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Application of deep learning in defect Detection

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Abstract—Defect detection has been the important link in the process of manufacturing enterprise production, is also one of the challenging parts, with the rapid development of science and technology and the introduction of " Industry 4.0 ", Intelligent Manufacturing, "Made in China 2025" put forward of the concept and development, manufacturing enterprises for the industrial product defect detection requirements are increasingly high, industrial product defect detection has also received more and more attention. In this paper, the application of deep learning in defect detection of industrial products is analyzed and discussed. Meanwhile, the traditional defect detection methods are summarized and compared with those using deep learning method. By combing and analyzing ICCV2019, the top conference in the field of computer vision, new technologies, new methods and new ideas that may be applied in the field of defect detection in the future were explored, and the challenges faced by them were analyzed in depth.

1. INTRODUCTION

Industrial products defect detection is an important part in manufacturing, due to force majeure factors in the process of manufacturing or other man-made factors, lead to the industrial defects such as surface defects, scratches, spots [1], influence the reliability of the industrial or use, serious and even the huge harm to life. Therefore, it is particularly important to carry out industrial product defect detection. Manual detection is a defect detection method often used in traditional manufacturing industry, which usually relies on the experience of quality inspectors to ensure the quality of products. Due to the uneven experience of inspectors and the limitations of human capabilities, this method has low efficiency, low accuracy and poor real-time performance in large-scale manufacturing scenes. With the further upgrading of the manufacturing industry in recent years, this method can no longer meet the requirements of high speed and high accuracy in modern industry. Deep learning and application [2] automatic defect detection technology can not only greatly improve the accuracy of detection of industrial products to improve testing efficiency, reduce labor costs, and promotes the integration of information, to upgrade the manufacturing of intelligent information to lay a solid foundation, has become the focus of the present study, got the attention of more and more, related publications have geometric index number of growth. Figure 1 shows the growth in the number of publications related to deep learning and defect detection over the past 20 years.
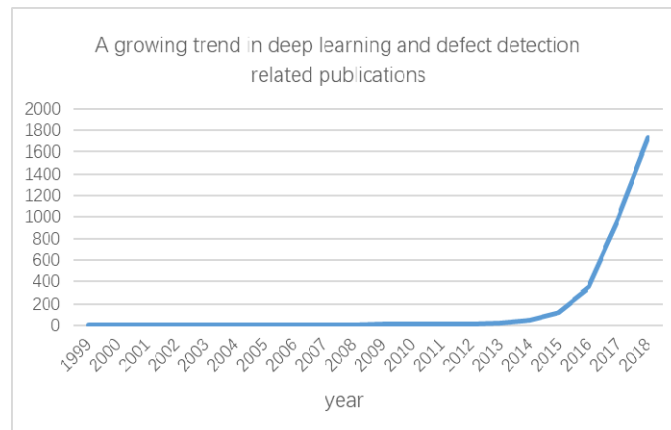
Figure 1.   Growth of publications related to deep learning and defect detection from 1999 to 2018(data from Google academic, keywords "deep learning" and "defect detection")

2. TYPICAL DEFECT DETECTION TECHNIQUES

Typical defect detection technologies include direct defect detection and pattern recognition based defect detection. Direct defect detection technology mainly includes X-ray detection, ultrasonic detection and magnetic particle detection. Direct defect detection technology is a technology that can directly detect and determine whether a product has defects. It can directly detect whether a product has defects. Defect detection technique based on pattern recognition is mainly automatic optical inspection method, by choosing appropriate light source and industrial camera collection and the surface of the product image, through some image recognition and processing algorithms to extract the work piece defect feature information, compared with zero defect work pieces, finally according to extract the feature information of surface defect detection.

2.1. Automatic optical detection

Automatic optical inspection technology is based on the human eye vision imaging and discriminant principle of the human brain intelligence by optical illumination of measured object and image sensor technology to obtain information, through digital image processing to enhance the target features, and then adopt the method of pattern recognition, by using some image processing algorithms extract characteristic information from the background image, and are classified and characterized, and then feedback to perform control mechanism, to realize the classification of the product, group or separation, the quality control in the process of production, etc. Automatic optical surface defect inspection technology has been widely applied in industrial, agricultural, biological, medical and other industries, especially in precision manufacturing and assembly industry, such as mobile phones, LCD, silicon wafers, printed circuit board, and other fields, automatic optical surface defect inspection technology exceptionally rapid development, all kinds of high-tech detection equipment emerge in endlessly, has the advantages of automation, high precision and high stability.

2.2. X-ray detection

X-ray detection is a nondestructive detection method that USES the different attenuation characteristics of the matrix material and the defects of the work piece to find the defects. After more than 100 years of development, X-ray detection technology has formed a relatively complete X-ray detection technology system consisting of X-ray photography, X-ray real-time imaging, digital plate X-ray imaging, and X-ray computer tomography, etc. from the original film radiography technology. X-ray detection has no strict requirements on the surface finish of the work piece, and the material grain size has little influence on the detection results. It can be applied to the detection of internal defects of various materials, so it has been widely used in the welding quality inspection of pressure vessels.

3. DEFECT DETECTION TECHNOLOGY IN DEEP LEARNING

3.1. The deep learning technique applied in defect detection

Data preprocessing is a very important part in the whole process of data mining. When we integrate the data from various data sources, the data is often incomplete and there are many noises and redundancy. The quality of the data directly affects the reliability of the mining model and the correctness of the decision. For the accuracy of data mining results, data needs to be preprocessed, which mainly includes three forms of data cleaning, data transformation and data dimension reduction.

3.1.1. *Depth auto coder:* The depth auto coder [5] is a neural network that USES back propagation algorithm to make the output value equal to the input value. It first compresses the input into a potential spatial representation, and then reconstructs the representation into the output. So in essence, the auto-encoder is a kind of data compression algorithm, and its compression and decompression algorithms are realized through the neural network. There are two main applications in defect detection, the first is to denoise the data, the second is to reduce the dimension of the data.

3.1.2. *Deep convolutional neural network:* Four basic ideas constitute a convolutional neural network [6], namely, local connection, Shared weight, pooling and multi-layer use. The first part of CNN is composed of convolutional layer and pooling layer, while the second part is mainly full connection layer. The convolutional layer detects local connections of features, and the pool layer merges similar features into one. CNN USES convolution instead of matrix multiplication in the convolutional layer. Deep convolutional neural network is widely used in defect detection and has excellent effect on the identification of defective parts in industrial products.

3.1.3. *A region-based convolutional neural network:* Region-based convolutional neural network (R-CNN)[7] USES regions for identification. R-cnn USES regions to locate and segment targets. The architecture is composed of three modules: a category-independent region proposal that defines the set of candidate regions, a large convolutional neural network (CNN) that extracts features from the regions, and a set of class-specific linear support vector machines (SVM)[8]. The characteristics of the network are very accurate identification of defects, but the disadvantages are that the operation time is long and the real-time performance is poor.

3.1.4. *ResNet:* ResNet [9] has low error and is easy to be trained through residual learning. Deeper levels of ResNet can achieve better performance than traditional CNN networks. In the field of deep learning, ResNet is considered an important step forward. Using deep residual network to detect defects can obtain higher accuracy.

4. DEFECT DETECTION TECHNOLOGY IN DEEP LEARNING

Although the typical defect detection method can accurate detection of some known defects, but their poor generality, defect detection method in specific categories cannot be directly applicable to other different kinds of defect detection and when some new defects or problems that need to manually design new test program, and deep learning technology can be more easily adapted to different defects. First of all, transfer learning [10] can make pre-trained deep networks effective for different applications in the same field. For example, the pre-trained image classification network is usually used as a feature extraction front end for target detection and segmentation networks. Using these pre-trained networks as a front end simplifies the training of the entire model and generally helps achieve higher performance in a shorter time. In addition, the basic ideas and technologies of deep learning in different fields are often transferable, which helps developers to learn and use the latest technologies quickly.

In literature [11], a deep convolutional neural network is used to detect defects in an industrial optical data set [12], and the methods of optical detection and machine vision are compared. The average precision of deep learning reaches 99.2%, while that of automatic optical detection is 98.2%. In

literature [13], the depth auto coder and convolutional neural network are used to detect the defects of composite materials, and the maximum detection accuracy can reach 92.1%. In reference [14], deep convolutional neural network was used to detect rail defects, with an average detection accuracy of over 92%. The literature [15] USES deep convolutional neural network to detect concrete cracks, and compares it with two machine vision methods. The results show that the average accuracy of the defect detection method using deep learning can reach 98.22%. Reference [16] USES convolutional neural network to detect metal surface defects, with a detection accuracy of 89.06%, and can be directly applied to defects of other types of materials. In reference [17], convolutional neural network was used to detect wafer defects, with an average accuracy rate of 98.2%. Literature [18] USES deep convolutional neural network to detect road cracks, with an average detection accuracy of 87%. Literature [19] USES region-based convolutional neural network for surface defect detection of canning containers, and compares some machine learning methods, which are respectively 95%, KNN 65.83%, and SVM 80.83%. Literature [20] USES region-based convolutional neural network to detect mobile phone screen defects, with an average accuracy of 99.23%. Literature [21] USES deep convolutional network for defect detection of rail fasteners, with an average detection accuracy of 99.9%. Reference [22] USES a depth auto coder for fabric defect detection, with the highest average accuracy up to 93.25%.

Table 1 is a typical defect depth study and test method of comparative analysis, can be seen from the table, deep learning detection technology compared to the typical defect detection methods, detection accuracy have improved, at the same time because of the defect detection is generally of image information processing, so the convolution neural network has been widely used in the field of defect detection. The defect detection technology of deep learning can be used for all kinds of defect detection.

TABLE I.   COMPARATIVE ANALYSIS OF DEEP LEARNING AND TYPICAL DEFECT DETECTION METHODS.

Application of the product	Typical defect detection techniques	Precision	Deep learning defect detection technology	Precision
Industrial optical data set	Automatic optical detection	98.2%	Deep convolutional neural network	99.2% [11]
Composite materials	____	____	Convolution neural network	92.1% [13]
Rail	____	____	Deep convolutional neural network	92% [14]
Concrete	Two kinds of automatic optical detection using different algorithms	Less than 95%	Deep convolutional neural network	98.22%[15]
		Less than 95%		
The metal surface	An automatic optical detection method combining multiple algorithms	69.76%	Convolution neural network	89.06%[16]
The wafer	____	____	Convolution neural network	98.2%[17]
The road	____	____	Deep convolutional neural network	87%[18]
Canned container	Two kinds of automatic optical detection using different algorithms	65.83%	A region-based convolutional neural network	95%[19]
		80.83%		
Mobile phone screen	____	____	A region-based convolutional neural network	99.23%[20]
Rail fastener	____	____	Convolution neural network	99.9%[21]

5. NEW TECHNOLOGIES THAT MAY BE USED IN THE FUTURE

Literature [23] improved YOLOv3 to enable the network to output the uncertainty of each detection box through the feature of Gaussian distribution, thus improving the accuracy of the network. YOLOv3 has extremely fast detection speed and has now significantly improved accuracy, making it possible to apply deep learning to real-time defect detection in the future.

Literature [24] all estimated the depth of a single image without depth information. At present, the application of deep learning in defect detection is still limited to the surface of industrial products. The depth estimation of a single image may be applied to internal defect detection in the future.

A method of automatic compression model is proposed in literature [25]. The current deep learning model is too large to be applied to defect detection, and the model optimization methods for different defect detection are not the same. Automatic compression model will greatly reduce this workload.

6. THE INADEQUACY AND DIRECTION OF DEEP LEARNING IN DEFECT DETECTION

1. At present, most of the applications of deep learning in defect detection are still in the laboratory exploration stage, which requires more practical application in the actual detection environment.

2. Firstly, the data used for various defect detection is not sufficient, and the data set is generally small, so the enhancement and expansion of the data set in the future will be particularly important.

3. It takes too long to train the defect detection model, and the development and application of transfer learning will also promote the progress of deep learning in the defect detection industry.

4. Currently, for some products requiring real-time detection, some deep learning detection methods are not fast enough. In the future, network optimization and model pruning of deep neural network will greatly speed up some models to reach the level of real-time detection.

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