	442624
max_pooling2d_30 (MaxPooling2D)	(None, 14, 14, 256)	0
dropout_23 (Dropout)	(None, 14, 14, 256)	0
conv2d_44 (Conv2D)	(None, 14, 14, 256)	37748992
max_pooling2d_31 (MaxPooling2D)	(None, 7, 7, 256)	0
dropout_24 (Dropout)	(None, 7, 7, 256)	0
conv2d_45 (Conv2D)	(None, 7, 7, 128)	13107328
max_pooling2d_32 (MaxPooling2D)	(None, 3, 3, 128)	0
dropout_25 (Dropout)	(None, 3, 3, 128)	0
conv2d_46 (Conv2D)	(None, 3, 3, 128)	6553728
max_pooling2d_33 (MaxPooling2D)	(None, 1, 1, 128)	0
dropout_26 (Dropout)	(None, 1, 1, 128)	0
flatten_4 (Flatten)	(None, 128)	0
dense_10 (Dense)	(None, 64)	8256
dense_11 (Dense)	(None, 36)	2340

Fig. 9. Details of the proposed LWCNN model.

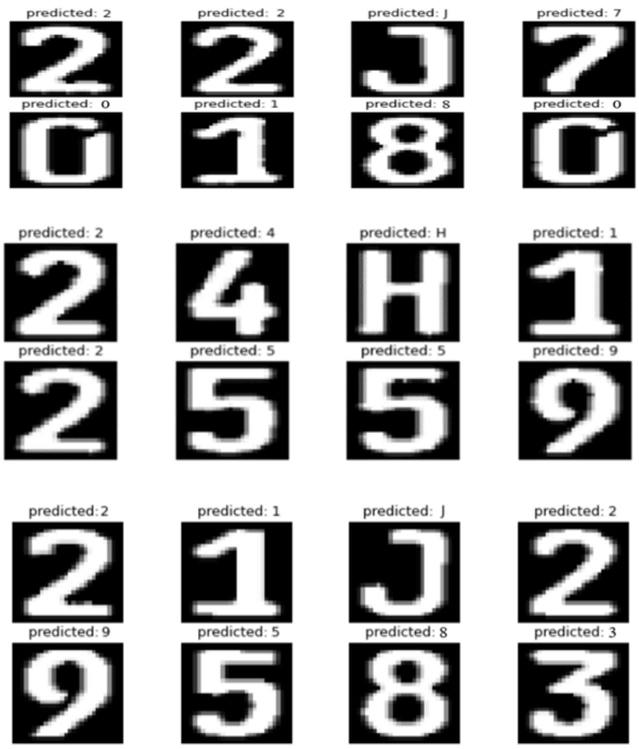

Fig. 10. Character prediction for the proposed LWCNN model.

IV. Implementation And Experiments

The Iraqi Vehicle License Plate discovery and recognition experiments were realized using a PC accompanying the following configuration properties: method type 64-bit computer software for basic operation, x64-based seller, in AMD Ryzen 5 3550H with Radeon Vega Mobile Gfx, 2.10 GHz; and a 16 GB RAM gossip Windows 10 with NVIDIA GeForce 1050. The LWCNN was implemented utilizing python 3.7 on Jupyter notebook [17]. In addition, we have taken advantage of the Keras [18] and Tensor Flow [19] libraries backend.

A. Training and Validation Accuracy.

In this section, we have two tests:

-digits test.

-PLs test.

In first test, dataset contains approximately 1,000 sample figures for each of the 36 figures. We used the first 28,800 samples from a total of 36,000 samples. The curves for the two together settings are proved in Fig. 9 and Fig. 10.

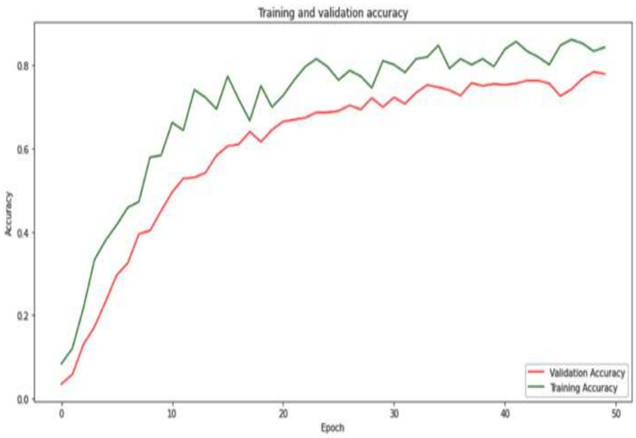

Fig. 11. Training and Validation accuracy of the proposed CNN model for LP recognition.

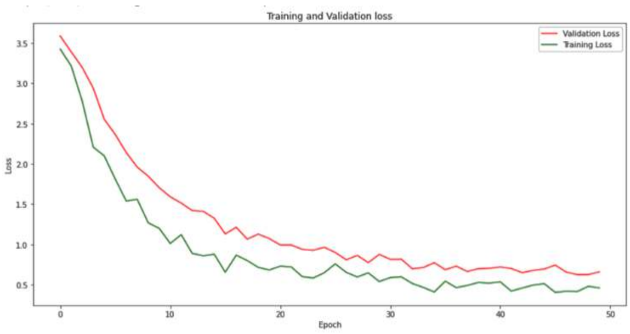

Fig. 12. Training and Validation loss of the proposed LWCNN model for LP recognition.

The accuracy and loss progress, as shown in Figures 11 & 12. Up until it reaches a saturated level when inaccuracy is extremely minor and it varies at a particular level, accuracy rises as the epoch advances. Although it is fading, the loss gets smaller as the period gets smaller until it reaches a specific saturation point. In other words, accuracy establishes the model's quality, whereas loss establishes the model's inferiority. High precision and low loss are typical characteristics of a successful model.

In the second test, we passed all the pictures of cars that we collected using a personal phone, from multiple regions, and under different conditions.

V. Evaluation Accuracy

-For digits test:

The performance measurements employed in this work are training and validation accuracy, which are the most often used metrics and are stated as follows in Eq (1) [20].

$$\text{Accurac} = \frac{TN + TP}{TP + FP + TN + FN} \quad (1)$$

Where, true positive (TP), False-positive (FP), True-negative (TN) and False-negative (FN).

Our model has been tested with original datasets with original dimensions [28 28 1]. It achieved 85% and 80% scores for training and validation accuracy, respectively.

-For PLs test:

We collected 306 models, as we mentioned before, with high resolution, and tested our model on all of LPs. We obtained on 300 images accurate detection; thus, we achieved 98% test accuracy, as follows in Eq (2).

$$\text{Accurac} = \frac{300}{306} \quad (2)$$

Fig. 13. LPs samples error recognition.

VI. Conclusions

This paper proposes an efficient method for LP detection and identification based on concept processing and lightweight convolutional networks affecting animate nerve organs. The presented work employs LWCNN to ensure character LPs are discovered from vehicle images. To ensure Character Recognition, an LWCNN model is projected, trained, and approved. The LP detection and acknowledgment process is divided into three steps: detection, figure pre-processing, and figure recognition. The proposed LWCNN models were tested on a real-world image dataset containing 306 Iraqi vehicle concepts. Under various lighting and weather conditions, the vehicle images were calm. The exploratory results obtained demonstrate the robustness and influence of the proposed approach. For character recognition, we received an accuracy of 85%, and 98% detection accuracy for the standard new PLs style. The accuracy was demonstrated by a higher proportion of correct results. Regarding future work, we will use some of techniques to reshape the LPs to some frames of has a bad view.

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