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A Deep Learning Image Recognition Method Based on Edge Cloud Computing

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Due to the continuous development of computer technology, digital image technology has penetrated all fields of production and everyday life. However, although the transmission and storage facets of this technology are quite mature, image recognition has always undergone constant improvement both in domestic and foreign research. Edge cloud computing and deep learning can both be used to effectively improve the data processing capacity. To ascertain the effectiveness of these methods, a study was conducted using the deep learning method of edge cloud computing for license plate recognition. This article examines the current image recognition methods that perform well, focusing mainly on the recognition of license plates, and exploring the ways in which the existing traffic monitoring and recognition system can be upgraded and improved by using the deep learning method of edge cloud computing. The principles related to deep learning in edge cloud computing were studied in detail, and on this basis, a Hadoop cloud platform was built and applied to the traffic monitoring and identification system. In addition, the algorithm and simulation of license plate recognition are introduced and analyzed. The research results show that license plate recognition based on the deep learning method of edge cloud computing method is feasible, and the overall traffic monitoring recognition system is faster and more accurate. Compared with the traditional monitoring recognition system, the recognition accuracy increases by 15% and the recognition speed is improved by around 7.5%.

Keywords: Edge Cloud Computing, Deep Learning, License Plate Recognition, Monitoring and Recognition System

1. INTRODUCTION

The development of cloud computing is related to the gradual development of parallel computing, distributed computing, and grid network computing. Cloud computing is a type of network computing, based on the mobile Internet, which can provide terminal hardware network services to various types of Internet network applications, Infrastructure network services, platform network services, and data storage network services that are widely used. Google is one of the main pioneers of this new technology. A search engine was built and launched independently on more than 200 enterprise sites and more than 1 million network servers has fully utilized cloud computing. As well as Google's cloud based applications, such as Gmail, Google Docs, Google Earth and Google Maps, Microsoft has embraced cloud computing with their cloud-based Office suite of products. Powerful cloud-based servers provide productivity and collaborative applications, along with real-time online storage, to multiple users concurrently. By using these servers administrators can harness the resources of the enterprise cloud computing platform without having to build their own on-site infrastructure, reducing the monetary costs of both R& D and purchasing their own equipment as well as reducing the amount of time spent on daily maintenance of the platform.

As early as the 1990s, researchers have launched in-depth scientific studies and continuous exploration into license plate image recognition technology [1]. The earliest proposed method is based on the technical study of license plate texture image analysis. This analysis method regards a license plate image as an image object with a specific color texture; by

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automatically detecting a corresponding texture object within two images, the frame to locate the corresponding license plate candidate area is highly accurate and technically targeted [2]. Another method is based on the comprehensive research of image edge feature detection, that is, the image is converted to grayscale and processed with image binarization to obtain two images with rich image edge features, and the two images are then transformed using the Hough transform method. The lines on the edge of each image correspond to the image boundaries parallel to each other in a specific position to form an area without license plate candidates. Another method is based on the analysis of license plate morphology. This analysis method mainly focuses on the analysis and research of some basic features of a license plate display area, such as license plate brightness, symmetry, angle, etc. Similar license plate area features are used to accurately locate the license plate [3].

In order to explore the feasibility of a deep learning license plate recognition method based on edge cloud computing the current license plate recognition method are introduced in detail, the current problems of these research methods are analyzed, and the related impact mechanism and related technology are discussed in this paper [4]. In previous research, Xue proposed the superiority of the deep learning technology of edge cloud computing, analyzed the feasibility of applying this method to identification technology, and introduced the research significance and research status of this aspect [5]. Han elaborated on the common algorithms and methods of license plate recognition in detail, explored in detail the feasibility of various algorithms, and discussed the relevant principles and algorithms involved in the recognition of license plates by modern traffic monitoring and recognition systems [6].

The main research aim of this paper is to improve license plate recognition using a deep learning method based on edge cloud computing. To reach this aim a Hadoop cloud platform was designed and built, the existing monitoring and recognition platform was placed on this platform, and the theoretical method of deep learning based on edge cloud computing was then used to adaptively modify the license plate recognition monitoring model. These modifications resulted in faster and more precise recognition of not only license plate information but also the vehicle model and manufacturer.

2. THEORETICAL BASIS

2.1 Image Recognition Concept

Image recognition is used to identify and classify a research object according to certain characteristics. For example, if the numbers between 0 and 9 are written on ten separate cards, image recognition can be used to identify the value written on each card. This type of identification occurs frequently in everyday life. However, due to constant changes within the world, the categories of things that people need to identify become more abundant, and the content becomes more complex. Especially with the improvement in the level of science and technology, related technologies can be used to convert the recognized objects into pictures or data, namely graphics and digitization. In the case of pattern recognition, both data and images are extracted from their sources and then classified into features.

The process of pattern recognition is broken into four parts. The first part is the acquisition of image information; and the second part is the preprocessing of the acquired image. The preprocessing process includes the use of relevant technical means to eliminate noise and distortion from the original image, disregard irrelevant features, and highlight the features that the recognition system pays more attention to. If there are multiple recognition targets in the original image, it is necessary to apply image segmentation technology to divide the original image into multiple images containing only one recognition target. The third part of the process is feature extraction. The feature parameters that have a greater effect on classification and recognition are extracted according to the pre-designed extraction principle to ensure the accuracy of the recognition. The fourth part is judgment or classification.

2.2 Vehicle Model and License Plate Recognition Technology

Various sensors are used in the recognition of vehicle models and license plates. There are many types of sensors, with one of the most common being a loop coil sensor. The basic principle of this type of sensor, for the recognition of a license plate, is to sense the electromagnetic induction generated by a vehicle when it passes over the sensor, and then to collect relevant information [7]. These sensors generally include three basic structures: coils, tuning loops, and detection modules. The basic principle of loop coil detection is the sensor detects the intensity of electromagnetic induction generated when the vehicle passes the sensor. This type of coil is generally positioned under the road surface. When a vehicle passes over the sensor, the amount of inductance changes and relevant information about the passing vehicle can be collected, such as its type or specific speed [8]. This method has a simple design, is low-cost, is easily administered, and is not affected by most weather conditions, however, it has a limited service life, is easily damaged by the pressure of heavy vehicles, and has a comparatively low recognition accuracy [9].

Another common sensor type is a geomagnetic sensor. A geomagnetic sensor detects changes of magnetic field in the local environment. The sensor uses these changes to determine if a vehicle is passing and collects information related to the vehicle. Specifically, when the vehicle passes the ground geomagnetic sensor, the metal within the vehicle, as well as the weight and structure type of the vehicle will cause a distortion of the magnetic field line and a change in the strength of the magnetic field. Laws governing the magnetic field can be identified through corresponding mathematical relationships [10]. The advantages of this method are that it is easy to install, requires only a small area, is simple to maintain, has a low installation cost, and provides high quality results. The disadvantages are that the geomagnetic sensors are expensive, and the speed of the vehicle can affect the measurement results.

2.3 Surveillance Video Image Recognition Technology

Before recognizing a vehicle in an image, preprocessing is an important prerequisite as the quality of preprocessing can improve the accuracy of vehicle recognition significantly. Moreover, when images are collected from video surveillance systems environmental factors at the time of collection can have a notable influence on the final result, such as weather conditions at the time, signal distortion, and whether there is signal interference. It is very important to carry out preprocessing of the received image information to reduce these environmental factors [11].

(1) Image grayscale processing

Grayscale processing of an image usually refers to changing the color image collected from a video to a grayscale image. These processing methods can reduce the data storage space needed, and can also increase the speed of image recognition. In

addition, as the recognition of the color of the vehicle model will not be taken into account in this paper, color within the image has no significance and can be discarded without consequence [12]. Moreover, an image usually includes the three primary colors, red, green and blue (R, G, B). These three primary colors can be combined to comprise 24-bit true color, and the grayscale process refers to taking the share of the colors R, G, and B. Each of the three primary colors are represented by an eight-bit binary number, and the value of the number determines the intensity of the color [13].

There are three main image grayscale algorithms:

(i) Maximum value method: the maximum value of the three primary colors is taken as the value of the three primary colors, as shown in Formula 1:

$$f(x, y) = \max\{r(x, y), g(x, y), b(x, y)\} \quad (1)$$

The grayscale image has a higher brightness after being processed by this grayscale processing method.

(ii) Average method: the average value of the primary color values of R, G, and B is used as the value of the three primary colors, as shown in Formula 2:

$$f(x, y) = (r(x, y), g(x, y), b(x, y))/3 \quad (2)$$

(iii) Weighted average method: as the three primary colors have different sensitivities, the weights used for weighted averaging are also different. The weight for the color green is the highest and the weight for the color blue is the lowest. Formula 3 shows:

$$f(x, y) = 0.298\mathrm{r}(x, y) + 0.587g(x, y) + 0.115b(x, y) \quad (3)$$

(2) Image filtering

The captured video image can be affected by fluctuations in weather conditions and the fluctuation of the signal of the other electronic components of the camera itself, which can directly generate random noise. Noise characteristics, and the physical characteristics of these random noises, can therefore be divided into two types of random noise phenomena: random noise and salt and pepper noise [14]. Random noise has different positions and random noise intensity when comparing two images. The main difference between random noise and salt and pepper noise is the position intensity of the noise within the random image [15]. To filter all of the noise contained within an image set, reflection noise must be reduced or removed from both of the main sources of noise [16]. The method for removing reflection noise is mainly reflection filtering, and it is of ten subdivided into two categories: filtering spatial domain reflection filtering and frequency domain reflection filtering [17]. The main function of spatial domain color filtering is to perform spatial domain calculation on the grayscale and value function of a picture. The benefits of this method are its fast mathematical operation processing speed, and it requires less resources.

2.4 Vehicle Detection Algorithm Based on Deep Learning

As an important emerging field in machine learning, deep learning has its origins in artificial neural networks [18]. The essence of deep learning is to take a large amount of data as a learning object, use a network of hidden layers as a means of learning and extracting features, and use powerful computing power to give meaningful results. At the same time, a convolutional neural network is a way to achieve deep learning, as it can automatically learn features from image data, avoiding the huge design task caused by the feature conversion in traditional manual graphic design. It is used to identify two-dimensional displacement, scaling and other various forms of two-dimensional convectional graphics with distortion in-variance, so this neural network is widely used in various computer engineering vision technology fields [19].

In order to design a robust vehicle detector that can operate in complex and varied real-world scenarios, a convolutional neural network is used to extract the vehicle features, and a classifier is then used to train the entire model [20]. As the next target detection algorithm is based on convolutional neural networks, it is necessary to first introduce the basic principles of convolutional neural networks and their specific convolution methods [21].

Convolutional neural network (CNN) is a type of artificial neural network. It belongs to a new type of deep image feed-forward artificial neural network. At present, it has been widely and successfully used in image recognition, target feature detection, Deep natural language processing and many other aspects [22]. The convolutional layer is the basic physical structure of the neural network. It is composed of three layers: an internal input and output layer, a hidden output layer, and an external output layer. The data calculation method obtains the final data output, and the network weights and parameters are then updated in real time through the reverse data propagation method, but the formation of the basic networking unit of each network layer type is very different. These layers are the convolutional network layer, the pooled network layer (pool) and all connection layers [23]. The convolutional neural network usually needs to receive one-dimensional input and as the output data is no longer only one-dimensional input data but two-dimensional input data, each layer in the network structure is composed of multiple two-dimensional data plane units, where two adjacent neurons on two layers are not connected with each other, and two neurons on the same layer are not connected with each other. The neural network in convolution is mainly based on the receptive field, weight domain and shared domain of multiple local domains and gives a single convolutional neural core, which enables the network to extract different features of the image [24].

Each convolutional layer is composed of multiple learnable convolution kernels. The size (width and height) of each convolution kernel is relatively small, but the depth is consistent with the input data. When performing forward calculations, let each convolution kernel perform convolution operations from left to right on the input data, from top to bottom, and at the same time, the step size of the convolution can be changed to achieve the purpose of controlling the size of the feature map. The padding operation can also convoy the edges of irregular data. The feature map obtained after convolution gives the response of the convolution kernel at each spatial location [25]. For example, let the convolution kernel learn to recognise an image of a car, then when it learns to a certain degree, the convolution kernel will be activated when it “sees” (using its receptive field) other types of cars, and “sees” the background (street, trees, etc.) are in a suppressed state. The vehicle is then detected and the relevant information is extracted under the condition of processing the relevant background. Common formulas in vehicle detection algorithms based on deep learning are shown in Formulas 4 and 5.

$$L(x, \mathrm{c}, l, g) = \frac{1}{N}(L_{conf}(x,\ c) + aL_{loc}(x, l,\ g)) \tag{4}$$

$$L_{\mathrm{loc}}(x, l,\ g) = \sum_{i}^{N}\sum_{\max} xjjsmooth(l_i^m - g_j^m) \tag{5}$$

3. CLINICAL EXPERIMENTAL RESEARCH

3.1 Experimental Location and Construction of Hadoop File System

The location of the experiment is a section of expressway from Jiangsu to Shandong. Due to the junction of the two provinces, there is a large volume of traffic on this section of the highway, so it is easier to check the feasibility of the system. To begin the experiment, a Hadoop cloud platform was built. In order to build this Hadoop cloud platform, the file system of the cloud platform needed to be built first. The Hadoop nodes to be built in this paper are very typical dynamic master-slave data system node structures, composed of a typical master node (Name Node) and multiple slave nodes (Data Node). In the entire Hadoop cluster, only one node called name-nodes is allowed to run at the same time. This node will be the master controller of all the servers of the entire system, used for the system management of all of the named data spaces of the entire HDFS and used to coordinate the client access to the file data system.

Table 1 A copy of the experimental data is stored on the same rack node.

Name of the node	Block data	Rack
OLOICK	SOK1245	HAD-1
GOIKS-1	CKJ363	CHD-1
DEOS-2	HJC1520	HEA-1

In order to make the system easy to operate, users of the system do not need to understand the underlying data segmentation method. When the client accesses the files on HDFS, it first obtains the location list of the data to be accessed from the Name Node, and then directly accesses the Data Node on the list and obtains the data information. This file processing method realizes the separation of control flow and data flow, that is, there is only control flow between the client and the Name Node, and only data flow between the Data Node, which greatly reduces the load pressure on the Name Node. It is divided into multiple data blocks and stored in different Data Node nodes, so that the client can access multiple Data Nodes at the same time, which improves the I/O parallelism of the entire system. A copy of the experimental data is stored in the nodes of the same rack, as shown in Table 1.

3.2 Experimental Function Model Construction

This paper builds a deep learning monitoring and recognition system based on edge cloud computing, using mainly a MapReduce function model. The MapReduce model built in this paper is a parallel distributed computing function model. Its function is to abstract the parallel computing work process that often runs on a large-scale computing cluster into two simple calculation functions: map (map) calculation functions and spruce (function reduction) calculation functions. Users simply write two programming functions ramp() and reduce() to automatically complete their corresponding data logic processing functions in order to achieve distributed data processing of large network data sets. The function models of map() and reduce() are used to build a function, as shown in Formula 6:

$$MAP\colon (key_{in}, value_{in}) - \{\{(key_j, value_j)\}|j = 1 \ldots k\} \tag{6}$$

Where key is the model coefficient and value is the model value. The input of the map() function is a pair of <key, value> values, which indicate to the system the data that the user needs to process.

MapReduce divides the rectangular data blocks (blocks) that each user needs to input according to a specific sorting rule into several equal-sized rectangular data splits and submits them to the users Map-tasks. User segmentation can be achieved by lentiform calling the get-splits() function method and RecordReader() function method application in the interface module to automatically define the rules for data block segmentation. Map-tasks parses and receives <key, value> after receiving the shard sent to the user, and parses a map() operation function shard that will be submitted to the new user, and a series of new shard <key, value> pairs are generated, a Map-tasks intermediate operation result can then be obtained after generating the three operation stages of collect, spill, and combine.

3.3 Experimental Image Processing

A large number of license plate recognition data obtained in this experiment are from monitoring images, and these images need to be processed correctly. This experiment uses the inter-frame difference method to process the experimental image. The main rationale of the inter-frame difference scoring method is to perform the inter-frame difference calculation of each gray pixel value of two high-speed adjacent car images, and accurately extract and find the existence through the continuous change of values. The pixels and focal points of the difference between frames are determined, and the high-speed moving vehicles are then separated from the image background. The specific operation method is used to perform gray-scale difference processing and video de-noising processing on two frames of a frame of video images, and then perform two different gray-scale processing values on two adjacent frames of the video image. A differential processing operation is conducted to determine whether a moving target already exists in one of the frames, and if there is one, mark it and extract it. Suppose the gray value of the pixels $x,\ y$ in the image of the math frame in the video is $f(x,y)$, and the gray value of the position corresponding to the adjacent frame is f(x,y), and the difference of the gray values between them is $d(x,y)$, Then the formula expression of the inter-frame difference method is shown in Formula 7:

$$d(x,\ y) = |f_{m+1}(x,\ y) - f_m(x,\ y)| \tag{7}$$

The advantage of the inter-frame difference method is that the algorithm is easy and the calculation speed is fast, but its shortcomings are also obvious. Some of the shortcomings include that it is sensitive to the influence of the outside world, the weather, including strong winds, and lighting when capturing the image may adversely affect the difference result. The most unfavorable reason is that the vehicle areas differentiated at varying vehicle speeds are very different, and the vehicle speed becomes an interference factor affected by the difference result, which greatly affects the subsequent extraction and recognition of the vehicle features.

In addition, multi-access analysis of the image is performed, which refers to the degree of blur of the image, not the size of the image. It is aimed at the analysis of the image at different resolutions. Its core point is to integrate a square integrator space decomposes to obtain a series of sub-spaces with different resolutions. As the features of images change at different scales, they have different sensitivities for different feature samples, so the recognition of features is more accurate at the appropriate scale. To achieve multi-access representation of an image, the most common methods are the image pyramid method and scale space expression. The central idea of the image pyramid method is to down-sample the image. Specifically, the $N \times N$ image (where N is the nth power of 2) is sampled separately in two directions on the plane, so the sampled image is a reduced image of the original image. An image expressed as $N/2 \times N/2$, in a continuous cycle, will form a series of multi-scale representations of the original image, forming an image pyramid.

Table 2 Common license plate symbols and related information in China.

License plate characters	Total plate length	Total plate width
CHUAN	420	140
YU	440	140
LU	420	120
QING	440	140

4. RESEARCH ON LICENSE PLATE RECOGNITION METHOD

4.1 Effect of Deep Learning License Plate Location and Correction Based on Edge Cloud Computing

The recognition of license plate positioning is the first step of license plate recognition. Whether the accuracy of the license plate positioning recognition is high or low will directly affect all the recognition processes of the license plate. At present, the common positioning methods of motor vehicle license plates include methods based on license plate mathematics and morphology, and methods based on multiple color symbol features. After using the morphology and color features of the license plate location method, and then comparing the advantages and disadvantages of this method and the target detection-based license plate location method, the subsequent system provides more choices and a wider range of application scenarios. Common license plate symbols and related information used in China are shown in Table 2:

Based on the research of traditional analysis methods in China, this paper innovatively proposes a color positioning analysis method for motor vehicle license plates based on color morphology and license plate color positioning features. First, video preprocessing is performed on an image to convert the image into a low-gray edge map. The purpose of this work is to reduce the amount of image data, and to facilitate the detection of the edge map through subsequent tests. Then, use two Sobel operators to respectively detect two edge images in the same vertical direction, and then filter the calculated two vertical edge detection image data, and then continue to process the image. The two morphological closure operations make the license plate area form a connected domain, so that

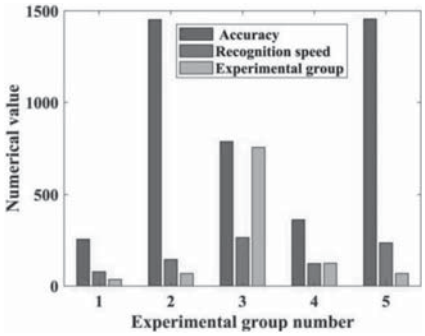

Figure 1 The accuracy and speed of license plate location based on the deep learning method of edge cloud computing.

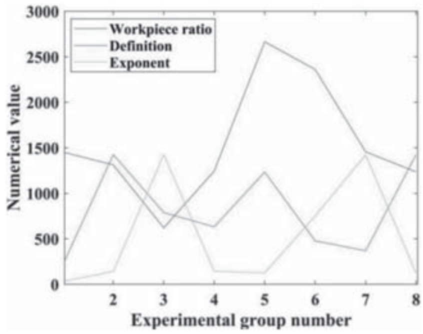

Figure 2 Efficiency and accuracy of the new calibration method.

subsequent detailed screening can be performed according to prior knowledge such as contour detection and color, and aspect ratio of the license plate. The accuracy and speed of license plate position recognition using the deep learning method based on edge cloud computing are shown in Figure 1.

As can be seen from the data in Figure 1, the accuracy and speed of this kind of deep learning method based on edge cloud computing for license plate positioning recognition are 25% higher than the traditional monitoring algorithms and methods.

4.2 Effect of Deep Learning License Plate Recognition Based on Edge Cloud Computing

The general projection methods for correcting Chinese license plate numbers mainly include three connected projection domain methods, redone transformation methods, rotation domain projection photography methods, and A transformation projection methods. Since the current Chinese small-scale license plate with Chinese characters contains a large number of Chinese characters, and most of the license plate Chinese characters may be incompletely connected, the small-scale license plate Chinese character correction technology method based on the connected domain of Chinese characters is relatively poor for the quality of Chinese character imaging files. Although the rotating ray projection photography method has a good processing effect on the correction of motor vehicle license plate numbers, the operational complexity of its processing algorithm is relatively large, which makes the overall calculation amount too large and affects the real-time nature of license plate recognition. In this paper, the Radon transform method is used to correct the license plate. This method is used as not only can it obtain the horizontal and vertical tilt angles of the license plate at the same time, but it also has a faster calculation speed. The efficiency and accuracy of this correction method are shown in Figure 2.

It can be seen from the data in Figure 2 that the deep learning license plate correction based on edge cloud computing is feasible, and the license plate correction in this way is more reliable and efficient. The correction rate reached 92%, and the correction efficiency is improved by about 25% when compared with the previous method.

5. LICENSE PLATE CHARACTER SEGMENTATION AND RECOGNITION

5.1 License Plate Character Segmentation Based on Deep Learning of Edge Cloud Computing

The single-character rectangular segmentation recognition algorithm of the license plate is used to segment and recognize a single complete license plate character from the entire rectangular image of the license plate, which is ready for the subsequent character recognition work. Because the recognition effect of segmenting characters is likely to directly affect the accuracy of the operation of the license plate information recognition, the segmentation recognition algorithm has gradually become the focus of technical research in the field of recognition. The experimental group chose character segmentation based on projection analysis.

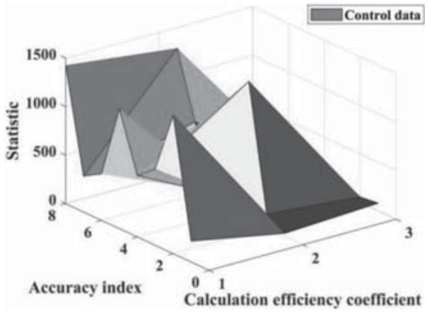

Figure 3 Computing efficiency and accuracy of license plate character segmentation based on edge cloud computing.

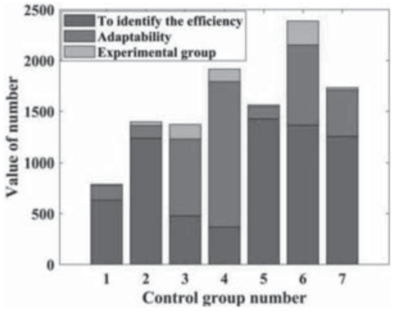

Figure 4 Efficiency and adaptability of deep learning license plate character recognition based on edge cloud computing.

As the camera may not be on the same straight line as the driving vehicle during the capture process, the license plate image may be tilted at a certain angle, which may affect the accuracy of character segmentation, especially when the tilt is severe. The deep learning license plate character segmentation based on edge cloud computing compared with the experimental group, and its calculation efficiency and character segmentation accuracy are shown in Figure 3.

From the data in Figure 3, it can be seen that the license plate character segmentation calculation efficiency rate of the experimental group and the control group differ greatly. The calculation efficiency is clearly higher than the experimental group, with a 5% increase, and similarly the accuracy is improved by 12%.

5.2 License Plate Character Recognition Based on Deep Learning of Edge Cloud Computing

The most critical part of the recognition system is the character recognition algorithm of the license plate, used to recognize the segmented character image and output it to the system in the form of text. The accuracy of the character recognition is closely related to the accuracy of the license plate positioning and character segmentation, therefore the selection of recognition algorithms is extremely important. A highly efficient and adaptable recognition algorithm determines the recognition performance of the entire system. The template matching recognition algorithm adopted by the experimental group is one of the most basic and common recognition algorithms. Its basic principle is to first create a character template library, and then to normalize the characters to be recognized separately from the template library. The characters of the license plate are matched, and the character with the highest matching degree is selected as the output result. The efficiency and adaptability of license plate character recognition based on deep learning based on edge cloud computing are shown in Figure 4.

It can be seen from Figure 4 that the efficiency and adaptability of license plate character recognition based on deep learning based on edge cloud computing is very good, which also confirms that the license plate recognition method based on deep learning based on edge cloud computing is feasible. The monitoring and recognition system is more accurate and faster for license plate recognition. Compared with the traditional monitoring and recognition system, the recognition accuracy is increased by 15%, and the recognition speed is increased by about 7.5%.

6. CONCLUSIONS

(1) This article discusses the selection of image recognition methods, and finds suitable image processing methods with the help of experiments on the accuracy of license plate recognition. Experiments showed that the deep learning method based on edge cloud computing has obvious advantages in image processing and has a high accuracy rate.

(2) The feasibility of license plate positioning and correction based on the deep learning method based on edge cloud computing are analyzed in this paper. The positioning accuracy and speed are very good, 25% higher than traditional monitoring algorithms and methods. The recognition speed also improved significantly, with results of 10% higher than previous methods. In addition, the license plate correction is more reliable and efficient. Compared with the general method, the correction rate

of the license plate reached 92%, and the correction efficiency is improved by about 25% compared with the previous methods.

(3) It has been experimentally verified that the efficiency and adaptability of license plate character recognition based on the deep learning method of edge cloud computing is very good, which also confirms that this method is feasible. The recognition system is faster and more accurate for the license plate recognition. Compared with the traditional monitoring and recognition system, the recognition accuracy is increased by 15% and the recognition speed is increased by about 7.5%.

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