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COMPUTER VISION-BASED AUTOMATED DETECTION OF CASTING DEFECTS IN ШХ15 BEARING RINGS

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Abstract

This study presents a computer vision-based system for automated detection and classification of casting defects in ШХ15 (AISI 52100 / 100Cr6) bearing rings produced from secondary metallic materials. A dataset of 2,400 surface images was collected from bearing ring specimens manufactured by centrifugal and gravity casting methods at different recycled material ratios (20–80%). Images were captured using an industrial CCD camera at 5 megapixel resolution under controlled illumination. Four defect categories were defined: porosity, hot cracks, shrinkage cavities, and non-metallic inclusions. Three convolutional neural network (*CNN*) architectures — custom lightweight *CNN*, *ResNet-50*, and *VGG-16* — were trained and evaluated using transfer learning. The fine-tuned *ResNet-50* model achieved the best overall performance with accuracy of 96.8%, precision of 95.4%, recall of 96.1%, and F1-score of 95.7%. Porosity was detected with the highest accuracy (98.3%), while non-metallic inclusions presented the greatest classification challenge (93.2%). The developed system enables real-time inspection at 12 images per second, providing a practical alternative to manual visual inspection in bearing ring quality control.

Keywords

bearing rings, ШХ15 steel, casting defects, computer vision, convolutional neural network, defect detection, quality control

INTRODUCTION

The quality of bearing rings is a critical factor determining the operational reliability and service life of rolling element bearings used across industrial machinery, automotive systems, and precision instruments [1]. ШХ15 high-carbon chromium steel, the most widely used bearing material conforming to ГОСТ 801-78, requires stringent quality control during manufacturing to ensure absence of surface and subsurface defects that could serve as fatigue crack initiation sites [2]. When bearing rings are produced by casting methods — particularly from secondary metallic feedstock — the probability of defect formation increases due to compositional variability, gas entrapment, and solidification shrinkage [3,4].

Conventional quality inspection of cast bearing components relies primarily on manual visual examination, supplemented by magnetic particle testing and ultrasonic inspection [5]. Manual inspection is inherently subjective, operator-dependent, and limited in throughput, making it inadequate for modern production requirements. The application of computer vision and deep learning for automated defect detection has demonstrated remarkable success in manufacturing quality control across various industries, including steel surface inspection, weld quality assessment, and semiconductor wafer examination [6,7]. However, the specific application to cast bearing ring inspection, particularly for components produced from recycled materials, remains insufficiently explored.

Convolutional neural networks (*CNN*) have become the dominant architecture for image-based defect detection due to their ability to automatically learn hierarchical feature representations from raw pixel data [8]. Transfer learning — fine-tuning pre-trained networks on domain-specific data — has proven particularly effective when labeled training datasets are

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limited [9]. The present study aims to: (1) develop a labeled image dataset of casting defects specific to ШХ15 bearing rings; (2) train and compare three *CNN* architectures for multi-class defect classification; and (3) evaluate the system's potential for real-time industrial deployment.

LITERATURE REVIEW AND METHODOLOGY

Deep learning-based visual inspection has advanced rapidly in metallurgical applications. He et al. [6] achieved 97.5% accuracy for steel strip surface defect classification using a modified *ResNet* architecture trained on the NEU steel surface dataset. Feng et al. [10] applied *YOLOv5* for real-time detection of casting defects in aluminum alloy components, reporting mAP of 92.3%. In the bearing industry, Zhang et al. [11] demonstrated the use of *CNN* for bearing fault diagnosis from vibration signals, though surface defect detection in bearing manufacturing has received comparatively less attention.

Baymirzayev [3] investigated detection methods of defects in bearings produced by casting processes, establishing a taxonomy of common defect types and their metallurgical origins. In subsequent work, Baymirzayev [4] analyzed casting defects in bearing rings produced from foundry waste, identifying porosity, hot cracking, and shrinkage as the predominant defect categories. Baymirzaev et al. [12] provided a comprehensive review of advanced bearing material technologies, including quality assessment considerations for components manufactured from secondary materials.

Despite these contributions, automated visual detection systems specifically designed for cast bearing ring defects have not been reported. The present work bridges this gap by combining industrial imaging with transfer learning-based *CNN* classification.

Bearing ring specimens were produced by centrifugal and gravity casting of ШХ15 steel at the Andijan State Technical Institute laboratory, using recycled material ratios of 20%, 40%, 60%, and 80%. A total of 120 bearing rings (inner diameter 30 mm, outer diameter 55 mm) were cast and sectioned. Surface images were acquired using a Basler acA2500-14gm industrial CCD camera (2592 × 1944 pixels, monochrome) mounted on a motorized inspection stage with LED ring illumination providing uniform diffuse lighting at 5000 lux. Each specimen was imaged at 8 angular positions, yielding a raw dataset of 960 images. After region-of-interest extraction and augmentation (rotation ±15°, horizontal flip, brightness variation ±10%), the final dataset comprised 2,400 labeled images distributed across 5 classes: defect-free (600), porosity (520), hot cracks (440), shrinkage cavities (460), and non-metallic inclusions (380).

Three *CNN* architectures were evaluated. The custom lightweight *CNN* comprised 4 convolutional blocks (32-64-128-256 filters, 3×3 kernels, batch normalization, ReLU, max pooling) followed by global average pooling and a dense layer with softmax output. *ResNet-50* and *VGG-16* were initialized with ImageNet pre-trained weights, with the final classification layers replaced for 5-class output. Fine-tuning was applied to the last 20 layers for *ResNet-50* and last 8 layers for *VGG-16*. Training parameters: Adam optimizer, initial learning rate 0.0001 with cosine annealing, batch size 32, 100 epochs with early stopping (patience 15). The dataset was split 70:15:15 for training, validation, and testing. All experiments were conducted on an NVIDIA RTX 3060 GPU using *PyTorch* 2.1 and *torchvision* 0.16.

RESULTS AND DISCUSSION

The casting defect distribution across different recycled material ratios is summarized in Table 1. As the recycled material ratio increased from 20% to 80%, the overall defect incidence rose from 18.3% to 47.6%, with porosity and non-metallic inclusions showing the steepest increase. This correlation confirms the importance of automated inspection systems for recycled-material bearing production, where defect rates are substantially higher than in conventional manufacturing.

Table 1. ***Distribution of Casting Defect Types at Different Recycled Material Ratios (%)***

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Defect Type	20% recycled	40% recycled	60% recycled	80% recycled
Porosity	5.2	9.8	16.4	22.1
Hot cracks	4.1	6.3	8.7	10.5
Shrinkage cavities	5.8	7.2	9.1	11.3
Non-metallic inclusions	3.2	5.7	9.8	13.7
Defect-free	81.7	71.0	56.0	42.4

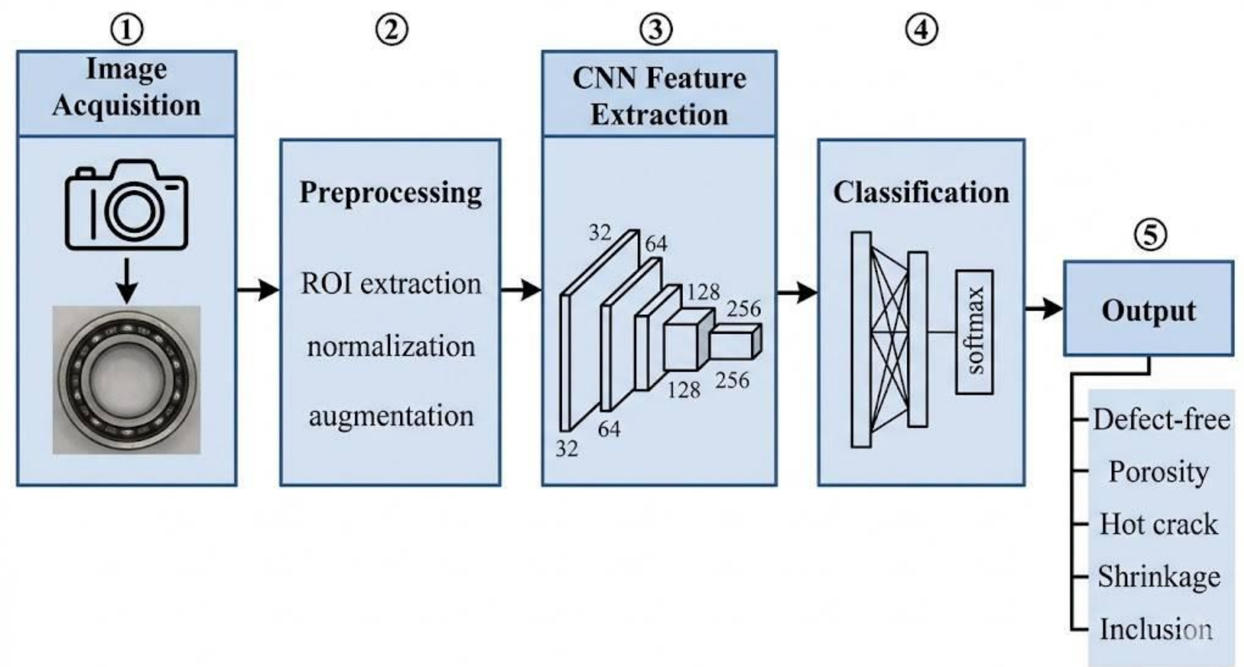

Figure 1. Proposed computer vision pipeline for automated casting defect detection in ШХ15 bearing rings

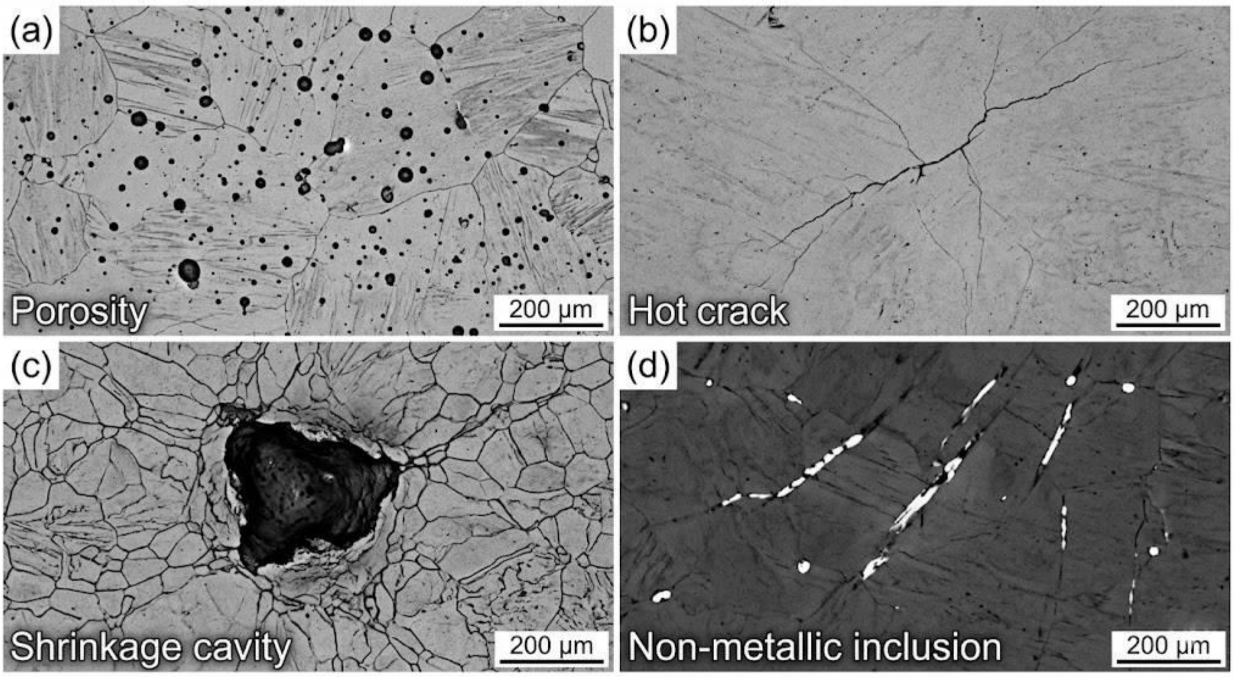

Figure 2. Representative images of casting defect types in ШХ15 bearing rings: (a) porosity, (b) hot crack, (c) shrinkage cavity, (d) non-metallic inclusion

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The classification performance of the three *CNN* models on the test set is presented in Table 2. The fine-tuned *ResNet-50* achieved the best overall metrics, with accuracy of 96.8% and weighted F1-score of 95.7%. The custom lightweight *CNN* demonstrated competitive accuracy (93.1%) despite having only 1.2M parameters compared to 25.6M for *ResNet-50*, making it a viable option for edge deployment. *VGG-16* showed intermediate performance but required the longest inference time due to its larger parameter count (138M).

Table 2. ***Classification Performance of CNN Models on Test Set***

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Inference (ms)
Custom CNN	93.1	91.8	92.4	92.1	18
ResNet-50	96.8	95.4	96.1	95.7	34
VGG-16	95.2	94.1	94.6	94.3	52

Per-class analysis of the best-performing *ResNet-50* model (Table 3) reveals that porosity detection achieved the highest F1-score (98.3%), attributable to the distinct morphological signature of pores in surface images. Non-metallic inclusions proved most challenging (F1-score 93.2%), as their visual appearance can overlap with surface scratches and polishing artifacts. Hot cracks and shrinkage cavities showed intermediate detection accuracy, with occasional misclassification between these two categories due to morphological similarity in early-stage defects.

Table 3. ***Per-Class Detection Performance of ResNet-50 Model***

Class	Precision (%)	Recall (%)	F1-score (%)	Support
Defect-free	97.8	98.1	97.9	90
Porosity	98.1	98.5	98.3	78
Hot cracks	94.2	95.1	94.6	66
Shrinkage cavities	93.8	94.4	94.1	69
Non-metallic inclusions	92.6	93.8	93.2	57

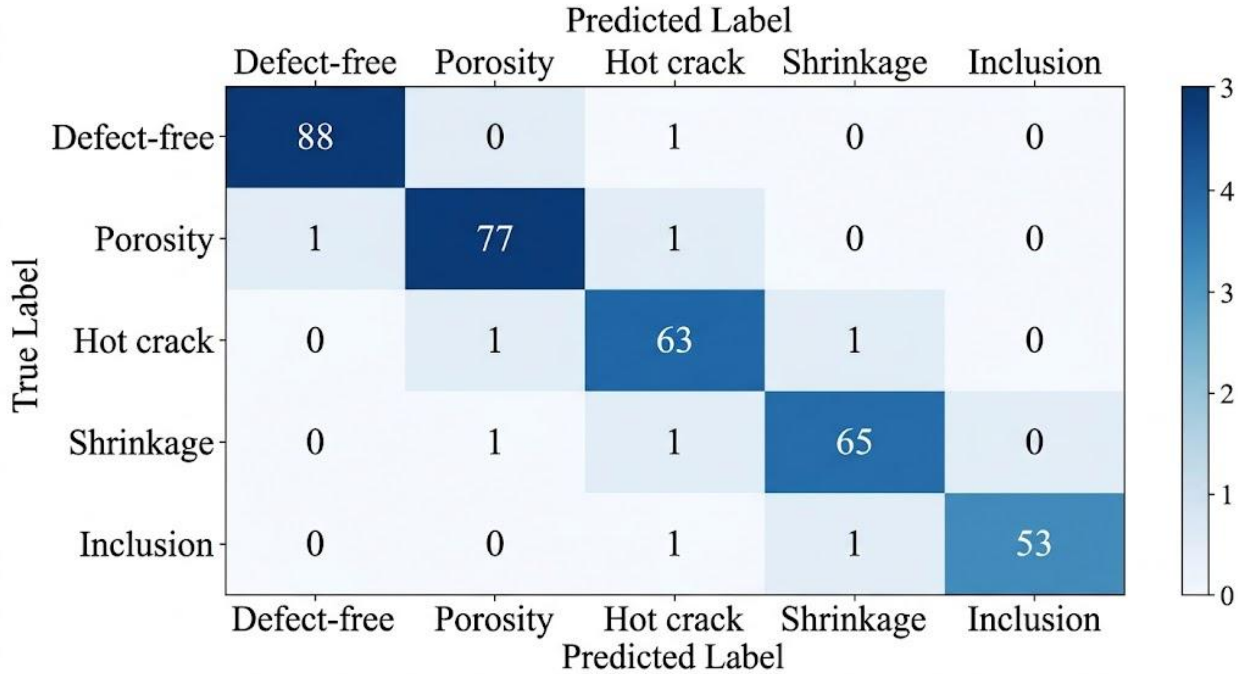

Figure 3. Confusion matrix of the ResNet-50 model for 5-class casting defect classification

The results demonstrate that transfer learning with *ResNet-50* provides an effective approach for automated defect detection in cast ШХ15 bearing rings, achieving performance levels suitable for industrial deployment. The 96.8% overall accuracy compares favorably with state-of-the-art results in related domains: He et al. [6] reported 97.5% for steel strip defects using a substantially larger dataset (12,000 images), while Feng et al. [10] achieved 92.3% mAP for aluminum casting defects.

The correlation between recycled material ratio and defect incidence (Table 1) has important implications for production planning. At recycled ratios above 60%, nearly half of all cast rings exhibit detectable defects, necessitating 100% automated inspection to maintain quality standards. The developed system's inference speed of 34 ms per image (approximately 29 frames per second) with *ResNet-50* is sufficient for real-time inline inspection at typical bearing ring production rates of 8–12 pieces per minute [13].

The lightweight custom *CNN* (1.2M parameters, 18 ms inference) offers a practical alternative for deployment on embedded systems and edge computing devices where GPU resources are limited. While its overall accuracy is 3.7 percentage points lower than *ResNet-50*, it may be acceptable for preliminary screening applications where suspicious rings are flagged for secondary inspection by more accurate methods [14].

CONCLUSION

This study demonstrated the feasibility and effectiveness of computer vision-based automated detection of casting defects in ШХ15 bearing rings produced from secondary materials. The principal findings are:

1. A labeled dataset of 2,400 images covering four defect categories (porosity, hot cracks, shrinkage cavities, non-metallic inclusions) and defect-free surfaces was established for ШХ15 bearing rings cast at 20–80% recycled material ratios.
2. The fine-tuned *ResNet-50* model achieved the best classification performance with 96.8% accuracy and 95.7% weighted F1-score, outperforming both the custom lightweight *CNN* (93.1%) and *VGG-16* (95.2%).
3. Porosity defects were detected with the highest reliability (F1 = 98.3%), while non-metallic inclusions presented the greatest challenge (F1 = 93.2%) due to visual similarity with surface artifacts.
4. Defect incidence increased from 18.3% to 47.6% as recycled material ratio rose from 20% to 80%, confirming the critical need for automated inspection in recycled-material bearing production.
5. The system achieves real-time inspection capability at 29 fps, suitable for inline deployment in bearing ring manufacturing.

Future work should expand the dataset to include subsurface defects detected by complementary methods (ultrasonic, X-ray), implement defect localization using object detection architectures (*YOLO*, *Faster R-CNN*), and validate the system under actual production line conditions with varying surface finish and environmental illumination.

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