Deep Feature Fusion for Hierarchical Defect Classification in Industrial Inspection Systems

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ABSTRACT
Defect classification in industrial components is critical to ensuring product quality, operational safety, and cost efficiency, as manufacturing industries face increasing defect rates due to high-speed production and complex processes. Studies indicate that a significant percentage of industrial failures originate from undetected surface and structural defects, leading to rework, downtime, and financial loss. This research is motivated by the need for accurate and automated defect detection in machinery parts, painted surfaces, and welded joints, including subtypes such as cracks, corrosion, paint blisters, scratches, porosity, lack of fusion, and weld spatter. The expected outcome is a robust classification system capable of reliably identifying defect categories and subcategories across these domains. Traditional defect inspection relies heavily on manual visual inspection, which is time-consuming, subjective, and prone to human error. Such manual systems struggle with consistency, scalability, and real-time deployment in modern industrial environments. In this work, RGB images of industrial components are utilized, followed by image preprocessing techniques including resizing and normalization to enhance feature consistency and model performance. Existing machine learning approaches such as K-Nearest Neighbours (KNN) and Decision Tree Classifier (DTC) are reviewed as baseline models for defect classification. The proposed approach employs Convolutional Neural Network (CNN)-based feature extraction combined with Logistic Regression (LR) for efficient and accurate classification. The system outputs precise defect classification results for machinery, paint, and welding components, including their respective defect subtypes, demonstrating improved accuracy and reliability over traditional methods.

Keywords: Industrial Defect Classification, Automated Defect Detection, Machine Learning, Quality Inspection, Predictive Maintenance

1. Introduction

In modern manufacturing industries, ensuring the quality and reliability of industrial components is critical for maintaining safety, reducing production costs, and meeting strict regulatory standards. Defects such as cracks, scratches, pores, misalignments, and surface irregularities can significantly affect the performance and lifespan of components used in sectors such as machinery, paint, welding, automotive, aerospace, electronics, and heavy machinery. Traditional visual inspection methods, which rely heavily on human expertise or handcrafted image features, are often time-consuming, subjective, and prone to errors, especially when dealing with large-scale production and complex defect patterns. In industrial manufacturing processes, machines equipped with cameras continuously capture images of machinery components, painted surfaces, and welded joints during operation. These images are transmitted to defect detection hardware through advanced communication protocols for systematic inspection. The analysis focuses on visual and structural characteristics such as surface condition, texture, alignment, and material consistency to ensure reliable quality monitoring across different industrial outputs.

Figure 1 shows the steady growth of the industrial defect detection market from 2020 to 2035. The market value increases consistently from about USD 1.76 billion in 2020 to nearly USD 6.07 billion by 2035, indicating rising adoption of AI-based inspection systems across industries. The accompanying line graph represents the year-on-year growth rate, which rises initially and peaks around 2025–2026, reflecting rapid expansion driven by advancements in AI and increased industrial automation. After this peak, the growth rate gradually declines, suggesting market maturation, while the overall market value continues to grow. The chart also highlights a projected compound annual growth rate of approximately 8.6% from 2025 to 2035, demonstrating strong long-term potential for AI-driven defect detection solutions.

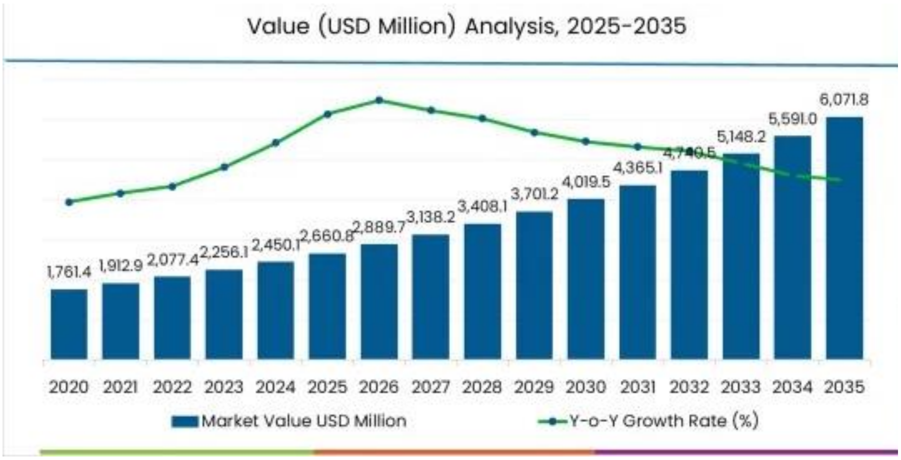

Figure. 1: Overview of industrial components.

Machinery defect analysis involves identifying issues such as corrosion, defective components, faulty wiring, cracks, lubrication failures, and overheating. Corrosion and overheating are detected through surface discoloration and deformation, while cracks and defective components are identified by visible fractures and dimensional irregularities. Faulty wiring is recognized through exposed or damaged insulation, and lubrication failures are observed through abnormal wear patterns and residue buildup. Early detection of these defects helps prevent equipment breakdowns and improves operational reliability. Paint and weld inspections further ensure product quality and structural integrity. Paint defects such as adhesion loss, blistering, chalking, cracking, fading, and sagging are identified by analyzing coating uniformity, texture variations, and color consistency. Weld defects including bad welds, burn-through, cracks, misalignment, porous welds, slag inclusions, undefined welds, and perfect weld conditions are assessed based on bead shape, continuity, penetration, and alignment. The identified defects generate feedback that enables machines to adjust process parameters and supports operators in maintaining consistent quality across machinery, paint, and welding operations.

2. Literature Survey

Azeddine Mjahad et al. [1] proposed automated quality control was studied for metallic cast components using machine learning and deep learning approaches for surface defect detection. Classical ML models trained on statistical features achieved excellent performance, with Random Forest reaching up to 99.4% precision switch capsule-based architectures achieving the highest accuracy and F1-scores. A 3D CNN applied to volumetric image inputs delivered comparatively lower but competitive performance. Very low per-image processing times demonstrated the suitability of the proposed methods for real-time industrial deployment. Nuno Lau et al. [2] Introduced an automated system was developed to improve industrial quality control by detecting surface defects on painted heating devices. Reflectometry and bright light-based illumination were combined with deep learning models to classify non-defective and defective surfaces. Transfer learning using pre-trained networks, particularly ResNet-50, achieved higher classification accuracy than a model trained from scratch. Decision-level fusion of dual-modal information expanded defect detection while maintaining low computational complexity. The system demonstrated fast, accurate, and robust performance suitable for industrial deployment. Esteban Cumbajin et al. [3] Observed Surface defect detection using machine learning had become an important industrial and research topic in recent years. This systematic review classified based surface defect detection methods according to surface types. Following PRISMA guidelines, 59 primary studies were analysed out of 253 identified records, focusing on industrial surfaces such as metal, building, ceramic, wood, and special surfaces. The analysis showed that metallic surfaces were the most studied (62.71%), classification was the most common task (49.15%), and transfer learning was widely adopted. The review also proposed a new taxonomy and highlighted trends and future research directions to support defect detection applications.

Jing Ren et al. [4] proposed Surface defect detection had attracted significant attention as a challenging research problem over recent decades. Traditional image processing techniques were effective for simple cases but struggled with complex textures, noise, and varying illumination. Deep learning emerged as a solution due to increased computational power and the availability of large labeled datasets. This review analyzed machine learning-based defect detection methods from supervised, semi-supervised, and unsupervised perspectives, including applications to X-ray images. Common challenges such as data imbalance, limited samples, and real-time constraints were identified along with potential solutions Hong-Dar Lin et al. [5] Introduced the model successfully adapted defect detection knowledge from older tools to new products while requiring fewer training samples. Experimental results from three assembly stations demonstrated high classification accuracy of up to 98.67%, along with improved effectiveness and efficiency compared to standard R-CNN models. Sensitivity analysis further confirmed that the system reduced training data requirements while maintaining strong and reliable inspection performance Wentao Liu et al. [6] Focused Feature Network to address the challenges of detecting sparse, diverse, and irregular defects on strip steel surfaces. It introduced supervised convolution, supervised deformable convolution, and a supervised region proposal strategy to enhance feature extraction and improve the quality of candidate regions. Experimental evaluations demonstrated that the proposed method achieved a mean Average Precision of 81.2% on the NEU-DET dataset and 72.5% on the GC10-DET dataset. Ablation studies further confirmed that each module contributed significantly to improved feature extraction efficiency and overall detection accuracy

Nam Lethanh et al. [7] proposed CNN and Vision Transformers (ViTs) were investigated for defect detection in civil and structural components using TensorFlow. An empirical study was conducted using a crack image dataset, where defect severity was classified into binary categories of with crack and without crack. Both models achieved accuracies exceeding 95% after 100 training epochs, with no significant difference in performance between CNNs and ViTs. The results demonstrated that low-cost drone-based image acquisition offered a more economical alternative to traditional high-speed inspection methods while maintaining high predictive accuracy. Seungchul Lee et al. [8] Introduced steel defect diagnostics was considered crucial in the steel-manufacturing industry due to its strong impact on product quality and production efficiency. This study proposed a deep structured neural network, specifically a (CNN) with class activation maps, to diagnose steel surface defects. The CNN model was extended beyond classification to localize defect regions, enabling real-time visual decision-making. Experimental results showed near-perfect performance, achieving 99.44% accuracy and a 0.99 F1-score, outperforming support vector machine and LR models. Eneko Intxausti et al. [9] proposed deep learning became important for industrial defect detection but was limited by scarce annotated X-ray datasets. This study used self-supervised pretraining with Sim Siam and Sim MIM on 27,901 unlabelled X-ray images to improve feature extraction. X-ray–pretrained models outperformed ImageNet-based methods, with Swin Transformers excelling in data-rich cases and CNNs in limited-data scenarios.

Jintao Fu et al. [10] Introduced defect detection in industrial CT images was challenging due to small defect sizes, low contrast, and noise. We proposed Defect R-CNN, incorporating an edge-prior convolutional block (EPCB) and a custom backbone (EP-Net) to capture defect boundaries and multi-scale features. On a nuclear graphite CT dataset, it achieved AP over 0.9, mAP-bbox of 0.983, mAP-segm of 0.956, outperforming Faster R-CNN, Mask R-CNN, Efficient Net, RT-DETR, and YOLOv11. The model reached 76.2 FPS, demonstrating a robust and efficient solution for high-precision, real-time defect detection. Vicky Pratama Putra et al. [11] proposed the demand for IC chips had risen, and defects such as fractures, delamination, and voids were analysed using SAT. A CNN model was developed to automate defect detection, replacing manual visual inspections. Flood-fill–based augmentation generated reliable training data, and varying batch sizes optimized model performance. Using 40× augmentation with a batch size of 32, the model achieved a missed detection rate below 0.4% and a false alarm rate of 0.1%, reducing operator strain and improving IC quality management.

Tengwei Yu et al. [12] Introduced ECT had been widely used for detecting surface defects, but traditional methods struggled with geometric characterization. A complex-valued CNN (CV-CNN) was developed to reconstruct defect morphology and classify defects using full amplitude and phase signals. Experiments on carbon steel showed 85% accuracy, outperforming CV-FCNN and enabling precise, intelligent NDT. Zhiduan Ni et al. [13] proposed a CNN-based YOLOv5 model was developed to detect defects like open circuits, short circuits, and missing holes, achieving over 90% precision and 91% recall. The study demonstrated reliable automated inspection and highlighted the importance of imaging sensors for model robustness Agnes Pechmann et al. [14] Introduced quality assurance in alumina um die casting had been critical due to internal defects like porosity reducing component integrity. Deep learning models (YOLOv5 and Faster R-CNN) were trained on industrial X-ray images, with position-specific models achieving F1-scores up to 0.87. Validation under real production conditions demonstrated feasibility Agnes Pechmann et.al [14], faster inspections, and potential for standardized, efficient, and sustainable quality control. Seokwoo Jang et al. [15] proposed sewer pipelines had been critical for urban sanitation, but traditional CCTV inspections were time-consuming and subjective. A CNN model based on ResNet50 was developed to classify non-defect and major defect categories from a 470,000-image dataset, achieving 92.75% accuracy with dropout and L2 regularization. Analysis showed that mislabelled or redundant images reduced performance, highlighting the importance of proper dataset curation for automated sewer defect detection.

3. Proposed system

The proposed approach improves consistency, scalability, and reliability, enabling effective defect identification across multiple industrial domains while reducing human dependency and inspection time. Figure 2 shows System Architecture, which presents an automated defect classification framework for industrial components using deep learning–based feature extraction and efficient machine learning classification. RGB images of machinery parts, painted surfaces, and welded joints are processed to identify surface and structural defects such as cracks, corrosion, paint blisters, scratches, porosity, lack of fusion, and weld spatter. Unlike traditional manual inspection and basic machine learning techniques, the system leverages CNN based feature extraction to capture discriminative visual patterns from images, followed by LR for accurate classification.

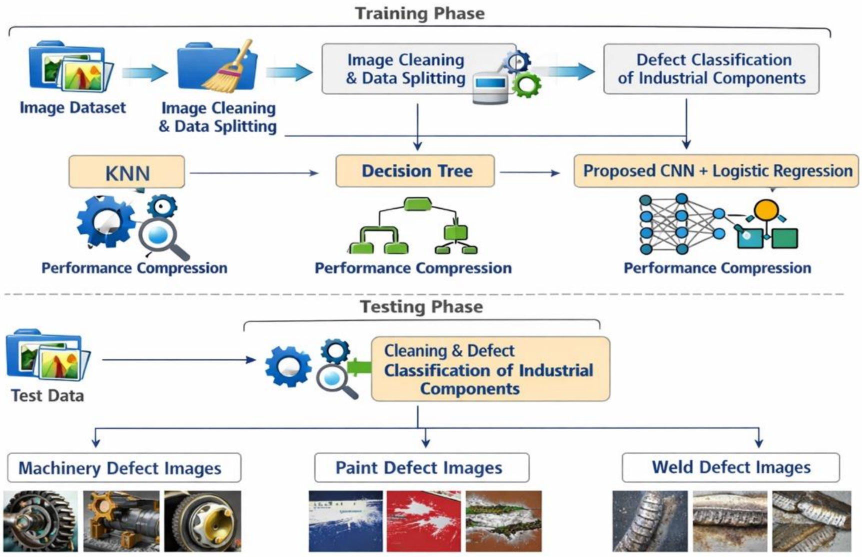

Figure 2: Proposed system architecture.

Image Dataset: A labelled dataset consisting of RGB images of industrial components is collected, covering machinery, paint, and welding defects along with their respective subcategories.

Image Preprocessing: The collected images undergo preprocessing operations such as resizing and normalization to ensure uniform input dimensions and improved feature consistency for model training.

Data Splitting: The pre-processed dataset is divided into training and testing sets to enable unbiased learning and evaluation of classification performance.

Existing KNN Model: A KNN classifier is implemented as a baseline method to analyse defect classification performance using distance-based similarity.

Decision Tree Model: A DTC is applied to learn rule-based decision boundaries for defect classification and to serve as another baseline for comparison.

Proposed CNN-LR: A CNN is used to automatically extract high-level and discriminative features from defect images, capturing texture, shape, and structural information. The extracted CNN features are fed into a LR to perform efficient and accurate multi-class defect classification.

Performance Comparison: The performance of the proposed CNN feature extraction combines with LR model is compared with existing KNN and DTC models using evaluation metrics such as accuracy and reliability.

Prediction Using Test Data: The trained model is tested on unseen images to predict defect categories and subcategories for machinery, paint, and welding components.

Integration with Tkinter: The final trained model is integrated into a Tkinter-based graphical user interface to enable user-friendly defect image input and real-time classification output.

4. Results Analysis

The results analysis section evaluates the performance and effectiveness of the proposed system in achieving accurate and reliable outcomes. It focuses on assessing the model using various evaluation metrics such as accuracy, precision, recall, and F1-score to ensure comprehensive performance measurement. The analysis also compares the proposed approach with existing methods to highlight improvements and advantages. Graphical representations and visualizations are utilized to clearly interpret the results and identify patterns or trends. Additionally, the robustness and generalization capability of the model are examined using test datasets. This section provides critical insights into the strengths and limitations of the system, ensuring its suitability for real-world applications.

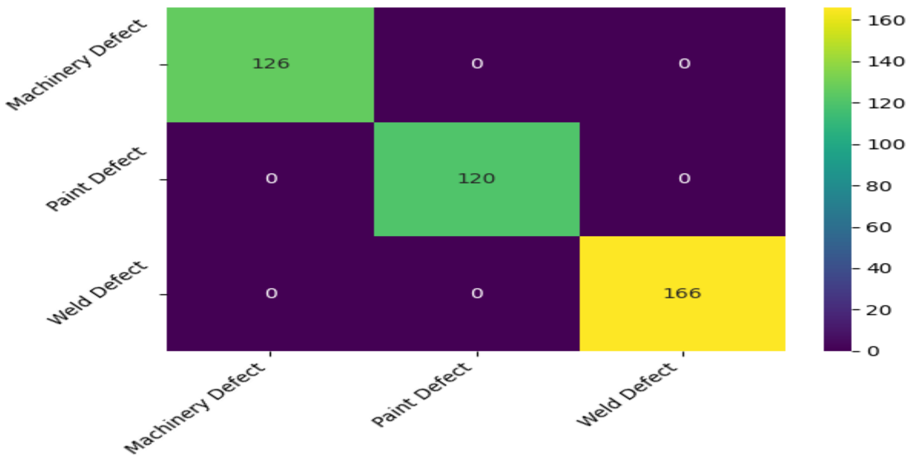

Figure. 3: Confusion matrix obtained CNN-LR for main class

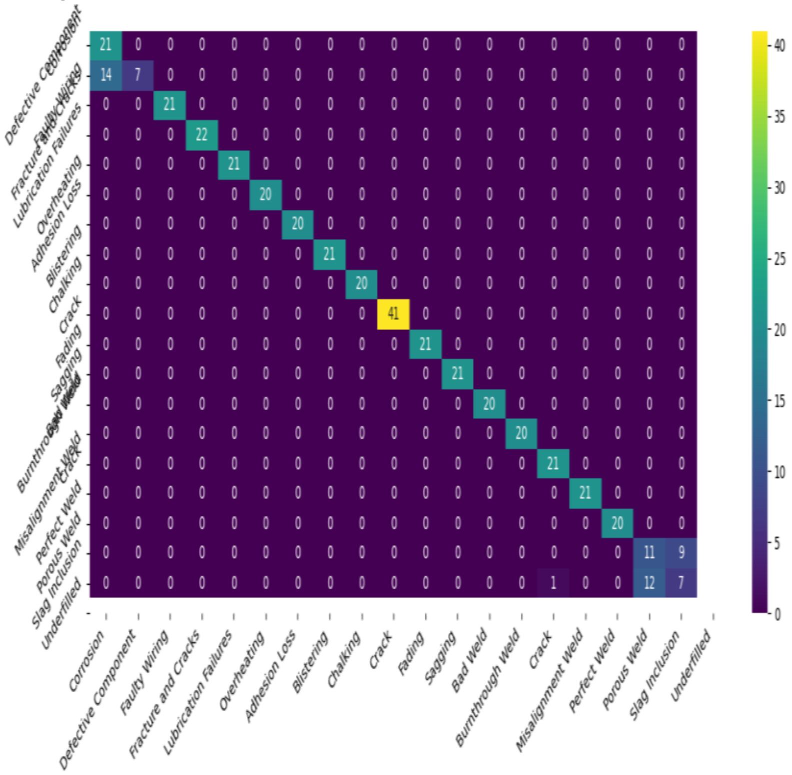

Figure. 4: Confusion matrix CNN-LR for sub class.

Figure 3 illustrates the confusion matrix representation of the proposed defect classification model, highlighting its performance across three categories: Machinery Defect, Paint Defect, and Weld Defect. The matrix demonstrates that the model achieves highly accurate classification, as indicated by the strong diagonal values of 126, 120, and 166 for the respective classes. The absence of off-diagonal values signifies that there are no misclassifications among the defect categories, emphasizing the robustness and precision of the model. This indicates that the classifier effectively distinguishes between different defect types without overlap or ambiguity. The results further confirm the model's strong generalization capability and reliability when applied to unseen data. The confusion matrix validates the effectiveness of the proposed approach in achieving high-performance defect detection and classification in industrial components. Figure 4 illustrates the confusion matrix of the multi-class defect classification model, depicting its performance across a wide range of defect categories such as corrosion, faulty component, fracture, lubrication failures, crack, porosity, slag inclusion, and underfilling. The matrix highlights strong diagonal dominance, with most classes achieving high correct prediction counts, indicating precise classification capability. Notably, classes such as crack and corrosion exhibit significantly higher true positive values, emphasizing the model's effectiveness in identifying prominent defect patterns. The minimal presence of off-diagonal values reflects very low misclassification rates, demonstrating the model's ability to distinguish between closely related defect types. Additionally, a few minor misclassifications observed in certain categories suggest slight overlaps in feature representation, but they do not significantly impact overall performance. The results confirm that the proposed model maintains high accuracy, robustness, and consistency across multiple defect classes.

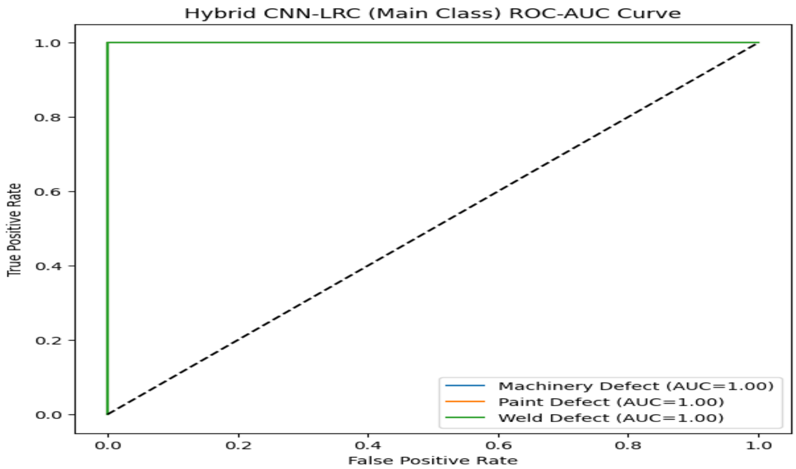

Figure. 5: CNN-LRC ROC-AUC Curve for main class.

Figure 5 illustrates the ROC–AUC curve of the Hybrid CNN–LRC model for main class defect classification, depicting the trade-off between true positive rate and false positive rate across Machinery Defect, Paint Defect, and Weld Defect categories. The curves for all classes closely approach the top-left corner of the plot, indicating near-perfect classification performance. The AUC value of 1.00 for each class demonstrates exceptional discriminative capability and confirms that the model effectively separates positive and negative instances without error. The alignment of the curves significantly above the baseline diagonal further emphasizes the superiority of the proposed model over random classification. This performance highlights the model's high sensitivity and specificity in detecting defect categories. Figure 6 illustrates the ROC–AUC curve of the Hybrid CNN–LRC model for sub-class defect classification, depicting the relationship between true positive rate and false positive rate across multiple fine-grained defect categories such as corrosion, faulty wiring, fracture, lubrication failures, crack, porosity, slag inclusion, and underfilled defects. The curves for most sub-classes are concentrated near the top-left corner, indicating excellent classification performance and strong discriminative ability. Several classes achieve an AUC value of 1.00, demonstrating perfect prediction capability, while a few categories such as corrosion, defective component, slag inclusion, and underfilled exhibit slightly lower yet highly competitive AUC values of 0.97. The consistent separation of curves well above the baseline diagonal highlights the model's effectiveness in distinguishing between complex and closely related defect patterns. This performance confirms the model's high sensitivity, specificity, and robustness across diverse defect categories.

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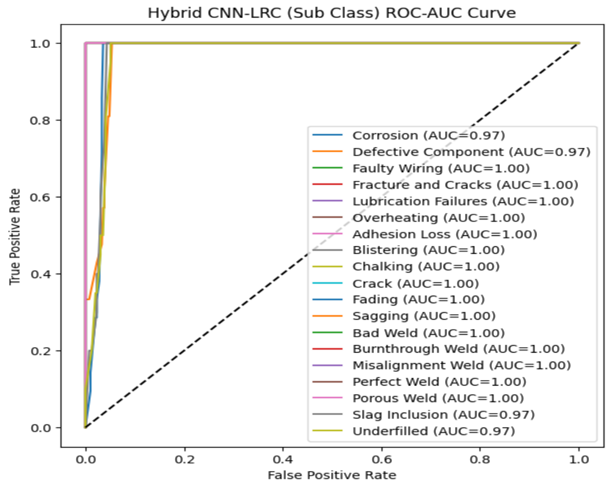

Figure. 6: CNN-LRC ROC-AUC Curve for sub class.

Table. 1: Overall comparison of main class.

Model	Accuracy	Precision	Recall	F1-Score
KNN	0.7476	0.7757	0.7297	0.6962
DTC	0.9684	0.9685	0.9685	0.9681
CNN-LR	1.0000	1.0000	1.0000	1.0000

The performance comparison table 1 presents the evaluation of different models, including KNN, DTC, and the proposed CNN-LR, based on key metrics such as accuracy, precision, recall, and F1-score. The KNN model achieved an accuracy of 0.7476, indicating moderate performance with relatively lower recall and F1-score values. In contrast, the DTC demonstrated significant improvement, attaining a high accuracy of 0.9684 along with balanced precision, recall, and F1-score. Notably, the proposed CNN-LR model outperformed all other methods by achieving a perfect accuracy of 1.0000, along with ideal precision, recall, and F1-score values. This superior performance highlights the effectiveness of the hybrid approach in capturing complex patterns within the data.

Table. 2: Overall comparison table of sub class.

Model	Accuracy	Precision	Recall	F1-Score
KNN	0.4272	0.4805	0.4173	0.3900
DTC	0.4272	0.4925	0.4014	0.3859
CNN-LR	0.9126	0.9195	0.9070	0.9014

The performance comparison table 2 presents the evaluation of KNN, DTC, and the proposed CNN-LR model using accuracy, precision, recall, and F1-score metrics. The KNN model achieved an accuracy of 0.4272, reflecting relatively low classification performance with limited recall and F1-score. Similarly, the Decision Tree Classifier (DTC) also recorded an accuracy of 0.4272, showing comparable but slightly varied precision and recall values. In contrast, the proposed CNN-LR model significantly outperformed the traditional methods by achieving a high accuracy of 0.9126. It also demonstrated strong precision, recall, and F1-score, indicating balanced and reliable predictions. This substantial improvement highlights the effectiveness of the CNN-LR model in capturing complex patterns and enhancing classification performance.

Figure 7 illustrates the qualitative prediction and explainable AI (XAI) analysis of the proposed defect classification system on an industrial surface image. The figure presents the original input image alongside the classifier output, demonstrating the model's capability to accurately detect and classify defects. The predicted results identify the main class as Machinery Defect and the sub-class as Corrosion, indicating precise hierarchical classification. The XAI analysis further provides interpretability by highlighting key attributes such as defect presence, industrial component identification, and severity level categorized as severe. This demonstrates the model's ability not only to classify defects but also to provide meaningful insights for decision-making. The consistency between the visual defect region and predicted labels confirms the reliability of the system.

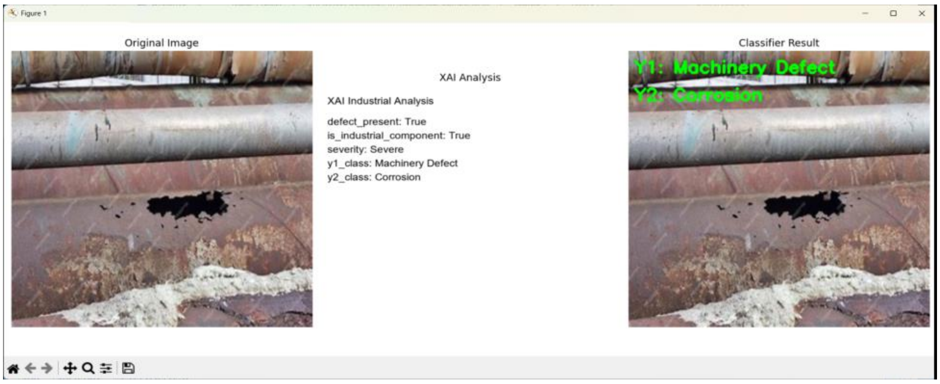

Figure. 7: Prediction results of corrosion.

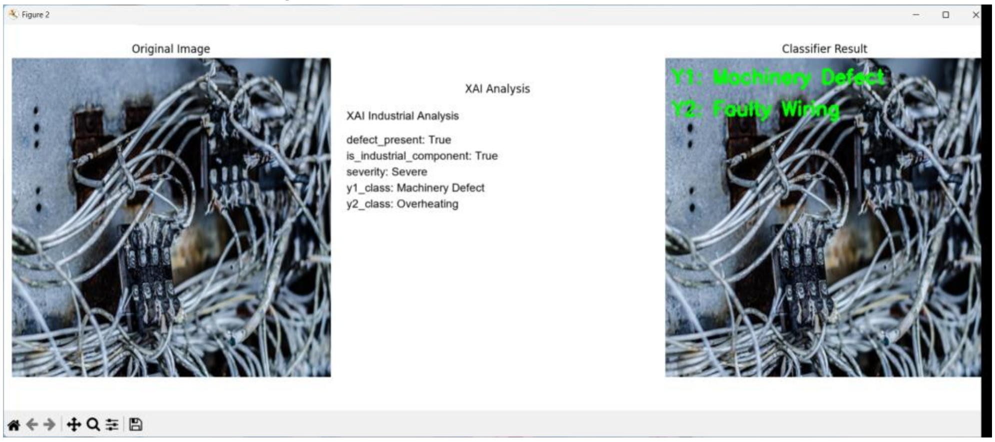

Figure. 8: Prediction results of faulty wiring.

Figure 8 illustrates the qualitative prediction and explainable AI (XAI) analysis of the proposed defect classification system on an industrial wiring image. The figure presents both the original input and the classifier output, demonstrating the model's ability to accurately identify complex defect patterns. The predicted results classify the main defect category as Machinery Defect and the sub-class as Faulty Wiring, indicating effective hierarchical classification. The XAI analysis further provides detailed insights, including defect presence, industrial component validation, and severity level categorized as severe. This enhances interpretability and supports informed decision-making in industrial environments. The alignment between the visual defect features and predicted labels confirms the robustness and consistency of the model.

5. Conclusion

The experimental results clearly demonstrate that the Hybrid CNN-LR model significantly outperforms the traditional KNN and DTC models in both main class and sub-class defect classification. In main class classification, the Hybrid CNN-LR achieves perfect performance with 1.0000 accuracy, precision, recall, and F1-score, compared to DTC which achieved 0.9684 accuracy and KNN which achieved 0.7476 accuracy. For sub-class classification, which is more complex due to fine-grained defect differentiation across 20 categories, the Hybrid CNN-LR achieves 0.9126 accuracy, 0.9195 precision, 0.9070 recall, and 0.9014 F1-score. In contrast, both KNN and DTC show significantly lower sub-class accuracy of 0.4272, with macro F1-scores of 0.37, indicating poor fine-level discrimination capability. The macro average comparison further highlights the superiority of the proposed model, where Hybrid CNN-LR achieves macro precision of 0.87, macro recall of 0.86, and macro F1-score of 0.86, while

KNN and DTC remain around 0.37 macro F1-score. Similarly, the micro average (overall accuracy) for the sub-class level is 0.9126 for Hybrid CNN-LR compared to 0.4272 for both KNN and DTC. These results confirm that deep feature extraction using CNN combined with LR provides highly discriminative representations for industrial defect detection, enabling robust multi-output classification across both major and fine-grained defect categories.

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