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Design and implementation of handwritten Chinese character recognition method based on CNN and TensorFlow

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***Abstract*—Chinese characters are an important medium for Chinese people to exchange information and perceive the world. With the advent of the information age, a large number of paper documents need to be electronically stored and shared. The recognition accuracy of paper printed Chinese characters and online handwritten Chinese characters has reached a high level. However, offline handwritten Chinese characters have a variety of styles and shapes. There is still a lot of room for improvement in the current recognition accuracy due to a large number of similar characters. This work proposes a "private customized" handwritten Chinese character recognition system based on convolutional neural networks. Users can train their neural network model according to their own writing style. The system includes four parts: character segmentation, Chinese character labeling, neural network training, and predictive recognition. The system can independently expand the data set during use, thereby continuously improving the recognition accuracy. The experimental results show that this method has a good recognition effect for Chinese characters, English letters, Arabic numerals, and punctuation marks, and the recognition accuracy rate can reach more than 98%.**

Keywords—handwritten Chinese character, convolutional neural network, character segmentation

I. INTRODUCTION

Although all aspects of life are moving in the direction of electronic development, handwritten Chinese characters still have a wide range of applications in financial bills, medical records, examination paper files, etc. With the advent of the information age and the era of big data, the electronic transfer of paper documents is a problem that needs to be solved urgently. Yet, handwritten Chinese characters are difficult to use due to the diverse writing styles, complex structure of characters, and a variety of similar characters. Identification has always been a hot issue of human concern.[1]

Handwriting recognition is mainly divided into online handwriting recognition and offline handwriting recognition; online handwriting recognition collects information such as the coordinates of the continuous trajectory written by the user in real time, and analyzes the sequence of strokes, the direction and speed of the pen, the point and the end of the pen, the coordinates of the points, etc, which can efficiently and accurately identify the corresponding characters. While offline handwriting recognition only obtains static two-dimensional image information by photographing paper documents and image processing. Therefore, its recognition accuracy is far inferior to online handwriting recognition [2].

The research enthusiasm for handwritten Chinese character recognition has never diminished. In the 1960s, IBM Corporation of the United States began to study the pattern recognition of printed Chinese characters. In 1977, Toshiba of Japan developed the first recognition system that could recognize more than 2,000 printed Chinese characters. Since the 1980s, Chinese scholars have begun to study handwritten Chinese character recognition. In 1996, the Institute of Automation of the Chinese Academy of Sciences developed an offline handwritten Chinese character recognition system, with a recognition accuracy rate of over 93.6%. Since the 1990s, the research direction in the field of offline handwriting recognition has turned to its application in real-world scenarios. For example, scenarios such as census data entry, financial and fiscal bill identification, express address number identification, automatic mail classification, and answer sheet scoring. Relevant researchers at home and abroad have also conducted a lot of research and experiments on offline handwritten Chinese character recognition. Some researchers have comprehensively used the advantages of convolutional neural networks and deep belief networks [3]in image analysis, and adopted a fusion comparison strategy which performs better than using these two methods alone; some researchers use the random elastic transformation algorithm[4] on the basis of deep convolutional neural networks, which not only expands the data, but also greatly improves the accuracy of recognition; there are also researchers trying to alleviate the gradient dispersion phenomenon in the training process, a recognition method based on feedback knowledge transfer[5] is proposed therefore.

II. THE OVERALL DESIGN OF THE PROJECT

Based on previous studies, this work designs and implements a "private customized" type of handwritten Chinese character recognition system. The system is designed with a graphical user interface based on Tensorflow2.0 and PyQt5, which is convenient for operation and use; this system is mainly for personal use, and realizes efficient electronic transfer of personal handwritten notes, manuscripts and bills. The overall implementation block diagram is shown in Figure 1.

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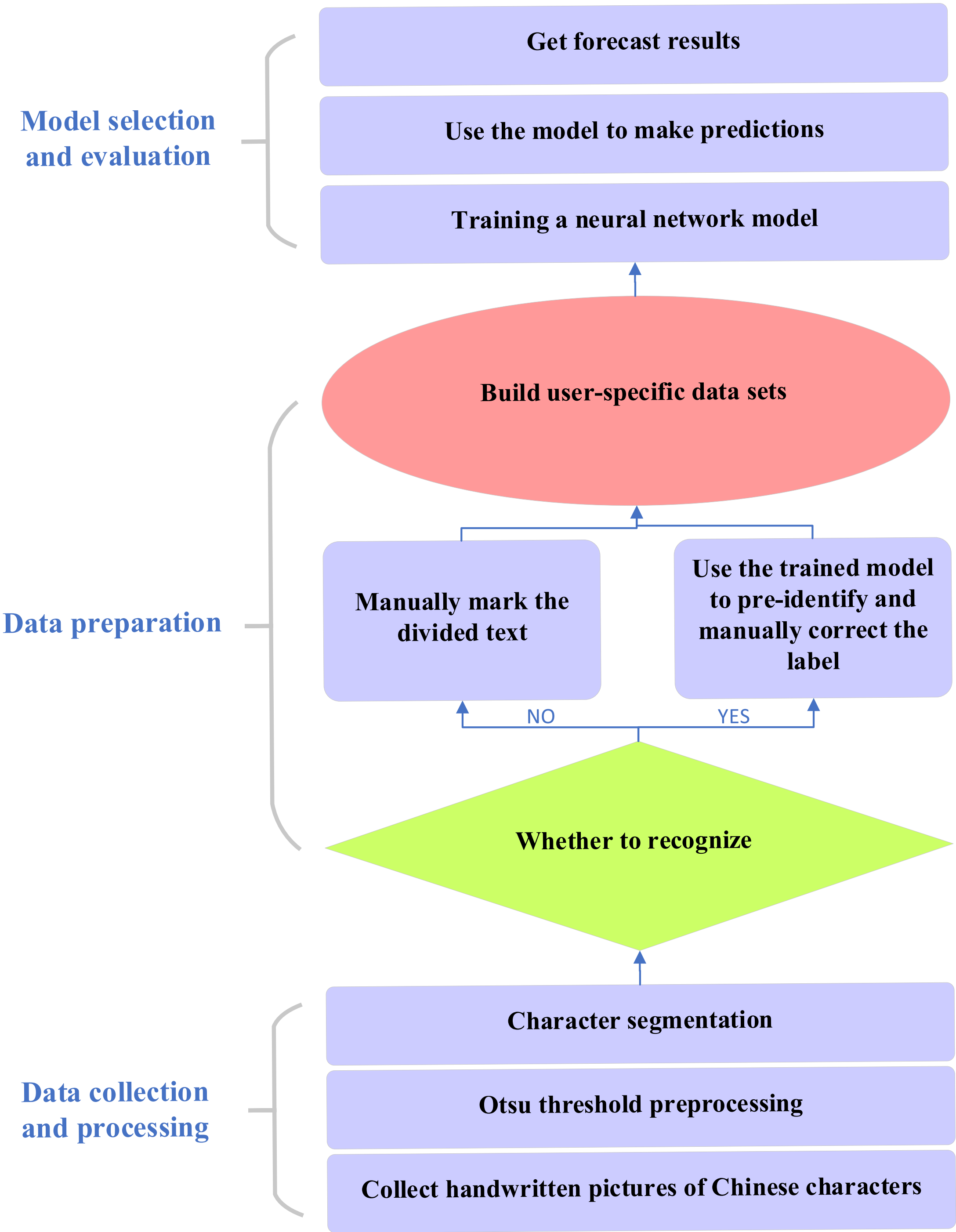

Fig 1. The overall implementation block diagram

III. Experimental Process

A. Character segmentation

1) Picture preprocessing:

Adjust the angle of the original picture taken by the mobile phone through the rotation operation, then convert it into a grayscale image, remove noise interference, then use the Otsu algorithm to convert the grayscale image into a binary image, and reverse it.

2) Segmentation of connected regions

Corrosion and expansion are the two basic operations of morphology. The essence of the erosion operation is to shrink the boundary of the image to eliminate adhesion and small objects, while the essence of the expansion operation is to merge the pixels in contact with the target area into the target object and make the target boundary expand to the outside. Since there are many characters with left-right structure and upper-lower structure in Chinese characters, they can easily be divided into two parts due to some user's bad habits. This work draws on the idea of expansion calculation, and the left-right structure and the upper-lower structure of Chinese characters can form a connected area and lay the foundation for the step of segmentation operation.

3) Find word order

After the above steps, each character constitutes a connected area, and then use the findContours method to

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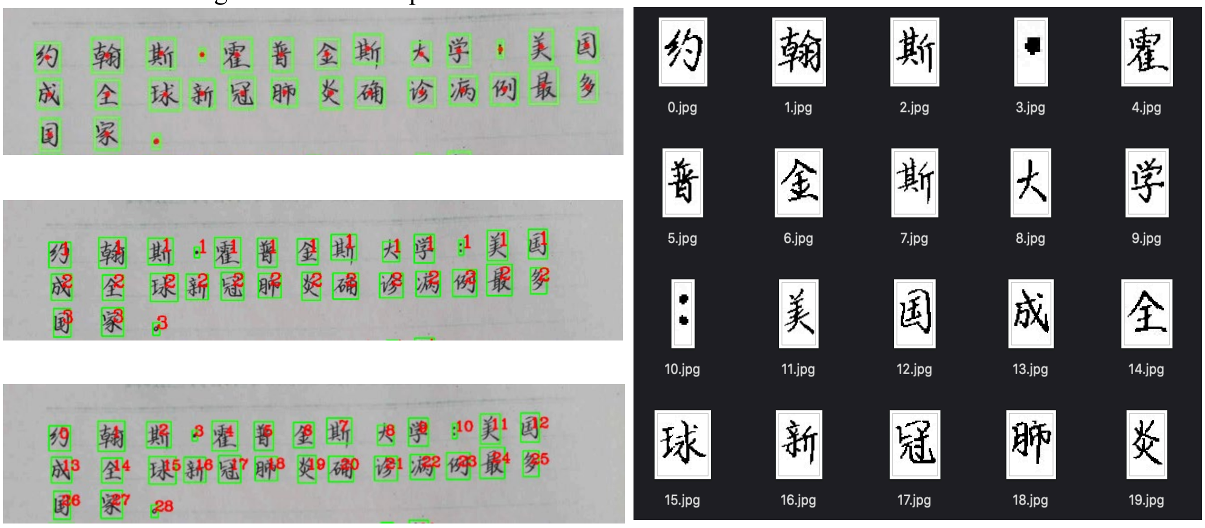
obtain the coordinates of the upper left and lower right corners of each character. Hence, the coordinates of the geometric center point of the area can also be obtained. However, the order of the connected region list found by the findContours method is chaotic, which will cause confusion in the word order of the segmentation result. Therefore, this work traverses each character, and takes the y coordinate value of the geometric highest point of the character and the y coordinate value of the geometric lowest point to form a search interval, finds the characters whose center point coordinates are in this interval, and marks them as belonging to the same line .Then, perform the same operation on all characters, and all lines can be divided correctly. Finally, sort the characters in each line according to their x-coordinates to get the correct order of each character. The method of finding the word order and the final segmentation result are showed in figure 2.



Mark the correct word order **Segmentation result**

Fig 2. Finding the word order and the final segmentation result

B. Mark characters

Labeling a single text picture image is the most time-consuming and laborious step, and it is also a key step that can directly affect the quality of the model. In order to improve the efficiency of data set annotation and make this system more user-friendly, when using this system for the first time, users can choose the model trained based on CASIA-HWDB1.1 offline Chinese character handwriting data set to make preliminary predictions before manually labeling. The user only needs to modify the incorrectly predicted data, and every time the user manually modifies the labeled data, it will be directly re-imported into the data set. Repeatedly, the user-specific data set is constantly expanding, and the model trained on the set will have better recognition accuracy for the user's personal handwritten data.

C. Training the neural network

With the continuous expansion of user data sets, thousands of image data are stored in hashes, occupying a large amount of disk resources and memory space. For this reason, this work considers using TFRecord format to store data sets. Storing the characteristic data and the label corresponding to the data as a binary file can make more efficient use of memory and improve the read and write efficiency of the disk. The design of the neural network model in this paper is based on the structure of the convolutional neural network and is designed according to the characteristics of handwriting recognition of Chinese characters.

The structure diagram of the neural network is showed in figure 3, and the parameters are shown in Table I:

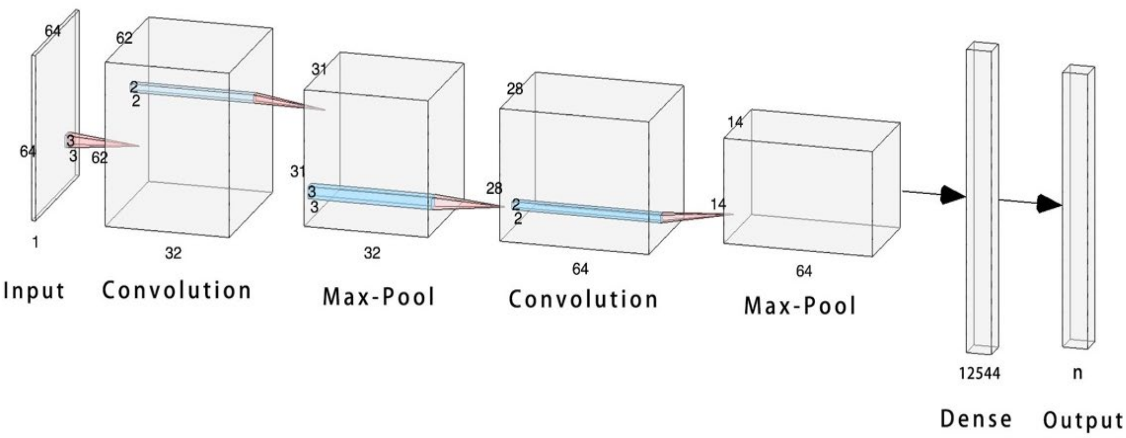


Fig 3.The structure diagram of the neural network

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TAB I: THE PARAMETERS OF THE NEURAL NETWORK

Neural network layer	Core size	Output feature map size
Input	-	64*64
Convolution	3*3	32*62*62
Max-Pool	2*2	32*31*31
Convolution	3*3	64*28*28
Max-Pool	2*2	64*14*14
Dense	1*1	12544*1
Output	1*1	Number of Chinese characters in the training set

During the network training process, the training accuracy curve and loss curve are showed in figure 4:

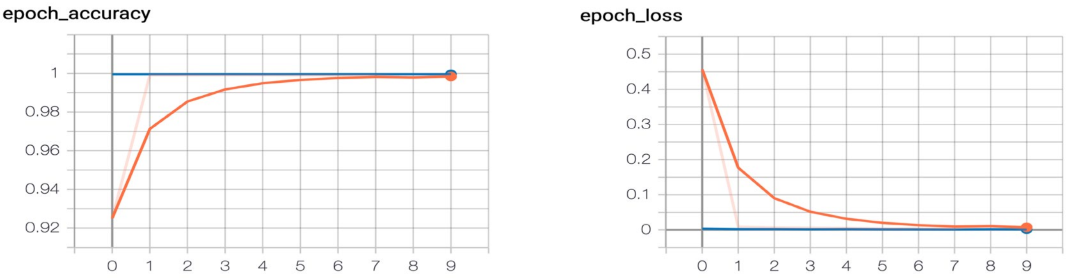

Fig 4. The training accuracy curve and loss curve

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. Experiment environment

The experimental development environment of this article: CPU is Intel i7 6890HQ, GPU is AMD Radeon Pro 460, 4GB video memory capacity, and memory is 16GB DDR3 2133MHZ frequency, and the operating system is Mac OS Catalina 10.15.3.

The deep learning development platform is TensorFlow2.0, the development language is Python 3.7.7. The development platform is Pycharm CE. The UI interface and realize graphical operations are designed by Pyqt5, QtDesigner. Using OpenCV, PIL computer vision library to process pictures and NumPy Numerical Operation Library for Matrix Operation.

B. The purpose of the experiment

1) Test the stability of the interface and functions of the "Chinese Character Handwriting Recognition System" described in this article;

2) Test the accuracy of the system's recognition of Chinese characters, English letters, Arabic numerals, and punctuation marks.

C. Experimental method

Use the camera to collect several handwritten pictures of the user's Chinese characters, and perform image preprocessing, character segmentation, and character labeling to obtain the training data set. The data set contains a total of 2995 labeled characters, which are imported into the neural network for training to get the neural network model 1. Use the CASIA-HWDB1.1 offline single-character Chinese handwritten text data set open sourced by the Institute of Automation, Chinese Academy of Sciences to train a neural network model 2. The model contains 3755 kinds of Chinese characters and 171 kinds of English letters, numbers and punctuation. Before marking the characters, use Model 2 to make predictions, and re-mark the pictures that have been predicted incorrectly on this basis to greatly reduce the workload.

D. Experimental results and analysis

For the 10 experimental pictures collected during the experiment, a total of 2362 test sets containing mixed characters of Chinese characters, punctuation marks, English letters and Arabic numerals, the prediction accuracy of Model 1 reached 98.137%, with 44 errors, and the recognition effect was good. However, the experimental effect of Model 2 is very poor for this test set. The reason is that the CASIA-HWDB1.1 offline single-character Chinese handwritten text data set only contains 3775 Chinese characters written by 300 volunteers, and the type of font is too single, resulting in the lack of versatility of the neural network model.

V. CONCLUSION AND OUTLOOK

This work implements a personal neural network model for handwriting recognition of Chinese characters. Users can train their own neural network model according to the characteristics of writing Chinese characters. Users can re-recognize the wrong Chinese characters every time they use a new picture to recognize them. And expand the exclusive training data set belonging to the user. The neural network model trained in this way becomes more and more accustomed to the user’s writing style, thereby significantly improving the recognition accuracy. After experimental verification, the method has a good recognition effect for Chinese characters, English letters, Arabic numerals, and punctuation marks, and the recognition accuracy rate can reach more than 98%. Although the recognition effect of this method is good at present, the method described in this article still has research potential and room for further optimization. In the future, research will be carried out in the following aspects:

1) Segmentation and recognition of scribbled characters and ligatures. The experimental pictures used in this article are all Chinese character writing pictures with large kerning and line spacing. For ligature pictures with small kerning, the adhesion between the characters will cause the normal division of individual characters.

2) Improve anti-interference ability. Naturally, it is impossible to require each picture to have a solid color

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background. Patterns and noise on the paper will interfere with the recognition effect, which needs to be further solved and optimized.

Improve the recognition effect of oblique pictures. The pictures taken by the user in real life are not absolutely horizontal and vertical. The tilt of the paper will cause the deformation of the segmented pictures and affect the recognition effect.

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