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Development of an Adaptive Entropy-Based GLCM Feature Extraction Method for Defect Detection in Welding Images

Sherly Agustini [1,a,*]; Okta Veza [2,b]; Albertus Laurensius Setyabudhi [3,c]; Nofri Yudi Arifin [4,d]

[1] *Information Systems Study Program, Faculty of Science and Technology, Universitas Ibnu Sina, Batam, Indonesia*
[2,4] *Informatics Engineering Study Program, Faculty of Science and Technology, Universitas Ibnu Sina, Batam, Indonesia*
[3] *Logistics Engineering Study Program, Faculty of Science and Technology, Universitas Ibnu Sina, Batam, Indonesia*
[a] *sherlyagustini96@gmail.com;* [b] *Okta@uis.ac.id;* [c] *abian@uis.ac.id;* [d] *nofri.yudi@uis.ac.id*
** Corresponding author*

Abstract

Quality inspection of welding joints is fundamental to ensuring structural integrity and reliability, particularly in high-risk industrial sectors. The use of image processing for welding defect detection offers a more objective and consistent approach than visual interpretation; however, the performance of detection systems strongly depends on the ability of feature extraction methods to represent image texture characteristics. Gray Level Co-occurrence Matrix (GLCM) is a widely used texture feature extraction method because it can quantitatively and interpretably represent spatial relationships among gray levels. Nevertheless, static GLCM configurations may limit its representational capability when images exhibit low contrast, non-uniform intensity distributions, or small and complex defect characteristics. This study aims to develop an adaptive entropy-based GLCM feature extraction method through the integration of Adaptive ROI, ROI Entropy, and Feature Fusion. The development adopts a Research and Development (R&D) approach. The GLCM-Entropy method was subsequently tested and compared with GLCM Before Development using 500 radiographic images obtained through X-ray inspection and evaluated using a confusion matrix. The test results show that GLCM Before Development achieved an accuracy of 91.40%, whereas GLCM-Entropy achieved 96.20%, with F1-scores of 87.09% and 97.42%, respectively. These results demonstrate that the integration of global and local texture information in GLCM-Entropy improves classification performance compared with GLCM Before Development.

Keywords— *Welding defect detection; Radiographic images; Gray Level Co-occurrence Matrix (GLCM); Adaptive entropy; Texture feature Extraction*

1. Introduction

In recent years, the development of Artificial Intelligence (AI) has driven transformation across various fields, including manufacturing and quality inspection. Advances in machine learning, deep learning, and computer vision have enabled pattern recognition, information extraction, and visual inspection to be performed more automatically and measurably. The application of AI in manufacturing has expanded across various activities, including quality assurance, maintenance, process optimization, and automated inspection (Gao et al., 2024). In the context of quality inspection, the combination of AI and computer vision is increasingly used to reduce dependence on manual inspection and improve the consistency of evaluation

processes (Sundaram & Zeid, 2023; Ettalibi et al., 2024; Ramesh et al., 2025). These developments indicate that image-based inspection systems have become an important component of the transformation toward smarter and more automated manufacturing systems.

In welding processes, quality inspection plays an important role because defects in joints can affect structural integrity and safety. Radiographic testing using X-ray images is one of the widely used non-destructive testing methods for identifying internal defects in welding joints (Li et al., 2023; Wang et al., 2024). However, radiographic welding images may exhibit noise, low contrast, intensity variations, and differences in defect size and shape, making automated detection challenging (Palma-Ramírez et al., 2024; Elhendawy & El-Taybany, 2025; Zuo et al., 2025). Recent studies have demonstrated rapid advances in deep learning approaches for defect classification and segmentation in radiographic images, including CNN, ResNet, U-Net, and adaptive approaches for low-quality X-ray images (Vasan et al., 2024; Yan et al., 2025; Xue et al., 2025; Cheng et al., 2025). Despite their promising results, these approaches still face challenges such as the need for large amounts of labeled data, annotation costs, class imbalance, and generalization across different image conditions (Shen et al., 2026; Qian et al., 2026).

In addition to deep learning, texture feature extraction approaches remain relevant because texture characteristics can be explicitly represented before classification. One widely used method is the Gray Level Co-occurrence Matrix (GLCM), which provides texture information based on relationships among pixel gray levels. In radiographic welding images, GLCM has been used to extract texture features and combined with several machine learning algorithms, including Random Forest (Ramana et al., 2024). Other approaches have also combined GLCM with GLDM, DWT, FFT, and other texture features to enrich image representation (Zhang et al., 2025). Studies on feature fusion indicate that combining information from multiple representations can help preserve defect characteristics with varying sizes and shapes (Liu et al., 2026; Liu et al., 2026). Meanwhile, ROI-based approaches have also been used to reduce background influence and focus analysis on regions containing defect information (Yang et al., 2023).

Based on these developments, there remains an opportunity to further develop GLCM-based methods that not only represent global texture characteristics but also consider local information within relevant image regions. This study develops GLCM-Entropy from GLCM Before Development by retaining four basic features, namely contrast, correlation, energy, and homogeneity. The development adds Adaptive ROI to identify relevant local regions, ROI Entropy to represent the degree of texture irregularity within those regions, and Feature Fusion to combine global and local texture information. In this study, entropy is used as additional information within the ROI and is not used to modify GLCM parameters. The resulting features are subsequently used for classification using Random Forest. The novelty of this study lies in integrating Adaptive ROI, ROI Entropy, and Feature Fusion into the GLCM feature representation for defect detection in welding images. This approach retains global texture information from GLCM Before Development while adding local information from regions with specific texture characteristics. This study aims to develop and evaluate the GLCM-Entropy method and compare its detection results with GLCM Before Development in identifying Minor and Major defect categories in welding X-ray images. Thus, this study provides a texture-based feature extraction approach that integrates global and local information to support defect detection in radiographic welding images.

The novelty of this study lies in the integration of Adaptive ROI, ROI Entropy, and Feature Fusion into the GLCM feature representation for defect detection in welding images. This approach retains the global texture information provided by GLCM Before Development while incorporating local information from regions exhibiting specific texture characteristics. This study aims to develop and evaluate the GLCM-Entropy method and compare its detection results with those of GLCM Before Development in identifying Minor and Major defect categories in welding X-ray images. Accordingly, this study presents a texture-based feature

extraction approach that integrates global and local information to support defect detection in radiographic welding images.

2. Method

The research framework illustrates the methodological development process for detecting welding defect severity. It presents the research stages systematically, beginning with image processing and method development and proceeding to defect detection and performance evaluation.

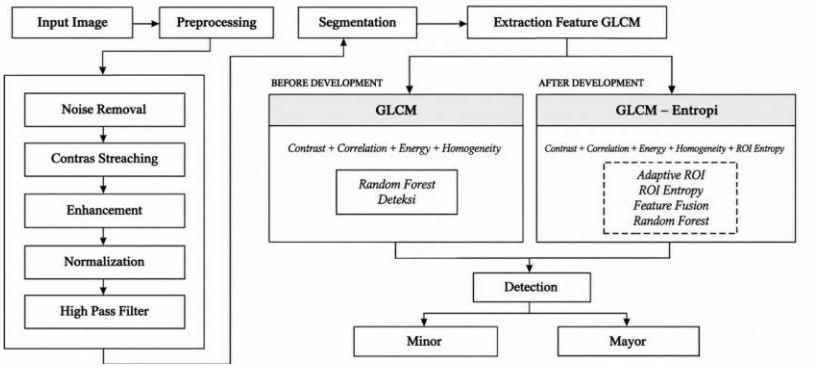


Figure 1. Framework of Adaptive Entropy-Based GLCM Feature Extraction.

Figure 1 presents the research framework, which systematically illustrates the method development process, starting from image input, preprocessing, segmentation, and feature extraction to the detection of Minor and Major welding defect severity. At the feature extraction stage, a comparison is made between the GLCM-based Before Development method and the After Development method, which represents the proposed method, followed by Random Forest processing. The comparison is conducted to determine changes and improvements in detection performance following the method development. The entire development process adopts a Research and Development (R&D) approach consisting of Identify Problem, Define Objectives, Design & Development, Demonstration, and Evaluation stages, allowing the method development and evaluation to be conducted systematically and measurably.

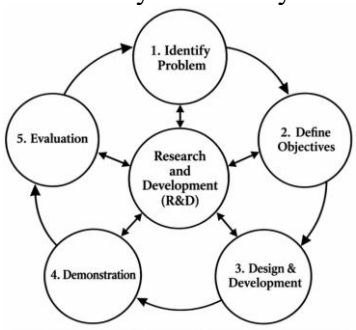


Figure 2. Framework of Adaptive Entropy-Based GLCM Feature Extraction

The dataset comprised 500 proprietary radiographic welding images obtained through X-ray inspection from a manufacturing company in Batam, Indonesia. The images were classified as Minor or Major based on the *Defect Area Ratio* (DAR), defined as the ratio of the defect area to the weld area within the ROI. The data were proportionally divided into training and testing sets while preserving the class distribution. Both GLCM methods were evaluated using identical *Random Forest* configurations and testing procedures to ensure a consistent comparison.

3. Results And Discussion

This study employs a Research and Development (R&D) approach to develop a Gray Level Co-occurrence Matrix (GLCM)-based texture feature extraction method for radiographic welding images. The research consists of five stages: Identify Problem, Define Objectives of Solution, Design & Development, Demonstration, and Evaluation.

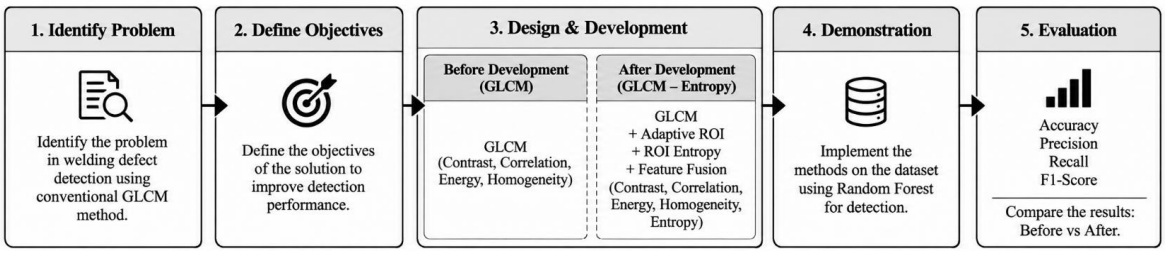


Figure 3. R&D Stages for Developing the Welding Defect Detection Method

The figure above shows the Research and Development (R&D) stages used to develop the welding defect severity detection method. The novelty lies in the Design & Development stage, where GLCM is enhanced through Adaptive ROI and ROI Entropy integrated using feature fusion. The extracted features from the Before Development and After Development approaches are subsequently used as inputs to Random Forest for detection. Testing and performance evaluation are then conducted using accuracy, precision, recall, and F1-score to measure improvements in detection performance after development.

3.1 Identify Problem

Detection of Minor and Major welding defects requires features that can accurately represent defect regions. The GLCM Before Development method uses contrast, correlation, energy, and homogeneity features but does not specifically exploit texture information within defect regions. This condition may affect detection accuracy and the reliability of welding quality control. Therefore, development through Adaptive ROI and ROI Entropy is introduced to improve detection performance while supporting industrial technological innovation in accordance with SDG 9.

3.2 Define Objectives

The Define Objectives stage establishes the direction and development targets based on the problems identified in the welding defect detection process. The development focuses on improving feature representation with greater emphasis on defect regions so that the information used for detection is more relevant. The primary objective is to improve the method's performance in detecting Minor and Major welding defect severity and to achieve better detection results than the GLCM Before Development method. Achievement of these objectives is quantitatively demonstrated through testing, performance evaluation, and comparison between the method before and after development.

3.3 Design & Development

The Design & Development stage designs the welding defect detection method by comparing the Before Development and After Development approaches. The Before Development method uses GLCM features consisting of contrast, correlation, energy, and homogeneity. Meanwhile, the novelty of the After Development method lies in the application of Adaptive ROI and ROI Entropy integrated with GLCM features through feature fusion, resulting in feature extraction that is more focused on defect regions. Both methods subsequently use Random Forest to detect Minor and Major defect severity, allowing the

contribution of the proposed development to be evaluated based on improvements in detection performance. The process is illustrated in Figure 4.

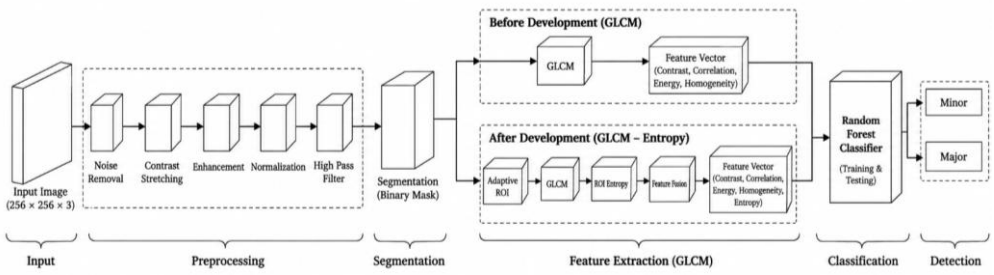
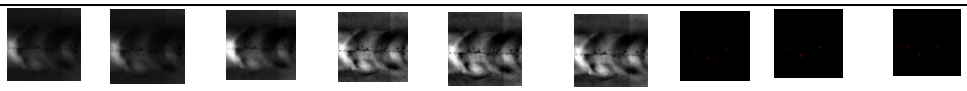
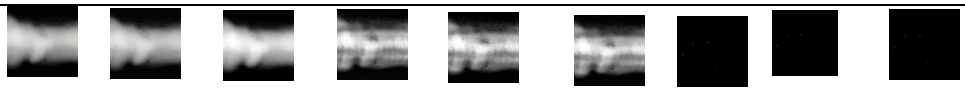
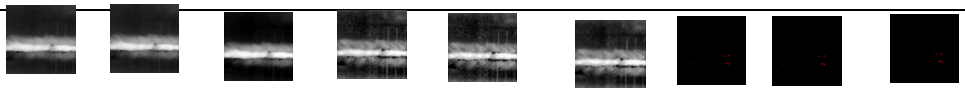
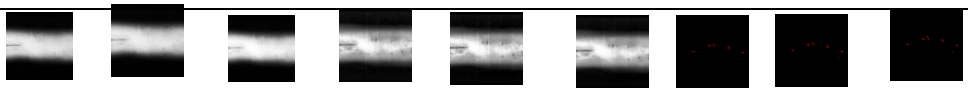
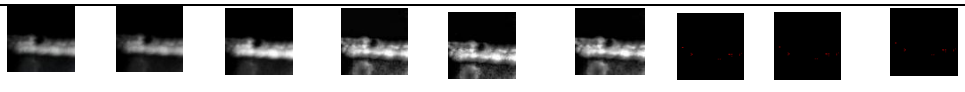
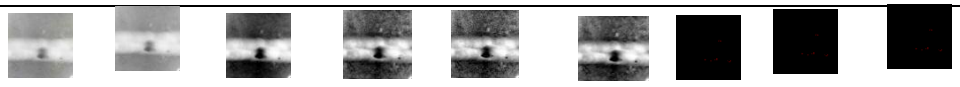
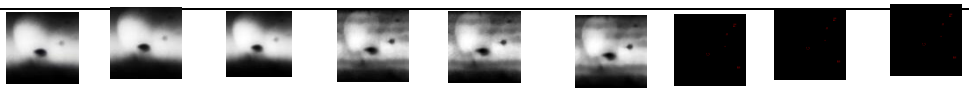


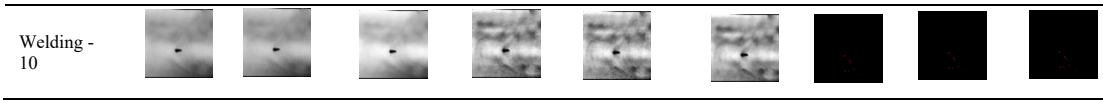
Figure 4. R&D Stages for Developing the Welding Defect Detection Method

3.4 Demonstration

During the Demonstration stage, the GLCM development was implemented using a dataset of 500 welding images through an application developed in MATLAB. The image data were input into the system and processed through preprocessing, segmentation, feature extraction, and detection stages. Experiments were conducted using the GLCM Before Development (GLCM) and GLCM After Development (GLCM-Entropy) approaches on the same dataset. The extracted features from both approaches were subsequently processed using Random Forest to detect Minor and Major defect severity, producing detection results that served as the basis for subsequent testing and performance evaluation. The outputs of each processing stage are presented in Table 1.

Table 1. Visualization of Image Processing Results at Each Detection Stage

Name	Image	Noise Removel	Contrast Streching	Enhancement	Normalization	High Pass Filter	Segmentation	Minor	Mayor
Welding - 1									
Welding - 2									
Welding - 3									
Welding - 4									
Welding - 5									
Welding - 6									
Welding - 7									
Welding - 8									
Welding - 9									



3.5 Evaluation

To visually demonstrate the differences in detection results, a comparison was conducted between the GLCM Before Development and the GLCM-Entropy After Development approaches. The detection visualizations were used to observe changes in the identification of Minor and Major defect severity on the same dataset. The detection results of both approaches are presented in Section 3.5.1.

3.5.1 Confusion Matrix Evaluation

The Minor and Major classes were determined using the *Defect Area Ratio* (DAR), defined as the ratio of the defect area to the weld area within the *Region of Interest* (ROI). Both methods were evaluated using the same dataset comprising 500 welding images.

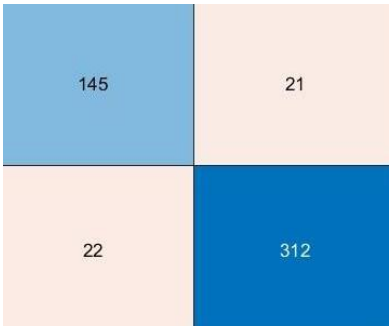


Figure 5. Evaluation Results of GLCM Before Development

Figure 5 shows the evaluation results of the GLCM Before Development method using a confusion matrix on 500 welding images. The test results indicate that 145 and 312 samples were correctly detected, while 21 and 22 samples were incorrectly detected.

Table 2. Accuracy Testing Results for GLCM Before Development

Method	Dataset	Accuracy	Precision	Recall	F1-*Score*
GLCM Before Development	500	91.40%	86.83%	87.35%	87.09%

Based on these results, the GLCM Before Development method achieved an accuracy of 91.40%, precision of 86.83%, recall of 87.35%, and an F1-score of 87.09%. These results were used as the evaluation baseline.

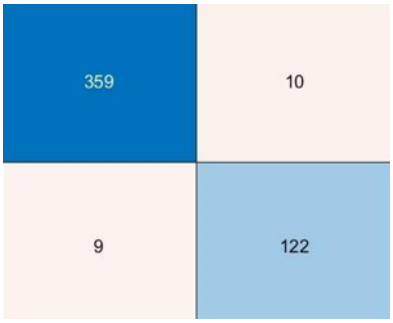


Figure 6. Evaluation Results of GLCM After Development

Com Figure 6 shows the evaluation results of the GLCM After Development method using a confusion matrix on 500 welding images. The test results indicate that 359 and 122 samples were correctly detected, while 10 and 9 samples were incorrectly detected.parison of GLCM Before Development and GLCM-Entropy Testing Results

Table 3. Accuracy Testing Results for GLCM-Entropy

Method	Dataset	Accuracy	Precision	Recall	F1-*Score*
GLCM-Entropi	500	96.20%	97.55%	97.29%	97.42%

Based on these results, the **GLCM-Entropy After Development** method achieved an accuracy of **96.20%**, precision of **97.55%**, recall of **97.29%**, and an **F1-score of 97.42%**. Compared with the **GLCM Before Development** method, GLCM-Entropy demonstrated improvements across all evaluation metrics, indicating better performance in detecting welding defect severity.

3.5.2 Comparison of GLCM Before Development and GLCM-Entropy Testing Results

The following table presents a comparison of the confusion matrix testing results for the GLCM methods before and after development. The comparison is based on accuracy, precision, recall, and F1-score to determine improvements in method performance for detecting welding defect severity. The test results are also used to evaluate the effect of Adaptive ROI and ROI Entropy on detection accuracy.

Table 4. Comparison of GLCM Before Development and GLCM-Entropy Testing Results

Method	Dataset	Accuracy	Precision	Recall	F1-*Score*
GLCM Before Development	500	91.40%	86.83%	87.35%	87.09%
GLCM-Entropi	500	96.20%	97.55%	97.29%	97.42%

Based on the comparison results, the GLCM After Development method achieved better performance than the GLCM Before Development method. Accuracy increased from 91.40% to 96.20%, accompanied by improvements in precision, recall, and F1-score. This indicates that the addition of Adaptive ROI and ROI Entropy improved welding defect detection accuracy.

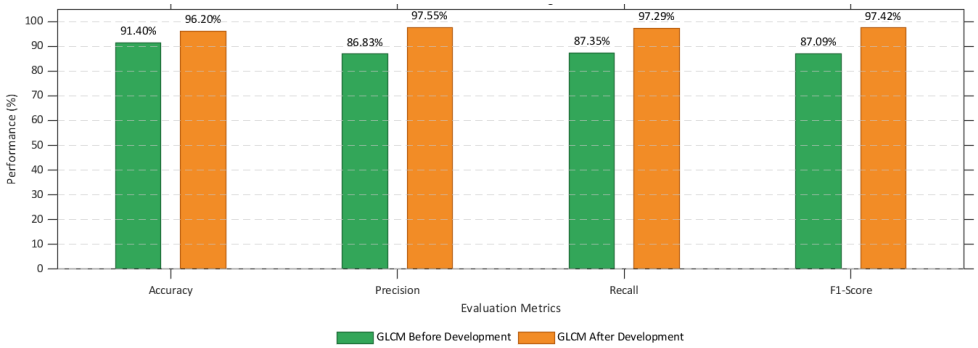


Figure 7. Performance Comparison Between the Conventional GLCM and the Entropy-Enhanced GLCM

4. Conclusions

The GLCM-Entropy method was successfully developed from the GLCM Before Development method through the integration of Adaptive ROI, ROI Entropy, and Feature Fusion to incorporate local texture information into radiographic images obtained from X-ray

inspection of welding joints. The development retains the four primary GLCM features used in the Before Development method, namely contrast, correlation, energy, and homogeneity, and complements them with local texture information obtained through ROI Entropy from regions determined using Adaptive ROI. The global and local texture information is subsequently combined through Feature Fusion and used as input to Random Forest for detecting Minor and Major categories. Through this approach, GLCM-Entropy extends the feature representation of the GLCM Before Development method by adding local information without replacing the GLCM features used in the baseline method.

Testing using 500 radiographic welding images showed that GLCM-Entropy achieved higher evaluation scores than GLCM Before Development. GLCM Before Development achieved an accuracy of 91.40%, precision of 86.83%, recall of 87.35%, and F1-score of 87.09%, whereas GLCM-Entropy achieved an accuracy of 96.20%, precision of 97.55%, recall of 97.29%, and F1-score of 97.42%. Based on the confusion matrix, the number of correct predictions increased from 457 images for GLCM Before Development to 481 images for GLCM-Entropy, while the number of incorrect predictions decreased from 43 to 19 images. These results indicate that, for the tested dataset, the addition of Adaptive ROI, ROI Entropy, and Feature Fusion was accompanied by improvements across all classification evaluation metrics compared with GLCM Before Development.

In addition to the improvement in classification metrics, a change in the distribution of detection results was observed between the two approaches. The GLCM Before Development method produced 166 Major images (33.20%) and 334 Minor images (66.80%), whereas GLCM-Entropy produced 369 Major images (73.80%) and 131 Minor images (26.20%). A comparison of the decisions generated by the two methods resulted in an overall agreement of 59.40%, a Cohen's Kappa coefficient of 0.3000, and a McNemar's test p-value of 1.556×10^{-61}. These results indicate a statistically significant difference in detection decisions between GLCM Before Development and GLCM-Entropy. Overall, the integration of Adaptive ROI, ROI Entropy, and Feature Fusion produced a different feature representation and, on the tested dataset, was accompanied by improved classification performance compared with GLCM Before Development.

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