

# DL Powered Industrial Components Defect Detection with Multi-Output Analysis

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## ABSTRACT

Industrial components are routinely subjected to demanding operational conditions, which can result in defects such as corrosion, cracks, weld imperfections, overheating, and surface degradation. Early and precise identification of these defects is crucial for maintaining reliability, ensuring safety, and minimizing maintenance costs. Traditional inspection methods rely heavily on manual observation, which is not only time-consuming but also inconsistent and error-prone, particularly when dealing with large datasets or subtle defect patterns. This study introduces an automated defect detection system that leverages both Deep Learning (DL) and Machine Learning (ML) techniques to overcome these challenges. The core of the proposed approach is a hybrid ConvLogiDefect (CLD) model that integrates Convolutional Neural Networks (CNN) with Logistic Regression (LR). The CNN is employed to capture and learn complex visual features from industrial images, while the LR classifier efficiently categorizes these features into specific defect classes. To ensure a thorough evaluation, conventional ML models such as K-Nearest Neighbors (KNN) and Decision Tree (DT) are also implemented and compared against the proposed method. The system is designed with a Tkinter-based Graphical User Interface (GUI), enabling users to perform dataset upload, preprocessing, model training, and real-time predictions in an intuitive manner. Additionally, a secure authentication module is incorporated to restrict access and protect system integrity. The proposed framework offers a reliable, scalable, and efficient solution for defect detection, reducing dependency on manual inspection while significantly improving accuracy, thereby supporting advanced industrial automation and smart manufacturing systems.

**Key words:** Industrial Defect Detection, Image Classification, Feature Extraction, Deep Learning, Machine Learning, Quality Control.

## 1. INTRODUCTION

The rapid advancement of internet technologies and digital media has led to an exponential growth in the volume of image data shared online. As a result, image classification has become an essential yet challenging task [1]. Traditional image classification relies on manual efforts, which are time-consuming, labor-intensive, and often inconsistent. With the continuous expansion of image datasets, manual methods are no longer suitable for efficiently retrieving and analyzing target images, as shown in fig 1. To address these limitations, automated approaches are required to extract meaningful information from large-scale image data. In industrial applications, for example, identifying defective components from a vast number of product images is crucial. Detecting and classifying defect images helps ensure product quality by determining whether components meet required standards [2]. However, manual inspection in such scenarios is inefficient and difficult to scale. In recent years, researchers have increasingly adopted computer-based techniques for image classification and defect detection. The development of advanced data-driven approaches has significantly improved both classification accuracy and processing efficiency [3].

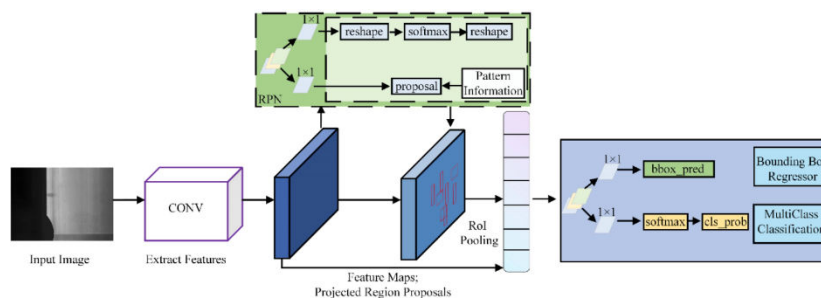


Fig. 1: Defect classification in industrial components

These techniques are now widely used across various fields, including engineering design, biomedicine, transportation, product quality inspection, and media analysis. For instance, biomedical images can be classified using annotated datasets combined with adaptive learning strategies. Similarly, real-time analysis of social media images enables timely understanding of critical situations and assessment of potential impacts [4]. In addition, integrating multiple data characteristics has enabled more precise image analysis, expanding applications in areas such as food engineering. With the continuous growth of data, efficient image classification has become increasingly important, particularly in industrial environments where large volumes of component images must be processed. Although manual inspection can achieve high accuracy due to human expertise, it suffers from high time costs and low efficiency. Advances in computing and artificial intelligence have enabled automated systems to process large datasets more effectively, resulting in improved accuracy and scalability. As a result, data-driven methods are gradually replacing traditional manual approaches [5].

## 2. LITERATURE SURVEY

Deniz, et al. [6] Developed a real-time defect detection framework for metal parts with holes, optimized for deployment on a Raspberry Pi 5 edge device. They fine-tuned and evaluated three DL models ResNet50, EfficientNet-B3, and MobileNetV3-Large on a grayscale image dataset (43,482 samples) containing various hole defects and imbalances. Through extensive data augmentation and class-weighting, the models achieved near-perfect binary classification of defective vs. non-defective parts. Notably, ResNet50 attained 99.98% accuracy (precision 0.9994, recall 1.0000), correctly identifying all defects with only one false alarm. MobileNetV3-Large and EfficientNet-B3 likewise exceeded 99.9% accuracy, with slightly more false positives, but offered advantages in model size or interpretability. Gradient-weighted Class Activation Mapping (Grad-CAM) visualizations confirmed that each network focuses on meaningful geometric features (misaligned or irregular holes) when predicting defects, enhancing explainability. Wang, et al. [7] Introduced an industrial anomaly-detection method based on component-level feature enhancement. This method introduced a component-level feature-enhancement module, which optimizes feature matching by calculating the structural similarity between global coarse-grained confidence features and local fine-grained confidence features, thereby generating enhanced feature maps to improve the model's detection accuracy for minor defects and local anomalies. Additionally, they proposed a region-segmentation method based on multi-layer piecewise thresholds, which effectively distinguishes between foreground and background in confidence maps, circumvents background interference and ensures the integrity of structural information of foreground components. Min, et al. [8] Aimed to further enhance its diagnostic capabilities by focusing on symmetrical components. Three-phase stator current signals are converted into zero, positive, and negative sequence components, and their time-domain feature vectors are systematically integrated into a single image representation. A Convolutional Neural Network (CNN) is then employed for fault classification.

The proposed method is model-free, requiring no explicit motor model, which offers greater flexibility compared to model-based techniques. Validation experiments were conducted on a rotor kit test bench under seven different conditions (one healthy condition and six mechanical/electrical fault conditions), with fault severities chosen to reflect practical scenarios. The symmetrical components-based image classification method demonstrated superior performance, achieving 99.76% classification accuracy and outperforming a widely used Short-Time Fourier Transform (STFT)-based spectrogram approach.

Morales Matamoros, et al. [9] Presented a systematic review of AI implementations whose target is to enhance production processes within Industry 4.0 and 5.0. The main methods analysed are DL, artificial neural networks, and principal component analysis, which improve defect detection, process automation, and predictive maintenance. The manuscript emphasizes AI's role in live auto part tracking, decreasing dependence on manual inspections, and boosting zero-defect manufacturing strategies. The findings indicate that AI quality control tools, like CNN for computer vision inspections, considerably strengthen fault identification precision while reducing material scrap. Furthermore, AI allows proactive maintenance by predicting machine defects before they happen. Rahmati, et al. [10] Developed a multimodal DL framework that integrates visual, acoustic and vibration signals to enable real-time, robust defect recognition in industrial components. Design/methodology/approach by fusing features from CNN for image data, recurrent neural networks (RNNs) for acoustic sequences and signal transformers for vibration time series, our architecture captures cross-modal correlations and temporal dependencies that are often overlooked in unimodal systems. The framework is trained and evaluated on a custom-built dataset comprising synchronized visual, audio and accelerometer recordings from industrial processes, encompassing both surface and internal defect types. Findings Experimental results on a simulated dataset demonstrate that the proposed model significantly outperforms unimodal baselines and conventional ML approaches, achieving up to 94.7% classification accuracy with minimal latency, suggesting potential suitability for deployment on edge devices, though real-world validation is needed to account for environmental complexities like noise and sensor drift.

Antosz, et al. [11] Focused on the identification of critical quality issues, including cracks, scratches, and dimensional deviations, which have been observed in the final stages of machining. A variety of classification algorithms, including neural networks (NNs), bagged trees (BT), and support vector machines (SVMs), were employed to efficiently analyse and predict defects. The results show that neural networks achieved the highest accuracy (94.7%) and the fastest prediction time, thereby underscoring their efficiency in processing complex production data. The BT model demonstrated stability in its predictions with a slower prediction time, while the SVM model exhibited superior training speed, though with slightly lower accuracy. They proposed that optimising key process parameters, such as temperature, machining speed, and the type of coolant used, can markedly reduce the prevalence of production defects. Rydzy, et al. [12] Developed an innovative software framework with AI capabilities to predict the quality of automobiles at the end of the production line. By utilizing ML techniques, this framework aims to prevent defective vehicles from reaching customers, thus enhancing production efficiency, reducing costs, and shortening the manufacturing time of automobiles. The principal results demonstrate that the predictive quality inspection framework significantly improves defect detection and supports personalized road tests. The major conclusions indicate that integrating AI into quality control processes offers a sustainable, long-term solution for continuous improvement in automotive manufacturing, ultimately increasing overall production efficiency. The economic benefit of our solution is significant. Currently, a final test drive takes 10–30 min, depending on the car model. If 200,000–300,000 cars are produced annually and our data prediction of quality saves 10 percent of

test drives with test drivers, this represents a minimum annual saving of 200,000 production minutes.

ELGhadoui, et al. [13] Aimed to explore and to verify the efficacy of three DL architectures InceptionV2, ResNet50, and Inception-Resnet unexplored in previous research on defect detection in the field of injection moulding. The methodology adopted includes two essential steps to achieve the desired objective. The first step consists of training and testing the three RCNN architectures retained on a small data set after having determined the best values of three hyperparameters considered learning rate, momentum, and number of iterations allowing the obtaining of a better detection accuracy. The second step consists of improving the architecture of the best model obtained here Inception v2 by using its last version v3, to consider and tune the values of additional hyperparameters Solver and Batch size—and to use a training large dataset after adding other parts and proceeding with the different data augmentation techniques. Lutfun Nahar, et al. [14] Investigated various calibration approaches to fine-tune the model confidence. To make the model more reliable, a rule-based approach is incorporated to classify defects based on confidence scores. Finally, a human-in-the-loop system is integrated to inspect the misclassified samples. Our results demonstrate that the model's performance and confidence are expected to improve further when many misclassified samples, along with human feedback, are used to retrain the network.

### 3. PROPOSED SYSTEM

The proposed methodology presents a structured, data-driven framework for detecting defects in industrial component images, aiming to enhance accuracy, efficiency, and reliability in quality assessment. It follows a comprehensive pipeline that begins with image acquisition and proceeds through preprocessing, feature extraction, model training, evaluation, and prediction, ensuring systematic data handling and analysis. The system integrates DL and ML techniques within a unified architecture, enabling robust recognition of complex visual patterns in industrial environments. A user-friendly interface allows users to upload images either individually or in bulk, serving as the central control point for executing all operations, with inputs transmitted to the backend as structured requests as shown in fig. 2. The backend processing environment acts as the orchestration layer, managing data flow, model execution, inference, and result generation while ensuring smooth communication between components. The raw input consists of diverse industrial images containing both defective and non-defective samples with variations in lighting, texture, and orientation, forming the basis for training and testing. Preprocessing standardizes the data through resizing, normalization, and noise reduction, converting images into consistent tensor formats suitable for further analysis. Feature extraction is performed using CNN, which captures high-level representations such as edges, textures, and defect-specific patterns like cracks or discoloration. These extracted features are then utilized in a multi-model classification framework, including a hybrid CLD model which combines CNN with LR model for primary prediction and baseline models such as KNN and DT for performance comparison. The system also supports multi-output classification, enabling detection of both primary defect categories and finer subcategories. Predictions are generated with associated confidence scores and displayed in real time through the interface, facilitating immediate interpretation by operators.

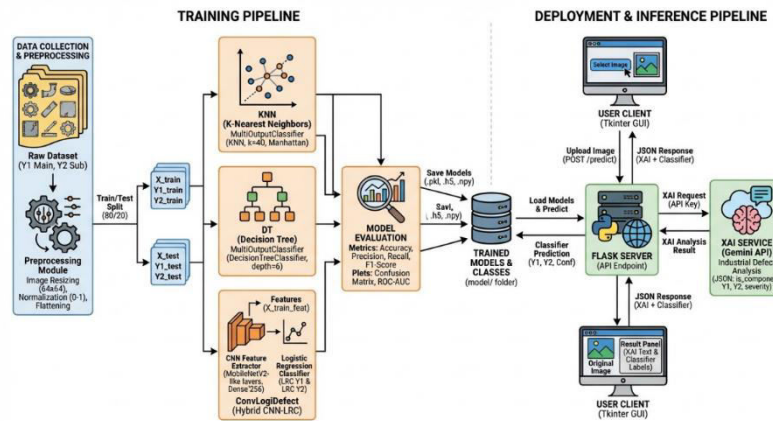


Fig. 2: Proposed system architecture.

Model evaluation is conducted using key metrics such as accuracy, precision, recall, and F1-score, along with confusion matrices and ROC curves to assess classification performance. Comparative analysis helps identify the most effective model for deployment in industrial scenarios. The architecture further incorporates secure authentication mechanisms to control access and maintain system integrity within manufacturing environments. Additionally, the system is designed for scalability, allowing seamless integration into high-volume production lines. It supports both real-time prediction for operational use and offline analysis for research and optimization. Overall, the framework ensures consistent, reliable, and efficient defect detection by combining advanced learning techniques with practical deployment considerations.

### 3.1 CLD model

The hybrid CLD model combines deep feature learning with classical probabilistic classification to achieve accurate industrial defect identification. In this approach, the CNN first processes the input image and extracts meaningful high-level features that represent shapes, textures, and defect patterns. These extracted features are then passed to LR, which performs the final classification into main defect categories and subcategories. This two-stage architecture allows the system to benefit from CNN’s ability to understand visual patterns and LR’s structured, reliable decision boundaries. By integrating both methods, as shown in fig 3. the model achieves strong generalization and improved classification performance across different defect types.

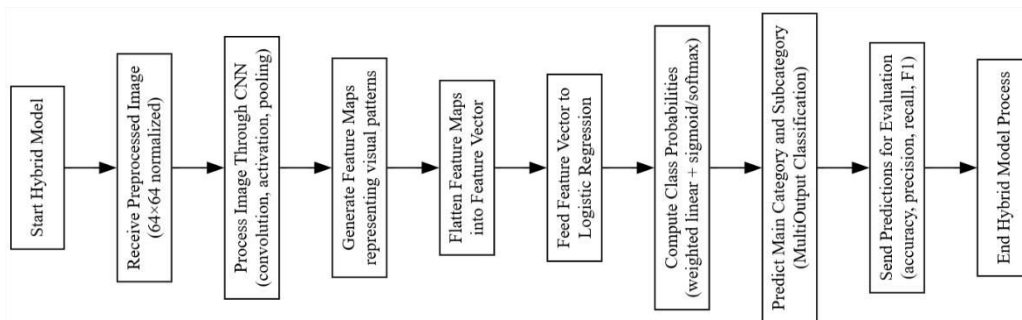


Fig. 3: CLD model internal workflow.

**Receiving Pre-processed Images:** The hybrid model begins by receiving the uniformly resized and normalized images from the preprocessing stage. These images provide consistent input across all samples, making feature learning easier. Each image is prepared in a structured and standardized form for effective processing.

**Extracting Deep Features Using CNN:** The CNN processes the image through convolution, activation, and pooling layers to capture visual patterns. As the image passes through these layers, hierarchical features representing edges, shapes, and textures are learned. The output of the feature layer becomes a compact numerical representation of the image.

**Flattening and Formatting Feature Vectors:** The extracted feature maps are flattened into a one-dimensional vector suitable for LR. This conversion ensures that the learned visual features are fed to the classifier in a numerical format. The resulting vectors act as high-quality descriptors of the defect image.

**Feeding Feature Vectors to LR:** The flattened feature vectors are supplied to the LR model as input. These vectors serve as the basis for generating probability-based decisions. LR analyses how strongly each feature contributes to differentiating between defect classes.

**Computing Class Probabilities:** LR calculates weighted sums of features and transforms them into probabilities. Each probability corresponds to how likely the image belongs to a specific defect category. This creates a stable and interpretable mapping from feature values to class labels.

**Producing Main Category and Subcategory Predictions:** With the MultiOutputClassifier setup, LR produces two outputs simultaneously. One output predicts the main defect category, while the other predicts the specific subcategory. This dual prediction mechanism supports the hierarchical nature of industrial defect classification.

**Forwarding Predictions for Evaluation:** The hybrid model sends the predicted labels to the evaluation module to compute performance metrics. Accuracy, precision, recall, and F1-score are calculated to measure classification quality. These metrics help assess the model's real-world reliability and compare its performance with other models.

#### 4. RESULTS AND DISCUSSION

Fig. 4 illustrates the performance evaluation of the CLD model for main class classification using both the confusion matrix and ROC-AUC curves. The confusion matrix shows that 126 samples are correctly classified as machinery defects, 120 samples as paint defects, and 166 samples as weld defects, with zero misclassification across all classes, indicating perfect prediction performance. This strong diagonal dominance reflects the model's high accuracy and stability in distinguishing between major defect categories. The ROC-AUC curves further depict the model's discriminative capability, where all three classes achieve an AUC value of 1.00, confirming optimal separability. These results collectively indicate that the model is highly reliable and effective for primary-level defect classification in industrial applications

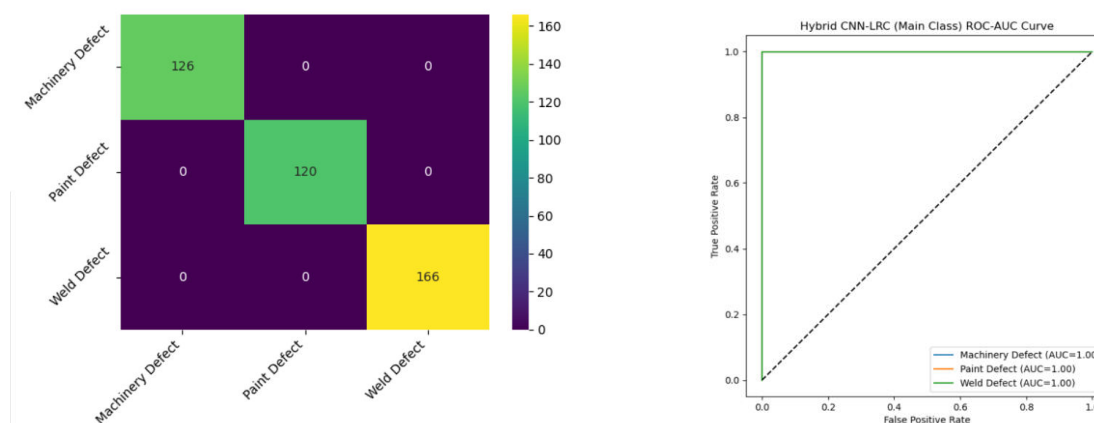


Fig. 4: Obtained confusion matrix and ROC-AUC curve main class for CLD.

Fig. 5 depicts the confusion matrix for sub-class classification, representing the model’s ability to identify fine-grained defect categories with high precision. The matrix shows several classes with correct predictions such as 21, 20, and 41 samples concentrated along the diagonal, indicating strong classification performance across multiple defect types. Most sub-classes exhibit accurate predictions in the range of 20–21 samples, while one class achieves a higher count of 41, demonstrating balanced learning. The presence of very few off-diagonal values indicates minimal confusion between similar defect categories. This confirms that the model effectively captures subtle differences in visual patterns such as corrosion, cracks, blistering, and other anomalies. The figure highlights the strength of deep feature extraction in enabling precise sub-category differentiation.

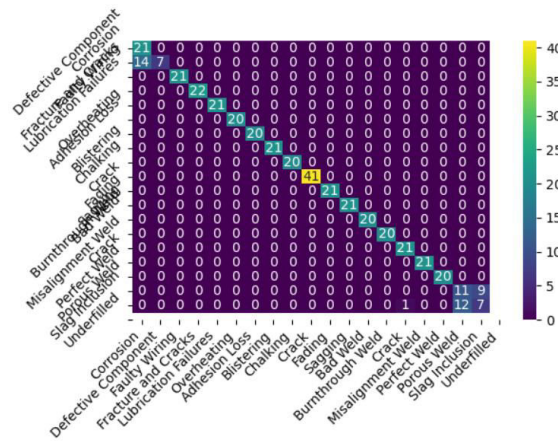
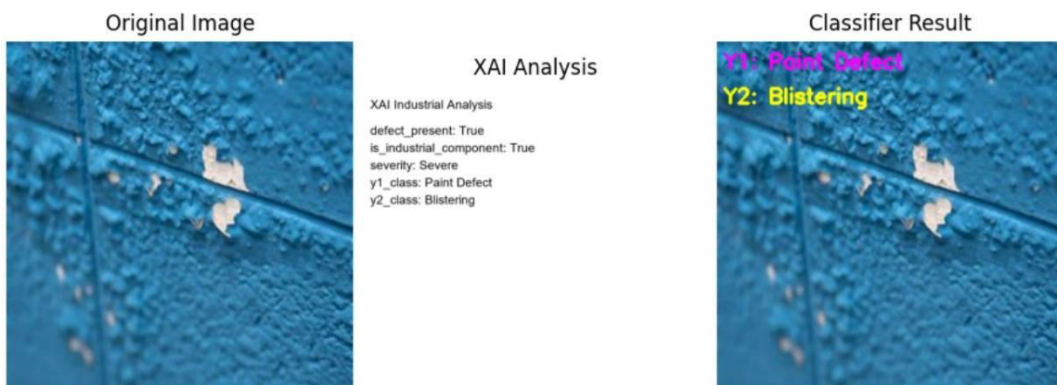


Fig. 5: Obtained confusion matrix of sub class for Model CLD.

Fig. 6(a) illustrates the multi-output prediction result for a sample image containing a surface-level paint defect. The model correctly identifies the primary class as paint defect and further classifies the sub-category as blistering, indicating localized surface degradation. The prediction also marks the defect as severe, highlighting the intensity of the damage present in the component. The consistency between visual characteristics and predicted labels demonstrates the effectiveness of feature extraction. The output confirms that the model can accurately detect coating-related issues.



(a)

Fig. 6(b) depicts the prediction result for an industrial component affected by a machinery-related defect. The model classifies the primary category as machinery defect and identifies the sub-class as corrosion, indicating material degradation due to environmental or chemical exposure. The prediction further labels the severity as severe, suggesting significant structural impact. The model successfully captures texture variations and irregularities associated with corrosion patterns. The

alignment between observed damage and predicted output validates the robustness of the classification approach.

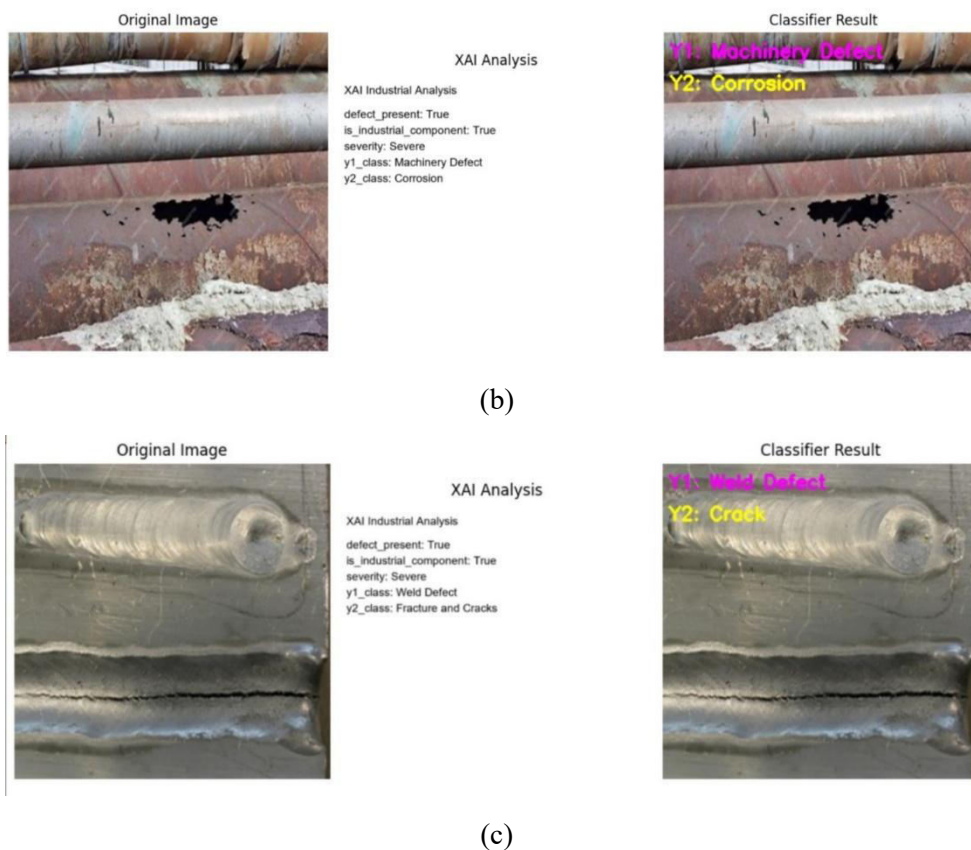


Fig. 6: Multi-Output Prediction of Industrial Defects on Sample Test Images.

Fig. 6(c) illustrates the prediction outcome for a weld-related defect present in the sample image. The model accurately detects the primary class as weld defect and further classifies it under the subcategory fracture and cracks. The severity is again indicated as severe, reflecting the critical nature of the defect in welded joints. The prediction demonstrates the model's ability to capture fine linear discontinuities and structural breaks. The consistency of results confirms strong learning of weld-specific defect patterns.

The comparative analysis evaluates the performance of multiple classification models implemented within the system, including KNN, DT, and the proposed CLD model. Based on confusion matrices and performance metrics such as accuracy, precision, recall, and F1-score, it is evident that traditional ML approaches like KNN and DT struggle to effectively differentiate between defect categories, resulting in significant misclassifications. KNN shows poor generalization, predicting most samples into a single class, while the DT exhibits inconsistent performance across categories, indicating its sensitivity to dataset complexity and feature distribution. In contrast, the CLD model, which integrates convolutional feature extraction with logistic-based classification, demonstrates superior performance with near-perfect accuracy and balanced precision and recall across all defect categories. This highlights the effectiveness of deep feature representation in capturing subtle texture variations and structural patterns within industrial components.

Table. 1: Performance Comparison (Main Class)

Model	Accuracy	Precision	Recall	F1-Score
KNN model	0.7476	0.7757	0.7297	0.6962
DTC model	0.9684	0.9685	0.9685	0.9681
hybrid CLD model	1.0000	1.0000	1.0000	1.0000

Table 1 presents the performance evaluation of different models for main class classification. The KNN model achieved moderate results with an accuracy of 0.7476, indicating limitations in handling complex feature patterns. The DTC model demonstrated significantly improved performance with an accuracy of 0.9684 and consistently high precision, recall, and F1-score, reflecting strong classification capability. The hybrid CLD model achieved perfect scores across all evaluation metrics, indicating highly accurate and stable predictions. This performance highlights the effectiveness of combining deep feature extraction with efficient classification. The results confirm that the hybrid approach outperforms traditional models in identifying primary defect categories.

Table. 2: Performance Comparison (Sub Class)

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

Table 2 illustrates the performance of models for sub class classification, which involves finer-grained defect identification. The KNN model showed low performance with an accuracy of 0.4272, reflecting difficulty in distinguishing closely related defect types. Similarly, the DTC model exhibited comparable accuracy with slight improvements in precision but lower recall and F1-score. In contrast, the hybrid CLD model achieved a high accuracy of 0.9126 along with strong precision, recall, and F1-score values. This indicates its superior ability to capture detailed patterns and subtle variations in defect features. The results demonstrate that the hybrid model significantly improves classification performance for complex sub class scenarios compared to traditional approaches.

## 5. CONCLUSION

This research presented an intelligent defect detection system that integrates DL and ML techniques for accurate and efficient classification of industrial defects. The hybrid CLD model effectively combined CNN-based feature extraction with LR-based classification, resulting in superior performance compared to traditional models such as KNN and DTC. The system demonstrated high accuracy in both main class and sub class predictions, ensuring reliable identification of defect types. The inclusion of a Tkinter-based GUI enabled smooth interaction, real-time prediction, and practical usability in industrial environments. The overall implementation reduced manual inspection efforts while improving consistency and speed. The results confirmed that the proposed system achieved robust, scalable, and high-performance defect detection suitable for modern automation needs.

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