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A Review of Automatic Casting Defect Recognition Methods Based on Deep Learning

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ABSTRACT

Casting defect detection is a crucial link in industrial production, directly affecting product quality and safety. Traditional manual inspection methods, due to their low efficiency, strong subjectivity, and high missed detection rates, can no longer meet the demands of modern intelligent manufacturing. In recent years, the breakthrough progress of deep learning technology in the field of image recognition has provided new solutions for automated casting defect detection. This paper systematically reviews automatic casting defect recognition methods based on deep learning, focusing on aspects such as algorithm improvements, practical applications, and future development directions. It discusses in detail the optimization strategies of object detection algorithms (such as the YOLO series, Mask R-CNN) and semantic segmentation algorithms (such as U-Net, Retina Net), and summarizes the latest achievements in industrial inspection system development. Finally, it prospects future research directions including self-supervised learning, unsupervised learning, and real-time quantitative analysis, aiming to promote the development of casting inspection technology towards intelligence and automation.

KEYWORDS

Industrial Application; Casting Defect Detection; Deep Learning; YOLO; Semantic Segmentation.

1. INTRODUCTION

Castings are integrally formed metal objects manufactured through different casting methods, and their quality directly impacts the safe operation of machinery. However, due to the complexity of the casting process and the diversity of raw materials, mold design, and processing conditions, various defects such as cracks, pores, shrinkage porosity, and inclusions inevitably occur during production. Castings with defects have a higher probability of failing under changing loads during use, and the severe consequences of failure are immeasurable. Therefore, adopting effective measures to achieve casting defect detection is of practical significance.

Although traditional manual inspection methods can identify casting defects to some extent, they suffer from problems such as low efficiency, strong subjectivity, and high missed detection rates, making it difficult to meet the requirements of modern intelligent manufacturing for high precision, high efficiency, and high reliability. In recent years, with the rapid development of deep learning technology in the field of image recognition, automatic casting defect recognition methods based on deep learning have gradually become a research hotspot. By constructing multi-layer neural network models, deep learning can automatically learn complex features in images, thereby achieving efficient and accurate detection of casting defects. This method not only overcomes the limitations of traditional methods but also provides an intelligent and automated new solution for industrial inspection.

The application of deep learning technology in casting defect detection covers multiple aspects such as object detection, semantic segmentation, and dataset construction. Object detection algorithms (such as the YOLO series, Mask R-CNN) and semantic segmentation algorithms (such as U-Net, Retina Net) perform excellently in casting defect recognition. By introducing techniques like attention mechanisms and multi-scale feature fusion, they significantly improve detection accuracy and efficiency. Furthermore, to address the difficulty of data annotation in industrial inspection, researchers have also explored new technologies such as self-supervised learning and unsupervised learning to reduce reliance on annotated data.

This paper systematically reviews the research progress of automatic casting defect recognition methods based on deep learning, focusing on algorithm optimization, practical applications, and future development directions. First, it introduces the application of object detection and semantic segmentation algorithms in casting defect detection and their optimization strategies. Second, it discusses the practical application of deep learning technology in industrial inspection system development. Finally, it prospects future research directions, including self-supervised learning, balancing real-time performance and lightweight design, integration of intelligence and automation, human-machine collaboration, and decision support, aiming to promote the development of casting inspection technology towards greater intelligence and automation.

2. APPLICATION OF DEEP LEARNING ALGORITHMS IN CASTING DEFECT DETECTION

2.1. Improvements in Object Detection Algorithms

Object detection is an important task in the field of computer vision. Its core goal is to identify and locate specific objects or targets from images or videos and determine their categories and positions. Object detection is widely used in fields such as autonomous driving, security monitoring, healthcare, and robotic vision.

2.1.1. Optimization of Object Detection Algorithms Based on the YOLO Series

YOLO (You Only Look Once) is a single-stage object detection framework based on a regression method. Its core idea is to transform the object detection task into an end-to-end regression problem. YOLO divides the input image into multiple grids and predicts bounding boxes and their corresponding class probabilities in each grid, thus achieving object detection and classification. This method is widely used in real-time object detection scenarios due to its efficiency and structural simplicity, showing significant advantages especially in applications requiring fast processing and real-time response. Li et al. proposed a casting defect detection method based on an improved YOLOv3. By introducing guided filtering technology to enhance defects in industrial digital radiography (DR) images, they generated standard defect samples and annotated them to create a dataset for network training. The improved YOLOv3 network model (YOLOv3_134) outperformed the original YOLOv3 model in both convergence speed and accuracy, with its mean Average Precision (mAP) increasing by 26.1%, meeting the requirements of industrial production for precision and speed. Mu Chunyang et al. proposed an improved YOLOv7-tiny algorithm; this algorithm improves the efficiency of large casting weld defect detection by introducing a channel attention mechanism. Ge Qianfeng et al. proposed an improved YOLOv5 algorithm. Through methods such as data augmentation, optimizing anchor box size using the K-means++ algorithm, introducing a CA attention mechanism module, and adding a small target detection layer, the detection effect for small aluminum casting turbine surface defects was significantly improved. Experimental results showed that the improved algorithm achieved a mean Average Precision (mAP) of 97.8%, providing an effective solution for intelligent manufacturing and automated production. Yan Zhilin et al. [7], addressing factors such as the variety of casting surface defect detection objects, inconspicuous targets, and diverse features, proposed a casting surface defect detection model based on an improved YOLOv5 algorithm. This algorithm replaces the CSPDarknet53 module with a C2f module, enhancing the gradient information of the lightweight network. Simultaneously, it introduces a CA attention mechanism, improving the model's generalization ability. Furthermore, replacing the coupled head module with a decoupled head module accelerates the model's fitting speed. These improvements significantly enhance the performance of the CCD-YOLOv5 model in casting surface defect detection. Chen Zihao et al. [8] proposed the TAE-YOLO algorithm. This algorithm introduces a lightweight Detect-TADDH detection head and YOLOv9's ADown downsampling module, reducing the parameter count by 43.5% and improving the mAP@0.5 metric by 8.5%, thereby increasing the efficiency of casting defect detection.

2.1.2. Multi-scale Feature Fusion and Attention Mechanisms

Cai Biao et al. proposed a casting X-ray DR image defect detection algorithm based on Mask R-CNN. This algorithm enhances images using guided filtering and utilizes the Mask R-CNN deep learning network to achieve graded classification and detection of casting defects. Experimental results show that this method can effectively detect defects in casting X-ray DR images, providing a solution for industrial casting defect detection using deep learning methods. Cong Ming et al. [10] proposed a defect detection algorithm based on deep learning called Retina Net-AACIDD (Retina Net for aluminum alloy casting internal defect detection). This algorithm significantly improves the detection accuracy for small target defects like bubbles and cracks through a channel-spatial mixed attention module (CS-Block) and multi-scale feature fusion. Li Sha et al. proposed a method for detecting casting defects in X-ray images by fusing local and global features. This method constructs a basic convolutional neural network by integrating an efficient channel attention module with ResNet-50 and designs a dual-branch network model. A Detail Information Location Extraction (DILE) module is introduced to extract discriminative information from local regions, and local images are combined with the original image to achieve the fusion of global and local features. The test set accuracy reached 98.3%, effectively solving the problem of detecting subtle defects in X-ray images.

2.1.3. Lightweight Model Design

Li Chuang et al. proposed an improved YOLOv3 algorithm. By introducing a lightweight Ghost Net backbone network and a spatial pyramid pooling structure, the model's parameter count was reduced, and its receptive field and anti-interference ability were improved. Additionally, introducing 1x1 convolutions and a channel attention mechanism in the FPN enhanced the feature extraction capability for small targets. Focal Loss was introduced during training to improve the model's prediction accuracy for positive samples. This algorithm demonstrated high robustness and accuracy in detecting casting weld surface defects.

Table 1. Performance Indicators of Improved YOLO Series Algorithms

Method	Improvement Strategy	mAP	Parameter Change	Applicable Scenario
YOLOv3_134 [4]	Guided Filtering + Anchor Optimization	+26.1%	→	Industrial DR Image Defect Detection
YOLOv5+CA [6]	CA Attention + Small Target Detection Layer	97.8%		Small Aluminum Casting Turbine Defects
CCD-YOLOv5 [7]	C2f Module + Decoupled Head	+3.2%	↓Lightweight	Multi-type Casting Surface Defects
TAE-YOLO [8]	Lightweight Detect Head + ADown Sampling	+8.5%	↓43.5%	Efficient Casting Defect Detection

Cai Zhenlin et al. proposed a lightweight object detection algorithm based on ShuffleNetv2-plus-YOLOX. By optimizing the network structure and parameter configuration, the efficiency and accuracy of the model in die-casting defect detection were significantly improved. This algorithm substantially reduces computational complexity while maintaining high detection accuracy, making it suitable for real-time detection scenarios. The performance indicators of the improved algorithms in the YOLO series are shown in Table 1.

2.2. Feature Extraction and Classification Methods Based on CNN

Lin [14] proposed a method for tracking casting defects based on a Deep Convolutional Neural Network (DCNN). By using a specific network structure and training strategy, efficient tracking of casting defects was achieved. The researchers used this method to conduct detailed analysis and localization of casting defects. Experimental results showed that this method exhibits high accuracy and robustness in defect tracking tasks. Mery [15] proposed a method for detecting aluminum casting defects based on a Convolutional Neural Network (CNN). By conducting experiments using the GDXray dataset, the effectiveness of this method in aluminum casting defect detection was demonstrated. A convolutional neural network was used to classify and locate X-ray images of aluminum castings. Data augmentation and model optimization improved the accuracy and efficiency of detection. Experimental results showed that this method exhibits good defect detection performance on the GDXray dataset, providing valuable references for future research. Ekambaram et al. proposed a method for identifying casting defects based on a Convolutional Neural Network (CNN). By using specific activation functions and network structures, efficient classification of casting defects was achieved. The researchers trained the model using nearly 7348 casting images, achieving a classification accuracy of 94% on the test set. This method can not only distinguish between defective and non-defective castings but also identify different types of defects, such as hot tears and flashes.

2.3. Innovations in Semantic Segmentation Algorithms

U-Net is a convolutional neural network architecture used for image segmentation, initially applied to medical image segmentation. Its network structure is U-shaped and symmetric, consisting of an encoder and a decoder. The encoder extracts image features through convolution and pooling operations, while the decoder restores the spatial resolution of the feature maps through upsampling. The innovation of U-Net lies in its skip connections, which connect the output of each convolutional layer in the encoder to the input of the corresponding layer in the decoder, allowing low-level detail information to be preserved and avoiding the loss of important spatial information during downsampling, thereby improving segmentation accuracy. This structure allows U-Net to achieve high segmentation accuracy even with limited training data, making it particularly suitable for medical image segmentation tasks. The U-Net network structure diagram is shown in Figure 1.

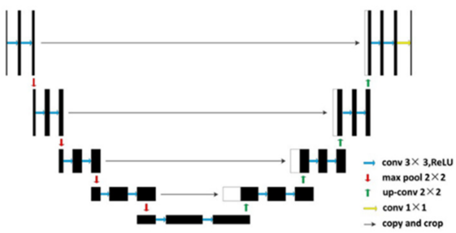

Figure 1. The U-Net network structure diagram

Wu Bo proposed an improved multi-scale defect segmentation deep learning model (ASCU net). By embedding a lightweight attention module in a multi-level feature pyramid, efficient segmentation and localization of multi-scale defects in X-ray images of aerospace titanium alloy castings were achieved. Experimental results showed that this model exhibits excellent performance with a Mean Intersection over Union (MIoU) metric of 90.4%. Xue Lin et al. [18] proposed a casting DR image defect detection algorithm based on deep learning semantic segmentation. This algorithm designed a mixed loss function on the original U-Net network model to alleviate class imbalance problems;

adopted the AdamW optimizer to accelerate model convergence while improving detection accuracy; and used the PReLU activation function instead of ReLU to improve the model's generalization ability. Experimental results showed that the improved U-Net model can effectively segment defects in precision casting DR images with high detection accuracy. Moreover, the model has a small number of parameters, making it suitable for deployment in industrial settings. The comparison of mainstream object detection and instance segmentation algorithms in terms of key indicators and applicable scenarios is shown in Table 2.

Table 2. Comparison of mainstream object detection and instance segmentation algorithms on key metrics and applicable scenarios.

Algorithm Name	Release Time/Version	Core Features	mAP
YOLOv5	2020	Single-stage, Anchor-based, PyTorch framework, excellent engineering	~55%
YOLOv7	2022	Single-stage, introduces trainable "Bag-of-Freebies"	~56%
YOLOv8	2023	Single-stage, Anchor-free, integrates classification, detection, segmentation	~53%
YOLOv9	2024	Single-stage, introduces Programmable Gradient Information (PGI)	~57%
RT-DETR	2023	End-to-end, Transformer-based, real-time	~54%
Mask R-CNN	2017	Two-stage, benchmark for instance segmentation	~37%
Faster R-CNN	2015	Two-stage, foundational work in object detection	~37%
DETR	2020	End-to-end, Transformer-based	~42%

3. PRACTICAL APPLICATION AND SYSTEM DEVELOPMENT OF CASTING DEFECT DETECTION

3.1. Embedded System Deployment

Yang Kai developed an application system for the original network model using the embedded GPU development board Jetson TX1. The trained YOLO network model was ported to the small embedded development board and tested on the Jetson TX1. For the images of precision castings to be detected, the recognition accuracy reached 97%. Among them, there were no missed detections for images of defective precision castings, and the false detection rate for images of non-defective precision castings was less than 4%. Wang Yuan et al., addressing the problem of difficult detection due to the complex surface and overly small defects of small aluminum casting turbines, proposed an improved YOLOv5 algorithm for detecting surface defects on small aluminum casting turbines and deployed the improved YOLOv5 algorithm to an embedded system. Tensor RT was ultimately chosen for model deployment and inference. Under laboratory conditions, the inference speed reached 4ms per image, meeting real-time detection requirements.

3.2. Industrial Inspection System Development

3.2.1. Binocular Vision Positioning System

Jing Peng [21] proposed a method for locating castings and their surface defects based on binocular vision, building an identification and positioning experimental platform. Camera calibration technology was used to determine camera parameters. The image, after being processed by the defect detection model, outputs category labels and bounding box pixel coordinates. Based on the disparity map generated by the CRES tereo stereo matching algorithm, the three-dimensional spatial position was obtained through the conversion relationship between coordinate systems. Experiments showed that the binocular system has good accuracy within an object distance of 1000mm, with the absolute error controlled within 4mm and the relative error controlled within 0.4%. It can accurately calculate the three-dimensional coordinate information of castings and surface defects, laying a foundation for in-depth research on industrial automated grinding robots.

3.2.2. Casting Process Data Management Software

Zhou Leyao et al. [22], addressing issues in the casting industry such as the lack of reliable management of material composition data, difficulty in saving and reusing casting structure models, and reliance on manual labor for casting defect detection, developed casting process data management software based on PyQt5. This software consists of three parts: material composition and performance library, casting structure and model library, and casting defect identification. It was packaged into a desktop application using Py Installer and can run on the Windows 10 system, offering high portability and providing strong support for the efficient management of casting process data. The comparison table of casting defect data sets is shown in Table 3.

Table 3. Comparison of Casting Defect Datasets.

Dataset	Number of Images	Defect Types	Resolution	Application Case
GDXray [15]	15,000+	Pores/Inclusions/Cracks	2K-4K	CNN Classification (Mery et al.)
Aluminum Casting Turbine [6]	3,200	Flashes/Short shots/Sand holes	1024x1024	YOLOv5+CA
Aerospace Titanium Alloy [17]	Not disclosed	Shrinkage porosity/Cold shuts/Hot tears	3000x4000	ASCUnet Segmentation
X-ray DR [9]	500+	Shrinkage cavities/Pores/Inclusions	16-bit grayscale	Mask R-CNN Graded Detection

4. FUTURE DEVELOPMENT DIRECTIONS

4.1. Self-supervised Learning and Unsupervised Learning

Self-supervised learning and unsupervised learning have great potential in solving the problem of insufficient annotated data. Traditional supervised learning methods rely on large amounts of annotated data, while annotating casting defect data requires professional skills and significant time. Self-supervised learning enables efficient learning with limited annotated data by utilizing the structural information of the data itself for pre-training. Unsupervised learning, through methods like clustering and dimensionality reduction, automatically discovers hidden patterns in the data, making it suitable for preliminary screening and classification of unannotated data. Future research can explore the application of self-supervised learning in casting defect detection, develop more efficient pre-training models, and combine them with unsupervised learning methods for preliminary data processing and feature extraction.

4.2. Balancing Real-time Performance and Lightweight Design

In industrial production environments, real-time detection is a key requirement for casting defect detection. However, complex deep learning models often require high computational resources, making it difficult to meet real-time requirements. Future research should further optimize model structures, adopt technologies like dynamic convolution and deformable convolution to enhance small target detection capabilities, and simultaneously reduce computational load through model compression and quantization. The combination of lightweight model design (e.g., Mobile Net, Shuffle Net) and hardware acceleration technologies (e.g., GPU, FPGA) will provide more efficient solutions for real-time detection.

4.3. Integration of Intelligence and Automation

Future casting defect detection technology will focus more on integration with intelligent manufacturing systems. By embedding deep learning detection algorithms into industrial robots and automated production lines, full-process automation of detection, analysis, and decision-making can be achieved. This intelligent integration not only improves production efficiency but also reduces human intervention, enhancing the reliability and consistency of detection results. Furthermore, combined with Industrial Internet of Things (IIoT) technology, real-time transmission of detection data and remote monitoring can be realized, further optimizing production management processes.

4.4. Human-Machine Collaboration and Decision Support

Although deep learning models perform excellently in defect detection, complete reliance on automated systems still carries risks in complex industrial environments. Future research should focus on human-machine collaboration, developing decision support systems that allow human experts to work synergistically with automated detection systems. Through visual interfaces and interactive feedback mechanisms, experts can quickly review and correct detection results, while the system can continuously optimize detection performance through continuous learning. This collaborative model not only improves detection accuracy but also enhances the system's interpretability and user trust.

5. CONCLUSION

Automatic casting defect recognition technology based on deep learning has made significant progress in recent years, bringing revolutionary changes to the field of casting quality inspection. From algorithm improvements to dataset construction, and then to practical applications and exploration of future development directions, this field has formed a relatively complete technological chain, laying a solid foundation for the intelligent and automated development of casting inspection.

In terms of algorithm improvements, object detection algorithms such as the YOLO series and Mask R-CNN have been continuously optimized. By introducing technologies like attention mechanisms and multi-scale feature fusion, they have significantly improved the accuracy and efficiency of casting defect detection. Semantic segmentation algorithms such as U-Net and its improved models also perform excellently in casting defect segmentation tasks, accurately locating and identifying defect areas. These innovations and improvements in algorithms not only enhance detection accuracy but also reduce reliance on large amounts of annotated data, providing more efficient and reliable solutions for practical applications.

In terms of practical applications, deep learning technology has been successfully applied to automated casting defect detection. The results of embedded system deployment and industrial inspection system development demonstrate that deep learning models can achieve efficient defect detection in actual production environments, meeting the real-time and accuracy requirements of industrial production, and providing strong support for the intelligent upgrade of the casting manufacturing industry.

Looking forward, casting defect detection technology still has broad development space. Self-supervised learning and unsupervised learning methods are expected to solve the problem of insufficient annotated data, further improving model performance. Optimization balancing real-time performance and lightweight design will make deep learning models more practical in resource-constrained industrial environments. The development of intelligent and automated integration will promote the deep integration of casting defect detection technology with intelligent manufacturing systems, achieving full-process automation of detection, analysis, and decision-making. Additionally, the development of human-machine collaboration and decision support systems will improve detection accuracy and system interpretability, enhancing user trust in automated detection systems.

In conclusion, the automatic defect recognition technology for castings based on deep learning has made significant progress, and through algorithm optimization, lightweight design, and system integration, it has promoted the effective implementation of industrial applications. The future research direction should focus on continuously improving algorithm methods, expanding practical applications, and exploring new technologies. By integrating self-supervised learning, real-time lightweight inference, and human-machine collaborative decision-making, it is expected to further achieve the intelligence and automation of casting inspection.

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