Development and Application of an Online Quality Inspection System for Prebaked Anodes

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Abstract

Prebaked anodes are a critical material in aluminum electrolysis production, and their quality directly impacts the efficiency and stability of the electrolytic aluminum process. Traditional anode assembly workshops heavily rely on manual operations for quality inspection of guide rods and carbon blocks, as well as for detecting carbon block loss. This approach suffers from low efficiency, high error rates, intense labor requirements, and difficulties in data management. To address these issues, Baotou Aluminum Group and Chalco Zhengzhou Research Institute of Nonferrous Metals jointly developed an online quality inspection system for prebaked anodes.

This system is capable of monitoring both external and internal defects of the anodes. For external defect detection, high-definition cameras are installed on the production line to capture digital images of the carbon block surfaces. Machine vision technology is then employed to integrate quality defect features of the anode carbon blocks into a deep learning algorithm model. By extracting detailed features and continuously iterating the model through accumulated data samples, the system achieves precise monitoring of surface defects on the carbon blocks. For internal defect detection, the system leverages the principles of elastic wave reflection and diffraction when encountering voids, cracks, or other porous media. It utilizes a non-destructive testing method based on the impact-echo technique. By extracting echo signals from three characteristic surfaces of the carbon anode and performing frequency domain analysis to generate interference spectra, the system accurately identifies internal defects within the carbon blocks.

The intelligent online inspection system for prebaked anode quality enables automated and rapid detection of both external and internal defects in carbon blocks. This significantly improves the quality of carbon blocks used in electrolytic aluminum production, reduces the labor intensity of manual inspections, and provides a robust foundation for efficient, low-consumption, stable, and environmentally friendly electrolysis production.

Keywords: Prebaked anode, Non-destructive testing, Machine vision, Deep learning

1. Introduction

As a key material for electrolytic aluminum, the quality of anode carbon blocks directly affects the efficiency and safety of production equipment. With the technological requirements for efficient, low consumption, and high stability of electrolytic aluminum production, higher demands have been placed on the quality of anode carbon blocks. In the production process of carbon anodes, it is inevitable to have appearance defects (such as cracks and pits) and internal defects (such as pores and inclusions), which lead to a decrease in mechanical strength, uneven conductivity, and affect the efficiency of electrolytic production, even causing production accidents.

The traditional anode assembly workshop heavily relies on manual operation in the quality inspection of aluminium rods and carbon blocks, as well as the detection of carbon block loss, which has problems such as low efficiency, large errors, high labor intensity, and difficult data management. The development of efficient and high-precision carbon block defect detection methods is an inevitable trend in the industry to improve production efficiency, reduce labor costs, and enhance product quality.

2. Principle of Carbon Block Defect Detection

2.1 Principle of Carbon Block Appearance Defect Detection

The appearance defects of carbon blocks are mainly characterized by the following types of typical features:

- Surface cracks: distributed linearly or in a network pattern, irregular edges, usually with high aspect ratios and directionality, and appearing as local gray level mutation areas in the image.
- Pits and protrusions: Most of them are irregularly shaped. Under light, pits appear as dark areas with smooth transitions at the edges; while protrusions, due to shadow effects, form local alternating light and dark features.
- Edge defect: Local loss of carbon block contour, manifested as a sudden change in geometric shape, can be detected through edge continuity analysis.
- Surface pollution and color difference: Oil stains, dust and other pollutants cause abnormal local reflectivity, which shows significant differences from the substrate material in specific bands (such as near-infrared).

These defects can disrupt the uniformity and continuity of material surfaces in optical imaging, providing distinguishable visual features for image processing-based detection. Therefore, the appearance defects of carbon blocks are mainly identified and classified automatically through optical imaging and image processing technology. The specific process of carbon block visual inspection is as follows:

1. Image acquisition and preprocessing. Using high-resolution industrial cameras combined with multi angle light sources (such as circular LEDs or coaxial light) for image acquisition and suppressing high light absorption interference on the surface of carbon blocks through diffuse reflection illumination. Grayscale, histogram equalization, and Gaussian filtering are applied to the original image to enhance the contrast between defect areas and the background, while suppressing noise.

2. Defect feature enhancement and segmentation. Complete image acquisition and preprocessing, use image processing techniques to analyze surface anomalies of anode carbon blocks and segment the images.

   - Crack defect segmentation method: using direction sensitive Sobel operator or Gabor filter to extract crack edges, combined with morphological processing (such as skeletonization) to remove pseudo defects.
   - Pit/bump segmentation method: Laplacian operator or local binary pattern (LBP) is used to highlight surface roughness features, and irregular areas are segmented through region growing algorithm.
   - Edge defect segmentation method: based on Canny edge extraction and Hough Transform to analyze contour integrity and locate geometric anomalies.

3. Multi feature fusion and classification. Extract the morphological parameters (area, perimeter, circularity), texture features (gray level co-occurrence matrix), and depth information (assisted by structured light 3D reconstruction) of surface defects on carbon blocks and construct multidimensional feature vectors. Classify defect types using Support Vector Machines (SVM)

or Convolutional Neural Networks (CNN) and implement quantitative evaluation by combining threshold judgment (such as crack length > 1 mm as unqualified).

4. System output and feedback. Generate defect distribution heatmap and detection report, label defect location, type, and level, and simultaneously link the production line for sorting or alarm.

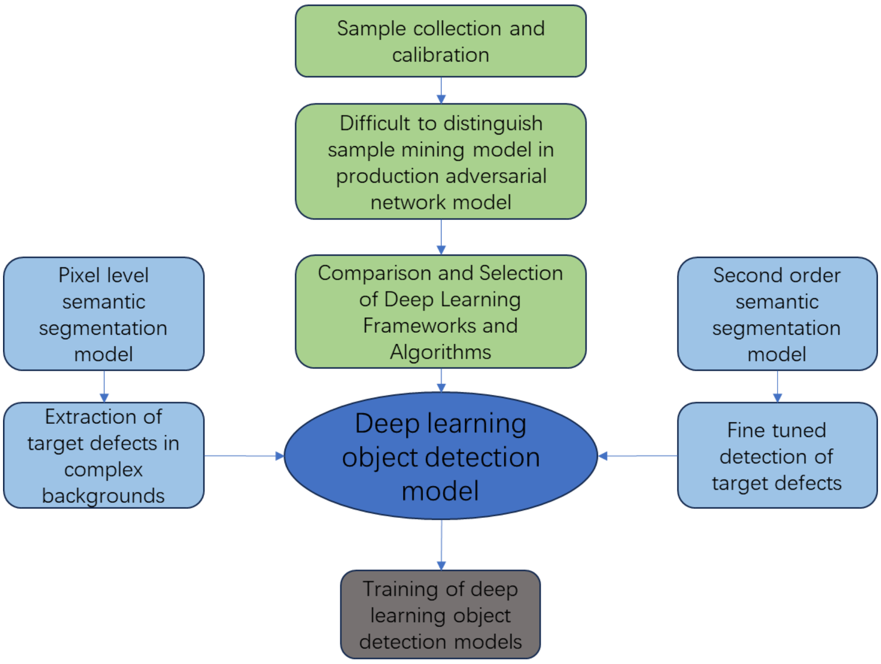

Figure 1. Deep learning model for carbon block visual defect detection.

In the object detection stage, this scheme developed an object detection model based on the algorithm. Then, using the GAN (Generative Adversarial Network) algorithm to generate fake defect image samples and partially real defect image samples to form a training set, the deep learning object detection model is trained (as shown in Figure 1**)**. Meanwhile, based on the training results, the Hard Negative Mining algorithm is used to optimize the sample structure.

The external defect detection technology based on image processing has advantages such as non-contact, high efficiency, high precision, intelligent analysis, low cost, data traceability, and strong system scalability compared to other detection methods. Compared with traditional manual detection, image processing methods reduce the missed detection rate from 15 % to below 0.5 % and improve detection efficiency by more than 10 times. Compared with 3D detection technologies such as laser scanning, the equipment cost is reduced by 60 % while meeting the requirements of detection accuracy

2.2 Principle of Internal Detection of Carbon Blocks

To address the aforementioned issues, our project team has developed a non-destructive testing method for carbon blocks based on elastic waves. This method achieves the localization and characterization of internal defects by exciting elastic waves on the surface of carbon blocks and analyzing their propagation characteristics in the material. Elastic waves are mechanical waves formed by the propagation of small vibrations of particles in solid materials, named after the elastic deformation of the material during their propagation process. The shock elastic wave used in this method is generated by an electromagnetic excitation device, which can directly reflect the mechanical properties of the material.

The theoretical basis of the shock wave echo method is the propagation and reflection laws of elastic waves in a medium. When elastic waves are excited on the surface of carbon blocks, three main waveforms are generated: P-waves (longitudinal waves), S-waves (transverse waves), and R-waves (surface waves). Among them, the propagation direction of P-waves is parallel to the direction of particle motion, and the propagation direction of S-waves is perpendicular to the direction of particle motion. By controlling the distance between the sensor and the excitation point (4 – 8 cm), it can be ensured that the P-wave becomes the main component of the echo signal. By using signal processing techniques such as noise reduction filtering and fast Fourier transform (FFT) to analyze the echo signal, combined with echo time calculation, the depth position of internal defects can be determined.

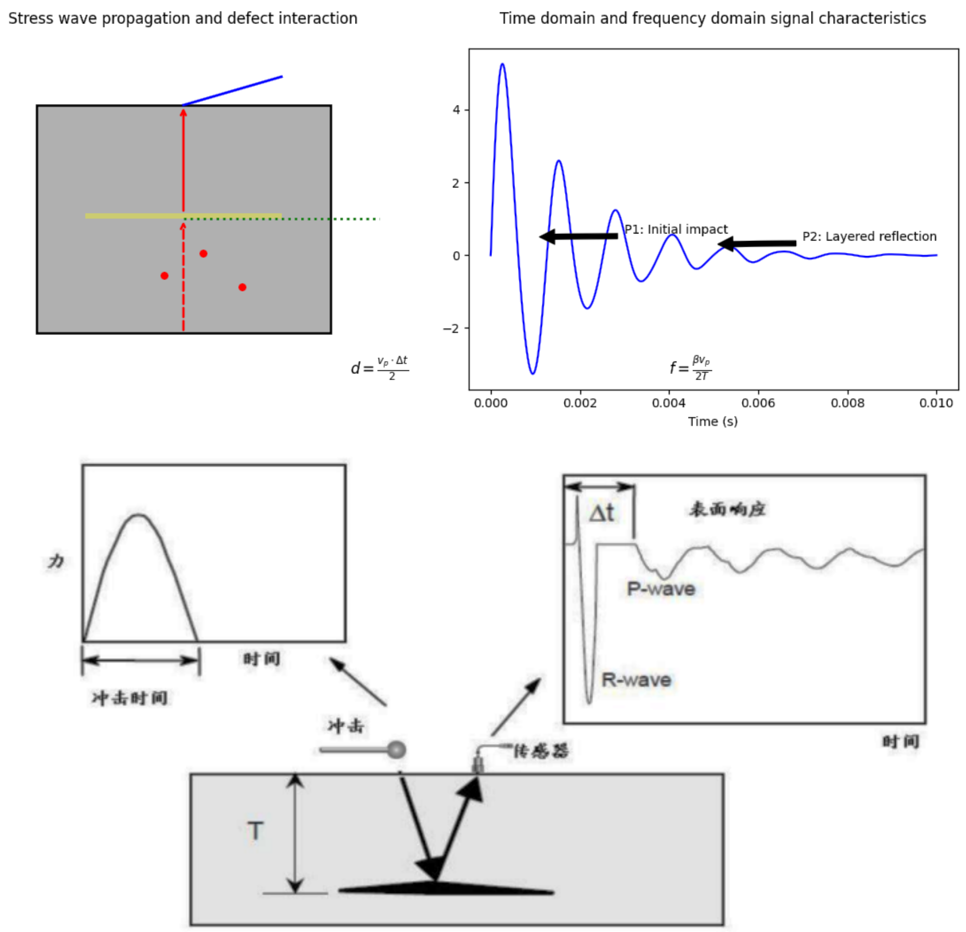

Figure 2. Schematic diagram of internal defect detection principle of carbon block.

This method utilizes three key mechanisms of interaction between elastic waves and defects: firstly, due to the difference in acoustic impedance between the defect and the matrix material, elastic waves will produce significant reflections at the defect interface. Secondly, closed type defects will form resonant cavities, generating standing wave resonances at characteristic frequencies. Finally, irregular defects can cause waveform distortion and dispersion effects. By capturing these characteristic signals with high-precision accelerometers and combining them with time-frequency analysis techniques, three important diagnostic features can be extracted: changes in wave velocity reflecting changes in material elastic modulus, signal attenuation characterizing defect size, and resonance frequency peak locating defect depth.

Experiments have shown that layered defects produce significant secondary echoes, and the time difference is proportional to the depth of the defect; Dispersed pores, on the other hand, exhibit abnormal enhancement of high-frequency components. The detection technology based on the impulse echo method has simple methods, no need for coupling agents, and high sensitivity. The characteristics of high detection efficiency and high accuracy, especially suitable for industrial online detection applications.

3. Systems Design

3.1 Design of Carbon Block Appearance Inspection Defect Testing System

The carbon block appearance defect detection system adopts a modular design, consisting of four main parts: optical imaging unit, motion control module, data processing and decision output system (as shown in Figure 2). The system is equipped with a 20-megapixel industrial camera and a circular LED light source array, combined with structured light 3D reconstruction technology, which can accurately capture surface defect features at the 0.3 mm level. The motion control unit uses servo driven conveyor lines and six axis robotic arms to work together, ensuring a detection and positioning accuracy of ± 0.1 mm. The external defect detection process for carbon blocks is shown in Figure 3 and Figure 4.

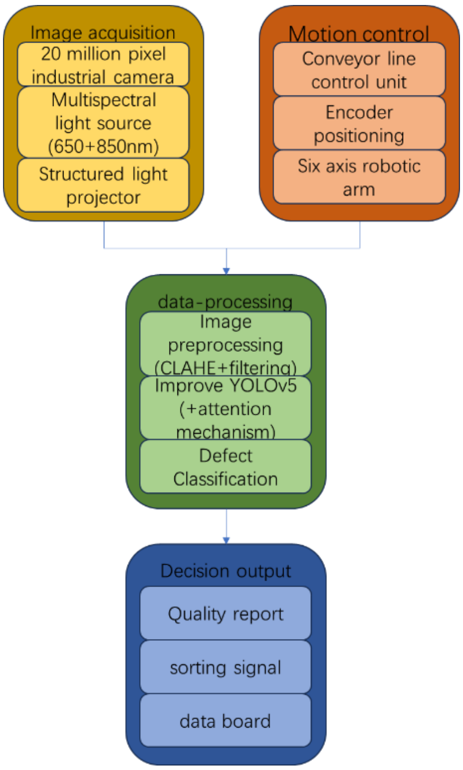

Figure 3. Structure diagram of appearance defect detection system.

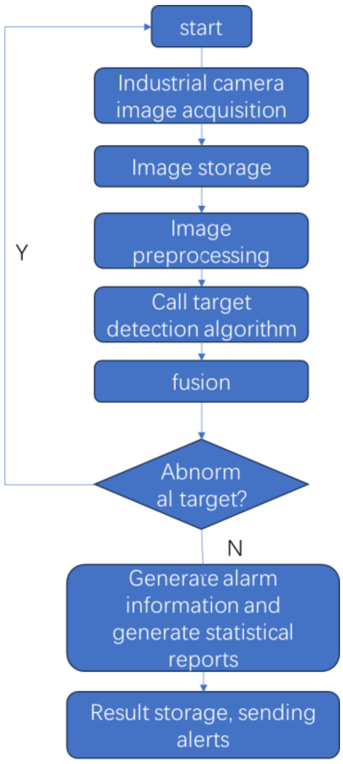

Figure 4. Appearance defect detection process diagram.

At the software algorithm level, the system first enhances the image through adaptive histogram equalization and Gaussian filtering and then uses an improved YOLOv5 deep learning model for defect detection. By adding an attention mechanism module, the recognition accuracy of typical defects such as cracks and pits reaches 99.2 %. The detection process is synchronized with the production line rhythm, with a single piece processing time controlled within 45 seconds and supporting a detection efficiency of 300 pieces per hour.

The system innovatively integrates multispectral imaging technology, effectively distinguishing between real defects and surface pollutants through collaborative analysis of visible light and near-infrared bands (650 nm/ 850 nm). The human-computer interaction interface displays real-time detection results and automatically generates quality reports containing defect location, size, and type, providing data support for production process improvement (Figure 4). Through industrial verification, the system has increased efficiency by more than three times compared to traditional manual detection, with a false detection rate of less than 1 %.

3.2 Design of Carbon Block Internal Defect Detection System

The carbon block internal defect detection system adopts shock elastic wave (IE) and multi-sensor fusion technology, and achieves accurate identification of defects such as pores, delamination, and cracks through non-contact detection. The system mainly consists of three core modules (Figure 6): the elastic wave excitation unit adopts an electromagnetic excitation device (with adjustable impact energy of 0.5–5.0 J and pulse width of 50–200 μs), which is combined with a force sensor to achieve closed-loop control of impact energy. The signal acquisition unit includes a three-axis acceleration sensor array (bandwidth 1–80 kHz) and a high dynamic range data acquisition card (24 bit ADC, sampling rate 100 kHz) to ensure accurate capture of weak signals; The motion control module achieves automatic positioning of detection points through a six axis robotic arm (with a repeat positioning accuracy of ± 0.1 mm), supporting optimized sensor spacing arrangement of 4– cm. The signals collected by the signal processing unit team are subjected to noise reduction and filtering processing; The intelligent decision-making system combines motion control status and processed signals to achieve accurate judgment of internal defects; Finally, the output execution unit is used for recording and sorting.

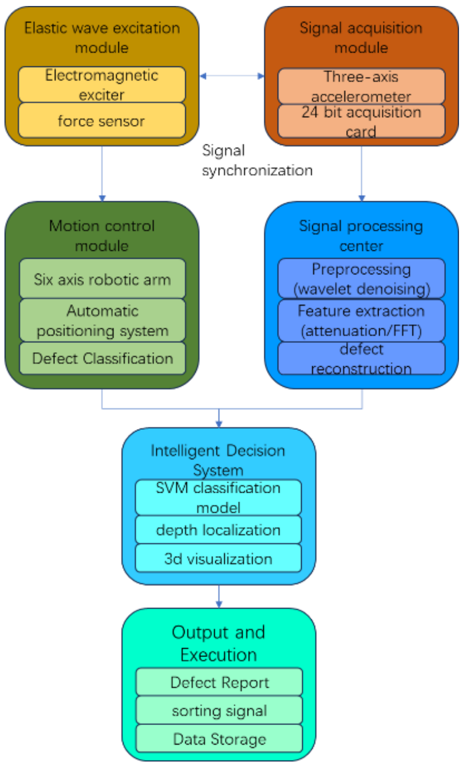

Figure 5. Framework diagram of internal defect detection system for carbon blocks.

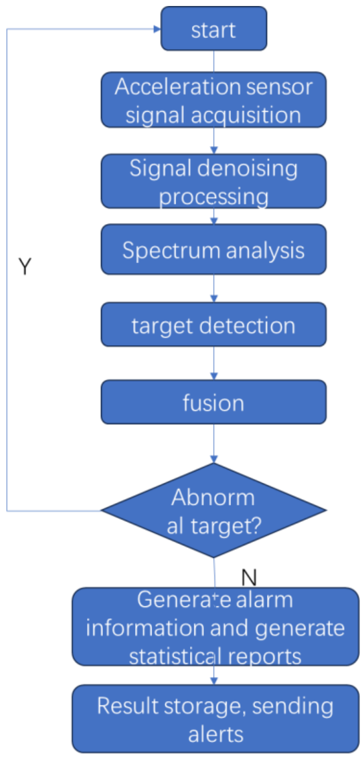

Figure 6. Flow chart for internal defect detection of carbon blocks.

The internal defect detection process is shown in Figure 6. The system adopts a hierarchical signal processing architecture: the bottom hardware layer completes signal conditioning and noise reduction and suppresses industrial environmental interference through wavelet threshold filtering (db4 wavelet basis). The mid-level feature extraction module combines FFT spectrum analysis and cross-correlation algorithm to calculate key parameters such as wave velocity (accuracy ± 1.5 %), attenuation coefficient, and resonance frequency. The upper level intelligent decision-making module is based on a fusion model of support vector machine (SVM) and deep learning, achieving defect type classification (accuracy 98.7 %) and deep localization (error ± 1.2 mm). Innovatively introducing time-frequency joint analysis technology, capturing defect characteristic frequency bands (1–20 kHz) through short-time Fourier transform (window length of 256 points), effectively distinguishing different defect types such as pores (high-frequency resonance) and delamination (low-frequency reflection).

4. Industrial Testing

The project team conducted a systematic industrial test verification in a large electrolytic aluminum plant, and the test process strictly followed the requirements of the quality management system (as shown in Figure 7 and 8). The experiment selected carbon blocks from three anode assembly production lines as the testing objects and adopted a stratified random sampling method to ensure the representativeness of the samples. The experimental process is divided into three stages: the first stage (1–2 weeks) involves equipment installation and debugging, optimizing sensor layout and detection parameters. In the second phase (3–8 weeks), comparative experiments will be conducted to simultaneously record the results of the system, manual testing, and X-ray testing. In the third stage (9–12 weeks), continuous operation testing will be conducted to evaluate system stability. During the experiment, each carbon block is established with an independent file to record complete detection data and process parameters.

Figure 7. On site testing equipment

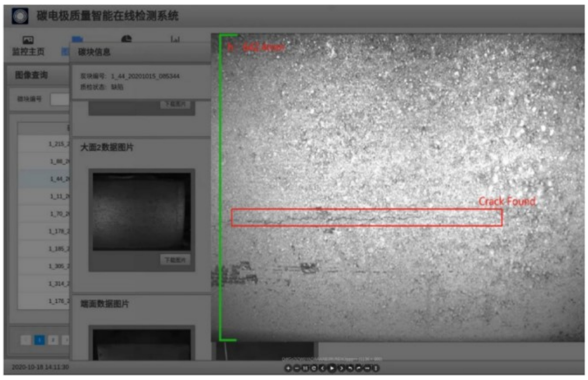

Figure 8. Visual defect detection results

The experimental results show that in terms of defect detection capability, the detection rate of surface cracks (length ⩾ 0.5 mm) by this system reaches 98.7 ± 0.5 %, the detection rate of internal pores (diameter ⩾ 1 mm) is 97.5 ± 0.8 %, and the detection rate of layered defects (area ⩾ 10 mm^2) is 96.2 ± 1.2 %. All indicators are significantly better than traditional detection methods.

In terms of detection efficiency, the average processing time of the system is 45 ± 3 seconds per block, which is 2.7 times higher than manual detection efficiency. Economic analysis shows that although the initial equipment investment is relatively high, the annual total cost is reduced by 71.8 % compared to X-ray testing in terms of comprehensive labour, maintenance, and other costs. The quality traceability system has successfully achieved 100 % archiving of inspection data, providing a complete basis for subsequent quality analysis. The experiment also found that when the thickness of the oxide layer on the surface of the carbon block exceeds 0.3 mm, the detection accuracy will decrease by about 15 %.

Table 1. Statistical results of industrial experiments.

Testing index	This detection system	Manual testing	X-ray testing	Performance improvement (more manual)
Crack detection rate (⩾ 0.5 mm)	98.7 % ± 0.5 %	82.3 % ± 3.2 %	99.1 % ± 0.3 %	+ 16.4 %
Pore detection rate (⩾ 1 mm)	97.5 % ± 0.8 %	Not detectable	98.9 % ± 0.4 %	-
Layered detection rate (⩾ 10 mm^2)	96.2 % ± 1.2 %	68.5 % ± 5.1 %	97.8 % ± 0.6 %	+ 27.7 %
Average detection time (seconds/block)	45 ± 3	120 ± 15	900 ± 60	Efficiency increased by 2.7 times
noise factor	0.8 % ± 0.2 %	5.2 % ± 1.5 %	0.5 % ± 0.1 %	- 4.4 %

5. Conclusion

This study aims to meet the quality control requirements of anode carbon blocks for aluminum and designs and validates a multimodal defect detection system that integrates optical imaging and shock elastic waves. Through theoretical analysis, algorithm innovation, and industrial experiments, the following main conclusions are drawn:

In terms of technological innovation, the system innovatively combines 20-million-pixel multispectral imaging with shock wave detection, breaking through the limitations of traditional single-mode detection. The proposed improved YOLOv5 IE fusion algorithm achieves synchronous detection of appearance defects (minimum 0.3 mm cracks) and internal defects (∅0.5mm pores) through attention mechanism and time-frequency joint analysis, with a comprehensive recognition accuracy of 99.2 %.

In terms of performance indicators, industrial verification shows that the system detection efficiency reaches 45 seconds per piece, supporting the full inspection requirements of the production line (300 pieces/hour). The key performance indicators are significantly better than traditional methods: crack detection rate (98.7 % vs 82.3 % manual), pore detection rate (97.5 % vs 98.9 % X-ray), and false detection rate (0.8 % vs 5.2 % manual). The system performs reliably in complex industrial environments, with an average fault free working time of 480 hours and a temperature adaptability of 0–50 °C.

This system provides an efficient, accurate, and economical solution for carbon block quality inspection, which has important engineering significance for improving the quality control level of the electrolytic aluminum industry.

6. References

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