Automatic License Number Plate Detection And Recognition

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1. Abstract

In this project, a system that can detect and recognize automatic license number is developed. Overall, we will leverage traditional image segmentation and deep learning-based image classification to complete this task. There are four parts in the following: In "Introduction", we will describe the aim and objective of this task as well as the background knowledge. In "Implementation", the detailed methodology will be introduced. Then we will evaluate the results and analysis the outcomes at "results and analysis". Finally, we conclude the project at "Conclusion".

2. Introduction

2.1 Aim and Objective

In recent years, with the popularization of the concept of intelligent transportation, license plate detection and recognition applications have spread across all aspects of our lives, including parking lot charging systems in communities, violation monitoring systems at intersections, and mobile handheld police systems for traffic police. With the advent of deep learning, the recognition accuracy of license plate detection and recognition algorithms based on deep learning has been further improved. At the same time, complex and changeable application scenarios put forward higher requirements for the accuracy of the algorithm. How to make the system work stably in a more complex environment has become the focus of research in recent years[1-3].

This project studies and implements an automatic license plate recognition system, which consists of license plate location module, character segmentation module and convolution neural network recognition module. This paper mainly studies the use of pytorch development platform, the construction of CNN convolution neural network, through the use of the collected license plate images, training neural network has good license plate recognition image ability.

2.2 Background research

License plate positioning is the first step in image processing by an intelligent license plate recognition system, and it is the premise of license plate correction, character recognition and other steps. For license plate location, the commonly used algorithms are divided into two categories: the first is the traditional license plate location algorithm; the second is the method based on machine learning.

In the existing license plate recognition systems, most license plate positioning systems are based on the color, edge, texture and other characteristics of the license plate. Up to now, a large number of license plate localization algorithms have been derived, such as morphological features algorithms, color features localization algorithms, and edge detection localization algorithms.

- ***Morphology-based license plate location method***

A common mathematical method in license plate recognition is mathematical morphology, which processes a collection of pixels and uses a specific structure in the image to locate the region. The basic principle of mathematical morphology is corrosion and expansion. The open operation is to corrode first and then to expand, which is used to deal with the small spikes in the license plate image and keep the area of the license plate area unchanged. On the contrary, the closed operation is to expand and then corrode, which is used for Bridging small cracks in license plate images and filling in tiny voids[4].

- **License plate location algorithm based on color feature**

Based on the color characteristics of the license plate, the RGB color license plate image is first converted to the HSV color space that is more suitable for the human visual system. Select suitable color characteristics by setting different hues, saturation and brightness[5]. Then the histogram equalization operation is performed to make the grayscale range of the image larger, and the contrast and clarity are enhanced, which is beneficial to the enhancement of the local contrast of the license plate image. Then detect the HSV component of the pixel points in the image, complete the license plate color detection, and complete the location of the best license plate area combined with prior knowledge such as license plate size.

- ***License Plate Location Algorithm Based on Edge Detection***

The color difference between the edge of the license plate and the surrounding area is large, which can reflect the obvious characteristics of the license plate area. Therefore, in the license plate location algorithm, the feature of the large brightness jump between the edge pixels of the license plate and the background is often used to quickly distinguish the edge of the license plate and realize the location of the license plate[6]. The algorithm first performs preprocessing operations on the license plate image, such as basic denoising, grayscale, enhancement and other operations, so as to obtain an image with a clear license plate boundary. By selecting an appropriate edge detection template, the boundary of the license plate area can be segmented so as to realize the location of the license plate.

- ***Convolutional Neural Network***

The basic CNN network generally consists of convolutional layers, pooling layers, activation functions and other parts. Among them, the convolution layer and the pooling layer are generally applied in the front part of the network. The convolution kernel is used to scan the image line by line, and the convolution operation is used for the image to extract the image code as a feature vector. In order to perform classification processing, the fully connected layer is usually selected as the last layer of the network, which realizes the mapping from the image feature space to the sample label space, and realizes the classification of the network output. The activation function can realize the mapping of a nonlinear neural network to linear expression and improve the expressive ability of the network. The license plate location algorithm based on a convolutional neural network usually does not need to denoise the image, data enhancement and other operations, and can directly use the license plate image as the input of the network, so as to realize the accurate location of the license plate.

The license plate recognition based on convolutional neural network can be divided into two categories. The first category is to use segmentation strategy, by segmenting the characters of the located license plates, and then sending the segmented characters into the network for training. The second type is to use the non-segmentation strategy to directly send the entire license plate into the network for training, so as to obtain the final recognition result. Generally speaking, the strategy of character-by-character segmentation of license plates relies heavily on segmentation algorithms, and once segmentation errors occur, it is easy to cause recognition errors. And a single improvement in the recognition accuracy of a character does not represent an improvement in the overall recognition performance. If the license plate characters are not segmented and a single convolutional neural network is used, the recognition accuracy is likely to be low due to the structural differences between Chinese characters and digital letters. Therefore, improving the overall efficiency of license plate recognition under the premise of as few segmentations as possible is still the focus of research.

Convolutional neural network is a feedforward neural network. Compared with fully connected neural network, convolutional neural network is more suitable for processing two-dimensional features, so it is often applied to image-related fields, such as image recognition and classification, and detection of objects in images. , Semantic segmentation of images and super-resolution reconstruction of images. A convolutional neural network at each layer can be viewed as a non-linear mapping from one feature space to another. Due to the addition of the back-propagation algorithm, the convolutional neural network can separate the multi-dimensional features of the input image through learning and training. For common image recognition and classification tasks, the input sample image will first go through a convolutional neural network, and the convolutional neural network will extract the features of the image and classify them according to these features. A convolutional neural network usually consists of three parts, a convolutional layer, an activation function layer, and a pooling layer. With the development of deep learning, Batch Normalization (BN) has also become an important part of Convolutional Neural Networks.

License plate localization can be regarded as a specific target detection task, so relevant scholars mainly improve the related network of target detection to make it better applied to the task of license plate localization. Aiman at Ref [7] introduced Faster-RCNN into the license plate detection task. By combining with ResNet-101, the final detection accuracy rate reached 97.2%, and the localization effect was significantly better than the traditional localization algorithm. By improving the YOLO model, Xie Lele at Ref [8] and others proposed a CNN-based MD-YOLO framework to detect multi-directional license plates with high accuracy. Hendry [9[]] et al. proposed a deep learning license plate recognition technology based on Darknet-YOLO. Based on the idea of YOLO's one-stage algorithm, detection and recognition are completed in the same stage. And reduce the original YOLO framework to 13 CNN layers, using 36 miniature YOLO models to achieve 36 types of character detection and recognition.

The most important part of the convolutional neural network is the convolution layer. The convolution operation of the convolution layer usually refers to the multiplication and addition operation corresponding to the convolution kernel and the input feature map. In a convolutional layer, the input feature map is a four-dimensional tensor of shape B*H*W*C, where B is the number of images, H is the feature map height, W is the feature map width, and C is the number of feature map input channels.

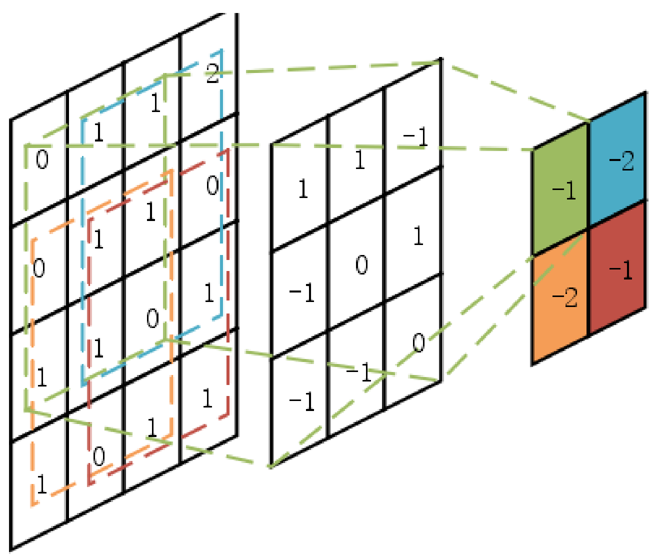

Figure 1 Convolutional Layer

The pooling layer can also be called a downsampling layer. Its main purpose is to reduce the amount of network data and parameters, while retaining the feature map information, and is conducive to solving the problem of overfitting. While reducing the amount of network data and parameters, the pooling layer also has the characteristic of scale invariance of features. For example, when a picture of a car is doubled, the human eye can still distinguish it as a picture of a car. This shows that although the image is doubled, the scale-invariant features of the car are preserved, and some redundant pixel information is removed. Common pooling operations include max pooling and average pooling.

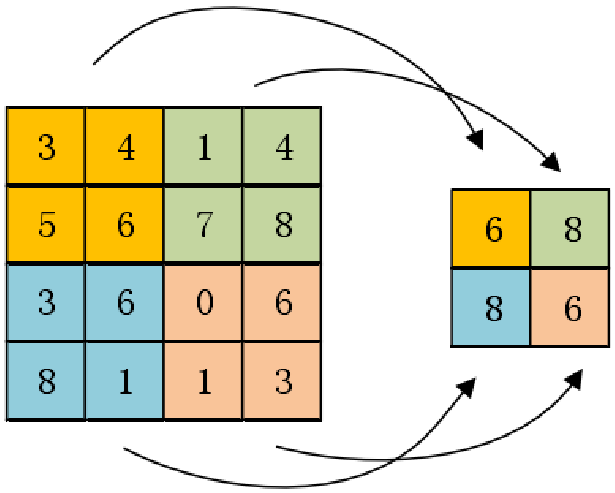

Figure 2 Maxpooling Layer

3. Implementation

In this part, we are going to introduce three steps to recognize the plates of license. The license plate location module first loads the trained license plate detection model, which mainly includes the trained network structure and parameters. After loading the data to be detected, the license plate positioning module realizes the positioning of the coordinates of the four vertices of the license plate, and then cuts the license plate part to obtain a picture that only contains the license plate area. The license plate character recognition module first corrects the located license plate image, and then realizes the segmentation of characters, and then sends the two divided images to different recognition networks for recognition, so as to obtain the final license plate recognition result.

3.1 Plate location Detection

In this section, we take one of images as example.

Figure 3 Image of Car

The first step is to Convert Image to Grayscale.

Figure 4 Gray image of Car

Then we will find the contours of image to locate plate.

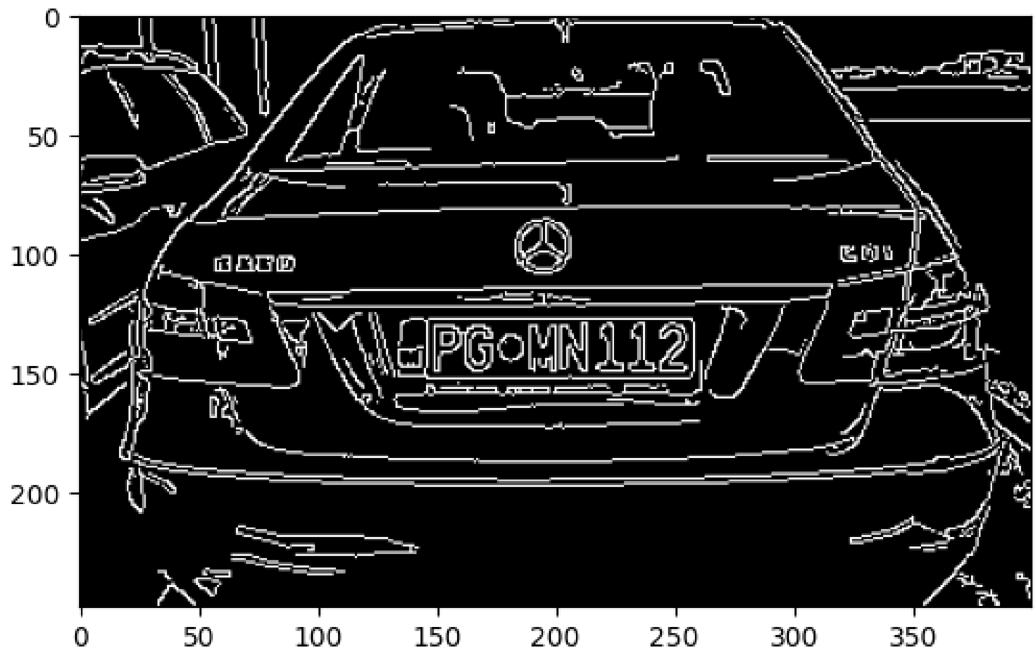

Figure 5 Contours image of Car

After noise reduction and Edge detection, we are going to find the countor of plate.

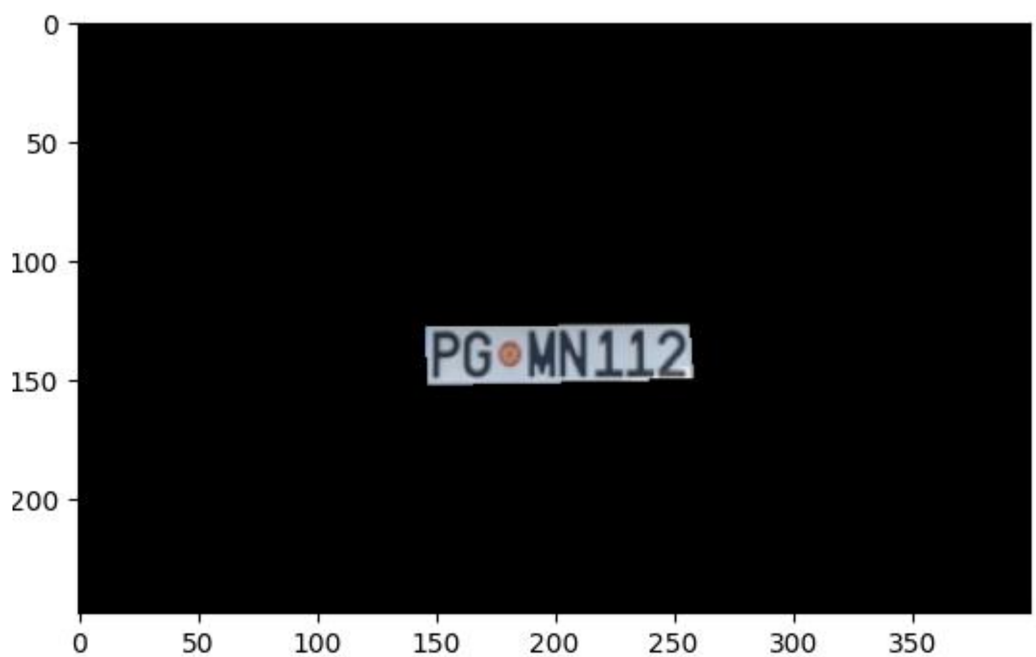

Figure 6 The Contours of lissence plate

Then we will resize the image to the plate size as Figure 7.

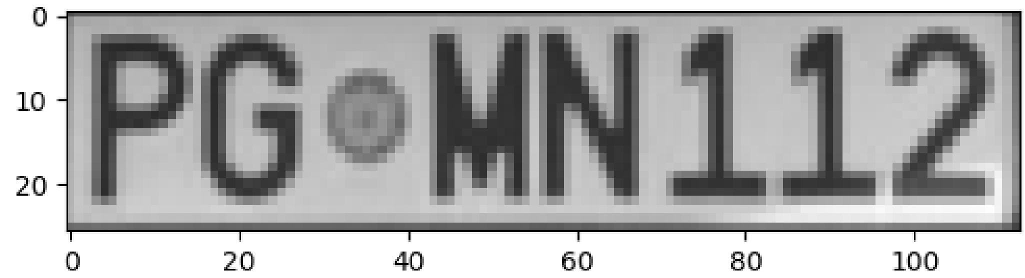

Figure 7 The image of lissence plate

3.2 Character segmentation module

To match the outlines to license plate or character templates, we are going to take the following step. The input is a grayscale image as Figure 8.

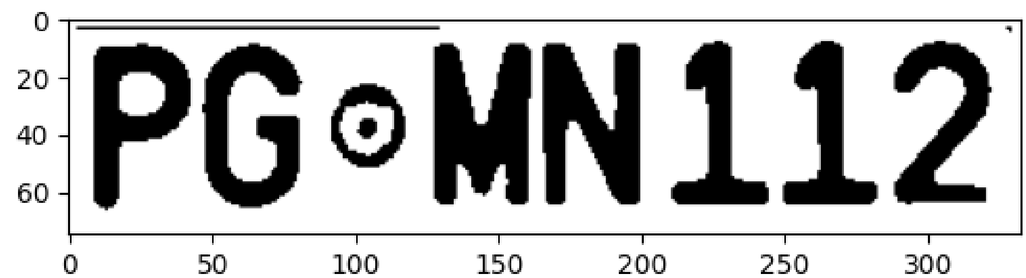

Figure 8 The gray image of license plate

- Find all contours in an image
- Retrieve latent dimensions
- Check up to 5 or 15 outlines of license plates or characters, respectively
- Detect contour in binary image and return coordinates of rectangle enclosing it
- Check the size of the outline to filter out characters by the size of the outline
- Stores the x-coordinate of the glyph for later use in indexing the outline
- Extract each character using the coordinates of the enclosing rectangle.(As Figure 9)
- Make results in categorical format: invert colors
- Returns characters in ascending order relative to the x-coordinate (leftmost character first)
- Split the whole figure into splitting figures belongs to each character.(As Figure 10)

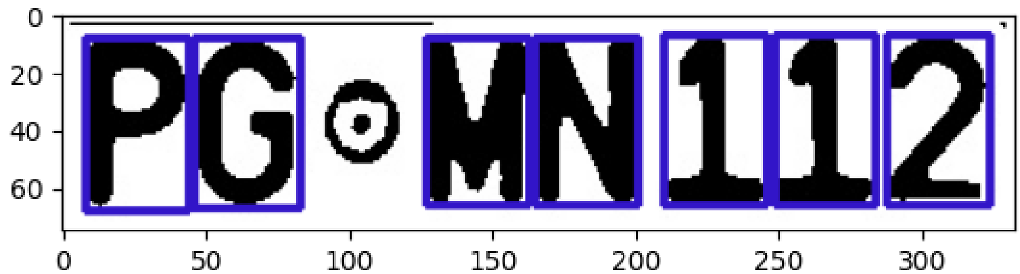

Figure 9 The Contours of each character

Figure 10 The split image of each character

3.3 Convolution neural network recognition module

After we have obtained each figure of the character, we need to train a model to recognize it. The first choice is LeNet-5[10], which is commonly used to classify the MNIST Handwriting Dataset.

LeNet consists of 2 parts:The first part includes two convolutional layers and two pooling layers which are placed alternatively. The second part consists of three fully connected layers.

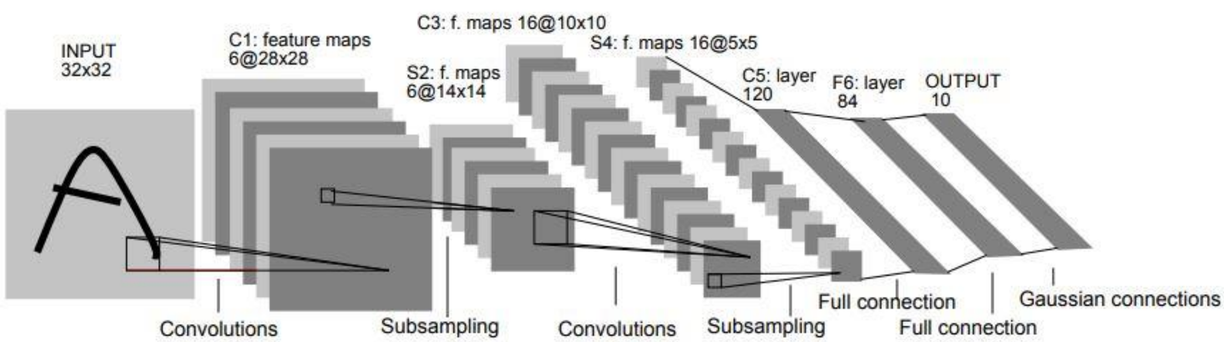

Figure 11 LeNet Architecture

LeNet-5 is commonly regarded as the pioneer of convolutional neural networks, consisting of a very simple architecture (by modern standards). In total, LeNet-5 consists of only 7 layers. 3 out of these 7 layers are convolutional layers (C1, C3, C5), which are connected by two average pooling layers (S2 & S4). The penultimate layer is a fully connexted layer (F6), which is followed by the final output layer. The additional details are summarized below:

However, we need to rectify the LeNet-5 to make it output 36 categories: “0123456789ABCDEFGHIJKLMNOPQRSTUVWXYZ”. The datasets can be seen in Figure 12.

Figure 12 The datasets of 36 characters

We will also normalize the image size of these 36 types of characters, and the unified size is 28×28 to obtain characters dataset.

4. Results and Analysis

4.1 LeNet Results

Here we split the data into 80% training sets and 20% testing sets. The training epoch is 200. The learning rate is 0.001 and the optimizer is Adam. Then in Figure 13, we can see that the loss converges to small value after enough iteration.

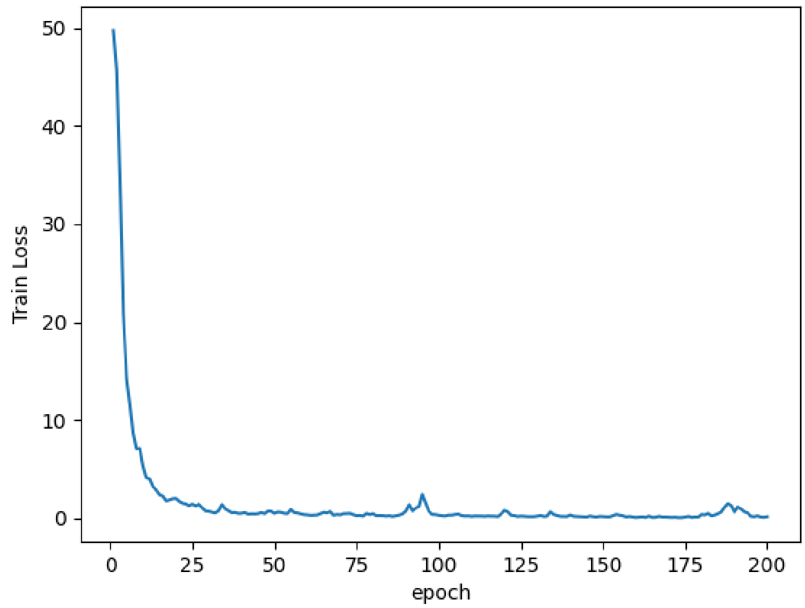

Figure 13 Loss convergence

In Figure 14, we can conclude that both the training accuracy and the testing accuracy is nearly 100% after enough training iterations. There is no obvious overfitting problem.

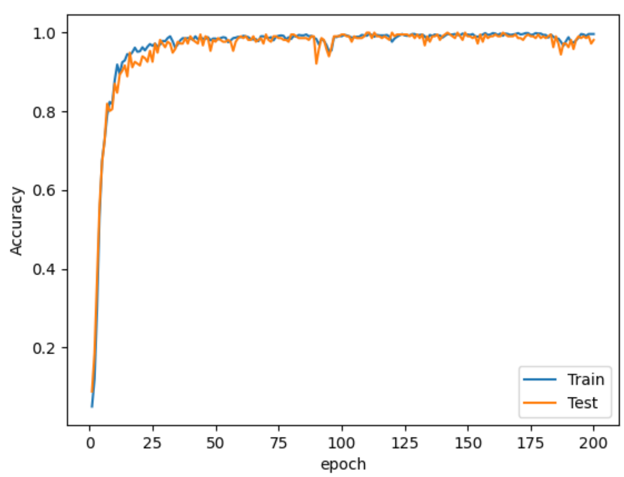

Figure 14 Accuracy

4.2 Detection Results

In Figure 15, we show some results of detections. We can find some interesting conclusions:

- The easiest license plate is white background and black character.

- “1” and “T” , “0” and “O”, “B” and “8” are most difficult to recognize. This is because that they are almost same in writings.
- Sloped license plates are not easy to detect.

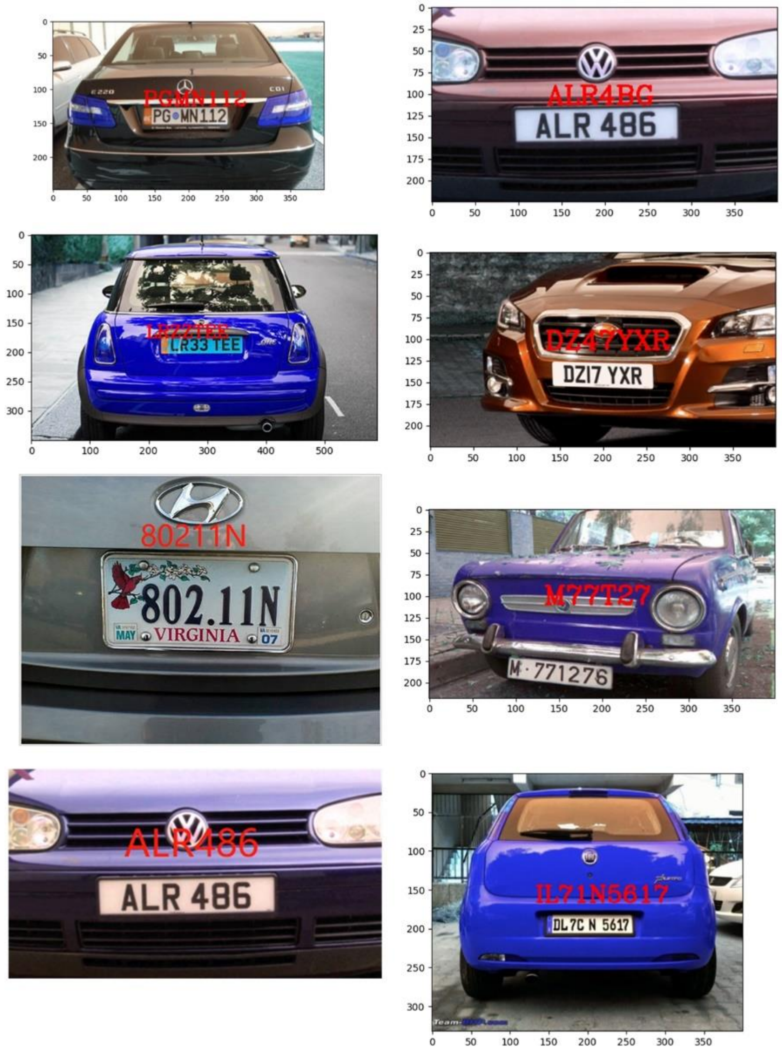

Figure 15 Detection results

5. Conclusion

The license plate recognition system is an important part of the vehicle management system. Accurate positioning and recognition of the license plate has been a hot spot in the research of intelligent traffic management systems. First of all, to solve the problem of license plate location in complex natural scenes, this project studies the license plate location algorithm based on tradititon contour segmentation algorithm using Opencv. Then, the LeNet-5 model structure is introduced. Finally, combine the license plate location module and the recognition module to construct a complete license plate recognition system. Experiments have proved that the algorithm in this project can realize the positioning and recognition of license plates.

Reference

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