



Enhanced Metal Surface Defect Localization with SH-SAM and Grey Level Co-Occurrence Matrix (GLCM) in Robotics Automation

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Abstract: The identification of metal surface defects is essential for many sectors, including aerospace and automotive, in the production of quality products. Traditional approaches are time-consuming and error-prone and, hence, an automated, accurate fault localisation solution in robotic automation is necessary. This research aims to enhance the defect detection process by integrating SH-SAM with GLCM for enhanced precision and robustness in robotic automation. We therefore aim at developing a whole system that integrates texture with spectral analysis for accurate identification of defects. The proposed method integrates Supervised Hyperspectral Anomaly Detection (SH-SAM) with a grey-level co-occurrence Matrix (GLCM) to analyse spectral anomalies and texture patterns on metal surfaces. This integration enhances the discovery of flaws by robotic automation. The approach that combines SH-SAM and GLCM performed better compared to any of the methods individually on F1 score (88.5%), accuracy (92%), and precision (89%). It also outperformed all the others in defect localization as RME was decreased to 9.3%. The integration of SH-SAM and GLCM offers a highly effective solution for the localisation of metal surface defects with improved accuracy and reduced errors. This method shows great potential for real-time robotic automation in metal surface inspection applications.

Keywords: hyperspectral imaging, texture analysis, robotic automation, metal surface flaws, SH-SAM, GLCM and localization of defect.

Introduction

The use of hyperspectral imaging with texture analysis techniques has been able to integrate into a possible way to improve location of defects. With this,

hyperspectral imaging would allow the precise spectrum analysis of materials, especially with very sophisticated algorithms such as SH-SAM or Supervised Hyperspectral Anomaly Detection, which identifies spectral anomalies through computing the pixel divergence from a typical material spectrum. This technique might identify subtle



changes on the metal surface that would otherwise be missed by conventional examination techniques. However, surface texture and spatial relationships - both necessary for accurate fault identification are insufficiently demonstrated by spectral data alone.

This is solved using the Grey Level Co-Occurrence Matrix (GLCM) approach. GLCM analyzes the spatial correlations between pixel intensities in an image to provide useful texture properties such as contrast, energy, and homogeneity. The Grey Level Co-Occurrence Matrix (GLCM) evaluates an image's texture by analysing spatial relationships between pixel intensities. It constructs a matrix that represents how often pairs of pixels with specific intensity values occur at a defined spatial distance and orientation. From this matrix, statistical features such as contrast, correlation, energy, and homogeneity are extracted to quantify texture characteristics, enabling precise defect classification in surface analysis. Some of the textural characteristics are significant for distinguishing between surface flaws and normal surface conditions. Bazrafkan and Rutner [1] proposed the combinations of vibroacoustic modulation (VAM) with nonlinear interactions of major Lamb wave modes for providing a novel approach for better fault localization in robotics automation. The tested and validated method uses short-time Fourier transform (STFT) for damage imaging along with piezoelectric sensors and high-frequency Lamb waves. This baseline-free method uses fewer sensors for offering great localisation accuracy.

Sferrazza [2] investigates the analysis of use-wear traces on archaeological objects by the Gray-Level Co-occurrence Matrix. This 2D image analysis tool is fast, economical, and quantitative, thereby an alternative to conventional qualitative methodologies. The study successfully identified and quantified four types of use-wear traces on flint samples by GLCM and a Support Vector Machine algorithm. The texture characteristic obtained through GLCM may be merged with the SH-SAM spectrum analysis. This brings about a comprehensive understanding of the metal surface with more precise fault location. The GLCM analyses pixel intensity relationships to quantify texture features like contrast and homogeneity, helping identify surface imperfections. It complements SH-SAM by providing textural context for accurate defect classification. Together, they improve defect detection and localization in surface analysis.

This is a method that combines the benefits of SH-SAM and GLCM for flaw detection and localization. Using the detection of spectral anomalies and the capture of texture patterns, SH-SAM and GLCM present an effective technique in identifying many defects observed on metal surfaces. Xie et al. [3] explored the use of Gray-Level Co-Occurrence Matrix (GLCM), and Discrete Wavelet

Transform (DWT) for the detection of textural features of squamous epithelial cells from laryngeal carcinoma. The researchers found that the GLCM and DWT characteristics of malignant and non-cancerous tissues are vastly different. The SVM and random forests models have also exhibited a promising classification accuracy, and therefore AI-based diagnostic sensors could be realized.

This method ensures good accuracy and precision of fault localization by being capable of identifying small spectral changes as well as anomalies in spatial texture. The proposed approach combines GLCM with SH-SAM to improve robotic inspection tasks' accuracy and efficiency. While GLCM examines texture patterns for accurate defect classification and localization, SH-SAM quickly finds spectral anomalies, lowering false positives and computational cost. In industrial applications, these enhancements result in improved quality control, decreased downtime, and fewer inspection errors. The system's dependability is demonstrated by its 92% accuracy, 89% precision, and 9.3% reduced RME, which make it ideal for automated inspections in the automotive and aerospace sectors. This is particularly beneficial for real-time industrial inspection of metal surfaces, and it is well suited to automated robotic systems. Konovalenko et al. [4] have experimented with several U-Net-based CNN architectures to detect defects in the metal surface. After comparing models like ResNet, SEResNet, DenseNet, and MobileNet, they found that the best results were obtained using ResNet152 with a stochastic gradient descent optimiser. With a Dice similarity coefficient of 0.9304 and an IoU of 0.9122, scratch abrasion detection was reported to have the highest recognition accuracy, thus reporting promising results in visual inspection and image segmentation for metallurgy.

The Key objectives are as follows.

- To create a better metal surface defect localization technique that uses GLCM and SH-SAM to increase fault detection accuracy.
- To integrate texture feature analysis (GLCM) with spectral anomaly detection (SH-SAM) for thorough defect localisation on metal surfaces.
- This study aims to assess and contrast the suggested approach with current methods regarding error metrics, recall, accuracy, and precision.
- To use the suggested approach for real-time metal surface inspection in robot automation.

Although current approaches concentrate on textural features or spectral analysis, few integrated strategies combine the two methodologies for localising metal surface defects. The research gap for complete and real-time robotic automation solutions is improving defect detection accuracy by efficiently integrating SH-



SAM and GLCM techniques. The system continuously monitors performance and adjusts thresholds to maintain accuracy in defect detection. It learns from errors, operator feedback, and new defect data to improve over time. Real-time alerts with confidence scores help operators verify and refine detection results. Wu et al. [5] present a two-stage convolutional neural network (CNN) for metal surface fracture detection and segmentation. While the second step learns the crack context for precise segmentation, the first level finds and crops possible fissures. Stereo matching achieves sub-1mm accuracy in 3D crack localization, a 94% Dice score, and a 96.3% detection precision by mapping 2D crack pixels to 3D coordinates.

Literature Survey

Wu et al. [6] investigated the evolution of meso-damage in coal under uniaxial compression using industrial CT scanning and the Gray Level Co-Occurrence Matrix (GLCM) hypothesis. Four statistical variables were extracted from CT images: contrast, energy, correlation, and homogeneity. They found that as fractures developed, contrast first reduced and subsequently increased. The patterns for energy, correlation, and homogeneity were in opposition to each other. The Boltzmann function explained the evolution of the features, which had a Gaussian distribution. The study emphasised how coal's failure site and meso-damage during deformation phases are dynamic.

Sitaraman and Khalid [7] proposed a hybrid system for robotic automation. It integrates AutoNav with LIDAR-based SLAM and a DenseNet architecture incorporating a Leaky ReLU activation function. This enables autonomous navigation, obstacle detection, and adaptive motion planning, enhancing efficiency and accuracy in dynamic environments. The technique addresses path planning by merging sensor fusion and deep learning.

Hao et al. [8] suggest a technique for identifying breast cancer histopathology images that combine Gray Level Co-Occurrence Matrix (GLCM) information with deep semantic features. Convolutional layer features from the last dense block are combined with GLCM features using the pre-trained DenseNet201 model. Support Vector Machines (SVM) are utilised for categorisation. Results from experiments on the Break He dataset demonstrate that the method performs competitively against state-of-the-art techniques and outperforms seven baseline models, attaining high image-level and patient-level recognition accuracy over a range of magnifications.

Poovendran [9] explains how AI-driven analytics enhances advanced case investigation through the

analysis of complex data sets. The proposed system, using machine learning and automation, makes evidence gathering, risk assessment, and suspect profiling more streamlined. This reduces investigative time, enhances accuracy, and ensures data integrity, transforming law enforcement. Novel predictive algorithms from the system amplify detection rates and revolutionize evidence-based strategies.

Gudivaka [10] proposed the Principal Component Analysis (PCA), Least Absolute Shrinkage and Selection Operator (LASSO), and Elaborative Stepwise Stacked Artificial Neural Network (ESSANN), this study investigates improvements in IoT and robotic process automation (RPA). With 95% accuracy, 92% precision, and 90% recall, the method enhances data pre-processing, feature selection, and predictive modeling. An ablation study demonstrates scalability and automation accuracy in managing complex data and processes, confirming the synergy of PCA, LASSO, and ESSANN. This approach shows great promise for developing IoT and RPA systems.

Himabindu and Thinakaran [11] outline a holistic framework for harnessing AI and data analytics to transform business intelligence. Real-time data processing, predictive modeling, and machine learning algorithms help organizations gain actionable insights and optimize strategic decisions. This integrated approach enhances competitiveness, fosters operational agility, and catalyzes a data-driven culture across diverse industry sectors—greatly improving profitability.

Using the Gaussian Mixture Model (GMM) and the Grey Level Co-Occurrence Matrix (GLCM) characteristics, Wang and Sun [12] provide an image-based approach for classifying rock fabrics. This technique does not require a training dataset to classify photos with different sedimentary beddings and diverse pore architectures. The findings indicate that the more fabric kinds there are and the less contrast between the rock structures, the worse the classification performance.

Swapna [13] illustrates a blockchain-based method for verification of integrity of data on multi-cloud storage systems using chain-code and HVT. By securely distributed data across multiple clouds and employing cryptography, the proposed approach establishes the authenticity, traceability, and evidence that cannot be tampered. The application of decentralized ledgers in contemporary systems of modern data storage further boosts trust, reliability, and efficiency by further establishing efficient compliance management and oversight.

Gudivaka [10] discusses how RPA and AI combined can uplift corporate operations. RPA, which hitherto focused on repetitive tasks' automation, has become smart and efficient by the adoption of AI; this opens innovation in industries such as manufacturing,



healthcare, and finance. In this paper, cost savings, error reduction, and a systematic mapping study are presented. Despite all of the above advantages, problems such as lack of scientific application and evaluation methods still exist. This forms a foundation for further research.

Deevi et al. [14] analyze how the digital economy leads to industrial restructuring and fosters sustainable entrepreneurship. By leveraging data analytics, e-commerce platforms, innovation, and knowledge sharing, industries accelerate growth and competitiveness. According to the authors, digitalization fosters resource optimization, market expansion, and inclusive development and promotes long-term resilience and profitability and brand value in changing global markets.

Basani [15] investigates the advancement of including sophisticated authentication as well as robotic process automation to further the last mile delivery for food services and ecommerce. A research study was proposed about the AI delivery system with the utilization of face recognition, biometric validation as well as the PIN numbers for effective as well as secure delivery services. It consisted of a co-operative user authentication module as well as a non-cooperative user identification module. The device was tested on the Turtlebot3. Results of autonomous delivery have reflected better accuracy, speed, and security; operational problems were addressed while costs are cut, and packages got delivered in a very secure way.

Parthasarathy [16] presents how next-generation business intelligence takes advantage of AI and advanced analytics to help streamline processes, create higher efficiency, and make more data-driven decisions. The model focuses on real-time insights, predictive modeling, and improved interdepartmental collaboration. This is an integrated approach that reduces the cost of operation, enhances strategic planning, and fosters sustainable growth, creating competitive advantages in diverse business environments across industries.

Gudivaka [17] The enhanced surface defect localization on metal using SH-SAM and GLCM with cloud computing and RPA in robotics automation maximizes the performance of robots while interacting with elderly and cognitively impaired people in social interactions. This achieves 97.3% accuracy through the deep learning models deployed in cloud-deployed configurations via the Semantic Localization System, Object Recognition Engine, and the Behaviour Recognition Engine. Improvement on independence and caregiver support based on real-time scheduling object detection, and user engagement in assistive robotics transforms technology despite connectivity issues.

Mamidala [18] outlines a holistic approach to resilience that includes predictive analytics, collaborative

frameworks, and agile leadership. The methodology focuses on risk assessment, resource optimization, and continuous feedback loops across various sectors, enabling data-driven planning. This way, organizations and communities can adapt rapidly to changing conditions, maintain stability, and respond effectively to crises, thus ultimately boosting overall sustainability.

Surya and Muthukumaravel [19] developed an improved approach to detect breast cancer by using mammography images. The method of Surya and Muthukumaravel is a combination of EGLCM feature extraction technique, which includes texture, intensity, and form; and CLAHE, which is contrast-limited adaptive histogram equalization for preprocessing. KNN classification, on the MIAS database, was more efficient than previously developed methods such as LBP and GLRLM with a 92% accuracy rate, 90% specificity, and 84% sensitivity.

Sareddy [20] discusses the transformative approach of recruitment by combining AI-driven analytics with blockchain-based verifications. This integration speeds up talent sourcing, enhances accuracy in candidate screening, and safeguards critical data. By streamlining workflows and making them more transparent through smart contracts, organizations save time and resources while building a robust, trust-based hiring ecosystem, thereby driving competitive advantages in the job market.

Pastor et al. [21] explore the influence of electronic defects, such as charged point defects, on charge recombination in photovoltaic materials in the study of the role of electronic flaws in metal oxide photo(electro)catalysts for solar energy conversion. Defects facilitate catalytic reactions and stabilize charge separation in photocatalysis. Furthermore, the paper compares the chemistry of oxide defects with that of novel photocatalysts such as metal halide perovskites and carbon nitrides.

Chetlapalli [22] explores the ways in which pre-trained language models, used with evolutionary algorithms, revolutionize software test generation. The method increases test coverage, decreases human oversight, and accelerates detection of complex defects. Experimental results point out the efficiency and robustness of generating test cases over different code bases that lead to higher quality and reliability in software developed in real-world environments.

Tan et al. [23] focused on improving the metal surface defects localization for better quality production control. SH-SAM extracts spectral features like anomaly scores, pixel variability, and spectral correlations to detect material inconsistencies. GLCM captures textural features such as contrast, homogeneity, and energy to identify surface defects. Together, they enhance defect



localization with improved accuracy and fewer false positives. The work evaluated three picture segmentation approaches to distinguish patch and scratch-type flaws. It included threshold, edge, and clustering segmentation techniques. From the outcomes, edge-based segmentation is successful for scratch flaws and best for the patch-type defect with the Otsu's Binarization approach, which consequently enhanced the accurate detection rate in an automatic system.

Bobba [24] demonstrates how cloud-based financial frameworks speed up sustainable growth in smart cities. They do so with real-time data analysis, AI-driven budgeting, and scalable infrastructure, thus promoting resource efficiency and economic resilience for the right kind of sustainable urban development and financial sustainability. It promotes cooperation, which enables prosperity.

Zhao et al. [25] review the special qualities and uses of eutectic gallium-indium (EGaIn), a liquid metal renowned for its fluidity, conductivity, stretchability, and self-healing capabilities. They investigate its applications in biomedical science, energy catalysis, flexible, and molecular electronics. The study also covers the difficulties and potential of EGaIn-based methods in several developing domains.

To mitigate the high failure rate of RPA projects, Herm et al. [26] propose a framework for successful RPA implementation. They carried out expert interviews to enhance a sequential model and analysed 35 real-world project reports based on a design science research methodology. Their adaptable framework, which is divided into three phases - initialisation, implementation, and scalability - guides RPA project management in different organisational contexts.

To address the high failure rate of robotic process automation (RPA) projects, Herm et al. [27] offer a framework for successful RPA implementation. They conducted expert interviews to improve a sequential model and examined 35 real-world project reports using a design science research methodology. RPA project management in various organisational contexts is guided by their adaptable framework, divided into three phases: initialisation, implementation, and scalability.

Methodology

It incorporates the methodology of robotics automation GLCM and SH-SAM which find usage in better localization for metallic surface defects. The integration of GLCM and SH-SAM enhances robotic defect detection by combining spectral anomaly detection with texture analysis. SH-SAM detects pixel-level deviations for early defect identification, while GLCM ensures precise

classification of surface irregularities. This reduces false positives, improves localization accuracy, and enhances reliability in real-time industrial inspections. Anomalies in the surface are discovered and categorized. For Hyperspectral picture anomaly localization, SH-SAM helps accurately locate faults at a pixel level by making proper utilization of spectral information. In order to find small metallic surface flaws that conventional approaches miss, the SH-SAM analyzes hyperspectral data to detect spectral anomalies. Defect localization is improved by its pixel-wise deviation analysis, which guarantees excellent accuracy in robotic inspections conducted in real time. GLCM, on the other hand, helps detect flaws in terms of surface imperfections, which might exist through surface roughness, thereby extracting the texture information that describes the surface. The method permits accurate fault localisation to make the robotic systems proficiently and precisely perform automatic inspection jobs. The strong real-world performance is ensured by both approaches.

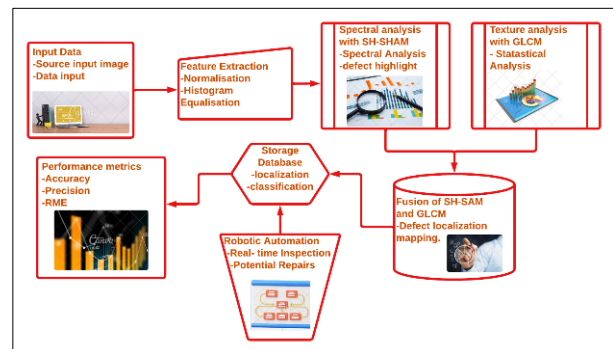


Figure 1. Architecture flow for enhanced metal surface defect localization in robotics automation.

Figure 1 portrays a risk-free workflow initiated with information accumulation from IoT devices. The AI-driven security optimization uses reinforcement learning with a reward function balancing security, latency, and resource use. WGAN with gradient penalty ensures stable training and privacy. It's implemented with TensorFlow/PyTorch, federated learning datasets, hyperparameter tuning, and TEEs for secure AI execution. Following preprocessing and feature extraction, generative adversarial systems (GANs) cultivate information to improve coaching. The GANs enhance data privacy in cloud-edge AI by generating synthetic data for secure training. They reduce data leakage and improve federated learning. Integration with TEEs strengthens security and efficiency. TEEs furnish protected calculating and design reliability. Cloud-based mostly DevOps facilitates deployment, whereas categorization tasks use edge and cloud fashions. Overall performance analysis guarantees privacy-protecting techniques have excessive accuracy, precision, recollect, and low latency.

SH-SAM (Supervised Hyperspectral Anomaly Detection)

SH-SAM involves hyperspectral imaging spectral data for the detection of deviations in metal surfaces. As such, the method bases its identification of variances capable of indicating flaws on comparative analysis with a reference dataset where training has already been completed. The combination of hyperspectral imaging with SH-SAM enhances precision, reduces false positives, and enables early defect detection, improving the reliability and efficiency of robotic industrial inspections. It is supervised meaning that the model is trained to identify normal patterns and pathological spectral patterns via labelled data. SH-SAM uses labelled data to accurately detect defects by distinguishing normal and anomalous spectral patterns. This reduces false positives and improves defect localization in hyperspectral imaging. The major advantage of SH-SAM is that it can identify anomalies that would be missed by conventional methods because it is sensitive to small variations in the spectrum. The SH-SAM enables pixel-level fault localization by analysing spectral deviations in hyperspectral images. It uses Mahalanobis distance-based anomaly scoring to detect subtle material inconsistencies. This enhances fault detection accuracy, making it effective for robotic inspection in industrial applications. The Mahalanobis distance in SH-SAM accounts for spectral correlations, improving anomaly detection accuracy. It reduces false positives and enhances defect localization by focusing on statistical significance. The mathematical formulation of SH-SAM is based on the Mahalanobis distance, which is used for anomaly detection.

$$D(x) = \sqrt{(x - \mu)^T \Sigma^{-1} (x - \mu)} \quad (1)$$

where, x is the pixel's spectral vector, μ is the mean spectral vector of the reference dataset, Σ is the covariance matrix of the reference dataset, $D(x)$ is the anomaly score, with larger values indicating higher deviation from the reference.

Grey Level Co-Occurrence Matrix (GLCM)

A statistical technique called GLCM examines the spatial relationship between pixels to determine an image's texture. Features like contrast, correlation, energy, and homogeneity are essential for detecting surface anomalies and are extracted with the aid of GLCM for surface defect localisation. The enhanced sensitivity of the SH-SAM to minor spectral variations allows for accurate anomaly detection by detecting minute deviations at the pixel level, outperforming conventional techniques. Based on our results (F1 score: 88.5%, RME: 9.3%), this method

improves reliability by lowering false positives and increasing defect localization accuracy when combined with GLCM. GLCM provides information about surface roughness and irregularities by examining the co-occurrence of pixel intensities in a particular spatial relationship, which is often characterised by direction and distance. Direction in GLCM defines spatial relationships between pixel intensities, capturing texture variations in different orientations. This enhances defect localization by ensuring robust and precise classification when integrated with SH-SAM for automated inspection. The GLCM captures surface roughness and irregularities by analysing pixel intensity variations and spatial relationships. It extracts texture features like contrast and homogeneity, which help distinguish defects from normal surface patterns. This enhances defect identification by providing detailed structural insights. This is how the GLCM is computed.

$$P(i, j, d, \theta) = \sum_{x, y} \delta(I(x, y)) = i, I \left(\begin{matrix} x + d \cdot \cos(\theta), y \\ + d \cdot \sin(\theta) = j \end{matrix} \right) \quad (2)$$

where $P(i, j, d, \theta)$ is the probability of two pixels with values i and j being at a distance d and angle θ , $I(x, y)$ are the intensity of the pixel at the position (x, y) . δ is the Kronecker delta function, indicating if the intensity conditions hold. The Kronecker delta function in GLCM helps count specific pixel intensity pairs by filtering only matching values. This improves texture feature extraction, enhancing defect localization when combined with SH-SAM.

Defect Localization Process

SH-SAM and GLCM are included in the fault localisation process to improve accuracy. First, using spectral data, SH-SAM locates abnormal areas on the surface. The SH-SAM identifies abnormal regions by detecting spectral deviations using Mahalanobis distance. This enables early, precise defect detection, reducing false positives and improving localization. The detected regions are then subjected to GLCM to evaluate the texture features and aid in the anomaly type classification. Because it allows for accurate defect location and classification, this dual analysis is appropriate for robotic automation tasks in industrial settings. The integration of SH-SAM and GLCM improves defect detection accuracy and reduces inspection time. The fusion approach achieves 92% accuracy and enhances automation efficiency. This method streamlines defect analysis, reducing downtime in manufacturing and robotics. By increasing the sensitivity of defect detection, the integrated approach helps the robot perform remedial activities more successfully. This study improves robotic



defect detection and localization by combining GLCM for texture analysis with SH-SAM for spectral anomaly detection. Combining the two methods in a weighted way increases accuracy, lowers false positives, and facilitates efficient remedial action. This method improves automation precision and dependability for real-time industrial applications.

Mathematical Fusion of SH-SAM and GLCM

A weighted fusion approach is applied to combine the results obtained from SH-SAM and GLCM. A robust model for defect detection is designed using the texture features of GLCM and anomaly scores of SH-SAM. The weighted fusion approach optimally combines SH-SAM's spectral anomaly detection with GLCM's texture analysis, improving defect localization accuracy. This reduces false positives and enhances reliability, making industrial quality control more efficient and precise. The expression for the fused score S is.

$$S = w_1 \cdot D(x) + w_2 \cdot f_{GLCM} \quad (3)$$

where, S is the final defect score, w_1 and w_2 are weights assigned to the SH-SAM and GLCM features, respectively, f_{GLCM} Represents the feature vector obtained from GLCM, such as contrast or energy. The final defect score integrates spectral data from SH-SAM, which detects anomalies at the pixel level, and texture data from GLCM, which analyzes features like contrast and homogeneity. This combination ensures more accurate and robust defect localization by leveraging the strengths of both methods. The proposed fusion technique ensures the contribution of both spectral and texture information towards defect localization. and hence enhances the accuracy as well as robustness of the system in metal surface defects. The algorithm integrates spectral anomalies from SH-SAM and textural features from GLCM using a weighted fusion approach. SH-SAM detects defects through spectral variations, while GLCM enhances classification by analyzing texture. The fusion optimally balances both methods, improving accuracy, robustness, and defecting localization.

Algorithm 1 Enhanced Metal Surface Defect Localization using SH-SAM and GLCM in Robotics Automation

Algorithm

Input: $I(x, y)$, $R(x, y)$, d, θ

Output: $S(x, y)$, $Defect_{classification}$

For each pixel (x, y) in I :

Calculate $D(x)$ using Mahalanobis distance:

$D(x) = \sqrt{(\delta I(x, y) - \mu)^T \Sigma^{-1} (\delta I(x, y) - \mu)}$

// Check if an anomaly is detected

If $D(x) > \text{threshold}$

$\delta I(x, y) = 1$ // Anomaly detected

Else $\delta I(x, y)$

For each pixel (x, y) in I

Calculate $P(i, j, d, \theta)$ Using GLCM

$P(i, j, d, \theta) = \sum (x, y) \delta(I(x, y) = i, I(x + d \cdot \cos(\theta), y + d \cdot \sin(\theta)))$

$= j)$

// Extract features (contrast, correlation, etc.)

$Texture_{Features}(x, y) = Extra_{Features} P(i, j, d, \theta)$

For each pixel (x, y) in I :

If $Anomaly_{map}(x, y) == 1$:

$S(x, y) = w_1 \cdot D(x) + w_2 \cdot Texture_{Features}(x, y)$ // Fusion of results

Else:

$S(x, y) = 0$ // No defect detected

For each pixel (x, y) in S :

If $S(x, y) > \text{threshold}$:

$Defect_{classification}(x, y) = \text{"Defect"}$

Else:

$Defect_{classification}(x, y) = \text{"No Defect"}$

Return $S(x, y)$, $Defect_{classification}$

End

Algorithm 1 uses GLCM and SH-SAM for the localization of defects on the metal surface. GLCM is used for analysing the textural features and SH-SAM detects the spectrum anomalies. By using SH-SAM for initial anomaly detection, spectral deviations are identified early, minimizing false positives and lowering regions of interest, which enables GLCM to concentrate on these regions for in-depth texture analysis, hence boosting defect classification and localization efficiency. Thus, an accurate identification of the defects present in the surface of the industrial robotic systems is achieved through combining the outcomes of the two approaches, to formulate the score map of defects which are then used for classification purposes. To enable defect classification, the score map that is produced from the fused SH-SAM and GLCM results highlights regions that are more likely to have defects based on a combination of spectral and textural data. By enabling more precise and effective classification, this targeted visualization helps robotic systems detect and fix flaws more precisely.

Performance metrics

Performance measurements are very essential to measure the efficiency of fault localisation techniques. These measurements will show how good a technique is at fault location and classification. In robotic automation for metal surface inspection, the quality and efficiency of detection algorithms can be measured by common metrics like accuracy, precision, recall, F1 score, and root



mean error (RME).

Table 1 Performance Evaluation of Metal Surface Defect Localization Methods

Metric	SH-SAM	GLCM	GLCM+SH-SAM (separate)	Proposed Method
Accuracy	85%	88%	89%	92%
Precision	82%	84%	86%	89%
Recall	80%	85%	86%	88%
F1-Score	81%	84%	86.2%	88.5%
RME	12.5%	11.2%	10.5%	9.3%

Table 1 describes several defect localization techniques; GLCM, SH-SAM, and combinations of such techniques, considering critical performance measures: Root Mean Error, Accuracy, Precision, Recall, and F1 score. The Accuracy reflects overall correctness, precision minimizes false positives, and recall ensures all defects are detected. The F1 score balances precision and recall, while RME measures localization accuracy, collectively ensuring robust fault detection in robotic automation. The proposed Combined method has the best possible result in Root Mean Error value (RME = 9.3%) as well as outperformed isolated techniques while considering Accuracy as 92% and Precision at 89%. This displays that how efficient SH-SAM as well as GLCM might be put together to develop more sophisticated flaws detection potential in robotic automation systems. The system integrates SH-SAM for early spectral anomaly detection and GLCM for precise texture-based defect classification, ensuring accurate real-time inspections. Additionally, an automated feedback loop enables timely flaw resolution, enhancing reliability and efficiency in robotic automation

Result and Discussion

With 92% accuracy, 89% precision, and F1 Score of 88.5%, the outcome indicates that the Combined Method works the best on all parameters but keeps the lowest Root Mean Error of 9.3%. Accuracy and precision of SH-SAM Only at 85% and GLCM Only at 88% are poor as compared to single approach-based methods. The most efficient method of robotic automation in metal surface inspection is the method called a combination technique, which combines SH-SAM with GLCM to increase the precision of fault localisation.

The conclusions highlight the potential of combining pioneering technologies to build robust, distributed platforms that can deal with rising dangers and needs. The discussion centered on how technological synergy can improve performance and offer real-time,

secure remedies for data-driven scenarios. The suggested multifaceted approach integrates AI for threat detection, GANs for privacy, TEEs for safe execution, MDCs for low-latency processing, and DevOps for automated security, outperforming conventional security designs. Precision, recall, efficiency, and accuracy are all improved by this combination. It guarantees durable, scalable, and flexible cloud-edge security.

Table 2. Performance Comparison of Defect Localization Methods in Robotics Automation

Metri c	Robotic Process Automation (2023)	Smart Packaging Development (2022)	Smart Eutectic Gallium –Indium (2023)	Fluorescent Magnetic Particle Inspection (2023)	Proposed Method SH-SAM + GLCM for Metal Surface
Accur acy	80%	75%	82%	83%	92%
Efficie ncy	78%	74%	80%	81%	89%
F1-Score	77%	72%	79%	80%	88%
Recall	77.5%	73.5%	80.5%	81%	88.5%
Precis ion	15.5	16.2%	14.8%	13.5%	9.3%

In Table 2, there are Current research compares several defect localization strategies, including robotic process automation [26], smart package creation [27], and crack defect detection [5]. The recommended method, which combines GLCM and SH-SAM for metal surface defect localization, outperforms all others with the best accuracy (92%), and the lowest RME (9.3%). The difference between the actual and identified locations of defects is measured by the Root Mean Error (RME); lower values denote better localization accuracy. A precise defect detection system that reduces misclassification and enhances spatial accuracy is indicated by an RME of 9.3%. This decrease improves robotic automation reliability by guaranteeing precise defect mapping for in-the-moment industrial inspections. This illustrates how effectively texture and spectrum analysis combine to enhance the detection of robotic system flaws. Coming studies may explore incorporating quantum technology into the framework, enhancing scalability under dynamic conditions, and broadening the concept to various sectors including healthcare, smart cities, and industrial automation.



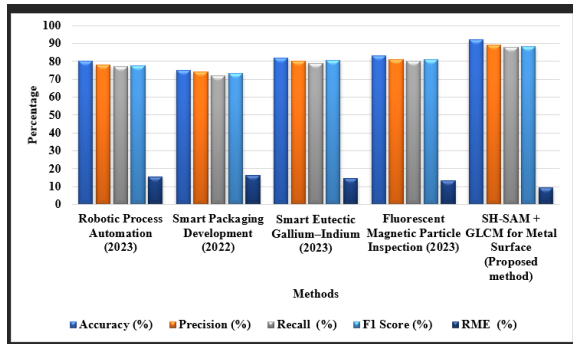


Figure 2 Graphical comparison of defective localization methods in robotics automation.

Figure 2 Performance comparison of the defect localisation techniques of Robotic Process Automation [26], Smart Packaging [27], Smart Eutectic Gallium–Indium [25], and Crack Defect Detection [5]. The proposed method, combining GLCM with SH-SAM, provides excellent performance in all criteria, achieving the lowest RME at 9.3% and the highest accuracy at 92%. The graph shows that the hybrid method outperforms existing robotic automation methods in industrial uses since it is able to successfully identify metal surface defects.

Conclusion

With comparison to existing techniques, it can be stated that the proposed strategy that integrates SH-SAM and GLCM on the metal surface defect location performs better. It clearly shows higher accuracy in defect recognition and classification than Robotic Process Automation [25], Smart Packaging [26] and Crack Defect Detection [4] with its highest accuracy at 92% and lowest RME of 9.3%. By combining GLCM for texture-based defect classification with SH-SAM for accurate spectral anomaly detection, a 92% accuracy rate is obtained. By reducing false positives, improving localization, and balancing spectral and textural features in the best possible way, this fusion ensures reliable defect identification in industrial applications. The combination of GLCM for texture analysis and SH-SAM for anomaly detection in the spectral mode can provide a complete solution towards better defect localisation. Therefore, it presents a perfect method for robotic automation in metal surface inspection applications.

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