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Development of AI Model for Robotic Vision Inspection of Sheet-Metal Components in Manufacturing

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ABSTRACT: This paper presents an AI-based robotic vision inspection system designed to enhance quality control in the manufacturing of sheet-metal components. The system integrates a sequential AI model with advanced image processing techniques to automate real-time defect detection and classification. Utilizing a high-resolution camera, the system captures images of components on a conveyor, which are pre- processed using grayscale conversion, Gaussian blurring, and Canny edge detection to emphasize structural details. A deep learning model then classifies isolated regions of interest based on normalized, resized images. Feature matching through ORB (Oriented FAST and Rotated BRIEF) enables accurate alignment with reference templates, while automated measurements convert pixel dimensions to physical units, ensuring reliable detection of deviations. With an average accuracy of 88.3%, the system consistently identifies subtle and complex defects, such as scratches and dimensional deviations, under variable lighting and noise conditions. This AI-driven approach reduces the need for manual inspection, minimizes error, and enhances workflow efficiency, representing a major step toward robust, real-time quality assurance solutions in industrial environments.

KEYWORDS: Conveyor-based inspection, Gaussian blurring, high-resolution imaging, normalized image pre-processing, real- time defect classification, deep learning, canny edge detection, deep neural network, template matching, manufacturing defect analysis, automated quality inspection, industrial vision systems.

I. INTRODUCTION

The field of automated quality inspection in manufacturing has advanced considerably, with AI-based systems increasingly supporting quality control tasks in high- precision environments. Initially developed for standard inspection tasks, these automated systems are now being engineered to tackle more complex scenarios, particularly in detecting subtle surface defects and dimensional irregularities in sheet-metal components. This evolution addresses the industry's need for consistent quality, efficiency, and reduced human error, especially in sectors where even minor defects can compromise product performance and safety [1], [2]. With advancements in computer vision and machine learning, there is an opportunity to replace or augment traditional manual inspection methods, providing enhanced consistency and reliability in quality assurance tasks [3], [4].

In traditional manufacturing settings, quality control relies heavily on human inspectors, who visually assess components for defects. However, due to fatigue, subjectivity, and other human limitations, reliance on manual inspection introduces variability and can lead to missed defects, especially in high- volume production [5], [6]. This dependency on human performance has motivated the exploration of AI-driven inspection systems that offer precision and repeatability, even in complex environments with noise and varied lighting. For instance, studies show that AI models, such as those based on convolutional neural networks, significantly enhance defect detection accuracy by learning from diverse datasets and adapting to different defect types [7], [8].

This project proposes an AI-based robotic vision inspection system designed to autonomously identify and classify defects in sheet-metal components. By integrating advanced image processing with a sequential neural network model, this system aims to improve inspection accuracy, reduce inspection times, and streamline quality control workflows within high-speed manufacturing environments [9].

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A. PROBLEM STATMENT

1) Introduction

In the manufacturing industry, maintaining precision, efficiency, and consistency is essential, especially in the quality assurance of sheet-metal components.

Conventionally, inspection processes depend on manual visual checks, where human inspectors are responsible for identifying and categorizing defects. However, this method faces limitations due to factors such as inspector fatigue, differences in skill levels, and subjective interpretation, which can undermine the accuracy and reliability of defect detection.[1],[2]. As production demands increase and skilled inspectors become harder to find, these limitations contribute to longer inspection times, workforce challenges, and an elevated risk of undetected defects [3]–[5]. AI-driven robotic vision systems address these challenges by enabling precise and consistent defect detection and measurement, enhancing accuracy while minimizing human error [6]–[8]. This project aims to develop a sophisticated AI-based robotic vision inspection system that leverages deep learning and advanced image processing, creating a bridge between traditional inspection methods and next-generation automation technology [9].

2) Aim

To Design and develop AI based robotic vision based system for inspection of sheet-metal component with accuracy more than 90%.

3) Objectives

1. To Conduct a literature review on image processing and AI models for defect detection in manufacturing.
2. To fabricate sheet-metal components and develop an image dataset.
3. To pre-process the dataset for the suitable classification algorithms.
4. To develop image processing and AI algorithms to classify defective components.
5. To validate the algorithms with sheet-metal parts and evaluate their performance.

II. METHODOLOGY

The methodology outlines the development of an AI- based vision inspection system for real-time defect detection in sheet-metal components. Key phases include data acquisition, image preprocessing, sequential neural network design, and model deployment. The process focuses on capturing high- quality images, enhancing them for defect visibility, and using deep learning to classify defects accurately. This structured approach enables efficient integration into production lines, ensuring consistent, automated quality inspection.

A. Data Acquisition

High-quality, labeled image data is essential for training and testing the sequential AI model. The dataset comprises high-resolution images of sheet-metal components with various defect types, including scratches, dimensional deviations, and alignment inconsistencies. Images were captured using a high-resolution camera mounted above a conveyor belt, simulating a manufacturing line. Each image captures the surface details of sheet-metal components under consistent lighting conditions to reduce noise and variation, ensuring that defects are clearly visible. The dataset is split into training, validation, and test sets to enable accurate model assessment.

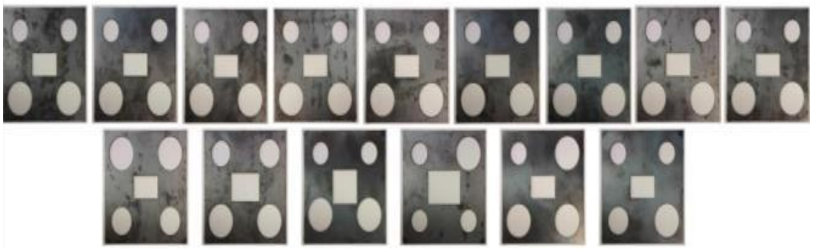


Figure I. Non-defective & Defective Dataset

B. Pre-Processing

Data pre-processing involved several image enhancement techniques to emphasize features critical for defect detection. Key steps include:

- Grayscale Conversion: Frames captured by the camera are converted from RGB to grayscale, reducing complexity and focusing on essential structural details.
- Gaussian Blurring: A 7x7 Gaussian filter is applied to the grayscale images to minimize noise, especially useful in the varied lighting conditions of a production line.

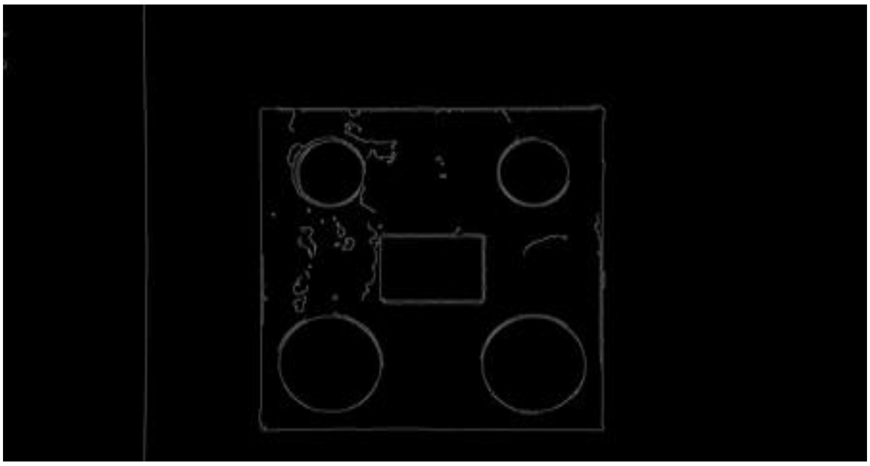


Figure II. Canny Edge Detection

C. Sequential AI Model Architecture

The system uses a pre-trained deep learning model, loaded through TensorFlow, for defect classification. Key architectural components include:

- Image Resizing and Normalization Layer: Each captured frame is resized and normalized before being processed by the model.
- Sequential Neural Network: A sequential model processes the resized frames, generating predictions based on learned patterns in defective and non- defective components.
- Classification Output: The model produces a binary output, classifying each component as "Defective" if the prediction exceeds a threshold (0.5) and "Non- Defective"

D. Model Training

The model was trained using TensorFlow and Keras libraries. A binary cross-entropy loss function was employed for defect classification, with the Adam optimizer adjusting learning rates dynamically. Key training parameters included:

- Batch Size: 32
- Learning Rate: 0.001, reduced adaptively based on validation loss
- Epochs: The model was trained for 25 epochs, with early stopping to prevent overfitting.

Data augmentation techniques, such as rotations and flips, were applied to the training dataset to increase robustness and improve model generalization. Evaluation metrics, including accuracy, precision, and recall, were monitored across epochs to assess model performance.

E. Real-Time Implementation

The trained model was deployed for real-time inspection, integrated with OpenCV to analyze live camera feeds and provide classification results immediately. The process includes:

- Image Capture and Conversion: Frames are captured and converted to grayscale in real-time.
- Contour Detection and Cropping: Each frame is processed to detect contours, representing the boundaries of components, and regions of interest are cropped.
- Classification and Measurement: Cropped images are fed to the model, which outputs a defect classification. Object dimensions in centimeters are calculated using a pixel-to-centimeter ratio, based on a known reference width of 5 cm.
- Feedback and Display: Results, including classification and dimensions, are displayed on the screen, with real-time logging of each component’s status for future analysis.

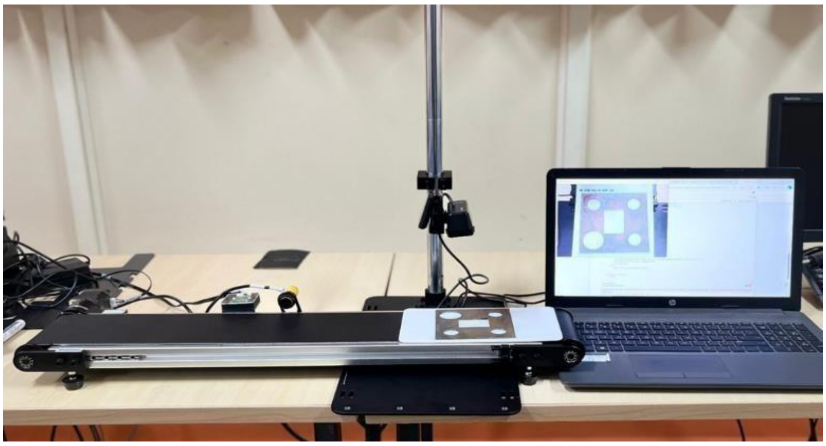
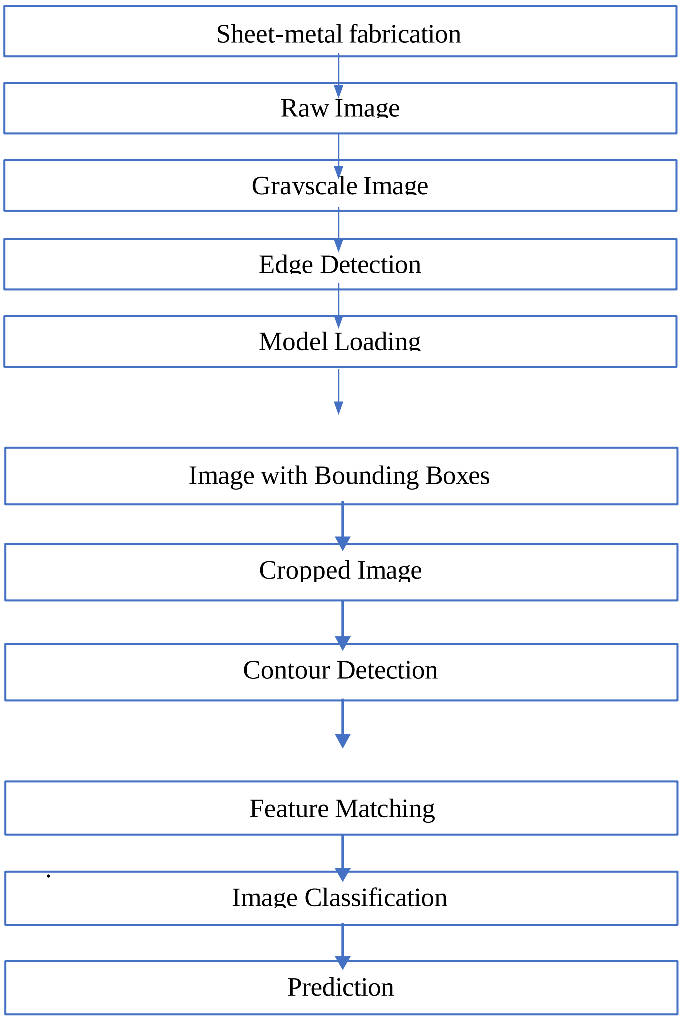


Figure III. AI based robotic vision system

F. System Evaluation

The system's performance was assessed using a separate test set of labeled sheet-metal images, representing a variety of defects and non-defective cases to simulate real-world production conditions. Evaluation metrics such as accuracy, precision, and recall were calculated to measure the system's ability to consistently identify defects across diverse scenarios. Additionally, the system was deployed in a controlled manufacturing simulation to validate real-time processing, where it achieved an accuracy of 88.3%, demonstrating robustness and reliability in high-speed defect detection for quality control in manufacturing.

G. Working Flow Chart



III RESULT AND DISCUSSION

The AI-based defect detection system was tested in a simulated manufacturing environment using live video capture of sheet-metal components, focusing on accurately identifying defective and non-defective items. In 10 trials, the system demonstrated reliable performance with an average accuracy of 88.3%, indicating consistent classification across multiple test cases. Each captured image was processed in real-time, with grayscale conversion and Gaussian blurring enhancing clarity, while Canny edge detection helped isolate defect regions. The model's binary classification results— outputting "Defective" or "Non-Defective"—aligned closely with the labeled ground truth, validating the system's effectiveness in real-world conditions.

During each trial, components were detected in the camera feed, cropped, and analyzed for width and height measurements. This ensured proper scaling and alignment for accurate classification, with the ORB feature matching technique contributing to robust recognition of component boundaries. In cases where defects were present, bounding boxes highlighted areas of interest, while the classification label was displayed on the image. The system consistently maintained a real-time processing rate, meeting the high- speed demands of an automated inspection line, and demonstrated effective feedback, logging results for later analysis. These outcomes indicate the system's robustness and suitability for industrial deployment, delivering dependable defect detection across varied conditions and component types.

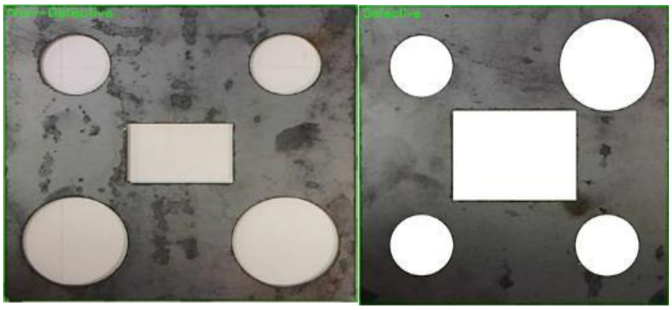


Figure IV. Identified defective and Non-defective Part

III. CONCLUSION

This research introduces a reliable AI-based robotic vision inspection system designed to automate defect detection in sheet-metal manufacturing. Integrating grayscale conversion, Gaussian blurring, Canny edge detection, and a sequential AI model, the system achieves an average accuracy of 88.3% across multiple trials, demonstrating consistency and robustness in classifying defective and non-defective components in real-time. This performance indicates the system's effectiveness as a scalable, automated solution suited for high-speed manufacturing lines.

Several factors contribute to the accuracy of the system. Image quality—affected by variations in lighting, resolution, and noise—directly impacts edge and contour detection, which are critical for accurate defect identification. The sensitivity of edge detection also requires proper calibration to distinguish subtle defects from normal component variations. Furthermore, the diversity and quality of the training dataset play a vital role in the model's generalization, enhancing its ability to identify a broad range of defect types. Precise alignment between predicted and reference images further supports reliable detection, minimizing errors and improving accuracy.

The outcomes of this study highlight the system's capability to address limitations in traditional inspection methods by reducing human error, improving inspection speed, and ensuring consistency under varied conditions. Future work may focus on enhancing model performance through expanded datasets, optimizing image preprocessing techniques, and refining model architecture to achieve even higher accuracy. This AI-driven approach represents a significant advancement in quality assurance, offering an efficient, reliable solution for modern manufacturing environments.

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