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Image Processing in identifying the Industrial Automation Impact using RestNet with Convolutional Neural Network

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ABSTRACT

The integration of Image Processing (IP) and Deep Learning (DL) techniques within smart Internet of Things (IoT)-based industrial automation systems has significantly advanced manufacturing efficiency. In industrial manufacturing, the precise mechanical inspection of components such as gears and bearings is critical; however, human factors often compromise the stability, efficiency, and accuracy of conventional testing methods. To address these challenges, this study proposes a novel edge detection approach leveraging a Convolutional Neural Network (CNN) with ResNet-152 for multidirectional edge detection of mechanical parts, enhancing feature detection precision. The method improves productivity, predictive maintenance, quality control, and overall operational excellence. The proposed model was evaluated against various DL methods and achieved an edge detection accuracy of 92.53%, surpassing traditional approaches. These results demonstrate the potential of the ResNet-152-based CNN in delivering high-quality, reliable defect detection in industrial environments.

Keywords: Convolutional Neural Network, Edge Detection, Image Processing, Manufacturing Industries, ResNet-152

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INTRODUCTION

With the rapid advancement of industrial modernization, automated manufacturing increasingly demands precise identification of mechanical parts, particularly in gears and bearing edge profiles (Goli et al., 2021; Zicari et al., 2021). In line with the trend towards standardization and serialization, high-quality and high-precision gears and bearings are essential for ensuring product reliability (Zhu et al., 2022). Accurate detection of key features in mechanical parts is therefore crucial in current industrial production, as it not only affects product quality but also underpins efficiency improvements and equipment safety (Lv et al., 2022).

Image Processing (IP) plays a foundational role in computer vision and computer science (Pandey et al., 2023; Bedi et al., 2023; Sharifani and Amini, 2023; Saberironaghi et al., 2023). It encompasses diverse algorithms and techniques for enhancing and analysing visual data, with goals including noise reduction, sharpening, and contrast enhancement. Such techniques are widely applied in fields such as medicine, photography, and video production. Due to the limitations of traditional contact detection—often associated with lower efficiency and higher error rates—non-contact IP-based detection has increasingly replaced conventional approaches. This transition has delivered higher accuracy and stability, but meeting the stringent demands of modern digital industrial systems remains a challenge (Lei, 2022; Capponi et al., 2022).

The primary purpose of automation systems in manufacturing and industrial contexts is to enhance productivity and operational efficiency. These systems integrate hardware and software to optimise processes such as production, inventory management, and quality assurance (Kshirsagar et al., 2023a; Dhingra et al., 2022a). Components such as Programmable Logic Controllers (PLCs), actuators, sensors, human–machine interfaces (HMIs), and communication networks form the backbone of such systems. The PLC functions as the system's "brain," executing programmed instructions to control machinery. Actuators and sensors handle input and output operations, while HMIs allow operators to monitor systems and make necessary adjustments. Collectively, these components are indispensable for modern production, contributing to quality improvement, cost reduction, and process optimisation (Mandal et al., 2022; Kshirsagar et al., 2022a).

Field Programmable Gate Arrays (FPGAs) have emerged as a powerful and flexible hardware platform with substantial computational capabilities. Over the past two decades, they have been widely applied in IP-based technologies. Leveraging extensive research and careful system design, the present work proposes a novel approach using FPGA-based IP methods to inspect mechanical components. This technique exploits the FPGA's parallel processing capacity and adaptability, enabling high-speed, accurate mechanical part detection through optimised design strategies. The novelty of this research lies in the integration of ResNet with IP technologies, tailored to meet the specific requirements of mechanical component inspection.

The objective is to reduce human error and resource waste, while improving the reliability and performance of detection systems, thereby fostering intelligent growth in the mechanical parts manufacturing sector. This is achieved by investigating automation with edge detection and evaluating the effectiveness of the Message-Passing Interface (MPI). The subsequent sections outline: (i) an overview of ResNet applications and related research in mechanical parts inspection; (ii) a detailed methodology integrating IP and MPI data for precise multidimensional edge detection using a CNN with ResNet; (iii) performance evaluation of the enhanced detection model; and (iv) a summary of the research findings.

LITERATURE REVIEW

With the advancement of computing and electronics, many instruments have evolved towards intelligence, multifunctionality, and miniaturisation. FPGA technology has proven highly effective for implementing diverse digital logic functions, and numerous researchers have explored its applications in recent years. Wang et al. (2022) proposed an acoustic resonance frequency monitoring technique implemented using FPGA devices to address the inadequate detection capacity of non-invasive oxygen sensors in healthcare. Comparative studies indicated a sensitivity limit of 1000 ppm with a 4 s response time, and a detection range from 1000 ppm to 100% oxygen concentration.

Kumar et al. (2022) developed a method for enhancing voice message encryption using a lightweight AES algorithm implemented on FPGA. Simulation studies revealed that this approach achieved substantially higher encryption performance than standard methods, suggesting strong potential for real-world applications. The rapid technological evolution in manufacturing has driven the adoption of automation, with machinery increasingly upgraded for digital integration. In this context, each mechanical component plays a critical role, prompting researchers to focus on improving detection and quality control processes. For example, Roy et al. proposed a detection approach combining autonomous fibre insertion machinery with optical coherence tomography for quality assurance in conventional manufacturing. Their method effectively assessed variations, identified production anomalies, and reduced process variability.

Brunella et al. (2022) addressed limitations in universal CPU technology for modern network interface cards by developing FPGA-based software solutions. Experimental results demonstrated the ability to execute dynamically loaded applications with high CPU core packet processing throughput and a tenfold reduction in packet forwarding latency. Similarly, Yang et al. (2021) investigated the anisotropic mechanical properties of stereolithography-manufactured parts. They found tensile strength varied significantly between planar and edge builds, with a 35% comparative range distribution, confirming anisotropic behaviour.

Recent studies have also explored the integration of machine learning (ML) and deep learning (DL) in manufacturing contexts. Kumar et al. (2023) reviewed process design and production control for additive manufacturing using ML. Kor et al. (2023) examined DL applications and digital twins within Industry 4.0. Abdalzaher et al. (2023) utilised AI for securing IoT-based smart systems, focusing on trust mechanisms to mitigate security risks. Uddin et al. (2023) evaluated the integration of IoT services with DL technologies, while Rahman et al. (2023) defined Industry 4.0 in terms of ML and IoT usage.

Other notable contributions include Al Shahrani et al. (2023), who demonstrated intelligent manufacturing automation powered by ML through the Internet; Xing et al. (2023), who applied DL and IP to automate A-line recognition in lung ultrasound images; and Sarker (2021), who provided a comprehensive overview of DL techniques, taxonomy, and applications. Yazdinejad et al. (2023) proposed an ensemble DL model for cyber threat detection in industrial IoT, and Chander and Kumar (2023) employed metaheuristic feature selection with DL-enabled cascaded recurrent neural networks for anomaly detection in IoT-based industrial environments.

RESEARCH METHODOLOGY

In this study, error detection is performed in two main stages. In the first stage, the image size and recognition rate of the input images are measured. In the second stage, errors are identified based on the placement and defects recorded in the MPI database of mechanical components. Figure 1 illustrates the proposed model for detecting defects in two different types of mechanical components.

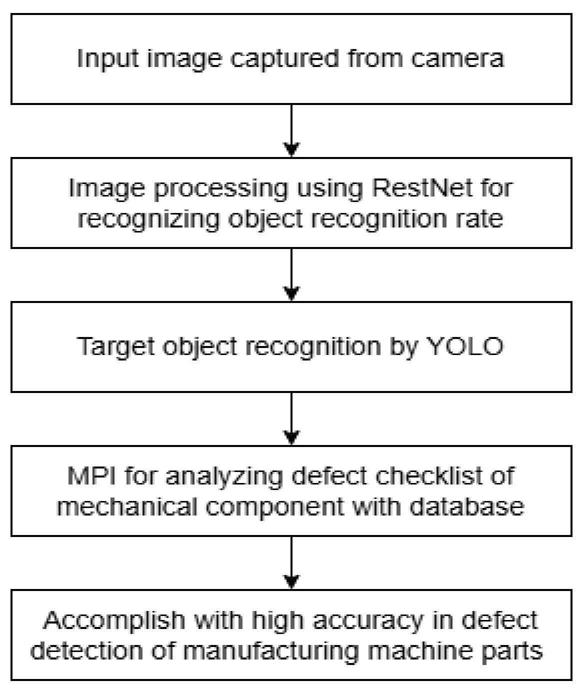

Figure 1 Flow diagram of defect detection method in manufacturing industry

The input image of the mechanical component is pre-processed using OpenCV, and the target object is recognised using a pre-trained YOLO model. After extracting the Region of Interest (ROI), the relevant area is analysed to detect errors in accordance with the factory's process standards. This approach is designed to reduce both economic and technical burdens for small enterprises, as it enables defect detection using externally captured images without the need for physical measurement tools.

For optimal application, certain conditions must be met:

1. The camera must be positioned at a fixed distance from the object.
2. Lighting conditions should remain consistent during image capture.
3. The camera's field of view should closely approximate that of the human eye.
4. Lens-induced distortion must be corrected using a distortion correction algorithm.

In the image processing and object recognition stages, additional factors are considered. For example, intentional vibration is introduced to simulate conveyor belt movement in manufacturing, particularly for fluid-containing objects. Since the inspection target may be in motion, the methodology accounts for temporal and positional variations caused by mechanical operations.

Image Preprocessing using RestNet-152

ResNet-152, a deeper yet less complex architecture than VGG, is employed for uncertainty recognition in both the training and testing datasets during the initial defect detection experiments. With 152 layers, ResNet-152 offers greater accuracy, scalability, and capability in detecting high-level patterns compared to conventional methods. Its deep architecture enables the extraction of complex and abstract image features, which is critical in this research. While ResNet-152 requires more computational resources and longer training times, its superior accuracy in mechanical part detection justifies its selection.

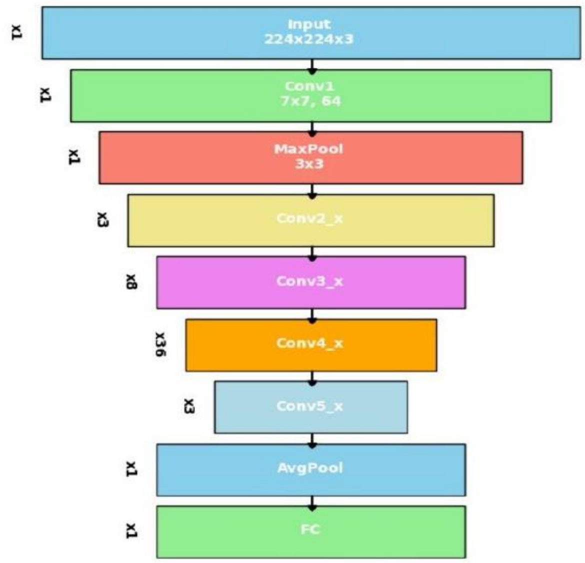

Figure 2 Architecture of RestNet -152

The architecture begins with an input layer accepting images of fixed size with three RGB channels, followed by an initial convolution layer (Conv1) using a 7×7 kernel to produce 64 channels. This output is downsampled to 112×112 pixels, then processed by a MaxPool layer to further reduce dimensions to 56×56 pixels. The subsequent residual blocks, a key feature of ResNet-152, enable the network to learn effectively while preventing gradient vanishing. The penultimate layer applies average pooling, and the final Fully Connected (FC) layer outputs classification results, restricted here to two classes: "Defect" and "No Defect."

A skip connection in each residual block allows the model to transmit information between layers without loss of relevance. YOLO, a single-shot object detection framework, is integrated with ResNet-152 to predict class labels and bounding boxes in real time. Compared to multi-stage detection approaches, YOLO offers faster and more efficient processing, even on low-power devices.

MPI-Based Data Transmission

Figure 3 shows the MPI database flow. The process begins in an idle state, moving to a startup state when the MPI issues a bus request. Depending on whether a read or write request is identified, the system transitions to the appropriate operational state. For transfers below 8 bits, read and write operations proceed directly. For transfers exceeding 8 bits, the system enters a reply mode, and upon a successful response, begins byte-by-byte data transfer. Invalid responses trigger a pause state, followed by termination and a return to idle mode. This mechanism minimises data loss and enhances detection accuracy.

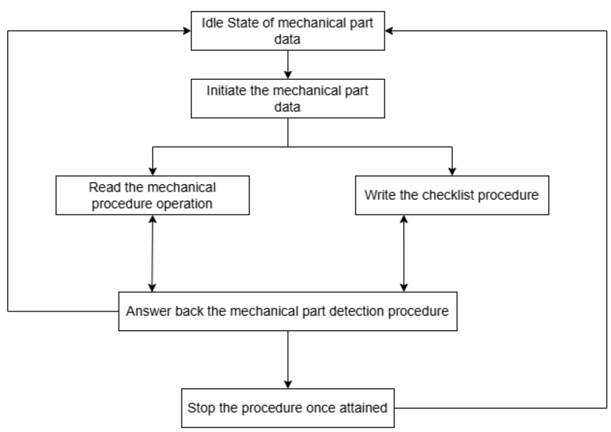

Figure 3 Flow chart of MPI database

RESULT AND DISCUSSION

The experimental evaluation was conducted using a precision optical platform comprising a camera, stage, and other IoT-enabled devices. Prior to testing, all equipment was properly connected and calibrated to ensure measurement accuracy.

Defect Detection Performance

The proposed defect detection approach was compared with conventional edge detection methods, including Roberts, Sobel, and Prewitt, as well as the integrated YOLO with ResNet model. Table 1 presents the performance metrics in terms of detection error percentage and detection time. The Roberts, Sobel, and Prewitt methods yielded detection errors of 28%, 36%, and 19%, respectively, with detection times of 18, 19, and 16 seconds. In contrast, YOLO integrated with ResNet achieved a significantly lower detection error of 8% and a faster detection time of 10 seconds.

Defect detection Methods	Detection Error (%)	Detection Time (Sec)
Roberts	28	18
Sobel	36	19
Prewitt	19	16
YOLO with RestNets	8	10

Table 1 Performance evaluation of proposed defect detection methods

The DAGM 2007 dataset was utilised to train and evaluate the models. This dataset contains ten categories and 10,000 images, with the first six categories forming the development set and the remaining four forming the competition set. Each development category included 1,000 "no defect" images and 150 "defective" images, while each competition category included 2,000 defect-free and 300 defective images. In this context, a defect-free image displays an intact background pattern, whereas defective images show identifiable imperfections.

Image Preprocessing and Comparative Evaluation

All images underwent preprocessing steps such as grayscale conversion, contrast enhancement, and noise reduction to improve quality. The edge detection techniques—Roberts, Sobel, and Prewitt—were implemented using their respective established algorithms for performance comparison. Mechanical components such as bearings and gears were mounted on the optical platform, and images were captured for evaluation.Performance assessment considered detection degree, detection time, and part edge image error. The YOLO with ResNet model demonstrated superior results in all metrics, indicating the benefit of combining deep learning-based object detection with advanced feature extraction architectures.

Implementation and Training Environment

The neural network models were developed and trained using Python, NumPy, scikit-learn, the PyTorch deep learning framework, and the matplotlib and torchvision libraries. The Kaggle platform's computing resources supported model training and evaluation. An application was developed to enable user interaction with the trained architecture for image classification and defect detection.

Model performance was influenced by factors including batch size, learning rate, number of training epochs, and the proportion of training data relative to the total dataset. Optimising these parameters was critical for achieving the high detection accuracy demonstrated by YOLO with ResNet.

Summary of Findings

Figures 4 and 5 illustrate the comparative detection errors and detection times, respectively. YOLO with ResNet consistently outperformed the traditional methods, providing faster detection and significantly reduced error rates. These improvements highlight the method's suitability for real-time industrial defect detection applications, where both precision and speed are crucial.

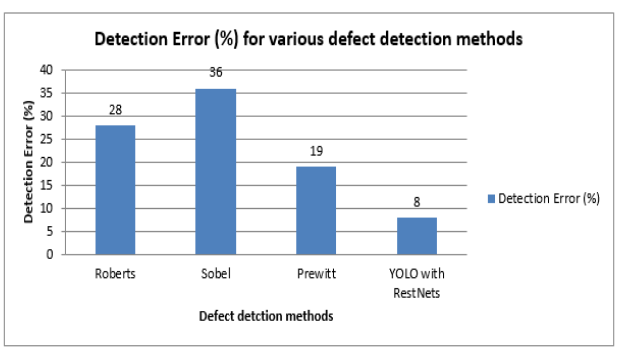

Figure 4 Comparison of detection error for various defect detection methods

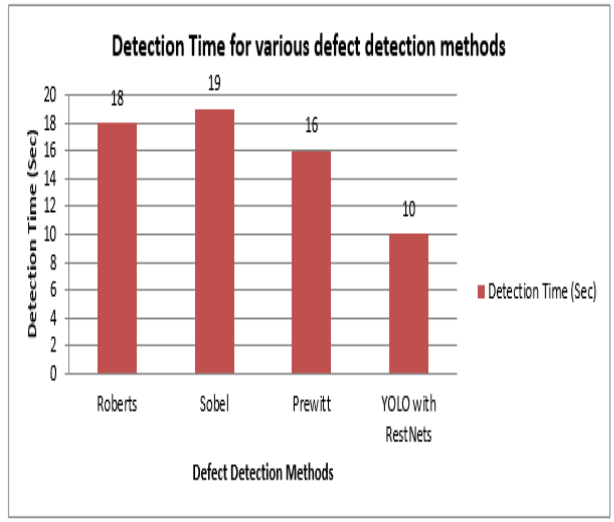

Figure 5 Comparison of detection time for various defect detection methods

CONCLUSION

With the continuous advancement of mechanical manufacturing technology, ensuring the quality of mechanical parts has become increasingly critical. Traditional MPI-based inspection methods suffer from limitations such as unstable manual operation, low efficiency, and high error rates. This study demonstrated that integrating ResNet-152 with YOLO for defect detection significantly enhances both accuracy and efficiency in identifying mechanical part defects.

The proposed method streamlines the early detection process, enabling faster response times for corrective actions and providing a reliable framework for quality control. By combining deep learning-based feature extraction with real-time object detection, the system effectively collects and analyses defect data, facilitating timely intervention and optimised maintenance strategies.

Despite achieving a low detection error rate of 10% and high operational efficiency in the experimental setup, certain challenges remain. Variability in mechanical part size and features, along with suboptimal image quality caused by noise, blurring, or poor lighting, can reduce detection accuracy. Furthermore, while the proposed method shows promise for industrial applications, it requires further optimisation to meet the stringent demands of large-scale manufacturing environments.

Future work will focus on incorporating FPGA implementations of the ResNet architecture to further enhance processing speed and scalability, ensuring the system meets the rigorous performance requirements of industrial-grade applications.

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