systems, tools like this can serve as a bridge between expert planning and everyday experience.

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USING COMPUTER VISION AND NEURAL NETWORKS FOR DEFECT DETECTION IN MANUFACTURING

Ph.D student: Viktor Sotnychenko
Research supervisor DSc, Professor Igor Yakovenko
Mechanical Engineering Technology and Metal-Cutting Machines Department
Language support supervisor DSc, Professor Tetyana Sergeyeva
Cross-Cultural Communication and Foreign Language Department

Abstract. The research explores the application of computer vision and neural networks for automated defect detection in manufacturing processes. Deep learning-based algorithms analyze visual data to identify defects, optimize quality control, and enhance production efficiency [1]. The study aims to reduce human error, increase detection accuracy, and minimize production losses.
Keywords: computer vision, neural networks, defect detection, deep learning, automation, manufacturing quality control.

Introduction

Topicality. Quality control is a critical aspect of modern manufacturing, ensuring product reliability and compliance with standards. Traditional inspection methods rely on manual assessment, which is time-consuming and prone to human error. The integration of computer vision and deep learning enables real-time defect detection, reducing operational costs and improving consistency in quality control [2].

The object of the research is automated defect detection in manufacturing processes.

The subject of the research is the application of computer vision and neural networks for defect identification and classification.

The goal of the work is to develop AI-driven methods for detecting and categorizing manufacturing defects, improving efficiency and precision in quality assurance.

The tasks of the study include:

1. Analyzing common defect types and their impact on production quality.
2. Developing a computer vision system using neural networks for real-time defect detection.
3. Implementing deep learning models to classify defect severity.
4. Evaluating system performance through experimental validation and industry trials.

The novelty of the research lies in the integration of advanced deep learning techniques into manufacturing quality control, reducing reliance on manual inspection and enhancing defect detection precision.

Methodology

The research employs a combination of image processing, deep learning models, and industrial automation techniques. High-resolution cameras capture real-time images of production lines, which are processed using convolutional neural networks (CNNs) trained on large datasets of defect images. Feature extraction techniques, such as edge detection and texture analysis, improve classification accuracy [3].

A key aspect of the methodology is the implementation of real-time monitoring systems that analyze defects at different production stages. The system uses deep learning models such as Faster R-CNN, YOLO, and ResNet to detect and categorize defects based on severity and type [4]. Experimental validation involves testing the system on various manufacturing setups, comparing its accuracy with traditional inspection methods.

According to recent studies, AI-based defect detection systems have demonstrated accuracy improvements of up to 95%, significantly reducing waste and increasing production efficiency [5].

Discussion

This research aligns with the principles of modern industrial innovation by addressing sustainability, human-centered approaches, and interdisciplinary collaboration.

Sustainability (Economic-Ecological-Social): AI-driven defect detection reduces material waste, energy consumption, and costs associated with rework and defective products. It supports sustainable manufacturing by minimizing resource wastage and improving operational efficiency.

Human-Centered – Wellbeing: Automating defect detection reduces the burden on manual inspectors, improving workplace safety and reducing cognitive fatigue. It ensures consistent product quality, benefiting end-users in industries such as automotive, electronics, and pharmaceuticals.

Impact-Oriented – Multi-Agent/Sector/Disciplinary Co-Creation: The study bridges expertise from computer science, manufacturing, and artificial intelligence. Its outcomes are applicable across multiple sectors, including aerospace, automotive, and consumer electronics, fostering collaboration between researchers, manufacturers, and AI developers.

Conclusions. The application of computer vision and neural networks in defect detection represents a significant advancement in manufacturing quality control. By leveraging deep learning for automated inspection, the research demonstrates improved accuracy, efficiency, and sustainability. The developed methodologies provide practical solutions for industries seeking to enhance production quality while minimizing costs and defects.

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