A Comprehensive Survey of Defect Detection in Manufacturing Products using Deep Learning Techniques

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Abstract - *To improve manufacturing of quality products and decrease production cost, image processing and machine learning based techniques are widely used now-a-days. Advances in Artificial Intelligence technologies which provides advanced tools to inspect products, analyzed the quality of products, helps us to improved manufacturing quality and quantity. However, to improve quality of products, proper inspection of manufacturing defects is crucial. Therefore, in this study, we discuss the existing image processing, computer vision and machine learning techniques that are often used to detect defects in the products and help to inspects them effectively. Deep learning based state-of-the-art studies are presented and compared. We also highlighted the benefits and limitation of existing algorithms which may help researchers to find a better solution such challenges. Finally, paper summarize the study by discussing most efficient approach for defect detection in manufacturing process.*

Key Words: **Quality control, defect detection, Object Recognition, Deep Learning, Image Processing and Computer Vision.**

1.INTRODUCTION

Defect detection and classification are two issues that must be approached as separate challenges within the artificial vision area. The majority of digital image processing issues arise from unique situations in which researchers are attempting to imitate or replace human eyesight and decision-making processes with artificial techniques. Internal holes [1], scratches [2] etc., and occur in the creation of mechanical goods in complicated industrial processes owing to design and machine production equipment failures, as well as adverse working circumstances. Because of their frequent usage, products can quickly corrode [3] and get fatigued [4]. These flaws raise business expenses, reduce the useful life of produced items, and waste a lot of resources, all while endangering people's health and safety. As a result, identifying flaws is a critical skill that businesses should have in order to enhance the quality of manufactured goods without impacting productivity. The advantages of automatic flaw identification over manual detection are clear. It not only adjusts to an inappropriate environment, but also operates with great accuracy and efficiency in the long term. Fault detection technology research may lower production costs, enhance efficiency, and enhance product quality, while also laying a strong foundation for the industry's intelligent transition.

As a result, numerous academics have evaluated defect-detection-related technologies and applications in order to give references for defect-detection technology application and study. In the industrial manufacturing line, quality control is critical. To measure the quality of a product or the output of a process, several techniques are being employed. Quality control techniques can be classed as destructive or non-destructive, depending on the approach used to discover a fault on a surface/volume, as illustrated in Figure1.

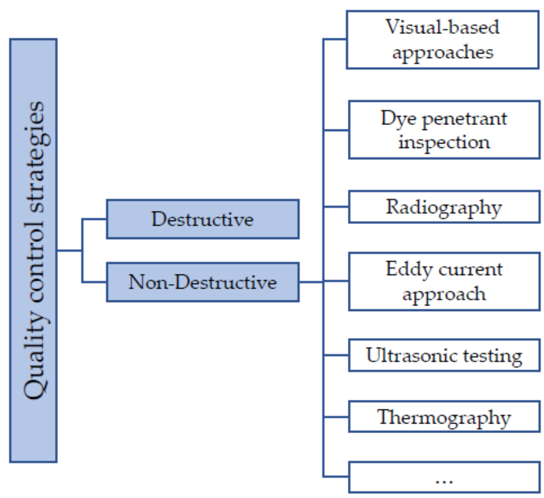

Figure 1: strategies of quality control

One of the most popular processes in business is the visual-based approach for fault identification. Traditional visual examination, on the other hand, is a non-measurable procedure with varied and subjective results. Because of the complexity and uniqueness of each problem to address, researchers have been forced to design new automatic flaw detection systems with stringent requirements. Such a system, however, is dependent on the material characteristics of the surfaces to be monitored as well as the surrounding circumstances. Indeed, due to dusty or resonant working locations, the environment hampers any implementation in industrial applications.

The process of describing a fault and categorizing it entails a succession of subjective choices. Because the size of flaws varies between industrial applications, the major features of a defect are determined by the detection procedure's desired accuracy and resolution. Before building and implementing an automated system in any industrial quality control application, it is strongly recommended to create a product quality standard.

2. EXISTING TECHNIQUES FOR DEFECT DETECTION

Defect detection technology is primarily used to detect fault or defect on the product surface and interior flaws. On the product surface, defect-detection technology relates to the identification of spots, pits, scratches, color variations, and defects. An example of defects in the products is shown in Figure 2.

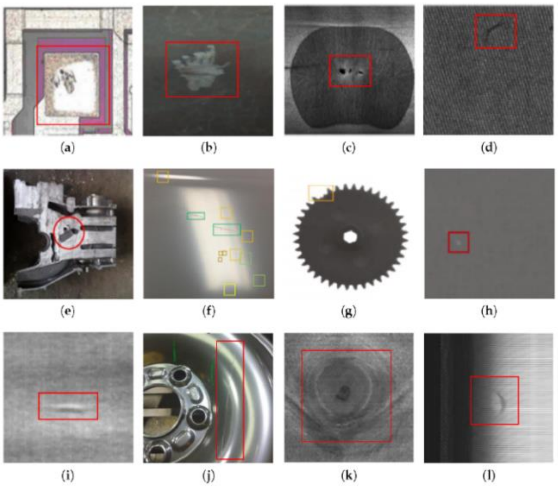

Figure 2: Defects in different areas of products

The magnetic powder is mixed with water, oil, or other liquid media in wet magnetic particle detection. Magnetic powder can recognize the exact site of defect with the help of liquid pressure and external magnetic field [5].

The angle between the fault surface and the ultrasonic propagation direction affects the ultrasonic testing impact [6]. The signal returned is strong if the angle is vertical, and the fault is quickly recognized. While, the signal returned is faint if the angle is horizontal, making it simple to identify a leak. As a result, in order to decrease leakage detection, the suitable detection sensitivity and associated probe must be used.

Image capture, defect detection, and classification are the primary components of machine vision detection. Machine vision is frequently utilized due to its quick, accurate, non-destructive, and low-cost features. The color, texture, and geometric characteristics of things are used by machine vision to identify them. The difficulty of image processing is determined by the quality of picture capture. In turn, the performance such as accuracy the rate by which systems detect a defects and classification of defects are directly influenced by the quality of the image processing method [7, 8].

Traditional defect-detection approaches, as well as well-known fault or defect detection using deep learning algorithms, clearly have benefits. Classical defect detection methods are quite specific. For example, Osmosis testing technique is only appropriate for identifying flaws in highly permeable and non-porous materials, although it has certain benefits over other approaches. However, most classic detection techniques still require manual help to complete, especially when instrument debugging is necessary prior to testing, and equipment development costs are significant, making it difficult to adapt and restricted by equipment life and manufacturing precision. Due to their adaptability and lack of reliance on human help, innovative defect-detection approaches, notably machine vision and deep-learning methods have become the most popular in recent years and are one of the main technologies for automating defect identification. The new technologies offer better inspection results and cheaper costs than classic defect detection approaches, but they still rely on huge volumes of learning data to drive model updates and increase inspection accuracy.

3. DETECT DETECTION USING DEEP LEARNING

Deep-learning technology has advanced quickly and achieved tremendous success in a variety of fields of study. A deep neural network structure with many convolutions layers is used in deep learning. The data may be better reached in abstract ways such as edge and shape to increase the efficacy of the deep-learning algorithm [9], by combining low-level characteristics to produce a more abstract high-level representation of attribute categories or features. As a result, several researchers are attempting to employ deep-learning technologies to detect product defects and enhance product quality [10, 11].

3.1 Defect detection using CNN [12]

CNN is a feedforward neural network that stands for "convolutional neural network." A CNN is made up of one or more convolutional and fully connected layers, as well as weights and pooling layers. Literature [13] is a popular LeNet convolution neural network topology. There are two ways to use the LeNet network structure to detect defects in images: one is to design a complex multi-layer CNN structure, use different network structures to add image content features, and complete end-to-end training to detect defects in images; the other is to combine CNN with CRF model, train CNN with CRF energy function as constraint, or optimize network prediction results with CRF. Detection of product flaws is also a goal.

3.2 Neural Network based Defect-detection [14]

The most crucial steps of an autoencoder network are coding and decoding. In the coding step, the input signal is transformed into a coding signal for feature extraction; in the decoding stage, the feature information is transformed into a reconstruction signal, and the reconstruction error is reduced by modifying the weight and bias to accomplish defect detection [15]. The distinction between autoencoder networks and other machine learning methods is that the autoencoder network's learning aim is feature learning rather than classification. It also has a significant ability to learn on its own and is capable of extremely nonlinear mapping. It can learn nonlinear metric functions to tackle the problem of complicated background and foreground region segmentation. In the subject of computer vision, particularly in picture segmentation, substantial progress has been made. The development of deep CNNs has resulted in significant gains in a variety of image processing jobs. A basic overview of CNNs is provided in this section.

In CNN, the input passes through a series of processing processes, referred to as layers, in order to be processed. Each layer I may be thought of as an arbitrary transformation xi+1 = f(xi; **θ***i*) with inputs xi, outputs xi+1, and parameters I with inputs xi, outputs xi+1, and parameters **θ***i*. The output is referred as feature map and can be presented as shown below.

$$f(\boldsymbol{x}) = f_N(\ldots\ f_2(f_1(\boldsymbol{x}_1; \boldsymbol{\theta}_1); \boldsymbol{\theta}_2) \ldots\ ); \boldsymbol{\theta}_N),$$

Figure 3 schematically depicts the convolution of a H x W x 1 kernel with an image, where H and W denoted the height and width of kernel. It is feasible to produce meaningful outputs, such as picture gradients, by convolving specific types of kernels with the input image. The first few convolutional layers in most contemporary CNN designs extract characteristics like edges and textures. Deeper convolutional layers in the network may extract information like object forms that cover a larger spatial region of the picture.

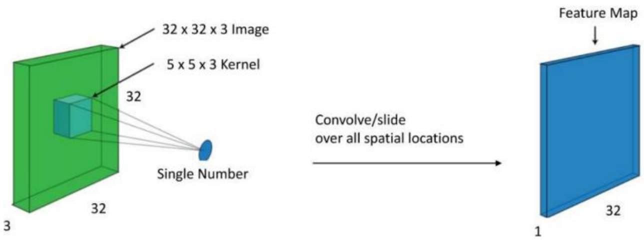

Figure 3: Features map generation using CNN.

3.3 ResNet based Defect-detection [16]

The architecture of residual model is similar to the convolutional neural network except it add few residual modules on the top of stacked convolutional operations. The residual network has a simple optimization process and may increase accuracy by increasing network depth. With the depth of the network increasing, the extraction feature rises, but it is simple to cause the activation function not to converge. CNN, Generative Adversarial Networks, etc. The objective of the deep residual network is to minimize the loss by optimizing the number of network layers while increasing the network structure, such that the output and input element dimensions of the convolution layer in the residual unit are the same. The residual unit of ResNet is shown in Figure 4.

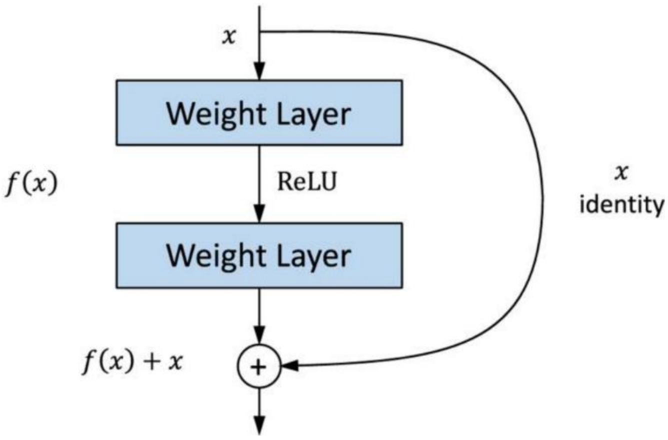

Figure 4: Residual unit of deep model

ResNet is trained to detect defect based on regions after training it with COCO dataset and Microsoft Common Objects in Context dataset. For a given input image, top 50 defect regions is found and shown in Figure 5.

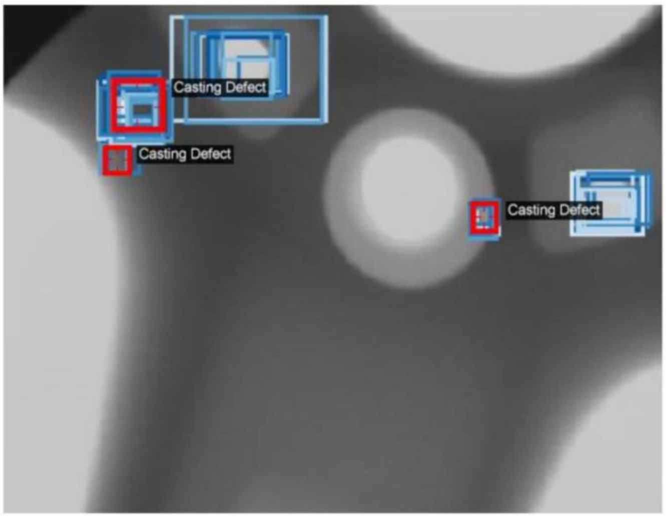

Figure 5: Detected top 50 defect regions

From the results, it is found that Residual Deep Neural network a segment image to find defect with and accuracy of 93 %.

3.4 Full Convolution Neural Network

A link between any two nodes between two adjacent levels is referred to as a completely connected layer. There will be more weight values in a fully connected neural network since it uses a fully linked operation, indicating that the network will demand more memory and processing. During the calculation of the fully connected neural network, the feature map generated by the convolution layer is mapped into a fixed-length feature vector. The complete convolution neural network can take any size input picture, and by sampling the feature map of the last convolution layer with the deconvolution layer, it can recover to the same size as the original image. such that a forecast may be made for each pixel while keeping the spatial information in the original input picture, and then categorize the upper sampling feature map pixel by pixel.

3.5 Recurrent Neural Network [17]

The recurrent neural network originates from the evolution direction of sequence data, with all cyclic units connected in a chain form, as the input. Convolution and pooling procedures are used by the CNN model to extract feature information from input layer test samples. The recurrent neural network replaces the CNN's convolution process with the recurrent convolution operation.

To find a crack in Prestressed concrete (PSC) box-girder, in [17], a Recurrent Neural Network is trained. A RNN is a type of artificial neural network in which hidden nodes are linked together by a directed edge to form a cyclic structure. This paradigm is well-known for its ability to handle sequential data like text, sounds, and signals. The RNN's most important property, as seen in Figure 6.

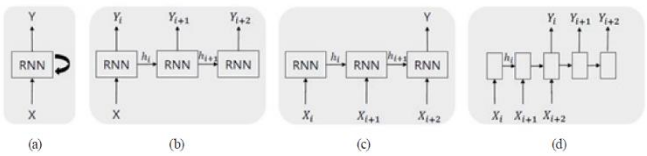

Figure 6: Architecture of RNN to detect defects.

The SoftMax function is used to categorize the class of input data in artificial neural networks. The SoftMax function classifies a given sample by using the output layer to normalize it. This function, for example, computes the likelihood of being positive by inputting data from the hidden layer while evaluating if a cancer is benign (1) or malignant (0). The SoftMax function used here is shown in equation below:

$$\text{softmax}(x) = \frac{e^{x_i}}{\sum_{k=1}^{K} e^{x_k}} \quad (i = 1, 2, 3, \ldots, K).$$

Experiments with several hyperparameters revealed that the optimum hyperparameters have an accuracy of 82.58 %.

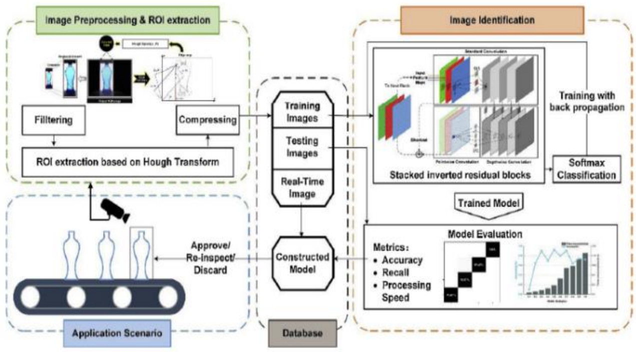

Figure 7: Proposed framework of deep model

3.6 Inverted ResNet and Hough transform based defect-detection [18]

An effective product inspection approach is suggested in this work in order to achieve a compromise between recognition accuracy and overall model complexity. Figure 4 depicts the complete picture processing and identification pipeline. Product images could be recorded and sent to the server as the conveyer belt went along, allowing for additional analysis. Defective goods may be recognized using the suggested technique in three stages: image preprocessing, ROI extraction, and picture identification.

Pre-processing: Proposed method pre-process input image first by smoothing it using Gaussian blur. The filter size used to remove noise using Gaussian function is 3x3. Once images are pre-processed, region of interest (ROI) are extracted from it.

ROI Extraction: Since extraneous background content may comprise a significant portion of the image, the collected images may not ensure that all included information is task-related, resulting in needless computations during the next identification stage. In practice, a lighting source is used to highlight defective items and guarantee that the collected photos are consistent. Fortunately, such a lighting source is generally rectangular or circular in form. As a consequence, the probabilistic Hough transform is used to swiftly determine the line or circle of the illumination source edge, which can subsequently be used to extract ROI from the filtered image.

Identification of Images: The goal of this stage is to identify the extracted ROI's detailed class. The picture identification module is built by cascading inverted residual blocks to achieve excellent classification accuracy and speed. Performance of model is evaluated by calculating accuracy and recall as shown in following equation.

$$\text{Accuracy} = \sum_{i=1}^{n} T_i / (\sum_{i=1}^{n} T_i + \sum_{i=1}^{n} F_i)$$

$$\text{Recall} = T_i / (T_i + F_i)$$

Where Ti and Fi presents truly classified and false classified samples. From the results, it is found that proposed method can detect defect with 99.60% accuracy.

According to the findings, all of the tested techniques employ well-preprocessed pictures. As a result, most deep learning algorithms, except than MLP, require greater computer resources to achieve higher inspection accuracy. MLP is the quickest, but it's also the least accurate, as it misses spatial information in the picture. Meanwhile, because MLP is parameter-intensive, it requires more storage capacity to cache and store the learned MLP.

4. DISCUSSION

In the past few years numerous image processing and machine learning based algorithms has been proposed to detect defects in the products manufacturing. Few approaches work well and produced acceptable accuracy. Texture based approach, fusion of texture with other features. Local binary pattern features and GLCM features based defect detection approaches are one of them. However, these approaches extract manual features which may not include unique pattern. Therefore, deep learning takes advantages over traditional algorithms for defect detection.

Due to automatic feature learning, NN is widely used for many detection and recognition problems. For detect defection, a number of studies have been done using deep learning and discussed in this paper. CNN performs well but it requires a lot of training times and processor. Moreover, as the depth of convolutional layer increases, training time also decreases. To overcome this limitation, a residual block based deep model which is also named as ResNet, is proposed. ResNet works well and produced significant improvement in the performance. It also required less training time even with large depth of convolutional layers. However, it may not be suitable for time series data. Therefore, recurrent neural network based deep model architecture is proposed. Recently, a inverted residual block based deep architectures along with Hough transform features is proposed to detect defects in the manufacturing products. From the results it can be concluded that the proposed system works well with real-time data and produces excellent results.

5. CONCLUSIONS

Industrial product quality is a key aspect of manufacturing, and research into defect-detection technology is crucial for ensuring product quality. This article gives a detailed review of product defect detection technologies in complicated industrial processes, as well as the current state of research. The experimental findings of fault detection strategies were extensively presented, and traditional defect-detection methods and deep-learning defect-detection approaches were contrasted and assessed. Meanwhile, defect-detection equipment was studied and assessed in conjunction with actual application requirements and the development of artificial intelligence technology.

We hope that the study will aid industrial businesses and researchers in understanding product defect-detection technology research development in the fields of deep learning and defect detection.

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