Research on License Plate Recognition Method Based on Artificial Intelligence Deep Learning

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Abstract: License Plate Recognition (LPR) is a significant technique in most of the applications related to modern traffic, which is widely used in various cases in society like traffic control, smart parking, traffic security, and so on. Due to the growing amount of motor vehicles and the complexity of nowadays traffic conditions, this page uses an automatic LPR system to solve the remaining problems of conventional LPR systems, including the lack of ability to treat datasets of extreme weather and heavy traffic. Deep learning of artificial intelligence is widely used in the network of this page, especially the Convolutional Neural Networks (CNN) network. By building two distinctive CNN networks, this model achieves end-to-end recognition through the application of AI deep learning, which eventually gets rid of the need for manual intervention. At the same time, by leveraging CNN's powerful feature extraction capabilities, the recognition accuracy of license plate characters is significantly improved. Besides, by using MobileNet and Single Shot MultiBox Detector (SSD) networks, the CNN network of license positioning is transplantable and light enough to be used in personal computers without the use of a complex computing system. In contrast to traditional character template matching recognition, the system on this page can handle license plate images in various complex conditions, including all sorts of lightning positions, tilt, blur, etc. The network also meets the requirement of real-time application. The results show that the enhancement can increase the LPR accuracy from 92.57% to 98.43% when blurry or low-quality images are used.

1 INTRODUCTION

Since the license plate is a bright and intensive dark spot of the whole image, a recognition that is capable of capturing and condensing the characteristics of the pictures is necessary (Habeeb, Noman, Alkahtani, et al, 2021). However, since the rapid development of modern society and the enormous number of cars on the roads, the traffic conditions have become more and more complex. Besides, the traditional LPR methods have faced the great challenge of lacking sufficient dataset and robustness as the low-quality analog cameras are not capable of ensuring the quality of images when facing extreme weather and busy traffic conditions. To solve these problems, this paper presents a methodology for engineering a system to enhance the detecting and recognizing procedures of license plates.

There are still many uncompleted aspects of the License Plate Recognition (LPR) method. For example, when meeting the images captured by low-resolution cameras or extensive noises, the Optical Character Recognition (OCR) system is not able to recognize the plate accurately (Hamdi, Chan, & Koo, 2021).

Besides, the conventional LPR method is deeply affected by light, shadow, dark spots, and the background scenes. By introducing AI deep learning to the LPR system, the system can figure deeper characteristics, which improves the recognition accuracy greatly (Weihong, & Jiaoyang, 2020). What's more, in the field of managing and mapping complex high-dimensional functions like chromatic images, deep learning stands for the best performance (Abedin, Nath, Dhar, et al, 2017).

Above all, a new way of deep learning is proposed for license plate images in this report. Besides, a reinforcement to LPR is shown in this paper. The contrast between the solution and the classical methods is exhibited in this paper.

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2 METHODOLOGY

2.1 Dataset Introduction

This paper uses two distinguishable datasets, one is used for training the license distinguishing and positioning network, and the other is used for character segmentation and recognition. The dataset used for license positioning contains about 2,000 photos which includes a diverse range of cars' images at the front side. In this way, can the research imitate the complex traffic conditions and the limited quality of images captured by low-quality analog cameras.

Since the problem of the low capability of detection of current modules is about to solve, the Chinese Car Parking Data set (CCPD) has been used for the training of character recognition, which is the size of 12GB, including over 30,0000 Chinese plates' images (Khan, Ilyas, Khan, et al, 2023; Hu, Li, Li, et al, 2020)).

Besides, this paper also used an open dataset from GitHub. The dataset includes the following characters: the Chinese abbreviation of 34 different provinces, 24 English letters, and 10 mathematic letters. The resolution of these images is 128*48, and the image type is jpg format. Sore of original data: CSDN: GitHub - SunlifeV/CBLPRD-330k: China-Balanced-License-Plate-Recognition-Dataset-330k, which is ideal for training and evaluating license plate recognition models.

2.2 Modle/Advantage

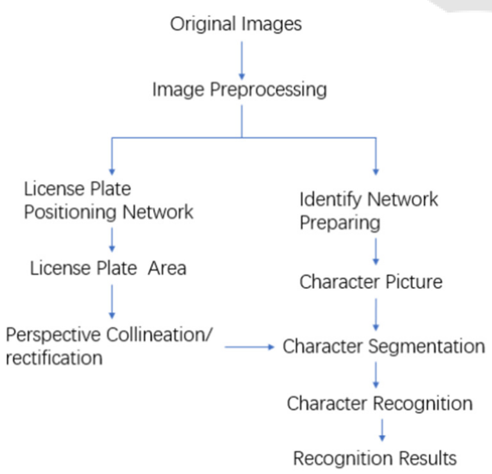

Figure 1: The specially ordered system of the LPR network and the steps used to translate the original license images to recognition results (Photo/Picture credit: Original).

As shown in Figure 1, the general LPR system can be divided into four parts: image processing, license positioning, character segmentation, and character recognition. As the detection and recognition of license plates are two separate modules, the LPR networks are always divided into two distinctive parts (Kessentini, Besbes, Ammar, et al, 2019).

In this page, the LPR network uses two distinctive deep-learning CNNs, which contain different data sets for training, including a license plate location model and a character segmentation and recognition model. Through image processing, the original images are processed to a resolution and size that is easy for the model to accept. While the identified network begins to prepare, the images then enter the license plate positioning network. In the license plate positioning network, the license plate area is framed and then transmitted to the recognition network after perspective collineation/rectification. After character segmentation and character recognition, the model will output the recognition result (In the form of text, stored in a Word document).

Convolutional Layer: The convolutional layer employs convolution operations to extract image features, which can be mathematically expressed as:

$$Y[i,j] = \sum_m \sum_n X\,[i+m, j+n] * K[m,n] \quad (1)$$

Where X is the entering image, K is the convolution kernel, Y is the output characteristic picture.

i refers to the line number in the output characteristic picture (Y), j refers to the column number in the output characteristic picture(Y). In other words, (i,j) is a spot in the output characteristic picture(Y).

m refers to the line number in the convolutional kernel (K), and n refers to the column index in the convolutional kernel (K). Also, (m,n) represents all elements of the convolution kernel.

$$Y[i,j] = \sum_m \sum_n X\,[i+m, j+n] * K[m,n] \quad (2)$$

This equation describes how to calculate the figure at the position of (i,j) in the output characteristic picture (Y).This process reaches the goal of sliding and scanning the convolutional kernel on the original images, which will condense the feature value of all images.

ReLU Activation Function: The ReLU activation function is used to add nonlinearity to the network.

$$f(x) = \max\,(0, x) \quad (3)$$

In this equation, x and $f(x)$ refer to the input and output of the ReLU activation function.

Batch Normalization: Batch Normalization is used to accelerate the training process and improve the stability of the whole system, which is realized through normalizing every single little amount of data.

Residual Block: Residual Block is used to solve the gradient vanishing problem of the CNN network, which can be realized by introducing skip connections. Mathematically represents as:

$$Y = F(X, \{W_i\}) + X \tag{4}$$

Where $F(X, \{W_i\})$ represents residual function, X and Y are the input and output.

2.3 The Convolutional Kernels Being Used and the Concrete Function Methodology

To realize the license plate locating, this module uses a CNN network, which includes the MobileNet module. Designed to classify the images, the MobileNet is a module containing 53 CNN layers (Jawale, William, Pawar, et al, 2023).

As a slight mobile module, MobileNet provides the whole model with a better embedded environment. Based on MobileNet, this program also compiles its own unique license plate recognition CNN network, which includes several convolutional kernels, ReLU activation functions, batch normalization, and residual blocks. Besides, the network also uses SSD as a component and auxiliary. The specific layer design is as follows:

The module begins with two convolutional kernels, and every convolutional kernel comes with a batch normalization layer and a ReLU activation layer.

Following is a max pooling layer.

Then comes two convolutional kernels (every single one is followed with a batch normalization layer and a ReLU activation layer) and a residual block.

Following, there is a max pooling layer.

This strategy (two convolutional kernels, one residual block, and one max pooling layer) repeats twice.

Finally, the last convolutional kernel is used to output the license plate location and bounding box.

2.4 The Process of the Experiment

License plate recognition can be divided into four steps: License Positioning, Image Processing, Character Segmentation, and Character Recognition.

2.4.1 License Positioning

The training of the license detection module:

A predefined module structure is being used to train the module.

Loading the training data, which includes the images and the related tags (the position of the plate).

Using a personally defined loss function to train.

After training, save the whole module.

The establishment of the module structure:

To create a module based on CNN, the network used residual blocks and an SPP（Spatial Pyramid Pooling） module.

The network employs ReLU and uses batch normalization to accelerate the training process to avoid overfitting.

The method of identifying the edge of the plate is used in the input images. (Lin, & Sie, (2019).

Likewise, the output of the module is a feature map, which is used to outline the position and bounding box of the license plate.

Using the trained module for license plate detection:

Loading the trained module.

Preprocessing the input images, including resizing and normalization.

Using the module to detect the license plate, output the position and edge of the plate.Saving the license plates as images.

2.4.2 Image Processing

The detected license plate images are resized to an uninformed resolution (80x240).

2.4.3 Character Segmentation and Character Recognition

The design of the CNN module includes several convolutional layers, pooling layers, batch normalization layers, and activation layers. The specific design is as follows:

1)Input layers: Accept the image resolution of 80x240x3.

2)Convolutional layers: Use a 3*3 convolutional kernel with an astride of 1 and padding set to ‘same’.

3)Batch normalization layer: Normalize each output of all the convolutional layers.

4)Activation layer: Use the ReLU activation function.

5)Pooling layer: Use a max pooling of 2*2 and a stride of 2.

6)Residual blocks: Are used to deepen the internet depth and improve the performance.

7) Output layer: Outputs the probability distribution of each character in the license plate. The outcome of the same image could vary in prediction characters (Alghyaline, 2022). So the probability distribution of each image is necessary.

2.5 Math Function Design

Convolutional layer:

$$Y = W * X + b \tag{5}$$

Where, W is the weights of convolutional kernels , X is the input feature map, and b is the bias term.

Activation function (ReLU):

The function is the same as function (3).

Polling layer (max pooling):

$$Y_{i,j} = {}_{m,n \in R_{i,j}}^{max} X_{m,n} \tag{6}$$

Where, $R_{i,j}$ is a block of the input feature map, $Y_{i,j}$ is the maximum value of the map.

Batch normalization layer

$$\mu_B = \frac{1}{m}\sum_{i-1}^{m} x_i \tag{7}$$

$$\sigma_B^2 = \frac{1}{m}\sum_{i-1}^{m}(x_i - \mu_B)^2 \tag{8}$$

$$\widehat{x_i} = \frac{x_i - \mu_B}{\sqrt{\sigma_B^2 + \varepsilon}} \tag{9}$$

$$y_i = \gamma \widehat{x_i} + \beta \tag{10}$$

Where, μ_B and σ_B^2 are the mean and variance, $\widehat{x_i}$ is the value after batch normalization, y_i is the output after scaling and shifting.

Loss function (Self-defined):

$$L = L_{probs} + L_{bbox} + L_{cls} \tag{11}$$

Where, L_{probs}, L_{bbox}, and L_{cls} are the loss of probability, bounding box, and category.

3 RESULTS AND DISCUSSION

In a huge amount of distinguishable environments, the license plate positioning accuracy can rise to 98.37%, with the final recognition accuracy rising to 97.43%. In the environment of Windos11(x64), the average recognition time of a single image of all sizes is 2.70s.

In recent years, AI deep learning has been widely employed in the LPR method (Gnanaprakash, Kanthimathi, & Saranya, 2021).

Instead of using the traditional YOLO module, the research of this page uses the combination of MobileNets and SSD for character recognition, along with a manually crafted CNN recognition module. MobileNet, a lightweight neural network module proposed by Google in 2017 specifically designed for mobile or embedded devices, can significantly lower the number of modules and computations when keeping a high accuracy to get used to the limited environment resources. The core technology of MobileNet includes Depthwise Separable Convolution, which decomposes the standard convolution into Depthwise Convolution (DW) and Pointwise Convolution (PW). Through these methods, can the network significantly reduce the complexity.

Compared with the widely-used LPR module constructed by You Only Look Once (YOLO), the method of this page has the advantages of being both lightweight and high-performance. Its smaller size module can save enormous storage space and computing costs when deployed or removed into embedded devices. Besides, it can significantly lower the computing costs. What's more, although the size of the network is small, its performance is not inferior to many large CNN networks. MobileNets is the upgraded version designed by Google company, which created the GoogleNet before the MobileNets.

However, the huge amount of the training data used in the training process of GoogLeNet is a crucial problem (Pham, 2023). Besides, since the partnership of FPN and TOLOv3, the quality of the devices is required while the speed is slow (Hu, Li, Li, & Wang, 2020). By contrast, MobileNets is much smaller in size when meeting nearly the same accuracy as Inception-v3 (PuarungrojM & Boonsirisumpun, 2018). As a result, the network created by this page can be successfully run on personal computers without the help of high-quality graphics cards. However, as the complexity being sacrificed, and the training sample are less than those of the general YOLO module, the recognition efficiency of this page is slightly lower than the LPR module using the YOLO method.

4 CONCLUSION

Through applying the CNN network of AI deep learning to the LPR network, the module introduced in this page achieves the end-to-end license plate recognition system, avoids unnecessary manual intervention, and realizes the complete license plate recognition process. With the help of the CNN, by contrast to the traditional character-matching license plate recognition method, this module has greatly improved the detection rate and robustness in processing license plate images in several complex conditions, like traffic jams, extreme weather, or low-frequency cameras, etc. At the same time, the CNN network also solves the problem of the real-time requirement of LPR.

The License plate recognition method can be divided into four separate parts: License plate recognition, Image preprocessing, Character recognition, and subsequent processing. In the network of this page, both the license positioning and the character recognition use the CNN network, which also has been carried out with appropriate training. The location module is based on the object detection framework (the combination of MobileNet and SSD), which outputs the bounding box and images of the license. After the operation such as cutting, correction, and scaling in the image preprocessing method, the images will be then transmitted to the character recognition network. In the character recognition network, the module uses a CNN network to recognize the processed images, and finally output all the probabilities of each character. In the subsequent processing process, the module avoids repeated detection and determines the final result based on the probability distribution.

In contrast with the traditional character template matching method, since the self-learning character of deep learning and sufficient dataset, the generalization ability of this module has been enhanced significantly. Besides, the module contains an enormous image preprocessing function and image optimization process, which can greatly expand the approaches of resources of the character and template, avoid the manual design, and reduce the development workload.

Apart from the other formal AI deep learning LPR method, the computing time of the network on this page is highly reduced. At the same time, using the CPU with weaker capabilities and higher resolution images, the module reaches the goal of being lightweight and portable, which lowers the costs compared to the other method based on high-quality CPU/GPU. However, due to the sacrifice of complexity and the smaller amount of training dataset, the accuracy of this module can not exceed the accuracy of the LPR module using YOLO.

Nevertheless, this module also has some disadvantages and shortcomings. The complexity of the module remains high, which costs many computing resources and time to train the module. What's more, compared with the traditional character template matching method, since CNN training needs a great amount of data, the recognition accuracy closely relates to the size and quality of the training dataset. The interpretability of the decision-making process within deep learning models is relatively poorer than the traditional character template matching method.

This page designs an accurate and correct LPR network based on AI deep learning, which shows good performance and robustness in practical applications. In the future, the goal of this research is to improve the module structure and design of the function further. At the same time, the exploration of combining the LPR technology with other traffic methods under many practical circumstances will be put on the agenda, like intelligent parking, and electronic toll collection (ETC).

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