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Intelligent Identification of Logistics Packaging Products Based on Neural Network

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Abstract: The rapid iterative update of Internet technology has driven the development of the e-commerce industry. And the consumption concept of modern people has undergone great changes, from the initial real economy to the e-commerce economy. A large number of consumers are shopping online, and merchants need to package these products and then deliver them to consumers through logistics. In the process of commodity transportation, it is necessary to classify the logistics. At this time, it can be distinguished by the type of packaging. For example, by identifying the logistics packaging(LP) information, the commodities such as fragile products, easy-to-moisture products, etc. are separated from general commodities, so that the sorting personnel know Which needs to be handled with ease. In this regard, this paper designs an intelligent identification system for LP products, and introduces artificial neural network (ANN) and AlexNet-convolutional neural network (CNN) models. More intelligent. In order to verify the recognition effect of the improved AlexNet-CNN model, the recognition accuracy of LP image datasets under different network residuals was compared. The results show that the recognition accuracy is higher when the network residuals are larger and the datasets are more.

1. Introduction

The development of e-commerce platforms promotes people's online consumption, and there are more and more logistics products, making consumers' requirements for LP products higher and higher. Among them, the various types of packaging and the description of packaging information make the research on the identification of LP more and more important.

At present, the use of neural network models for item recognition in the logistics industry has many uses. For example, in logistics warehousing management, the LP products are printed with barcodes consisting of "black bars" and "white bars". The special light source on the scanner illuminates the barcode to reflect the coded light, the detector accepts the coded light signal and converts it into an electrical signal, converts it into digital coded information through the analog-to-digital conversion circuit, and then decodes it by the decoding software to complete the reading of the information. After identification, it means that the object has been scanned and put into storage [1, 2]. In the image recognition of LP products, R-CNN is used to extract the image features of the packaging products, but the disadvantage is that it is necessary to extract features for each candidate frame that may be redundant. In order to solve this problem, some scholars propose a Fast R-CNN model, using ROI-Pooling in the network to fix the feature size, only need to extract features from the entire image and intercept the features of the corresponding candidate frame from the image, which greatly reduces the detection time [3]. In warehousing logistics management, RFID technology can reduce out-of-stock losses and achieve transparent management of warehousing and logistics. Some logistics companies use RFID technology for warehouse management, which promotes the standardization of warehouse management and improves the efficiency of goods in and out of the warehouse. The RFID tag is fixed on the container, and the goods in the container are bound to the fixed tag [4]. In general, the extensive application of neural networks and recognition technology in the field of logistics has been the focus of research in recent years, and it is hoped that subsequent research in this area can provide reference for object recognition in other fields.

This paper first introduces two neural network models, namely ANN and CNN, and then expounds the research situation of neural network in item recognition, and analyzes the recognition system of LP product based on neural network in recognizing packaging product image. Finally, the application of the AlexNet-CNN model in the identification of LP products illustrates the effectiveness of neural network identification and detection.

2. Neural Network Model

2.1. ANN - M-P Neuron Model

In the human and animal brains, the transmission and processing of information depends on the self-activation of biological neurons and the interaction with each other. When a neuron is activated, it will release the corresponding chemical substances to other neurons connected to it. In the neuron, the internal potential of these acted neurons will change, and different potential changes will produce different activation responses, and the activated neurons will continue to propagate this activation response to other connected neurons [5, 6].

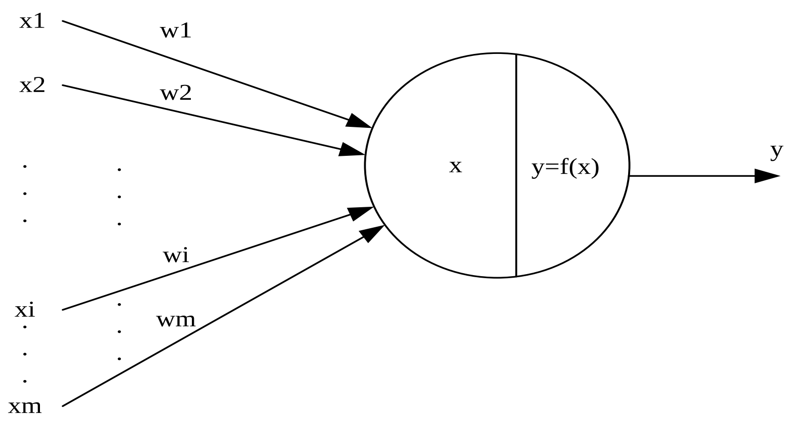

Figure 1. M-P neuron structure

In this structure of Figure 1, the input data x is m-dimensional data, which can be represented as a vector X=[x1, x2,... xm]. The connection between the input xi of each dimension and the neuron represents the operation of multiplying the weight. The neuron sums the results of all input connection operations and adds a bias, and then the summation result is obtained by nonlinear processing with an activation function. The final output, the calculation process is shown in formula (1):

$$y = f\left(\sum_{i}^{m} wi \cdot xi + k\right) \tag{1}$$

Among them, xi is the i-th dimension input data in the input data X, wi represents the weight corresponding to xi, and k is the bias term added after the summation. In the initial M-P neuron model, the bias term k is the neural the threshold θ of the element, the accumulated sum of the multiplication of the input and the weight is subtracted from the threshold θ, and if the threshold θ is exceeded, the neuron is activated, and the mathematical expression is shown in formula (2). Among them, $f(\cdot)$ is the activation function to nonlinearize the input operation, and y is the output of the neuron model. Now the neuron model generally adopts the former bias term method [7, 8].

$$y = f\left(\sum_{i}^{m} wi \cdot xi - \theta\right) \tag{2}$$

2.2. CNN - Alexnet Model

The AlexNet model takes images with a resolution of 227*227 as input. The size of the convolution kernel and the parameters of the pooling layer refer to the settings of ResNet and GoogLeNet; because the network adopts the AlexNet network structure as a whole, the number of network layers is much less than that of ResNet and GoogLeNet, so the number of convolution kernels still retains that of AlexNet [9]. The pooling layer parameter setting mainly considers the dimension of the feature map. In order to make the feature map input to the fully connected layer generally unchanged relative to AlexNet, the parameters of the convolution layer remain unchanged compared to AlexNet without adding padding. Compared with AlexNet, there is only a difference in the number of convolution kernels. The setting of the number of convolutions refers to the rules in VGGNet and increases by 2 times [10, 11].

3. Neural Network-Based LP Identification System

3.1 Application Research of Neural Network in Item Recognition

For the task of LP identification, the image object identification based on artificial neural network has a wide range of applications, and it is necessary to face a large number of categories of problems. In the initial stage, the identification of items in a specific range can be studied. The number of item categories in a specific range is limited, and accurate classification can be achieved with the support of a large amount of data [12]. However, for general item recognition, it is difficult to obtain a large amount of training data for all types of goods. The detection model integrating conventional positioning and classification cannot be applied without the support of a large amount of data. The separation of positioning and classification can train a generalized item detection model to achieve a generalized detection model. Item detection, only locates the item target, and then uses transfer learning and other methods to achieve fine classification of the extracted target [13, 14].

Usually the classification and localization tasks in the target detection network share network parameters, which can greatly reduce the amount of parameters and computation, but the classification task and the detection task have slightly different image features [15]. After the latest detection algorithm starts to share the basic network parameters for classification and positioning, two independent prediction branch networks, such as RetinaNet, the prediction branch network is small. You can focus on learning to optimize a task, which is beneficial to improve the accuracy of network prediction.

3.2. Data Processing

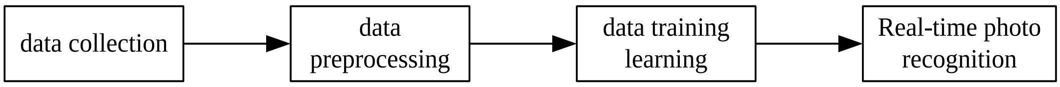

Figure 2. System data flow

Figure 2 shows the data flow of the four stages of the system. In the image collection stage of LP products, if enough image data is collected for each packaging product, the accuracy of subsequent image training and learning will be greatly improved. Therefore, it is required that each LP product must collect enough different images [16]. While collecting, the collection efficiency must be taken into consideration, and manpower time must be minimized; the collected product images must take into account different scenarios, such as dim lighting, blurred camera focus, and irregular placement of packaged products. After enough original image data is collected in the packaging image acquisition stage, the original image data needs to be preprocessed. The preprocessing requires that the effective area of the LP image must be accurately marked, and noise reduction and normalization should be performed. ; Make original classification of LP. The package information is counted and stored in the database, which is convenient for subsequent real-time identification and settlement [17].

After the image collection and preprocessing of all LP products are completed, the image data needs to be trained and learned to generate image recognition results for real-time identification of LP images. At this stage, the model of the artificial neural network needs to be considered. In the training and learning stage, the efficiency of the entire training and learning should be considered, so that the training and learning time should be as little as possible, and the accuracy of the training and learning results should be as high as possible [18].

In the stage of real-time identification of LP images, the system is required to capture images in real time and identify them in real time. When the user places the package on the system identification device to the time when the user's hand leaves the package, the whole process lasts 2 to 3 seconds. Therefore, the system requires less than 2 seconds for real-time identification.

4. Experimental Results and Analysis of LP Detection

In order to verify the effectiveness of the AlexNet-CNN model's detection method for LP, this paper conducts experiments on two different basic networks, which are residual 50 and residual 101 respectively. Secondly, the amount of data is extremely important for the training of deep networks. In order to verify the influence of the data volume on the LP product identification network, the original data (OD) has 1000 LP product images, and on the basis of the original training set, 1000 LP product images are added as data-enhanced images to train the network. Package images are called new datasets. This paper designs the following four sets of experiments: (1) Use the OD set to train on the AlexNet-CNN model recognition network with a residual of 50 in the basic network; (2) Use the new dataset to train the recognition network with a residual of 50 in the basic network

(3) Use the OD set to train on the recognition network whose basic network is residual 101; (4) Use the newly added data set to train on the recognition network whose basic network is residual 101. During the experiment, use the recognition system designed in this paper to continue to recognize. As shown in Table 1, the recognition results of the OD and new data of the AlexNet-CNN model when the network residual is 50, as shown in Figure 3, the OD and new data of the AlexNet-CNN model when the network residual is 101 recognition result.

Table 1. Recognition results (%) of the improved AlexNet-CNN model when the network residual is 50

Group	Raw data(AP)	Add data(AP)
Group 1	83.4	83.9
Group 2	82.7	86.6
Group 3	86.4	91.3
Group 4	88.1	89.7
Group 5	85.2	92.4

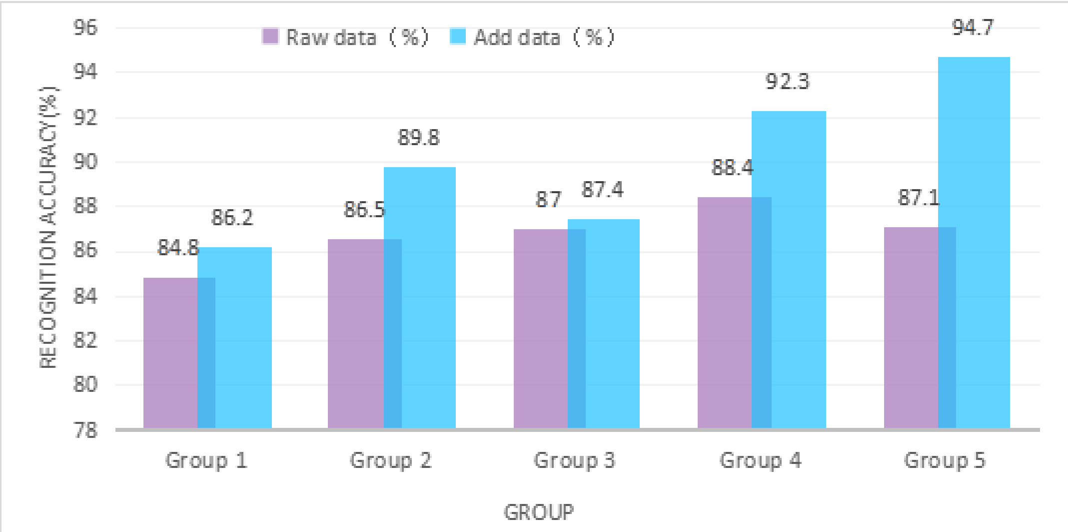

Figure 3. The recognition result (%) of the improved AlexNet-CNN model when the network residual is 101

Judging from the identification results of the OD with residuals of 50 and 101 (Experiment 1 and Experiment 3) the AlexNet-CNN model has achieved more than 80% recognition accuracy of LP, and achieved good detection results. Judging from the recognition results of the newly added data with residuals of 50 and 101 (Experiment 2 and Experiment 4) the AlexNet-CNN model has a recognition accuracy of more than 85% for LP, and the detection results are good.

Table 2. Recognition results of LP for different datasets

Experiment	mAP(%)
Residual 50 - Raw Data	85.16
Residual 50 - new data	88.78
Residual 101 - Raw Data	86.76
Residual 101 - New Data	90.08

Table 2 obtains the results of the impact of data volume on the identification network of LP products. Since the residual 101 has stronger feature extraction ability than the residual 50, the mAP of the detection network at the residual 101 is higher than that of the residual 50 detection network.

The detection network with residual 50 improves the mAP of the new dataset by 4.25% compared to the ODset; the detection network with residual 101 improves the mAP of the new dataset by 3.83% compared to the ODset. Whether in the network with a residual of 50 or 101, the recognition accuracy of the new data is higher than that of the OD, indicating that increasing the amount of data can greatly improve the recognition accuracy of the LP detection network.

5. Conclusion

In this paper, aiming at the application of neural network in the identification of LP products, the process of processing the image data of packaging products by the recognition system is proposed. The AlexNet-CNN model is used to detect the recognition accuracy of the image of LP products when the network residuals are 50 and 101. It affects the recognition rate, and because the network feature extraction ability of residual 101 is stronger, the AlexNet-CNN model has a higher recognition rate when detecting network residual 101.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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