Product Intelligence Detection Technology based on Deep Learning

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Abstract: In order to determine the appropriate method and improve the accuracy of intelligent product quality detection, the paper introduces multiple algorithms to achieve intelligent detection by using deep learning. Combined with specific industrial scenarios, product quality intelligent detection solutions mainly include data acquisition, data modeling and product quality intelligent recognition. Compared with the traditional methods, the product quality intelligent detection technology with deep learning has higher detection precision, stronger generalization ability and shorter development cycle. The combination of intelligent detection algorithm and industry manufacturing is not only conducive to the full automation of the industrial line, but also to further accelerate the industrial intelligent upgrade.

1. Introduction

The intelligent upgrade of industrial manufacturing is the direction of industrial intelligence development. The accelerated development of artificial intelligence technology has built the foundation of industrial manufacturing intelligence. The core of intelligent upgrade is to achieve comprehensive sensing and acquisition based on massive industrial data. The computer realizes intelligent decision-making and control through end-to-end data deep integration and modeling analysis. Data is collected through hardware sensors using deep learning to solve relatively complex problems. For example, image processing methods based on deep learning are implemented to product visual quality detection, use deep learning technology to intelligently detect product visual quality and guide the optimization of manufacturing process. Combined with the industrial manufacturing industry, knowledge maps of industrial fields can solve global and industrial problems.

With the development of deep learning, researchers hope to use the artificial intelligence method to fully exploit the data of the information itself, maximize the data drive and reduce human intervention. Driven by the above problems, this paper studies the intelligent detection of product visual quality and applies deep learning to the recognition and classification of product image defects. By optimizing the neural network model, the computer can automatically identify the defective products. Besides, in order to improve the computing power and speed up the operation of the algorithm, GPU parallel computing is adopted, which processes multi frame image data at the same time. This method not only improves the efficiency of enterprises but also ensures the quality of products.

In this paper, the intelligent detection technology in industrial manufacturing is studied and the image recognition technology in deep learning is applied to the intelligent detection of product visual quality. This paper mainly discusses the development of deep learning, image recognition algorithm and the realization of intelligent detection scheme of product visual quality combining with specific industrial scene. Finally, the conclusion and future work are summarized.

2. The Development of Deep Learning

With the continuous advancement of technologies such as Internet technology, network technology, and computer running storage, deep learning has gradually developed into a mainstream algorithm. In 1989, the Convolutional Neural Network (CNN) was proposed by LeCun et al., which opened the era of deep learning. In 2006, Hinton et al. proposed a self-learning initialization parameter, and then gradually tuned to solve the learning problem of deep network [1]. In 2011, the ReLU activation function was proposed, which can effectively suppress the problem of gradient disappearance [2]. In 2012, Hinton led the students to win the ILSVRC championship by constructing the convolutional neural network AlexNet [3], and entered the high-speed development period of deep learning. The flourishing development of deep learning has attracted a large number of researchers to conduct relevant theoretical research.

Compared with traditional image processing methods, CNN can accurately identify the visual information contained in the image after the image is simply preprocessed [4]. It is good at processing image data and has achieved good results in the field of images, proving its ability to process complex data and predictions. For example, in the field of image recognition classification, CNN can extract deeper feature information from input images based on supervised or semi-supervised methods, which has greatly promoted the development of target recognition classification. In 2012, Prof. Hinton and his students made an unprecedented achievement in the ImageNet image recognition classification competition. Compared with the 2011 champion algorithm of the competition, the top-5 error rate was reduced by 16.4%. And the ZFNet [5], which was fine-tuned on the AlexNet model, won the 2013 ImageNet Image Recognition Category Competition. In 2014, GoogLeNet [6] won the championship by deepening the convolutional neural network. In the same year, the VGG [7] network proposed by the University of Oxford Computer Vision Group and Google DeepMind researchers won the runner-up. In 2015, Kaiming He and others proposed the residual structure. On this basis, the deep residual network ResNet [8] was constructed and won the ImageNet image recognition classification competition.

With the help of convolutional neural networks, image recognition classification technology has developed rapidly. At the same time, computing power has also been greatly improved in recent years. GPUs are widely used in personal computers, enabling researchers to train complex neural network models, which greatly reduces the research cost of deep learning.

3. Product Quality Detection System

The product quality detection system includes sensor technology, image processing technology, deep learning and pattern recognition technology. It is an automated product quality detection system for obtaining high detection accuracy and high detection speed. The product quality detection system mainly consists of the following four parts. They are the light source system, the image acquisition module, the quality detection module and the communication module. The construction of the product quality detection system is shown in Fig. 1.

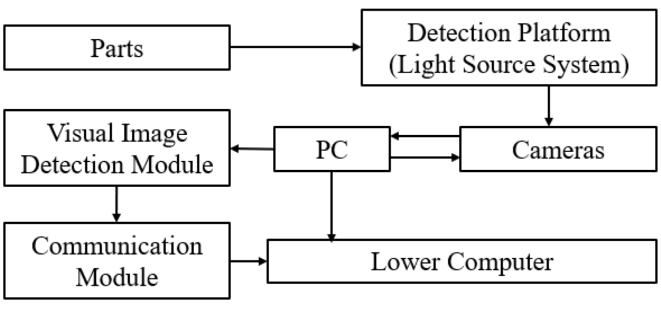

Fig. 1 The structure of product quality detection system.

The algorithm design of the product quality detection system mainly includes three parts. As shown in Fig. 2, they are establishment of image database, model training and test. The train and test of the samples are the core part of the quality detection system.

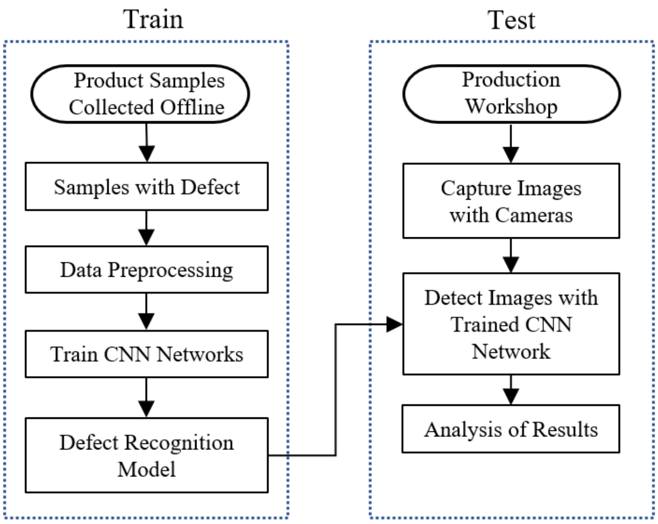

Fig. 2 Structure of the product quality detection algorithm.

(1) Identify product defect categories and establish an image database. Sample images are taken offline to screen out product images with defects. The defect images are divided into several categories according to the characteristics and causes of the defect.

(2) Train a CNN network for product quality detection offline. As shown in Fig. 3, image preprocessing is first performed on the training data. The preprocessed data is then sent to the convolutional neural network for feature extraction. The extracted features are classified based on the SoftMax layer, and the one with the highest classification score is the category to which the input image belongs [9-12].

(3) Test and optimize the product quality detection model. For trained models, further model testing is required on the test set. If the model can achieve better classification results in both the training set and the test set, it is proved that the model is generally generalized.

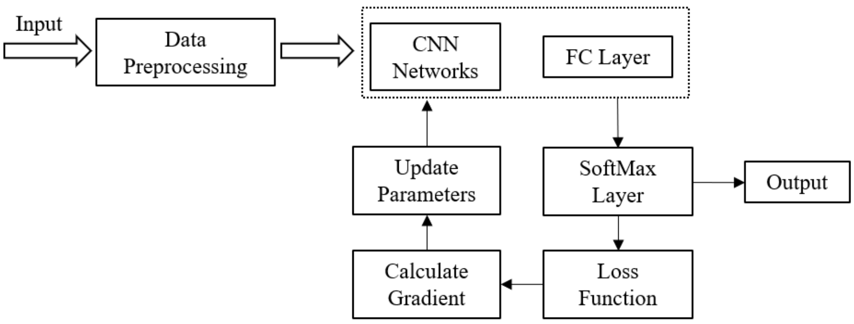

Fig.3 The model training of product quality detection.

Tacking the surface defect detection of the aluminum material as an example, the product quality detection network is introduced. As shown in Fig. 4, the surface defects of aluminum materials mainly include scratch, paint bubble, dirty point and so on. Defect detection algorithm mainly extracts image features in the part image, and then identifies defect type, which belongs to image classification task.

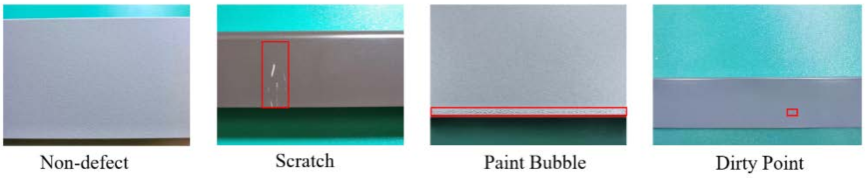

Fig. 4 The surface defect detection.

In the traditional algorithms, the defect detection mainly adopts the sample comparison method. The algorithm subtracts the image to obtain the difference value between the selected standard image and the sample to be tested, and then confirms whether the sample to be tested has defects. The disadvantage of this method is that comparison is susceptible to displacement, rotation and so on. Besides, the process is cumbersome.

The part defect detection algorithm proposed in this paper adopts deep learning, which has certain robustness to rotation, translation and size transformation. The network structure is shown in Fig. 3. For aluminum material sample images, they are divided into scratch, paint bubble, dirty spots, no defects and so on. In the training phase, data enhancement (symmetry, rotation, illumination transformation, etc.) and data normalization are first performed on the training samples. Then we use the general convolutional network to extract image features, and the fully connected layer for classification.

The general convolutional network can adopt different network structures according to different service requirements, such as VGG and DenseNet.

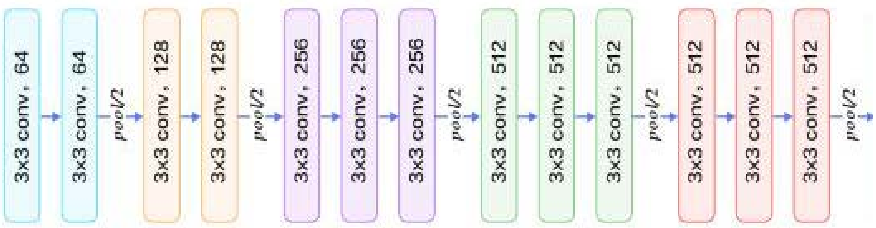

Fig. 5 VGG network.

The VGG network in Fig. 5 has a total of five convolution blocks. Every block is followed by a maximum pooling layer. The convolution layer is used to extract features. And the maximum pooling layer can not only be used to down-sample but also remove redundant features. The advantage of the VGG network is that the structure is simple, it only needs a small number of iterations to start convergence, and the training time is short. However, after the VGG network reaches a certain depth, it is prone to degradation, that is, the accuracy reaches saturation or even begins to decline.

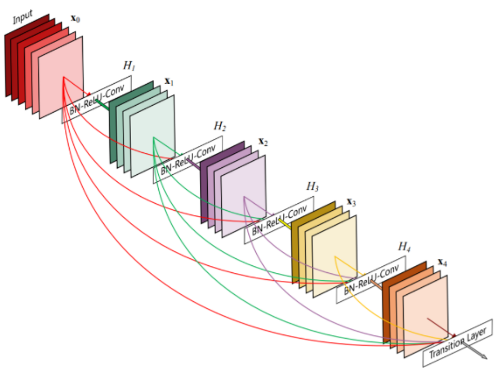

Fig. 6 Dense connection module in DenseNet.

Compared with VGG, DenseNet includes a dense connection mechanism as shown in Fig. 6. DenseNet consists of multiple densely connected modules [13]. Since the dense connection module needs to maintain the same feature dimension internally, the layer between each densely connected module is called a conversion layer. And the convolution layer and mean pooling layer are mainly used for down-sampling. Dense connection mode effectively alleviates the phenomenon of gradient disappearance, enhances feature propagation, encourages feature reuse, and greatly reduces the amount of parameter.

The surface defect detection of the aluminum material system based on deep learning has a good performance in detecting accuracy and detection speed by comparing with the traditional defect detection methods. And it shows great robustness to lighting, rotation and so on.

Through the above experimental analysis, it is found that visual detection has obvious advantages in the stability of the detection process, the accuracy of the detection results and the economic benefits. The application of visual detection technology will greatly improve efficiency of the appearance detection work during the product quality detection process. And it will further improve the automation of the production line and save a lot of labor costs.

4. Conclusion

With the intelligent upgrading of industrial manufacturing, visual detection of product quality in industrial manufacturing has become an important factor in the industrial production chain. The appearance detection of traditional industrial manufacturing products relies more on manual inspection to realize the recognition of the appearance of the products and eliminate the defective products. However, it has low efficiency and high missed detection rate. With the rapid development of deep learning, intelligent detection technology combining with big data can improve detection efficiency and accelerate industrial intelligent upgrade.

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