Design of Tire Damage Image Recognition System Based on Deep Learning

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Abstract. In view of the problems of low efficiency, prone to misjudgment, and complicated identification levels in the current market, the use of manual judgment methods for the cause of tire damage. A method of tire damage image recognition based on convolutional neural network algorithm is proposed, and an intelligent tire damage image recognition system is designed. Through image processing, feature extraction, classification and identification of the input tire damage image, the computer can automatically output the cause of the damage. The experimental results show the feasibility of this method and also improve the shortcomings of traditional manual judgment of the cause of tire damage.

1. Introduction
Nowadays, China’s tire industry has developed to a considerable scale, and the total output of tires is among the highest in the world. During the use of tires, due to the effects of deformation, pressure, high and low temperatures, a large number of damaged tires are generated. But now the factory's identification of broken tires is mostly by manually observing the damage on the tire surface and judging the cause of the damage based on experience. The manual identification procedure is cumbersome, requires a lot of manpower and material resources, the efficiency is relatively low, and the human error is very large.

At present, domestic and foreign researches on the identification of the causes of tire damage are still in their infancy, and there are few studies on using computers to automatically identify tire damage images. By processing the tire pattern image, Chu Min combined with the linear equation to propose a straight line recognition system that can recognize the image of the automobile tire pattern [1]. Yin Lie dong proposed a multi-model collaborative recognition method for tire X-ray image defects that combines Faster-RCNN algorithm, PCA algorithm and numerical statistics method to make up for the deficiencies of a single model through mixed detection of multiple models [2]. Bian Kalong proposed a method for acquiring features based on convolutional neural networks, establishing a network model and using the model to achieve defect detection of tire X-ray images [3]. Li Yang proposed a rapid tire identification and sorting method based on machine vision, which uses the characteristics of NCC template matching to quickly match the fixed number of tires to achieve rapid identification of tire number information [4].

The above literature does not involve the problem of identifying the cause of tire damage in the study of tires. In this paper, by analyzing the current identification methods of tire damage reasons and the successful application of deep learning in face recognition [5-6], flower recognition [7-8] and other
fields, a deep learning-based convolutional neural network algorithm for tire damage. The method of image recognition, with a view to improving the lack of identification of existing tire damage causes.

2. System Design
With the increasingly mature application of deep learning in image recognition technology, this paper designs a tire damage image recognition system based on deep learning. The system mainly includes two parts: training and testing. The training part consists of a sample library of tire damage image specifications and a tire etiology feature library. By preprocessing and segmenting the tire damage image, a standardized sample database is obtained, and the convolutional neural network algorithm model is used to extract and classify the standardized sample database to obtain the tire etiology database. The testing part includes the output of the test set and the cause of tire damage. The specific structure of the system is shown in figure 1.

![Figure 1. Tire recognition image recognition system based on deep learning.](image)

3. Data Collection
In order to study the image recognition algorithm of the tire damage image, it is first necessary to collect a large number of tire damage images and make a training data set of the tire image recognition system. According to the different causes and manifestations of tire damage, the recognition system designed in this paper selects four main causes of damage as the objects of image recognition, namely: shoulder air, shoulder gnawing, crown rupture, and missing carcass. The specific example of tire damage image is shown in figure 2.

The sources of the data set in this article mainly include 1052 images of broken tires crawled from the Internet using crawler technology, and 1436 images taken by smart-phones of commonly used brands in the domestic market. Among all the obtained images, 60% of the damaged images are randomly selected as the training set, and the rest are used as the testing set. The specific classification of the data set is shown in table 1.
Table 1. Classification of tire damage image data set.

| Data Set       | Shoulder Space | Shoulder Gnawing | Broken Crown | Missing Carcass |
|----------------|----------------|------------------|--------------|----------------|
| Training Set   | 369            | 408              | 395          | 322            |
| Test Set       | 246            | 271              | 263          | 214            |
| Total Number   | 615            | 679              | 658          | 536            |

4. Data Set Processing

When collecting data sets, due to the complex image acquisition environment or a certain degree of image quality loss during image imaging, the data set needs to be pre-processed before application. The preprocessing operations mainly include image graying, denoising, contrast enhancement, batch cutting, binarization, scaling, data enrichment, etc.

4.1. Grayscale Image

In this paper, the weighted average method is used to grayscale the image so that R = G = B in the RGB model of the image, and the three components are weighted average with different weights to reduce the amount of data processing required. The graying formula of the image is as follows:

\[
\text{Gray}(i, j) = 0.229 \times R(i, j) + 0.578 \times G(i, j) + 0.114 \times B(i, j)
\]

4.2. Image Denoising

Since the image sensor is susceptible to various factors, the collected video image will generate a lot of noise during digitization and transmission. The interference of the transmission channel is the main reason for the image being polluted by noise during the transmission process. This paper uses median filtering to eliminate noise in the image. Median filtering is a neighborhood operation similar to convolution, but different from Gaussian filtering. It is not calculated by weighted average summation, but instead of the median value of the gray value of each point in a neighborhood of a point in the digital image sequence. The isolated noise points are eliminated by replacing pixels with a large difference in the surrounding gray values with values close to the surrounding pixels. The calculation formula of median filtering is as follows:

\[
g_{\text{median}}(x, y) = \frac{1}{3} \left( f(x-1, y-1) + f(x-1, y) + f(x-1, y+1) + f(x, y-1) + f(x, y+1) + f(x+1, y-1) + f(x+1, y) + f(x+1, y+1) \right)
\]

4.3. Image Enhancement

The distortion and deformation of the image, the blurring of the target's edge features and the appearance of isolated and prominent black and white dots on the image all make the image quality unsatisfactory and affect the image processing effect. Therefore, image enhancement technology is needed to improve the image quality. In this paper, the histogram equalization method is used to improve the image by adjusting the histogram information of the input image. Let function \( g(x, y), f(x, y) \) denote the gray level of the processed image and the original image, where \( x = 1, 2, \ldots, M; y = 1, 2, \ldots, N \). Map the original grayscale \( f \) to \( (x, y) \) at \( g \).
First of all, calculate the grayscale information of the image and calculate the grayscale histogram of the original image. Then use the distribution of the cumulative gray histogram to calculate the mapping relationship from $f$ to $g$, and repeat the calculation until all the mapping relationships from $f$ to $g$ are found. Finally, the pixels in the original image are gray-scale converted to enhance the image quality.

4.4. Image Segmentation
The purpose of image segmentation is to separate the target from the background to prepare for subsequent image recognition, classification and retrieval, and is one of the most critical technologies in the image processing process. This paper uses threshold-based image segmentation: Four thresholds are used to divide the grayscale histogram of the image into four categories. The pixels in the image whose grayscale values are in the same grayscale category belong to the same object. The basic principle can be described as:

$$g(i, j) = \begin{cases} 1 & f(i, j) \geq T \\ 0 & f(i, j) < T \end{cases}$$

Among them, $T$ is the threshold, for the image element $g(i, j) = 1$ of the object, for the background image element $g(i, j) = 0$. Its purpose is mainly to find a threshold value $T$, and use $T$ to divide the input image $f(x, y)$ into two parts, the background and the target.

5. Tire Broken Image Recognition Algorithm
In recent years, the research of convolutional neural networks in image recognition technology has developed rapidly, which has greatly improved the performance of image recognition. This paper uses a deep learning-based convolutional neural network algorithm as the basis for tire damage image classification and recognition, including three layers of convolution layers, two layers of fully connected layers, the activation function uses ReLU, and the Dropout and Softmax functions as classifiers to train tire damage image to get the training model. The algorithm structure is shown in figure 3.

**Figure 3.** Algorithm structure of convolutional neural network.
Algorithm training steps:
First input the normalized image of the tire damage that has been preprocessed in the input layer.
The image is extracted through a convolutional layer to obtain a feature map. The convolutional layer formula is as follows:

\[
out(x, y) = f \left( \sum_{f_i=0}^{N_f} \sum_{K_x=0}^{K_x} \sum_{K_y=0}^{K_y} \omega_{f_i} (k_x, k_y) \ast \ln \left( x + k_x, y + k_y \right)^{f_i} + \beta^{f_i} \right)
\]  

(4)

Among them, \( f(\cdot) \) represents the non-linear activation function, \( \beta^{f_i} \) is the offset value; \( out(x, y) \) represents the value at the output feature map coordinate \((x, y)\), \( \omega(k_x, k_y) \) represents the weight value at the convolution kernel coordinate \((k_x, k_y)\); \( \ln(x + k_x, y + k_y) \) represents the input feature map coordinate \((x + k_x, y + k_y)\); \( k_x, k_y \) represents the size of the convolution kernel; \( f^i \) represents the \( i \)th input feature value; \( N_{f_i} \) represents the number of input feature maps.

After the convolution layer is connected to the pooling layer, the pooling layer can reduce the resolution of the image and reduce the amount of parameters on the one hand by downsampling operation, and on the other hand can obtain the robustness of translation and deformation. After alternately setting the convolutional layer and the pooling layer to extract feature information, the number of feature maps increases and the resolution decreases. After each convolution layer, a ReLU activation function is set to increase the nonlinearity of the network. The formula is as follows:

\[
f(x) = \max(0, x)
\]  

(5)

The fully connected layer abstracts and nonlinearly fuses the feature map extracted by the convolutional layer, and then inputs the learned features into the Softmax layer for classification. The definition of the Softmax function is shown in the formula:

\[
P(y = j|x) = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}
\]  

(6)

Among them, \( j = 1, \cdots, K \) represents the category, \( K \) is the total number of categories, \( z \) represents the feature vector of the extracted damaged image, \( x \) is the input tire damage image, and \( y^\prime \) is the predicted cause of the tire damage.

The tire damage image is input from the input layer, calculated by the convolutional neural network, and finally the Softmax layer outputs four confidence levels, indicating that the damage in the tire image belongs to the possibility of the above four damage causes. The fully connected layer maps the feature image to the sample label space to obtain the tire etiology library.

6. Use the Trained Network Model for Testing
Use the image of the tire damage image test set to test the algorithm. The test image passes the convolutional neural network algorithm model, compares the extracted feature information with the information in the tire etiology library, and outputs the cause result. The test results are shown in table 2.
Table 2. Duration and accuracy of different tire damage image recognition.

| Table 2: Duration and accuracy of different tire damage image recognition. |
|-----------------------------------------------|
| Recognition rate | Fetal shoulder gnawing | Crown rupture | Carcass loss |
| Training time/m | 8.3 | 9.5 | 8.9 | 8.1 |
| Tasting time/s | 0.04 | 0.05 | 0.04 | 0.03 |
| Recognition rate/% | 67.3 | 67.8 | 67.1 | 67.9 |

The experimental results show that the convolutional neural network model constructed in this paper has a recognition accuracy of only about 67% for tire damage images. Although the recognition accuracy is not high, it can still indicate that it is feasible and effective to use deep learning to perform image recognition on tire damaged images.

7. Conclusion
In recent years, image recognition technology has been increasingly advanced, and deep learning has become more and more widely used in this area. In this paper, through the learning of convolutional neural network algorithm, a tire damage image recognition system based on deep learning is designed. Using deep learning to self-learn features from the data, establish a tire etiology feature database, enable the computer to automatically recognize the input tire damage images, improve the traditional manual recognition, and bring certain benefits to the industry of tire damage identification. This article also has certain limitations. Due to the limitations of resources and manpower, the number of samples in the data set is not large enough, which will be further improved in subsequent research. In addition, how to further improve the accuracy of identifying the cause of tire damage is also the focus of future research.

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