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RECOGNITION OF TRADITIONAL CHINESE MEDICINES THROUGH TENSORFLOW TECHNIQUES FOR PUBLIC HEALTH ENHANCEMENT

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Abstract

Traditional Chinese Medicines (TCM) have become increasingly popular as a means of disease prevention, diagnosis, and treatment for humans in recent years. However, the lack of easily accessible information and extensive knowledge regarding Chinese herbs presents a challenge. TCM specialists typically rely on manual recognition to identify herbal medicine. This research paper introduces an innovative method for detecting and identifying Chinese herbs using image processing, specifically a tensor flow approach. The study focuses explicitly on three types of Chinese herbs: LianZi, ShanZhiZi, and MoShiZi, which serve as input data. Various experiments were conducted using images of single, paired, and multiple Chinese herbs, as well as a mixture of these varieties. Each category contained thirty test images for each variety of herb. Unbelievably, the results demonstrated a recognition accuracy of up to 87.77%. In addition, the study demonstrated that Chinese herbs were simpler to detect under split conditions than under closing conditions. This paper's innovative image processing approach represents a significant advancement in TCM research and development, providing a reliable and efficient method for identifying Chinese herbs, which will ultimately benefit public health.

Keywords: Image Detection; Image Recognition; Chinese Medicine; Tensor Flow; Public Health

1. INTRODUCTION

For many decades, Chinese herb identification and recognition have been carried out manually. This is due to the herb's complex characteristics, such as color, shape, and texture, making the identification and recognition process highly complicated (Cope et al., 2012). To address this issue, there is a need to develop an automatic identification system for leaves. The texture of Chinese herbs can provide valuable information on the selected region, such as color and intensities.

The potential for image identification and recognition of Chinese herbs is immense, as traditional methods of identification require extensive professional knowledge, and with numerous species and categories, it can be challenging to identify them all (Sun & Qian, 2016). To address this issue, modern technology can make the process much easier by using image processing software to automatically identify and recognize Chinese herbs (Pang et al., 2022; Xu et al., 2021). The software can extract essential information such as area, perimeter, and Feret diameter (L, 2012), as demonstrated in studies by Momin et al. (2017) and Ambika & Supriya (2018). However, limitations still exist. For example, Tech et al. (2018) calculated the area of an object by identifying the set of pixels with the same light intensity, requiring the dataset to be captured under constant lighting conditions. Su et al. (2018) normalized the direction of depth images to 0 degrees automatically using an image processing algorithm,

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whereas in this research, all images were manually rotated to a vertical form. The images were captured in color, so thresholding methods (Cohen, 2010) or classifiers to determine the foreground or background, as used in Senthilkumaran & Vaithegi (2016), were not considered.

Understanding and recognizing Chinese herb through machine or software remains a significant challenge in image processing (Alzubaidi et al., 2021). Sarikan & Ozbayoglu (2018) utilized decision trees (DT) (Safavian & Landgrebe, 1991) to classify motorcycles and cars, but the major drawback of the study is overfitting. Therefore, this study aims to create an image processing algorithm that can recognize and identify Chinese herb. This algorithm will extract the Chinese herb's features and apply them to image processing techniques to recognize the herb, enabling anyone interested in Chinese herb to use the algorithm to search for it by scanning or typing the name. As a result, not only will this project benefit the Chinese herb industry, but it will also be beneficial to the general public, including those who are not experts in the field.

2. METHODOLOGY

Our research began with collecting image data. Since the raw image data cannot be directly used, a labelling algorithm was employed for pre-processing. The data was then trained and tested using the TensorFlow algorithm in Python. The recognition algorithm was then executed on the input data, and the accuracy of the recognition was recorded. If the accuracy of recognition is not satisfactory, the iteration process will be continued. The flowchart of our study is illustrated in Figure 1.

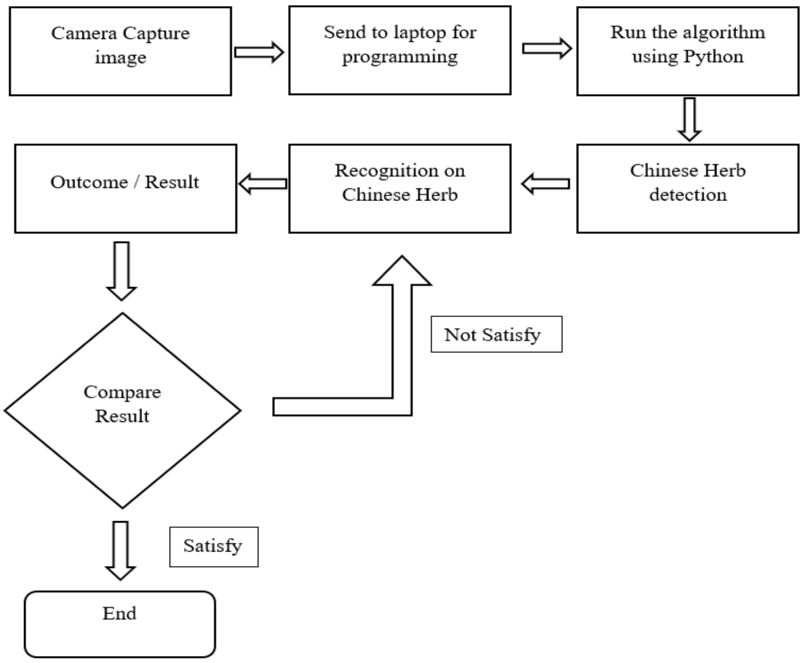

Figure 1: Flowchart of the research

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2.1 Data Collection

To optimize the performance of our algorithm, we conducted a thorough review of data collection methods used by previous researchers. Tech et al. (2018) standardized the height of image capture to 23cm, using a fixed camera position, to ensure consistent leaf detection within a certain area. Apart from this, Chan et al. (2022) had proposed two capturing distance including 10cm and 20cm from the Chinese herbs. Sunoj et al. (2018) used a white foam board measuring 500mm in length and width as a background for capturing images. This provided a clear white background for capturing images and projective transformation was used to correct any distortions.

In our study, we reduced the height to 15cm and used a white background to ensure larger, clearer, and more easily recognizable Chinese herb images during the training process. The camera settings were adjusted to standardize the capturing environment. For example, Ambika & Supriya (2018) used a mobile camera with a resolution of 400 x 600, while Husin et al. (2012) used a digital camera with 7.1 Megapixels, scaled down to 4800 pixels to increase processing time.

In our research, we used a HUAWEI Mate 20 Pro smartphone, which has an AI-Painting Photography function that adjusts the contrast for clearer images. The images were initially captured at a resolution of 8 Megapixels before being scaled down to 1 Megapixel (960x1280) to improve processing time. Figure 2 illustrates the configuration of our image capture process.

Figure 2: Fixed height of 15cm with a white background to capture the Chinese herb

Once the image of the Chinese herb has been captured, it was stored in the folder as a database to train and test the recognition algorithm. Some of the image captured are shown in Figure 3.

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(a) (b) (c)

Figure 3: Images of LianZi (a), MoShizi (b), ShanZhiZi (c) after capture using phone

Having a high-quality database is crucial for accurately detecting and storing the features in the initial phase of image processing. Categorization of different types of Chinese herbs is necessary and for each type, 50 distinct and clear images will be captured from various angles and planes (front, back, left, right, up, and down) as suggested by Soltani et al. (2018). In our study, we have focused on three specific types of Chinese herbs: LianZi, ShanZhiZi, and MoShiZi.

2.2 Label Images and IDs

The first step in the training process is to label the images using LabelImg, which is to categorizes the type of Chinese herb. The labelled images and their corresponding IDs can be seen in Figure 4.

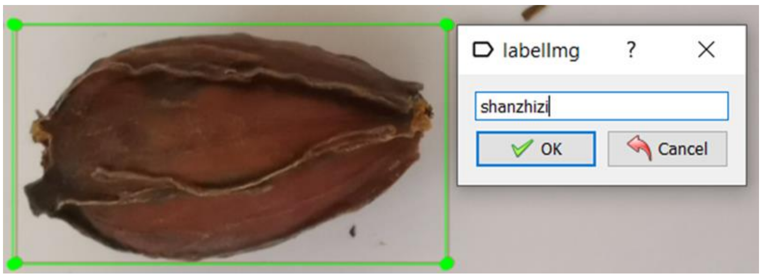

Figure 4: RectBox to make boundary of square shape

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A RectBox is utilized to create a square boundary around each label, as depicted in the figure. LabelImg is a Python-based graphical image annotation tool that features a Qt graphical interface. Since there are only three types of Chinese herb used in this research, the tool requires only three item IDs, as illustrated in Figure 5.

```
item {
  id: 1
  name: 'moshizi'
}

item {
  id: 2
  name: 'lianzi'
}

item {
  id: 3
  name: 'shanzhizi'
}
```

Figure 5: Create the ID and name using notepad

2.3 Configure and Training

The next step involves training the data using the command "python train.py --logtostderr--train_dir=training/--pipeline_config_path=training/faster_rcnn_inception_v2_pets.config" in the anaconda command prompt, as recommended by Lodeiro (2019). Once the program has successfully loaded the training data, TensorFlow will commence the training process, which may take up to 30 seconds or more to start. The training process of the TensorFlow is illustrated in Figure 6.

```
INFO:tensorflow:Starting Session.
INFO:tensorflow:Saving checkpoint to path training/model.ckpt
INFO:tensorflow:Starting Queues.
INFO:tensorflow:global_step/sec: 0
INFO:tensorflow:Recording summary at step 0.
INFO:tensorflow:global step 1: loss = 2.6708 (5.383 sec/step)
INFO:tensorflow:global step 2: loss = 3.0352 (0.251 sec/step)
INFO:tensorflow:global step 3: loss = 3.4884 (0.204 sec/step)
INFO:tensorflow:global step 4: loss = 2.9733 (0.193 sec/step)
INFO:tensorflow:global step 5: loss = 2.2184 (0.191 sec/step)
INFO:tensorflow:global step 6: loss = 2.0321 (0.554 sec/step)
INFO:tensorflow:global step 7: loss = 2.0424 (0.211 sec/step)
INFO:tensorflow:global step 8: loss = 2.0252 (0.208 sec/step)
INFO:tensorflow:global step 9: loss = 2.0053 (0.194 sec/step)
INFO:tensorflow:global step 10: loss = 1.3622 (0.193 sec/step)
INFO:tensorflow:global step 11: loss = 1.8027 (0.197 sec/step)
INFO:tensorflow:global step 12: loss = 1.2485 (0.196 sec/step)
INFO:tensorflow:global step 13: loss = 1.0712 (0.193 sec/step)
INFO:tensorflow:global step 14: loss = 1.6604 (0.189 sec/step)
INFO:tensorflow:global step 15: loss = 1.2657 (0.192 sec/step)
INFO:tensorflow:global step 16: loss = 1.4351 (0.193 sec/step)
INFO:tensorflow:global step 17: loss = 1.2152 (0.192 sec/step)
INFO:tensorflow:global step 18: loss = 1.1165 (0.197 sec/step)
INFO:tensorflow:global step 19: loss = 1.6557 (0.192 sec/step)
INFO:tensorflow:global step 20: loss = 1.7777 (0.200 sec/step)
```

Figure 6: The TensorFlow begin the training

(Source: Lodeiro, 2019)

The loss was recorded for each step of the training process as shown in Figure 6. It was found that the loss decreased linearly as the training progressed. Lodeiro (2019) reported a similar trend in their research, where the loss started at around 3.0 and dropped significantly to 1.5. However, the rate of loss reduction slowed down as the number of steps increased. According

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to Lodeiro (2019), the loss value should consistently be below 0.05, which would require approximately 10 hours for 20,000 steps. The performance of the CPU and GPU significantly affects the duration of the training process. To prevent data loss, the computer generated a checkpoint at regular intervals. This feature allowed the computer to restore the data and resume the training process from the previous checkpoint in case of errors. The frozen inference graph was generated from the final checkpoint.

3. RESULTS AND DISCUSSION

This paper uses various categories of images, such as those grouped into one, two, or four similar Chinese herbs, as well as combinations of different types. Each category consists of 30 test images for each Chinese herb type. Successfully recognized images are identified by a rectangular box, which includes the name of the Chinese herb and the percentage of similarity displayed above the box. An example of a successful recognition can be seen in Figure 7.

Figure 7: Sample of successful recognized image

The results showed that the recognition of images of one and two types of Chinese Herb was accurate, with minimal errors. However, the percentage of errors increased for images of four of each type of Chinese Herb and the combination of all types of Chinese Herb. Table 1 summarizes the average percentage of errors for each category.

Table 1: The average percentage error on each category

Types	% of Error (Average)
One Similar	4.44
Two Similar	5.55
Four Similar (Close)	61.1
Four Similar (Split)	24.44
Combine all types	87.77

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One of the key findings of this research is the increased difficulty in recognizing multiple types of Chinese herbs within a single image, as evidenced by the higher percentage of errors in Table 1. This can be attributed to a variety of factors, including variations in the size of the same type of Chinese herb, overlap between different herbs, and close proximity between herbs of different sizes. These results suggest that further research is needed to improve recognition accuracy in more complex image scenarios and highlight the novelty of this study in addressing this important challenge. Various factors can contribute to errors in different categories, and one of them is image quality. Poor-quality images have low resolution and fewer pixels, which can affect the accuracy of recognition. To improve accuracy, images with a resolution of 10 megapixels or higher should be used because they provide more data for feature selection and extraction. As the efficiency of feature extraction improves, so does the accuracy of recognition. It is critical to note that the number of trained images also plays a crucial role in the recognition accuracy. To improve the accuracy, it is suggested to increase the number of images for each type of Chinese Herb to more than 100 images. The current set of 50 images might not be sufficient to capture all possible orientations and angles, resulting in a lack of important features to train the system. Therefore, collecting more images can significantly enhance the training process and the system's ability to recognize Chinese herbs accurately. It is also recommended to consider including images of Chinese herbs in their natural environment, as this can provide a more comprehensive dataset for training and improve the accuracy of the recognition system.

4. CONCLUSION

In this research, a novel approach using image processing has been proposed to recognize Chinese herb in static condition. The results of different categories, including one, two, and four of each type of Chinese herb, as well as a combination of all types, have been presented. The study highlights the significant impact of image quality and resolution on the accuracy of testing data. The researchers recommend increasing the number of trained images to improve accuracy. It is interesting to note that Chinese herb is more easily detected in split conditions than in close conditions, and recognition of one or two of each type of herb is easier than recognition of a combination of all types. The use of TensorFlow and OpenCV in Python has proved effective for image recognition. However, the proposed method is limited to static images, and future research could focus on dynamic and real-time image detection of Chinese herb. The development of dynamic recognition could be highly beneficial in Industry 4.0, where machines could make autonomous decisions without human involvement.

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