SSRG International Journal of Electronics and Communication Engineering
ISSN: 2348-8549/ https://doi.org/10.14445/23488549/IJECE-V12I7P111
Volume 12 Issue 7, 137-147, July 2025

Original Article

Development of a Welding Defect Detection System in Metalworking Parts Using Digital Image Processing with Deep Learning

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Received: 06 May 2025 Revised: 07 June 2025 Accepted: 08 July 2025 Published: 31 July 2025

Abstract **-** *In metalworking industries dedicated to the manufacture of parts, a large number of welds are required, yet not all industries employ advanced technologies for detecting welding defects. As a result, quality control is often performed manually by workers, leading to longer processing times and a higher likelihood of misidentification of defects due to human error. This introduces additional costs to the manufacturing process. This article presents the implementation of a welding defect detection system for metalworking parts using Digital Image Processing (DIP) techniques combined with deep learning. The proposed system utilizes Convolutional Neural Networks (CNNs) trained to identify defects in analyzed metal parts, such as porosities, holes, cracks, bubbles, among others. Additionally, the system integrates a user interface designed to display detected defects in real time and alert supervisors, enabling timely decision-making in production. Finally, this research includes a cost-benefit analysis comparing the proposed system to the traditional method, with the aim of facilitating future real-world testing. The results demonstrate that this technology reduces production times and costs in metalworking welding plants.*

Keywords **-** *Deep Learning, Digital image processing, Welding defect, Metalworking parts.*

1. Introduction

According to a 2023 report by the Ministry of Production of Peru [1], one of the most economically significant industries is metalworking manufacturing. This industry accounted for 11.4% of the manufacturing sector's Gross Value Added (GVA), amounting to approximately USD 21 million and 1.5% of the national Gross Domestic Product (GDP), amounting to approximately USD 162 million. In 2021, the metalworking industry had grown by 48.3%, driven by the gradual recovery of economic activity following the COVID-19 vaccination efforts. In 2022, the growth remained positive (+10.6%), bolstered by rising demand from the mining and construction sectors [1].

Welding is one of the most critical processes in the metalworking industry, as the structural integrity of fabricated systems depends heavily on its quality [2]. However, despite the industry's growth in recent years, many plants still rely on manual or semi-automatic weld inspection methods, significantly reducing efficiency and production capacity.

In the metalworking industry, various traditional methods are employed to detect welding defects in manufactured parts, including visual inspection, liquid penetrant testing, magnetic particle inspection, radiography, and ultrasonic testing [3]. The selection of methods depends on the part's characteristics and the customer's specifications, though visual inspection remains a mandatory test.

The visual inspection is typically conducted by quality engineers or trained operators. This process involves examining weld joints for surface defects such as cracks, porosity, or irregularities in the surface that indicate damage. However, manual inspections are susceptible to human error, including inspector fatigue, lapses in concentration, or overlooked small defects [4]. These shortcomings may lead to undetected weld flaws, potentially causing rework, safety risks, and financial losses.

As industries advance toward automation and Industry 4.0, there is a growing demand for integrated inspection systems capable of real-time, high-precision defect detection without disrupting production throughput.

In this context, Artificial Intelligence (AI) has proven instrumental in classifying and detecting welding defects through image processing [5]. Currently, multiple AI-based strategies have emerged for this purpose, including machine learning and deep learning.

Traditional machine learning methods, such as Support Vector Machines (SVM), Random Trees (RT), and K-Nearest Neighbors (KNN), are widely used in industrial applications. These algorithms require a previous extraction stage, where relevant characteristics like contours, color histograms, or textures are identified from images. While effective in controlled laboratory environments, these methods often underperform in real-world settings due to challenges like variable lighting, noise, and inconsistent camera angles. Such limitations render them impractical for real production lines. In contrast, deep learning techniques have revolutionized image processing. In particular, Convolutional Neural Networks (CNNs) demonstrate superior adaptability and accuracy in varying scenarios by automatically extracting features directly from raw data. Implementing systems that integrate this technology is critical for enhancing production efficiency in the metalworking industry.

This article presents the development of a cost-effective system for detecting weld defects in metalworking parts using Digital Image Processing (DIP) techniques combined with deep learning. The proposed system uses CNNs trained to identify various defects in the analyzed components, including porosities, cracks, bubbles, among others. The system incorporates a user interface that displays detected defects in real time and alerts supervisors, enabling prompt production decisions. Additionally, the research provides a comprehensive cost-effectiveness analysis comparing the system with traditional methods, with the goal of facilitating future real-world implementation. This technology demonstrates significant potential for optimizing production efficiency in industrial manufacturing environments.

This article is organized as follows: Section 2 reviews relevant literature and related work. Section 3 details the complete methodology of the proposed system. Section 4 describes the system's hardware and software design, along with its implementation in an industrial environment. Section 5 presents and analyzes the results. Section 6 discusses these findings. Finally, Section 7 presents concluding remarks.

2. Related Work

In [6], Cheng et al. propose a deep learning model for welding defect detection using CNNs for image feature recognition. The authors emphasize that steel quality depends on rigorous inspection at three stages: material reception, assembly process, and final finishing. Their results demonstrate that this model accurately identifies production defects (such as impurities, material damage, pores, weld undercuts, etc.) while eliminating the complicated manual feature extraction, achieving 92.54% recognition accuracy.

In [7], Yang et al. apply the state-of-the-art single-stage object detection algorithm YOLO v5 to steel pipe weld defect detection and compare its performance with the two-stage Faster R-CNN algorithm. Their method processes X-ray images because this industrial non-destructive testing method can effectively detect internal defects. Experimental results show a significant improvement in accuracy (up to 97.8% on average) for weld defect detection. This method also completes the multi-classification tasks and meets real-time detection requirements. Additionally, this approach successfully accomplishes the multi-classification task and meets real-time detection requirements.

In [8], Huang and Kovacevic propose a laser vision system model for non-destructive testing of welding quality. The system employs a laser vision sensor based on the principle of laser triangulation, which comprises a structured pattern generator, a laser generator, a focusing lens, an image sensor, and an optical filter. Through image processing and visual analysis of 3D profiles, this setup captures the geometric characteristics of welds. The system accurately identifies the position and classifies the size (from small to medium) of welding defects. Unlike conventional 3D range sensors, it utilizes efficient yet simple algorithms, including a graphical programming language, data operation modules, image processing, motion control, and user interface design, making it more suitable for industrial applications. The authors conclude that visual analysis of 3D profiles enables precise detection of defect presence, location, and dimensions, facilitating reliable non-destructive weld quality inspection.

In [9], Ebrahimi et al. focused on gas and oil pipelines and relied on a different method for detecting weld defects: image segmentation, an area growing method, correct image resolution, such as radiographic ones, and less subject diversity. This model divided a portion of the image to determine a pixel as the starting point and expanded the area outside this point due to the similarities between these pixels. Based on the histograms, the authors automatically evaluated the start and end of the image of the weld bead. Afterwards, they applied a mix of several standard algorithms to determine defects in the figure. The result of this article covers the shortcomings of previous models; however, the article suggests that each defect should be separated from the surrounding area and processed as image enhancement algorithms contribute significantly to the defect results.

In [10], Niederwanger et al. investigated the advantages of incorporating 3D laser-scanned weld geometries into elastic strain analysis for fatigue life prediction. Additionally, the authors quantified the capability to analyze experimental disintegration across various fatigue parameters. The authors further recommended assessing the implementation of non-local parameters in the fatigue life model, noting that 3D-scanned weld geometry data may yield reduced reliability for the samples examined in this work.

In [11], Raveen Kumar et al. highlight the challenges in weld defect detection, noting that some defects may escape detection during final supervisor inspections. Then the authors implemented image processing software and hardware through the application of computer vision and machine learning. In the document, a camera and an artificial intelligence system were implemented to make the detection and location of defects more precise, reaching an accuracy of 97.2%. With the MATLAB language and Machine Learning, proving to be effective with the functions of higher-order quadratic, cubic, etc. algorithms.

In [12], Dong et al. integrated several tools for weld defect analysis. First, they create a database containing all imperfection characteristics from weld digital images, which include edge detection, threshold segmentation, detection channels, and multiple parameters such as gray scales, equivalent area, and correlation. Then, they develop a prototype system using Support Vector Machine (SVM) classifiers to categorize and identify defects in pipe weld images. The in-situ nature of their model enabled better automatic defect identification than other image processing algorithms.

In [13], Deng et al. identify limitations in conventional non-destructive testing methods (acoustic and manual detection) for wind turbine blade inspection, particularly regarding defect detection accuracy. To address this, they developed a digital image processing system employing log-Gabor filters. However, the system demonstrated two key limitations: the inability to detect small or thin defects and the limited or insufficient processing time, which is critical for operational optimization. Despite these constraints, the approach achieved a 92% detection accuracy rate.

In [14], Szőlősi et al. investigate the optimization of weld bead defect detection using deep learning techniques, demonstrating their significant potential for industrial image processing applications. The study employs the You Only Look Once (YOLO) algorithm, a real-time object detection system that simultaneously identifies and classifies objects in images. The researchers compiled a comprehensive image database using manual welding samples and conducted comparative performance analyses of YOLO versions v5 through v8. Their two-phase training process revealed YOLO v7's superior performance, establishing it as the preferred tool for automated defective weld detection. However, the study identifies a key limitation: defect detection is only effective if the precise defect location is provided; this takes us to the segmentation problem.

In [15], Naddaf-Sh et al. conducted an experimental evaluation of deep learning approaches for automated weld defect detection, comparing transformer-based models with RetinaNet performance. While they achieved promising results using YOLO v8 with an optimized confidence threshold, the study highlights the need for further investigation into additional parameter optimizations to enhance detection accuracy. The researchers emphasize that exploring these parameter effects could lead to more robust performance in industrial welding inspection applications.

In [16], Yang et al. evaluated the harmfulness of defects to different objects. The authors propose a fast, automatic method that locates welding defects using the U-Net network. This language expands a dataset to facilitate network training, achieving good performance to improve the system process, from the integration of digital X-ray images to achieving high accuracy in locating welding defects.

In [17], Chen et al. present a pyramid network of features referenced in Faster R-CNN, incorporating a novel visual attention mechanism. Their deep-learning-based approach implements a Squeeze and Position Attention Mechanism (SPAM) to detect defects of varying shapes and locations. The methodology employs geometrically transformed data augmentation to enhance training, demonstrating particular effectiveness in identifying low-contrast small targets against complex backgrounds. While the model achieves robust detection accuracy, the study does not address the practical implementation costs for industrial applications.

In [18], Yun et al. consult several companies to take the idea of implementing Deep Learning to achieve the highest accuracy in automatically detecting welding defects in radiographic inspection images. They developed a method to integrate defect characteristics by preprocessing images with the CLAHE language (Contrast-Limited Adaptive Histogram Equalization), which showed an improvement in the performance of weld bead background detection and optimal revelation of defect characteristics with the help of preprocessing and the average of the mean accuracy for training data.

In [19], Deng et al. developed a deep-learning-based model for weld defect detection and image recognition. The study analyzed asymmetric laser welding images from asian industrial sources using a combined approach of industrial image processing algorithms and deep learning techniques. The implemented solution features a deep convolutional neural network with an enhanced adaptive clustering method, supplemented by Transfer Learning (TL) to improve defect detection and image classification accuracy. While the model demonstrates significant reliability, the research highlights the need to address sample appearance inconsistencies introduced by the TL approach.

Some years ago, technology was not as advanced as it is today. Manual Non-Destructive Testing (NDT) was subject to human error, which companies had to tolerate. Currently, few companies automate these tests due to a lack of trained workers, time, and cost. The studies mentioned above utilize various deep learning techniques. Many of these investigations yielded positive results, but with certain limitations regarding processing time, image resolution, and the inability to detect small defects in the images. The authors did not include in their research a cost/benefit analysis of the proposed system, optimal production times for releasing elements, or the programming for identifying defect sizes according to American Welding Society (AWS) and American Society of Mechanical Engineers (ASME) standards. AWS focuses on welding and structural manufacturing, while ASME emphasizes design and model-based manufacturing. All of this is based on tolerances to determine whether the structures are acceptable or not.

3. Methodology

This article presents the development of a cost-effective system for detecting weld defects in metalwork parts using Digital Image Processing (DIP) techniques combined with deep learning. Figure 1 illustrates the block diagram of the complete proposed system. The proposed methodology consists of five stages: image acquisition, preprocessing, feature extraction, user interface, and analysis and evaluation. In the final stage (analysis and evaluation), necessary measures are implemented to assess and verify the accuracy of the proposed system, ensuring its readiness for testing in a real-world environment.

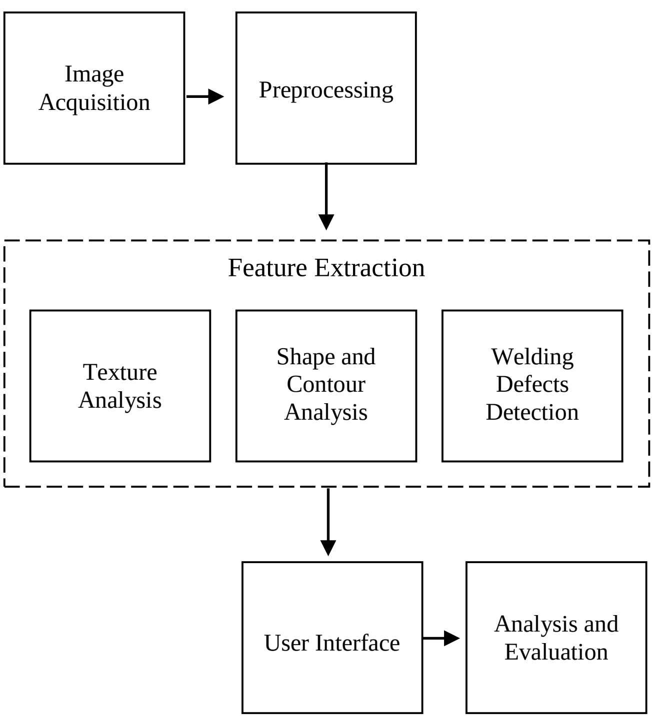


Fig. 1 Block diagram of the proposed system

3.1. Image Acquisition

The proposed system uses a high-resolution depth camera mounted atop the structure to capture images of parts passing through the system. Figure 2 illustrates the inspection system's model and the camera's positioning. This design was selected for compatibility with most metalworking production lines. By positioning the camera at a 90° angle, the system avoids poor-quality captures, and the depth camera's capabilities simplify distance estimation [20].

The depth cameras enable 3D reconstruction of the part and its weld, facilitating easy identification of imperfections. Additionally, they measure the distance from the camera to the part, allowing accurate estimation of defect size and depth.

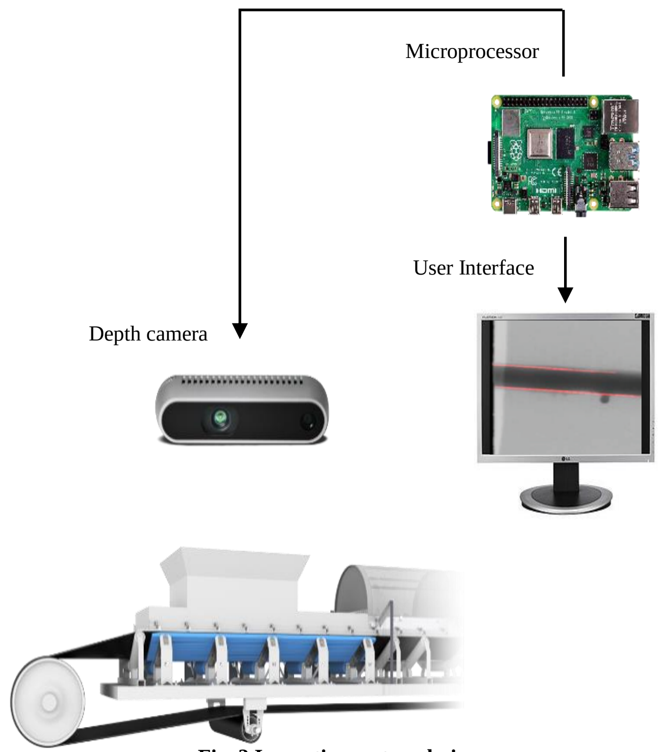


Fig. 2 Inspection system design

3.2. Preprocessing

The preprocessing stage is essential to improve the clarity and focus of the images captured by the camera because, in an industrial and metalworking part manufacturing environment, noise and lighting variations are present, among other visual defects. This preprocessing begins with sending the images to the microprocessor to introduce a Gaussian filter, which is responsible for preserving the edges and minimizing high-frequency noise caused by dust and small particles.

In addition, a histogram equalization is applied to improve the contrast of the captured image, allowing the system to better see fine details despite the lighting variations. Finally, the preprocessing also detects the region of interest of the part, in this case, the weld, as seen in Figure 3. This is useful for reducing the computational load because it allows the relevant section of the image to be isolated and the rest to be discarded for subsequent analysis.

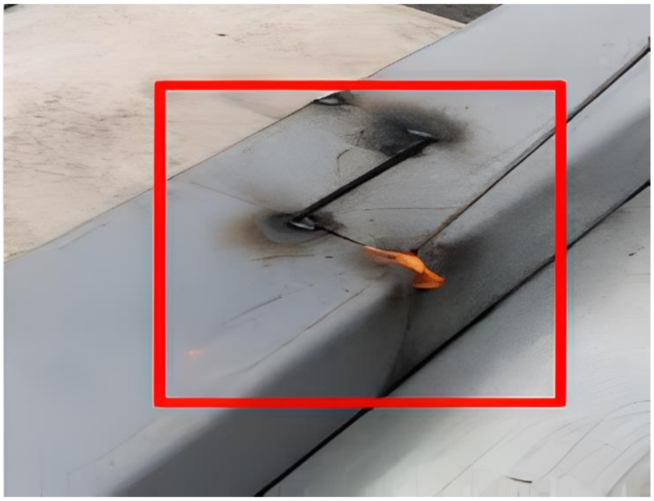


Fig. 3 Region of interest detection in the image frame

3.3. Feature Extraction

The system extracts key features from preprocessed images of the surface of metal parts using three types of analysis: texture, shape, contour, and welding defects. The weld defect detection model utilizes these extracted features as inputs, which were specifically selected for their ability to identify cracks, pores, bubbles, and other defect types.

3.3.1. Texture Analysis

The system captures the part's surface texture by calculating texture features using local binary pattern metrics and gray-level co-occurrence matrix analysis. These features enable the detection of defect patterns on the surface that result from poor welding practices.

3.3.2. Shape and Contour Analysis

The system employs edge detection algorithms, such as the Canny edge detector, to highlight weld defect contours. Additionally, shape descriptors (such as aspect ratio, defect perimeter, and circularity) are calculated to identify irregularities, including porosity, bubbles, and cracks [21]. This method enables rapid defect detection, automatically alerting operators to remove defective parts for rework.

3.3.3. Welding Defects Detection

The system employs color thresholding and the Hough transform to detect defects in the weld area. The Hough transform identifies circular shapes characteristic of bubbles or porosity, while color thresholding detects darker regions or areas with color variations that indicate cracks or weld protrusions [22].

3.4. User Interface

Once a welding defect is detected in the image, it must be revealed to the operators. To facilitate this process, the system incorporates a visual user interface. This interface displays the analyzed source image and the corresponding defect information identified by the detection system.

3.5. Analysis and Evaluation

This study uses four indices to analyse the performance of this method. The precision index is calculated as

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Where True Positive (TP) is the number of correctly identified welding defects, and False Positive (FP) is the number of good welding incorrectly identified as defects. The recall index measures the proportion of correctly identified welding defects on metalworking parts relative to the total number of welding defects on the workpiece in the dataset. The recall index is calculated as

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Where False Negative (FN) is the number of undetected welding defects, and in this study, it represents the background error of misidentification. The F1 score index is calculated as

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{3}$$

and it is an indicator for high Precision and recall. The Average Precision (AP) represents the global performance of the proposed system, and it is introduced to solve the problem of single-point value limitation of Precision, recall and F1 score. The average Precision is calculated as

$$AP = \sum_{k=1}^{N} \max_{\hat{k} \geq k} P(\hat{k}) * \Delta r(k) \tag{4}$$

Where $\max_{\hat{k} \geq k} P(\hat{k})$ is the interpolated Precision at point k, and $\Delta r(k)$ is the increase in the recall value between consecutive points. Additionally, this study evaluates the economic feasibility of the proposed system, cost, return on investment, and savings. The operator's hourly cost is

$$C_{hour} = \frac{salary\ per\ month}{hour\ per\ month} \tag{5}$$

Where $salary\ per\ month$ is the monthly salary of the operator and $hour\ per\ month$ are the hours worked per month. The total cost of manual inspection of the parts is

$$C_{manual} = T_{total}\ x\ C_{hour}\ x\ N_{workers} \tag{6}$$

Where T_{total} is the total time used and $N_{workers}$ is the number of inspectors involved. With this data, the monthly savings from using the proposed system are calculated as

$$S_{monthly} = C_{manual} - C_{system} \tag{7}$$

Where C_{system} is the monthly operating cost of the system. The Return On Investment (ROI) is calculated as

$$ROI = \frac{C_{initial}}{S_{monthly}} \tag{8}$$

Where $C_{initial}$ is the system implementation cost. Finally, the accumulated savings in month n are calculated as

$$S_{accumulated}(n) = \; n \; x \; S_{monthly.} \tag{9}$$

4. Experimental Development

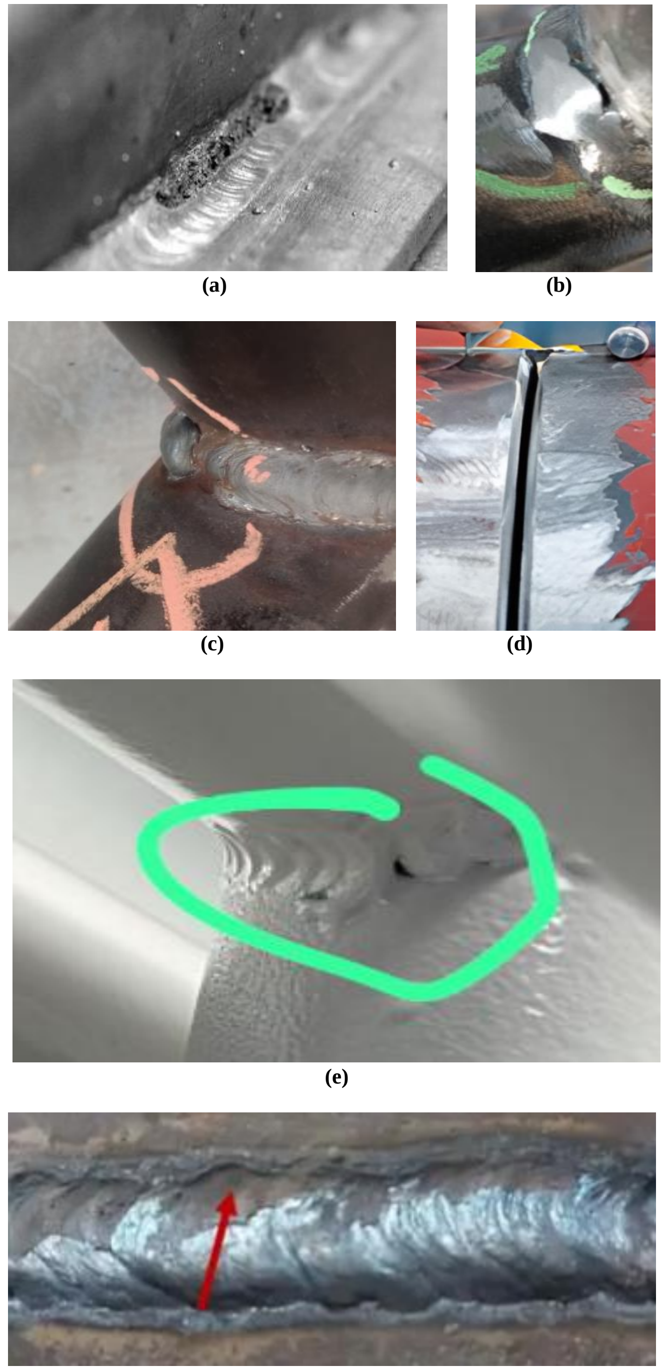
4.1. Welding Defect Analysis

Welding defects are flaws that occur during the welding process. Some defects may be superficial, while others may be internal. These defects are caused by various factors, such as improper amperage, incorrect techniques, or poor-quality materials.

To apply digital image processing and deep learning models, it is necessary to evaluate and identify various welding joint defects, such as slag inclusion, lack of fusion, reinforcement excess, misalignment, pores, and undercut, as shown in Figure 4. All of these defects have a tolerance level according to the American Welding Society (AWS) standards, which are shown in Table 1.

Table 1. Defect tolerances according to AWS standards

Welding Defects	Tolerances
Slag Inclusion	Not allowed in trapped or surface slag; if visible, it is totally rejected.
Lack of Fusion	Not allowed, lack of fusion between base metal and weld metal, lack of fusion between passes and incomplete fusion in visible roots of butt welds, if they are visible, they are totally rejected.
Excess Reinforcement	≤ 3mm
Misalignment (Hi-Lo)	≤ 3mm
Pores	Individual pores: < 2.4 mm. Grouped porosity is not permitted.
Undercut	Less than 0.8mm is permitted with no length restrictions. Nothing greater than 1.6mm is permitted in any length; it will be rejected.



(a) (b) (c) (d) (e) (f)

Fig. 4 Welding defects analyzed: (a) Slag inclusion, (b) Lack of fusion, (c) Excess reinforcement, (d) Misalignment (Hi-Lo), (e) Pores, and (f) Undercut.

4.2. Hardware Development

The welding defect detection system for metalworking parts involves the development of hardware required for proper operation. The first stage of this process includes a high-resolution depth camera (Intel RealSense D435) used to capture images of components passing through the production line. This camera is mounted on a fixed, elevated structure, positioned perpendicular to the components for optimal coverage and image capture. The system also incorporates a fixed LED flashlight to minimize lighting variations and a polarizing filter to reduce glare and shadows, both critical for homogenizing captured images.

The captured images are transmitted to a local processing unit equipped with a Raspberry Pi 4 Model B+ (8GB RAM), which handles real-time image processing and welding defect detection. The system architecture prioritizes low latency to facilitate rapid decision-making in the workplace. Finally, the Raspberry Pi 4 displays the processed images on a screen via a custom user interface, which presents all relevant processing data and alerts operators about potential welding defects in the inspected components.

Table 2 outlines the costs of the hardware components for this system. After calculating expenses, the total hardware cost for implementing this inspection system was USD 730.40, with an additional monthly maintenance cost of USD 50.00.

Table 2. Cost of system components

Description	Cost (USD)
Raspberry Pi 4B with 8GB RAM	170.0
Intel RealSense D435	400.0
LED Flashlight	39.9
Display	90.0
Support Structure	30.5
TOTAL	730.4

4.3. Software Development

The developed system utilizes a deep learning algorithm, specifically a Convolutional Neural Network (CNNs) model, to detect welding defects in metalworking parts. The process begins with image acquisition using a high-precision depth camera that captures the surface of metal parts under controlled conditions to minimize optical distortions.

The acquired images pass through preprocessing, including conversion to grayscale to enhance data quality. Next, the region of interest is segmented to isolate the weld area for precise analysis.

During the feature extraction stage, key parameters such as edges, textures, and contours are identified using morphological analysis and edge detection methods. Due to the relatively small dataset size, it is divided into training and validation sets in an 8:2 ratio. When a weld defect is detected, the system saves the relevant data for analysis and displays it on the user interface. This functionality enables rapid fault detection and allows operators to take immediate action.

Figure 5 shows the complete flowchart of the developed algorithm. After multiple training iterations with the CNNs, both the training set and validation set produced a model containing optimized weighting and bias parameters.

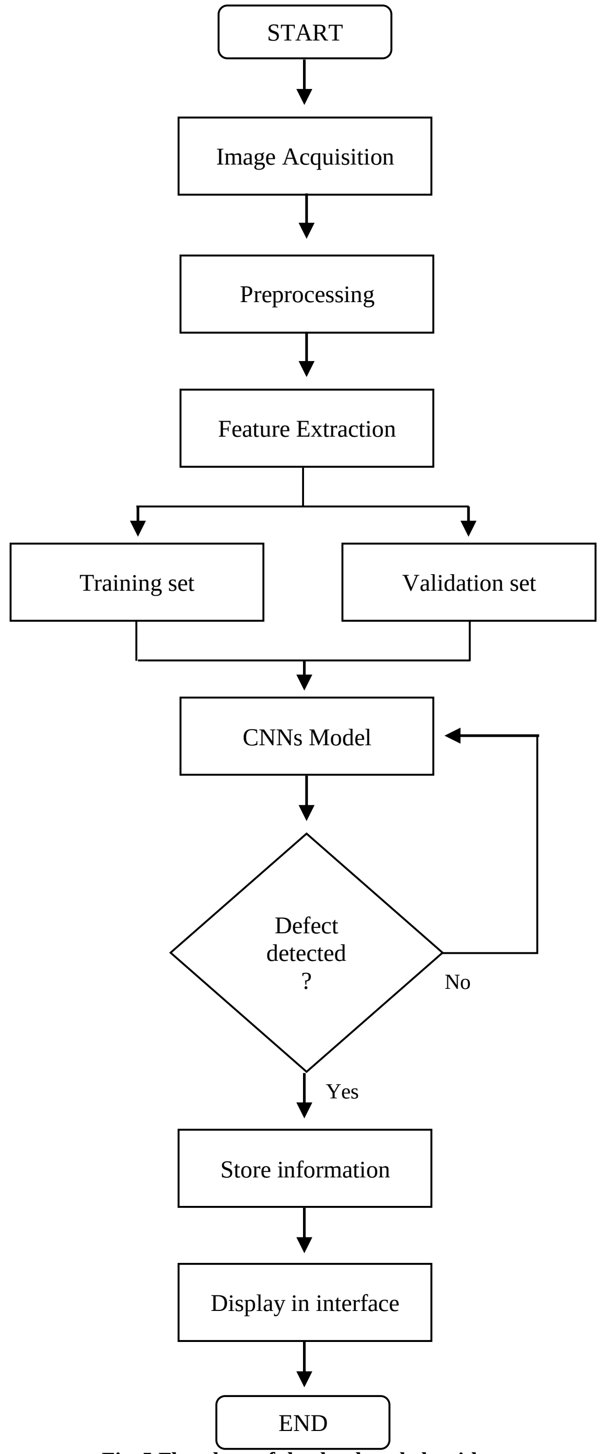


Fig. 5 Flowchart of the developed algorithm

4.4. Test Environment

The proposed system was tested in a controlled real-world environment, directly in the quality control stage of a metalworking industry, over a period of 26 days. Only small parts were considered for testing because the developed system's structure is compact (100 × 80 × 80 cm), and larger parts cannot pass through. The dataset consisted of images captured using an Intel RealSense D435 camera, positioned at a fixed distance of 80 cm from the weld bead under constant lighting conditions. A total of 1,133 metalworking parts of varying sizes and shapes, exhibiting different welding defects identified during inspections, were evaluated during this period. Additionally, the inspection time and accuracy of the traditional method used by the industry were assessed for comparison in the results section. Figure 6 shows two images taken during the tests conducted in the metalworking industry.

(a)

(b)

Fig. 6 Tests carried out in the metalworking industry: (a) Construction process, and (b) Parts analyzed by the system.

5. Results

5.1. System Performance

The proposed system was evaluated for its ability to detect weld defects in metalworking parts in accordance with AWS standards. The test data was analyzed, and the average values for Precision, recall, F1 score and Average Precision (AP) are presented in Table 3. After testing, the system achieved an overall defect detection accuracy of 91.3%, with a recall rate varying from 85% to 94.2% on the type of defect. These high recall rates indicate that the system effectively identifies defects, significantly reducing the risk of missed defects. However, the accuracy rate also indicates the presence of some false positives, primarily caused by dirt and irregular textures on the metal parts that were mistakenly classified as defects.

Table 3. Performance metrics obtained during testing

Type of Defect	Precision (%)	Recall (%)	F1-Score (%)	AP (%)
Slag inclusion	91.3	87.6	89.4	88.9
Lack of fusion	93.1	90.2	91.6	91.0
Excessive reinforcement	88.5	85.0	86.7	86.3
Misalignment (Hi-Lo)	90.8	92.5	91.6	90.7
Pores	95.0	94.2	94.6	94.1
Undercut	89.0	86.8	87.9	87.3
Average	**91.3**	**89.4**	**90.3**	**89.7**

5.2. Time Comparison between Traditional Inspection and the Proposed System

Table 4 compares the traditional human visual inspection method performed by two operators and the proposed automated system based on digital image processing with deep learning. The evaluation spanned 26 days, during which a total of 1,133 metalwork pieces were inspected.

The proposed system was directly compared to traditional visual inspection methods performed by quality assurance operators, commonly used in the metalworking industry. Visual assessments conducted by operators are often biased, prone to errors, and slow down production due to the time required to inspect each part.

In contrast, the automated system achieved higher accuracy with an average time reduction of over 82.5%. This improvement stems from the system's ability to operate continuously without interruptions due to fatigue or distractions. The optimized detection algorithm enables around-the-clock performance, unlike traditional methods.

Table 4. Comparison between traditional inspection time and the proposed system

Aspect	Traditional Inspection (2 Operators)	Proposed System
Total parts inspected	1133	
Total inspection time (h)	26.28	4.61
Average inspection time per part (s)	83.50	14.65
Error risk due to fatigue	Medium-High	Low
Real-time defect feedback	No	Yes
Detection consistency	Variable (operator dependent)	High

5.3. Cost and Return on Investment

The proposed system is analyzed by comparing the traditional manual weld inspection method with the implementation of an automated system based on computer vision and deep learning. This comparison aims to evaluate the financial viability of the proposed system in the hypothetical case of its installation on a metalworking production line.

To conduct the analysis, a total of 1,133 metalworking parts were inspected by two inspectors working standard hours. The total time spent by both operators on the inspection process was approximately 26.28 hours. Considering their monthly salaries of USD 440.72 each, the total cost of manual inspection for the batch was estimated using Equations (5)-(9), which establish a baseline for comparison. Assuming they worked 26 days per month at 8 hours per day, the hourly cost rate was C_{hour} = USD 2.12. The total manual inspection cost for both workers C_{manual} = USD 111.43. Taking into account the monthly operational cost of the proposed system C_{system} = USD 50, the savings yielded by using the automated defect detection system are $S_{monthly}$ = USD 61.43 per month.

This analysis shows that the system can operate autonomously with a moderate initial investment and low recurring costs. The USD 61.43 in monthly savings allows the initial investment to be recovered in approximately 12 months, even in a conservative scenario where the number of inspected items remains constant. Once the financial break-even point is reached, each additional month represents direct savings for the welding company.

Figure 7 illustrates the projected accumulated savings over a 12-month period compared to the operating costs of the automated system. The savings curve shows that after the return on investment is achieved, the system substantially improves the profitability of the industrial inspection process.

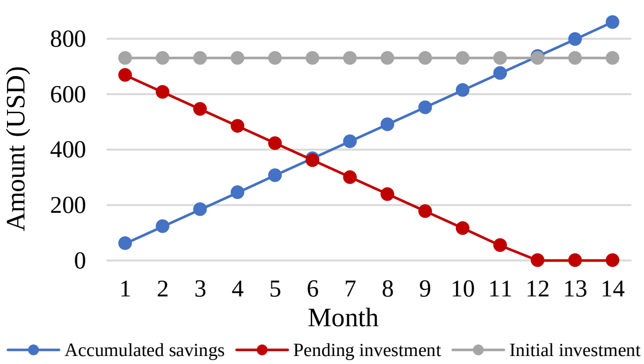


Fig. 7 Tests carried out in the metalworking industry

6. Discussion

The system's high accuracy demonstrates the benefits of optimizing inspection time in industrial processes. By fully automating inspection, the proposed system eliminates human inspection, which is often susceptible to fatigue or visual limitations. The deep learning model was also trained to recognize complex defect patterns that might be missed in traditional inspections, significantly improving detection accuracy, consistency, and process repeatability.

Unlike manual inspections performed by operators, the system provides real-time images of metalworking parts with weld defects, enabling immediate corrective action. This prevents defective products from being sold, avoiding costly rework and reducing production expenses. From an economic standpoint, the system's initial investment pays for itself within a year, generating continuous savings by replacing labor previously dedicated to inspection. Another key advantage is the improvement in final product quality, which enhances reliability while preventing field failures and reprocessing.

The system demonstrated superior performance in identifying weld flaws compared to conventional detection methods. This confirms that the dedicated CNNs classification model is effective at detecting defects with high contrast, though identifying smaller defects or those with atypical characteristics may require additional refinement.

During field testing, several challenges emerged. The system generated false alerts primarily due to two factors: mud accumulation on the tires and variable natural lighting conditions in the testing environment. Additionally, while the system's profitability begins after 12 months of operation, this timeline reflects the small production volume of the company. In larger industrial settings with continuous welding operations, the return on investment would be achieved significantly faster.

Future research could address these limitations by implementing deep-learning-based noise reduction techniques, employing advanced image preprocessing methods, or incorporating an automated camera lens cleaning system to maintain optimal imaging conditions.

7. Conclusion

This study presents the development of an automated welding defect detection system for metalworking parts, combining digital image processing with deep learning techniques, specifically using a convolutional neural network. The system successfully detects various welding defects, including slag inclusions, lack of fusion, excessive reinforcement, misalignment (Hi-Lo), porosity, and undercut. A user interface was integrated to provide real-time analysis feedback to production line operators.

Experimental results demonstrate the system's detection capability with an average precision of 91.3% and an average recall rate of 89.4%. In efficiency comparisons with traditional visual inspection methods, the system achieved an 82.5% reduction in inspection time per part, enabling rapid, uninterrupted analysis of large quantities of metalworking components.

The economic analysis evaluates the system's implementation viability for metalworking production lines. Comparing the system's construction cost and monthly operational expenses against the hourly wages of two dedicated visual inspection technicians revealed monthly savings of USD 61.42, with a 12-month return on investment period. While this ROI period may appear lengthy, it reflects the company's small production volume. In larger industrial settings with continuous 24/7 welding operations, the payback period would be significantly shorter.

Future work will focus on advancing the system's maturity level to enable deployment in real-world industrial environments without requiring researcher supervision. Key improvements will include enhancing the system's robustness against environmental challenges typical in metalworking facilities, such as airborne dust and image noise. Additionally, the detection algorithm is being optimized to achieve faster processing times while expanding its capability to analyze larger and more complex parts.

Acknowledgments

The authors of this article wish to thank San Pablo Catholic University for its continued support and for providing the necessary knowledge for the development of this research.

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