Remote Detection System for Defect Images Based on WebSocket and HttpsWSS

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Abstract: ***To solve the problem of high costs in large-scale deployment and updates of defect inspection systems in current practical scenarios, this paper designs a complete remote detection system for defect images. First, a new defect image detection algorithm is developed to achieve the purpose of defect detection. Then, by combining WebSocket and HttpsWSS, the communication and transmission between the on-site images to be detected and the cloud server, as well as the transfer of detection results to on-site devices, are realized. Then, according to the defect detection brain, the client software is deployed to the device side, responsible for collecting images and receiving detection results. Finally, based on business requirements, the underlying algorithm, communication mechanism, central platform, and device side are organically connected together to form a remote detection system for defect images. Experimental test results show that the proposed system has higher defect detection accuracy.***

Keywords: Artificial Intelligence; Defect Image; WebSocket; HttpsWSS; Large-scale Deployment and Update.

1. INTRODUCTION

With the deepening of competition in the manufacturing industry, the need to reduce costs and increase efficiency has become increasingly urgent. Based on automated and intelligent equipment, more and more problems of defect detection can be solved, and the quality of shipped products can be improved [1]. The recognition of defective images poses a great challenge to defect recognition technology due to its variability and instability [2]. In addition to the difficulty of identifying defects themselves, there are also problems with the mass implementation of defect detection systems on-site and subsequent updates and deployments. These issues will be discussed in detail in this paper.

In order to locate defective targets in images, researchers have carried out a series of studies and achieved corresponding results. Zheng and Jiang (2025) proposed a new methodology for extracting Chinese terms from scientific publications [1]. Zhu et al. (2026) addressed the motion control of flexible-joint robotic arms for variable-station warehouse sorting using proximal policy optimization [2]. Gong et al. (2023) provided a comprehensive review of neural network lightweighting techniques [3]. Jiang et al. (2025) introduced UMH-ID, a framework unifying multi-expert attention and hard contrastive learning for robust IoT intrusion detection [4]. Gao et al. (2025) presented a hierarchical reasoning and LoRa-enhanced large model framework for root cause analysis in distributed systems [5]. Zhang X. (2026) developed a hybrid LSTM-GARCH model that integrates volatility factors from the US financial markets [6]. Han et al. (2026) proposed a dual-scale model with collaborative reasoning and multi-feature fusion for robust detection of AI-generated images [7]. Shen et al. (2026) constructed a survival risk prediction model for colorectal cancer patients based on graph convolutional networks and TCGA multi-omics data integration [8]. Tian et al. (2025) introduced a business intelligence approach to ad recall using cross-attention multi-task learning for digital advertising [9]. Liu X. (2025) examined the application of GPU parallel computing in image processing [10]. Lu et al. (2025) employed the Faster R-CNN model for flame detection [11]. Liu Y. (2025) conducted a systematic evaluation of deep learning architectural efficacy for plant image classification [12]. Gao W. (2025) explored the international intelligent operation model of industrial electrical enterprises under the dual-track collaboration of digitalization and greening [13]. Shen et al. (2025) applied the Whale Optimization Algorithm to financial payment fraud detection [14]. Mao H. (2026) proposed a clustering-based approach to image compression using the K-means algorithm [15]. Finally, Jie Z. (2024) applied artificial intelligence technology to industrial defect detection [16].

To solve the above problems, this paper designs a new remote defect image detection system. The proposed system aims to accurately identify defects and complete deployment and updates quickly, standardly, and automatically. The problem of defect detection is solved through artificial intelligence algorithms, and the problem of mass deployment of the system on-site is solved by combining network technology and software engineering to ensure batch automatic updates of the system on-site. Finally, the detection accuracy of the proposed system is tested.

2. REMOTE DETECTION SOLUTION FOR DEFECT IMAGES

In actual application scenarios, solely relying on rule-based image detection algorithms often fails to detect all defects. Since defects possess uncertain characteristics and are difficult to define in advance using rule-based algorithms, AOI devices based on traditional image detection technologies are unable to meet the requirements of defect detection with numerous variations. Therefore, the detection technology in this paper combines traditional image detection and deep learning detection technologies to design a new detection algorithm. Additionally, on-site, there are often several or dozens of production lines that require the deployment of defect detection systems. In the past, the traditional approach was to individually install stand-alone software on the device computers for application, which led to low efficiency and was prone to differences between devices. During subsequent equipment upgrades, when the detection program needed to be upgraded, it was inevitable to individually update and upgrade the detection software on the device computers, which was extremely inconvenient. To address the need for batch implementation of defect detection, this paper designs a new detection system as shown in Figure 1. Images are collected at the device end and the images to be detected are transmitted to the analysis system deployed in the cloud through network technology. The analysis system in the cloud processes and analyzes the defect images based on traditional images and deep learning. The cloud transmits the detection results back to the device end via the network to assist in detecting defective products on-site. Finally, rapid control development based on foot pedals is developed to enhance the on-site application capabilities, forming the defect recognition system of this study. The original image to be recognized is shown in Figure 1, where "B" in the image is a defect and will be detected subsequently in this paper.

Figure 1: Image to Be Detected

2.1 Defect Detection Based on Artificial Intelligence

To detect defects while ensuring no false alarms, this study combines traditional image detection and deep learning detection. Generally speaking, the characteristic regions presented by qualified product images are all regular, while those of defect targets are the opposite. Usually, the higher the contour degree of a certain target, the lower the regularity of its region:

$$C = 0.2 \times \frac{L}{A} + 0.7 * L\text{num}+0.1 \times \frac{A}{Az} \tag{1}$$

Among them, C is the contour degree, L is the defect perimeter, A is the defect area, Lnum is the number of sides, and Az is the area of the smallest circumscribed rectangle of the defect.

To quickly and accurately locate the defect features in the image, this paper uses the sift operator to implement. First, the robust features of the input image are extracted through the classic sift operator, and then the gradient of each feature point is calculated:

$$G_x(x, y) = I(x + 1, y) - I(x, y) \tag{2}$$

$$G_y(x, y) = I(x, y + 1) - I(x, y) \tag{3}$$

Among them, G_x and G_y are the gradient values of the image in the horizontal and vertical directions respectively, and I is the input image.

Based on the output gradient values of models (2) and (3), the corresponding eigenvectors are obtained by means of the Hessian matrix:

$$H = \begin{bmatrix} G_x G_x & G_x G_y \\ G_x G_y & G_y G_y \end{bmatrix} \tag{4}$$

$$m(x,y) = \sqrt{G_x^2(x,y) + G_y^2(x,y)} \tag{5}$$

$$\theta(x,y) = \tan^{-1}\frac{G_x(x,y)}{G_y(x,y)} \tag{6}$$

Among them, H is the Heaaian matrix; θ is the gradient direction of the feature point.

According to the feature point data obtained from the above process, the complete SIFT feature vector can be formed and used as the input quantity for subsequent ICP calibration. The segmentation model adopted in this paper is mainly implemented based on PconvUnet, while the classification model is implemented based on Resnet. The PconvUnet execution model is as follows:

$$y = f(\textstyle\sum_i^n W_i^* x_i) \tag{7}$$

Among them, y represents the output activation; W represents the weight; x represents the input activation; f represents the non-linear activation function, n represents the number of elements, and i represents the serial number.

Subsequently, select the largest pixel value among the four pixel values as the value of the corresponding element of the output matrix:

$$\text{ga=MAX}\begin{pmatrix} c & d \\ e & f \end{pmatrix} \tag{8}$$

Among them, ga significantly accelerates the training speed and improves the accuracy.

To ensure the adaptability of the system, it is necessary to normalize the activation result y :

$$y = \frac{x-u}{\sqrt{a^2+b^2}}c + d \tag{9}$$

Among them, y is the output activation; x is the input activation, a、b represents the distribution on the input level, and c、d represents the distribution on the output level.

Since the system developed in this paper uses deep learning technology and establishes a general model by widely collecting pictures of various actual application scenarios, the deep learning intelligent model generated and trained by it can identify pictures and their defect targets in various situations.

2.2 Remote Detection Mechanism Based on WebSocket and HttpsWSS

The main purpose of the remote detection system in this paper is to connect many device computers on-site to the cloud computing center. The device-side computers are responsible for receiving real-time images to be detected and then transmitting them to the cloud. After the cloud analyzes the images, it transmits the results to the device-side computers in real time, and the device-side computers then pass the results to the motion module according to the analysis results. The data communication between the device-side computers and the cloud mainly relies on WebSocket and HttpsWSS, and communicates through the Socket network cable to start the defect recognition program on the server. This system uses this low-cost communication form and protocol to complete the connection between the device side and the cloud. To establish a network communication connection, at least a pair of port numbers is required. In the proposed detection method, communication is mainly achieved through the WebSocket network interface and connected to the cloud server. By integrating the httpsWSS and Web-Socket communication mechanisms, the advantages of the proposed method can be maximally presented, mainly reflected in three aspects: data transmission, information control, and cost reduction.

In the process of implementing WebSocket in this system, a WebSocket communication request is sent based on the network browser, and then the cloud server sends a response. This process can be called a connection path. Through WebSock-et, only one connection needs to be made between the web browser at the program backend and the cloud server. Then, a data transmission channel is formed between the device-side computer program and the cloud analysis and calculation side.

In terms of data transmission protection and efficiency in this paper, information packets are mainly captured through the Http-sWSS technology to see whether the data is transmitted in plain text. Compared with ordinary HTTPS, the method in this paper has the following characteristics: a comprehensive encryption technology is adopted in information data encryption, which not only protects the factory production information but also improves the transmission efficiency. In terms of identity verification, the defect detection system authenticates the client through a certificate to ensure that the correct corresponding cloud server is accessed.

To achieve remote information transmission and detection based on WebSocket and httpsWSS, the page of this system is based on JSP+HTML and uses the browser method to send and receive data. The web page style is based on css3 and css2, the script is based on Javascript and jquery, integrated into the UI, adopting the style of amazeui/layui, the chart library is based on echarts, and the pop-up layer component is based on layer.

The development language is based on Java to implement all backend logic judgments. The framework is based on springmvc and spring to achieve the industrial purpose of modularization and plug-in. Information persistence and stability are based on hibernate/dbutils, caching is based on ehcache/redis, the message queue is based on acitveMQ, the data transmission between the front and backend is based on WebSocket and HTTP interfaces, the third-party SDK is based on cloud file storage services, etc. The class library management is based on maven, the database is based on MySQL, and the web service is based on nginx+tomcat.

Based on the segmentation technology and deep learning recognition technology, a corresponding image defect recognition mechanism is formed to detect defects. Taking Figure 2 as a sample, according to this process, the recognition result is shown in Figure 3. It can be seen that the defects in the image are accurately recognized and the defect contours are accurately located.

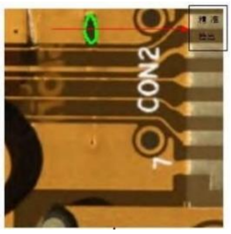
Figure 3: Defect Detection Result

3. TESTING AND ANALYSIS

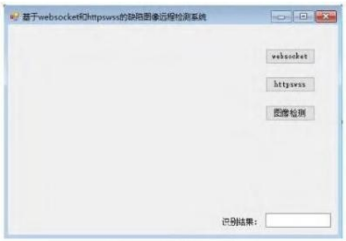
The experimental platform for this test is VS and Pytorch. The configuration of the device-side computer used in the experiment is an I7 processor and 16G of memory, and the cloud server is an I9 processor and 64G of memory. The network foundation of the system in this paper is built based on WebSocket and Http-sWSS, and the detailed network-side technology is as described above.

As shown in Figure 4(a), there is significant interference from the surrounding information of the defect to be recognized, which has a great impact on the defect recognition algorithm. Figure 4(b) shows the system interface developed in this paper. This study combines artificial intelligence detection technology and network communication transmission technology. As shown in Figure 5, it can be seen that the detection in this study is correct and the remote defect image detection system in this study is stable.

To highlight the superiority of the proposed system, a test experiment is established by comparing the method in this paper with the methods. The test results of the three are shown in Figures 5 - 7. Reference starts from the analysis of detection line faults and proposes the development of remote intelligent diagnosis for the detection line, which solves some problems to a certain extent and achieves the purpose of remote detection. Although this study solves some problems, the C/S architecture has its own limitations, and the system's stress response is still not ideal in terms of program update and deployment. As shown in Figure 6, the detection is incorrect and the defect detection cannot be well completed. Reference starts from the analysis of detection line faults and proposes the development of remote intelligent diagnosis for the detection line, which solves some problems to a certain extent and achieves the purpose of remote detection. This study simply relies on signal remote communication. Although it solves some problems, it does not introduce a data analysis mechanism and a defect detection evaluation system, and the effect does not meet the engineering requirements. As shown in Figure 7, the detection is incorrect.



(a) Object to be tested



(b)系统界面图

Figure 4: System UI Interface and Object to be Tested

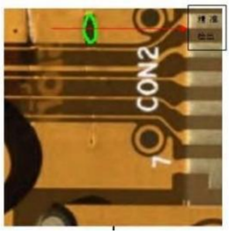


Figure 5: Detection Results of the System in this Paper

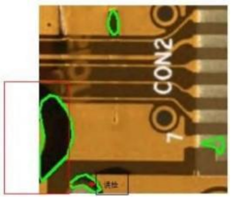


Figure 6: Detection Results of Reference [3]

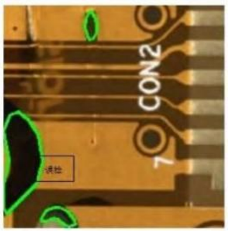


Figure 7: Detection Results of Reference [4]

4. CONCLUSION

To solve the problem that it is difficult to batch and standardize the implementation of current defective images, this paper starts from artificial intelligence detection algorithms and communication network technologies respectively. According to the characteristics of defective images, it conducts intelligent analysis and detection of images. Combining traditional communication data technologies, WebSocket technology, and HttpsWSS, a robust remote detection mechanism for defective images is established, providing an algorithm guarantee and a data communication foundation for the accuracy and stability of defect recognition. At the same time, this paper has developed a large-scale engineering system that combines algorithms and network communication, which can quickly send the detection results to the device-side computers through the network. It can also update each program and deploy it synchronously to each device-side computer through the network, preparing for the large-scale implementation and automated maintenance of the software system.

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