Metal Surface Defect Identification Method Based on Deep Learning

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Abstract

Aiming at the problems of various defect types, sizes and shapes in the process of identifying metal product surface defects, a deep learning model based on multi-scale residual convolutional network is proposed. The network uses ResNet50 as the feature encoder to extract feature maps with different resolutions to capture multi-scale feature information, thereby improving its ability to identify defects of different sizes; it also uses Multi-Layer Perceptron (MLP) for multi-scale Adaptive fusion of features enables information interaction and feature refinement between features such as image texture and boundaries obtained by shallow convolution and complex semantic feature information extracted by deep convolution to improve network model recognition performance. Experimental results show that the algorithm proposed in the article has an accuracy of 98.06% on the NEU-DET data set, and has higher recognition accuracy than other models.

Keywords

ddeep learning, defect recognition, multi-scale features, Multi-Layer Perceptron.

1. Introduction

With the advancement of the industrial revolution, metals have gradually become extremely important raw materials in production, life and industrial manufacturing. The continuous upgrading of metal smelting and metal processing technology has made products based on iron, aluminum, copper and other metals and their alloys as main materials widely used in automobiles, ships, construction, aerospace, manufacturing and other industrial fields. During the manufacturing and processing of metal parts, due to improper personnel operation or production process problems, metal products will produce scratches, burrs, holes, stripes, wear, cracks and other defects, which greatly affect the appearance quality and performance of metal products[1]. Therefore, it is very necessary to detect and identify metal surface defects during the production process.

At present, manual visual inspection is still widely used in industrial production. For metal surface defect detection, this method has problems such as low detection efficiency, low recognition accuracy, poor stability, and high labor intensity[2]. With the rise of neural networks and deep learning, in order to solve the above problems, scholars have applied deep learning technology to metal surface defects in recent years to achieve fast, accurate, and automated identification. Compared with traditional manual recognition methods, the main advantage of deep learning is that it does not require manual feature selection and design. Instead, it learns image features through automatic methods, and performs feature extraction and classification. It has strong versatility and robustness. For example, Tang Donglin et al[3] proposed a metal defect identification method using a shallow convolutional neural network fused with the Transformer model, which showed good performance; Chen Zongyang et al[4] proposed an improved MobileNetV2, a network-based method for identifying surface defects in metal coatings. Although these methods have achieved good results, in practical applications, there are many types of surface defects in metal products with varying sizes and shapes, making it difficult to accurately identify and classify them.

In view of the existing problems in current research, this paper proposes a multi-scale residual convolution network for metal surface defect recognition, as shown in Figure 1. The network uses ResNet50 to extract multi-scale features and uses a multi-layer perceptron to adaptively fuse shallow features. Layer image texture features and deep image semantic information are used to improve the network's feature extraction and learning capabilities for defects of different sizes on metal surfaces, especially small-size defects, thereby improving model robustness.

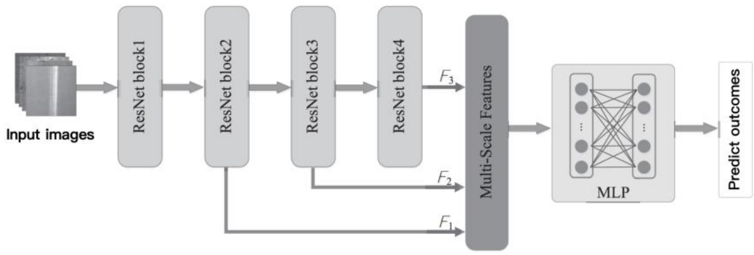

Figure 1: Network structure of this article

2. Network structure

The multi-scale residual convolutional network structure proposed in this article mainly consists of two parts: a multi-scale feature extractor and a multi-layer perceptron. Given an input image, ResNet50[5] is used as the feature encoder to extract feature maps with different resolutions {F1,F2,F3}. Then, the adaptive average pooling operation is used to convert it into a unified dimension, and concat is used to splice and combine the feature maps in the channel dimension to obtain multiple F_{ms}:

$$F_{\mathrm{ms}} = \mathrm{concat}\{F_1', F_2', F_3'\} \tag{1}$$

$$\{F_1^{'}, F_2^{'}, F_3^{'}\} = \mathrm{Avg_pooling}\{F_1, F_2, F_3\} \tag{2}$$

F_{ms} is the multi-scale feature information contained can improve the network's feature extraction and learning capabilities for defects of different sizes. Multi-layer perceptrons are further used to effectively integrate these multi-scale information and achieve adaptive fusion of features to obtain more advanced feature information. The specific process is as follows:

$$F_{\mathrm{out}} = MLP(F_{\mathrm{ms}}) \tag{2}$$

The formula: MLP is composed of two fully connected layers (Fully Connected Layers) and a ReLU (Rectified Linear Unit) activation function composed of numbers. Based on this, the image texture and edges obtained by shallow convolution are features such as boundaries and complex semantic extracted by deep convolution perform information interaction and feature refinement to obtain more discriminating features F_{out} for metal surfaces Defect classification.

3. Experiments and results

3.1. Dataset and experimental settings

This article uses the metal surface defect data set NEU-DET[6]released by Northeastern University to collect six common surface defects of hot-rolled steel strips, That is, rolling scale (RS), plaque (Pa), cracking (Cr), pitted surface (PS), inclusions (In) and scratches (Sc). The dataset includes 1800 grayscale images, with 300 samples per category.

This paper divides the NEU-DET data set into the training set, verification set and test set are 1080 and 360 images respectively, and 360 pictures for model training and analysis. The experiments in this article were implemented on Pytorch, and the environment was built under the Jupyternotebook framework. In model training, the input image is adjusted to a resolution of 224×224, Adma is used as the training optimizer, the learning rate is 0.0003, the training batch batch_size is 64, and a total of 100 epochs are trained.

3.2. Analysis of experimental results

Accuracy is used as the evaluation index of model performance, and the same data set and experimental environment are used to compare the network model proposed in this article with the existing advanced classification models[7-11] Compare. The experimental results are shown in Table 1. The recognition effect of the network in this paper is better than other models in the NEU-DET data set. The accuracy of SENet and Res2Net increased by 0.56% and 2.23% respectively. This shows that the network in this paper is more suitable for the recognition of complex defects on metal surfaces. The features such as image texture and boundaries obtained by shallow convolution and the complex semantic feature information extracted by deep convolution are used for information interaction and feature refinement to learn complementary multi-scale feature information and achieve higher recognition performance.

Table 1: Comparison of model comprehensive performance

Model	Accuracy/%
VGG16[7]	96.11
ResNet50[5]	97.22
DenseNet121 [8]	97.50
GhostNet[9]	93.61
SENet[10]	97.50
Res2Net[11]	95.83
This article network	98.06

4. Conclusion

This paper proposes a metal surface defect identification method based on a multi-scale residual convolutional network. The network draws on the structural design of the deep residual network and integrates feature maps of different levels and scales to make full use of the shallow layers of the image. Texture features and deep semantic features can better alleviate the problem of difficult feature extraction of metal defects of different scales. Experimental results show that the proposed network can effectively identify metal surface defects and has higher identification accuracy than other models.

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