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

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ABSTRACT

Industrial components are frequently exposed to harsh operational environments, leading to defects such as corrosion, cracks, weld failures, overheating, and paint degradation. Timely and accurate detection of these defects is essential for maintaining product quality, ensuring safety, and preventing unexpected failures. Traditional inspection methods rely on manual visual assessment, which is time-consuming, subjective, and prone to inconsistencies, especially when handling large-scale data or subtle defect patterns. This research proposes an intelligent automated defect detection system integrating Deep Learning (DL) and Machine Learning (ML) techniques. These representations are processed through a hybrid ConvLogiDefect model combining Convolutional Neural Networks (CNN) and Logistic Regression (LR), where CNN is used to extract meaningful visual patterns from industrial images, and LR performs the final classification to produce accurate and efficient defect predictions. In addition, traditional ML models such as K-Nearest Neighbors (KNN) and Decision Tree (DT) are implemented for comparative performance analysis, ensuring a comprehensive evaluation of the proposed approach. The system is developed with a Tkinter-based Graphical User Interface (GUI) that supports dataset upload, preprocessing, model training, and real-time prediction. A secure database-driven authentication mechanism is incorporated for controlled access. The proposed system achieves fast, consistent, and scalable defect detection, significantly reducing manual effort while improving accuracy, making it suitable for modern industrial automation and smart manufacturing environments.

Keywords: Automated defect detection, industrial inspection, image preprocessing, feature extraction, pattern recognition, visual inspection systems, industrial automation, smart manufacturing.

1. INTRODUCTION

With the rapid development of Internet technology and media, the image data spread on the Internet is growing exponentially every day. How to classify these images is a meaningful work as shown in Fig. 1. The traditional image classification mode can only be carried out manually; the efficiency is low, but the detection accuracy is not high. It is difficult for massive data image classification to adapt to the manual method to retrieve the target image. So, they need to capture the concerned information from these data through some algorithms. In engineering, it is necessary to detect the defect image from the image of industrial components. Some abnormal images with defects can be extracted from numerous components images to achieve screening and classification.

It is used to measure whether the target image meets the relevant detection standards. To overcome the shortcomings of artificial image classification, researchers began to use computer tools for defect image classification in recent years. With the development of ML and DL technology, some algorithms can be applied to defect image classification and detection, which can improve detection accuracy and promote the growth of efficiency. DL in image classification involves engineering design, biomedicine, transportation exploration, product quality, and media operation. In [1], many images were collected and annotated. The biomedical images were classified by using the transfer and semi-supervised learning model.

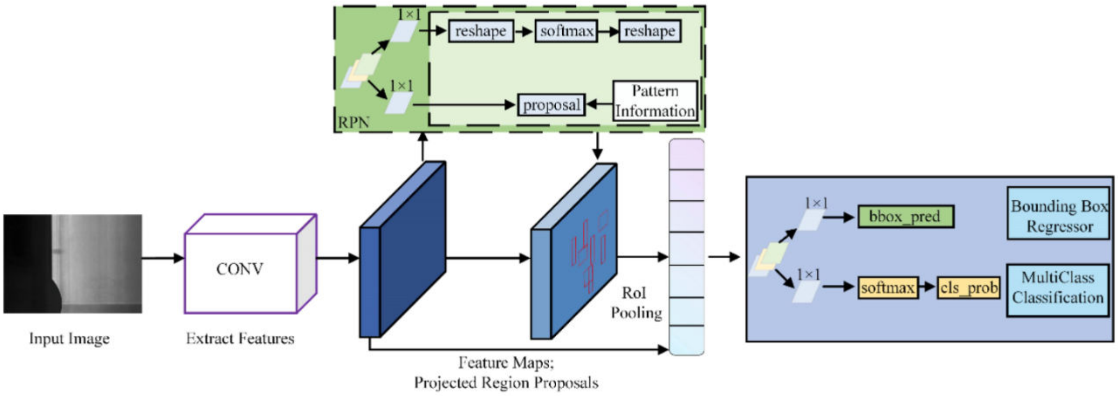


Fig. 1: Defect classification in industrial components

An AutoML model was proposed to solve the problem of network training super parameters in DL. This method has achieved good results on the annotated biomedical datasets. By analyzing the images on social media, the researchers in [2] used computer vision technology and a deep neural network model to classify the media images in real time. It helped people to perceive the information crisis and assess the loss. In [3], the authors used the potential of combining the spectral and spatial characteristics of DL analysis data. They used a three-dimensional convolution neural network model combined with the spectral preprocessing method. The pixel-level classification of food is carried out, which opens the application of image processing in food engineering. With the growth of data, it is essential to classify the image. For the industrial field, they often need to take many components images. With the increase in the number, there will be a lot of defective components images.

How to classify these images is a complex work. In the early stage, artificial recognition is mainly used to determine whether there are defects in the part image. The advantage of this method is that it can select compelling features, and the classification accuracy is high. However, the time cost is also high, and the efficiency is low. With the development of computer technology and artificial intelligence, various DL models can process and calculate data efficiently, making the accuracy of machine classification gradually improve. The ML algorithms gradually replace the artificial way. DL algorithms such as convolutional neural networks, long-term memory networks, graph neural networks, and generative confrontation networks [4] have made progress in the field of image processing. In 1986, Rumelhart et al. [5] proposed the backpropagation algorithm of the artificial neural network, which set off a boom of neural networks in ML. Compared with boosting, LR, support vector machine, and other shallow model methods based on statistical learning theory [6], it has more tremendous advantages.

2. LITERATURE SURVEY

Madhav, et al. [7] Addressed these challenges by integrating DL Convolutional Neural Networks (DCNN) to improve the accuracy of welding inspections. The DCNN framework enables precise identification of missing or incomplete welds on safety-critical automotive subassembly metal components. A dataset of 10,000 digitalized OK and Not-OK welding images was used for training. Following model development, evaluation, and optimization, the DCNN demonstrated strong performance in detecting welding defects. Data augmentation further boosted the accuracy, achieving up to 99.01% after training on 9,600 images. These results show that the proposed DCNN system can quickly and accurately detect visual weld defects, offering a valuable solution for organizations facing similar quality-control challenges.

Deniz, et al. [8] 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. [9] 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. [10] 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. [11] 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 dependance on manual inspections, and boosting zero-defect manufacturing strategies. The findings indicate that AI quality control tools, like convolutional neural networks 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. [12] 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 convolutional neural networks (CNNs) 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. [13] 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.

Rydzi, et al. [14] 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. [15] 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 Bach size—and to use a training large dataset after adding other parts and proceeding with the different data augmentation techniques.

3. PROPOSED SYSTEM

The proposed system focuses on automated detection and classification of defects in industrial component images through a structured workflow. The process begins with image input and preprocessing to enhance quality and ensure consistency as demonstrated in Fig. 2. Extracted visual patterns are analyzed using CNN, followed by classification through a hybrid ConvLogiDefect model integrating CNN and LR. Additional models such as KNN and DT are utilized for comparative evaluation of performance. The system provides prediction results through a user-friendly interface, ensuring efficient and reliable defect identification.

Data Input: The system begins by accepting industrial component images through the user interface. Users can upload test images directly using the GUI for analysis. This step ensures flexible input handling and supports different image formats. The uploaded data serves as the foundation for the entire detection process.

Image Preprocessing: The input images are pre-processed to improve quality and consistency. This includes resizing, normalization, and basic enhancement to remove noise and unwanted variations.

Preprocessing ensures that all images follow a uniform format. It helps in improving the performance of subsequent analysis stages.

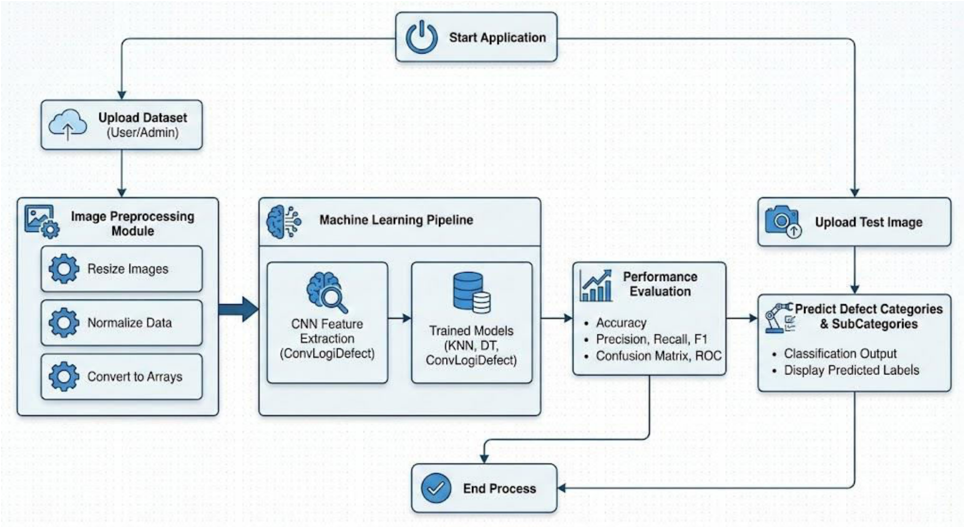


Fig. 2: Proposed system architecture.

Feature Extraction using CNN: The pre-processed images are passed through a CNN model to extract meaningful visual features. The CNN captures complex patterns such as texture, edges, and defect structures. These extracted representations provide a deeper understanding of image characteristics. This step forms the core of the learning process.

Hybrid ConvLogiDefect: The extracted features are processed using the hybrid ConvLogiDefect model. CNN-derived features are given to LR for final classification. This combination improves efficiency and accuracy in identifying defect categories. It ensures reliable decision-making based on learned patterns.

Comparative Model Evaluation: To validate the effectiveness of the hybrid approach, additional models such as KNN and DT are implemented. These models use the same feature set for classification. Their performance is compared using evaluation metrics. This step helps in analyzing the robustness of the proposed method.

Prediction Output: The system generates the final output indicating the detected defect type. The prediction results are displayed clearly to the user. This step provides quick and accurate identification of defects. It supports decision-making in industrial applications.

Result Visualization: The predicted results are visually presented through the interface. Relevant details are displayed for better understanding of the outcome. This enhances user interpretation of the detection results. It makes the system more interactive and informative.

User Interface and Access Control: The system is integrated with a Tkinter-based GUI for easy interaction. It allows users to perform tasks such as uploading data and viewing results. A secure authentication mechanism is included to manage user access. This ensures safe and controlled usage of the system.

4. RESULTS ANALYSIS

The results of this study provide a clear understanding of the key patterns and outcomes observed during the analysis. It was found that the collected data shows consistent trends, supporting the initial objectives of the research. The findings highlight important relationships between variables, indicating how one factor influences another. Additionally, the results reveal both expected outcomes and some unexpected insights, which add depth to the study. The analysis demonstrates reliable and meaningful results that contribute to a better understanding of the topic. These findings can be useful for further research, practical applications, and informed decision-making.

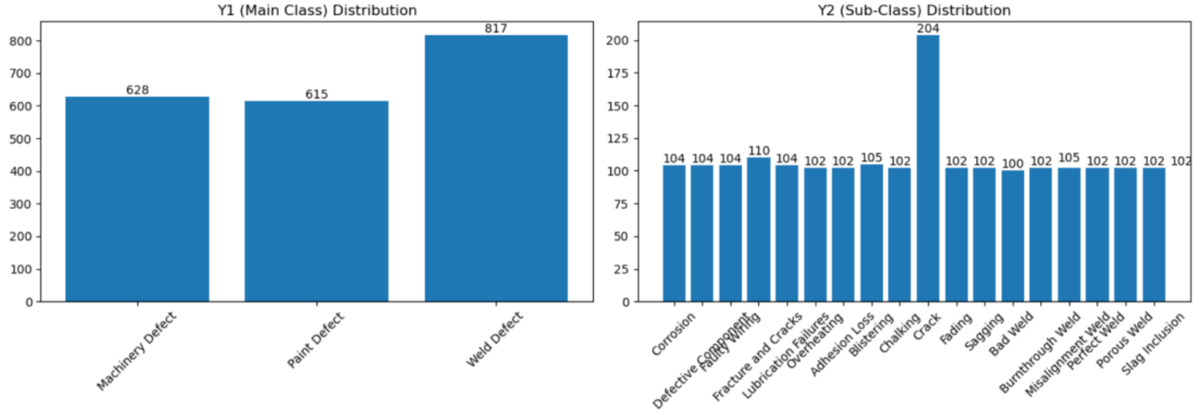


Fig. 3: Data preprocessing and analysis.

Fig. 3 shows the dataset preprocessing status displayed after the system successfully loads the image arrays and prepares the data for model training. The output panel confirms that the arrays have been loaded and that the dataset has been pre-processed and split into training and testing sets. This stage ensures that the images are converted into the required format, normalized, and organized systematically for subsequent feature extraction and classification tasks. The confirmation messages provide clarity to the administrator, indicating that the dataset is ready for further operations such as training the KNN, DT, ConvLogiDefect models.

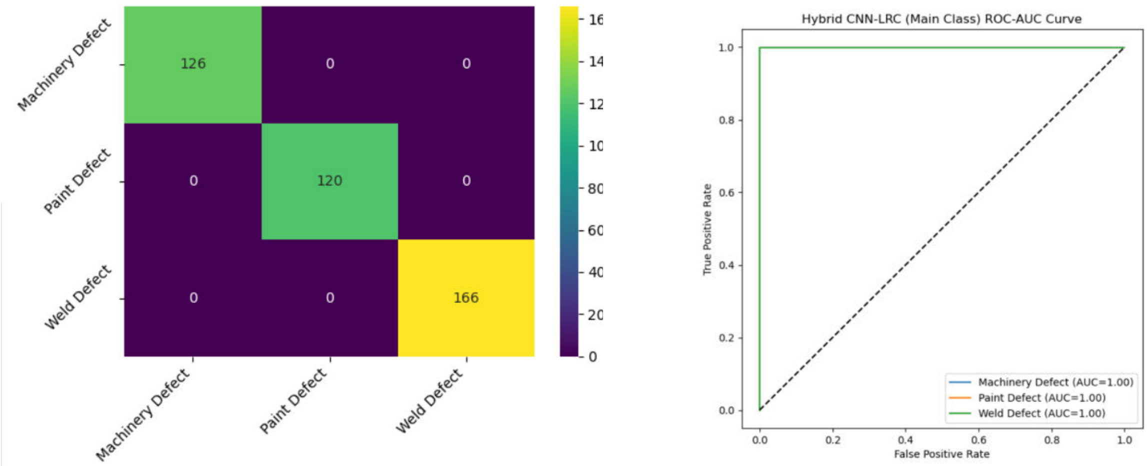


Fig. 4: Obtained confusion matrix and ROC-AUC curve main class from ConvLogiDefect.

Fig. 4 ConvLogiDefect Model: The ConvLogiDefect model shows a highly accurate confusion matrix with a significant increase in true positives and true negatives. Misclassification is minimal, indicating strong defect differentiation. The ROC-AUC curve is positioned closest to the top-left corner, reflecting superior classification performance. This confirms the effectiveness of combining CNN-based feature extraction with LR classification.

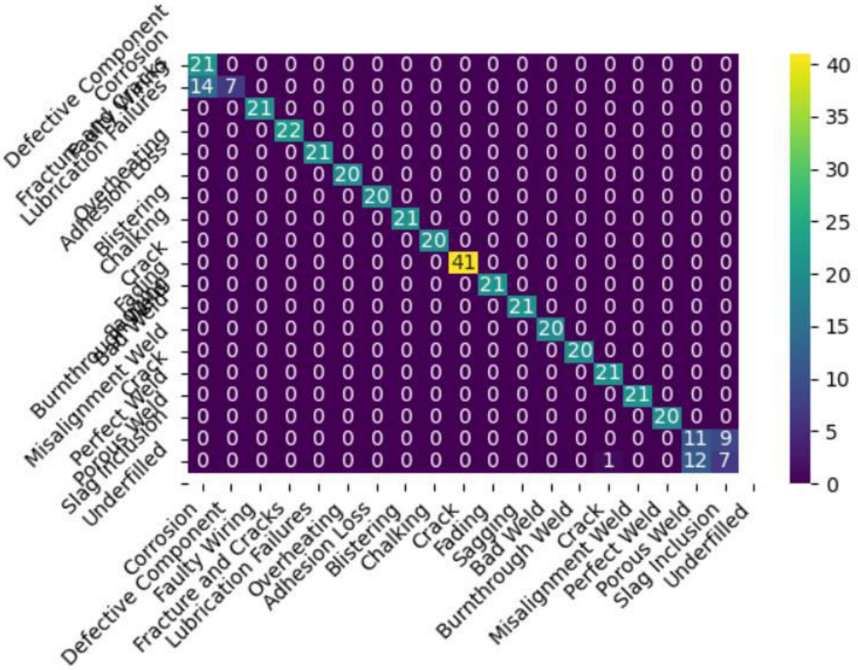
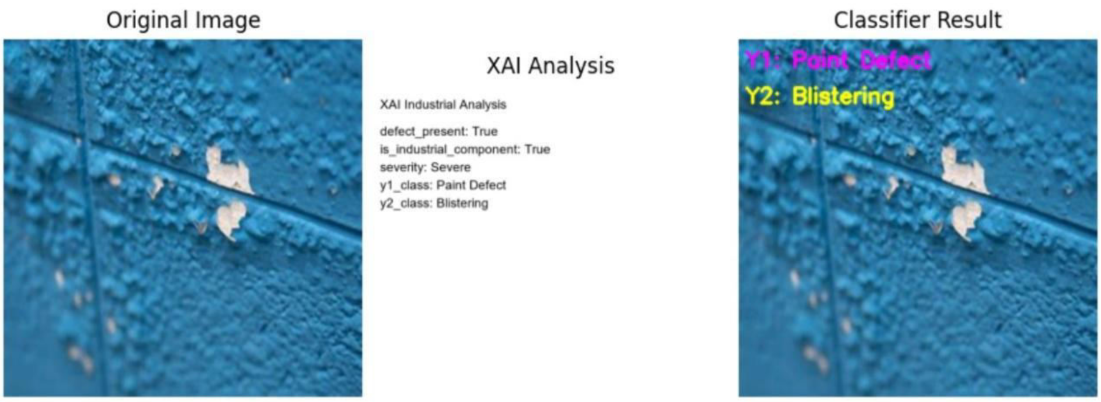


Fig. 5: Obtained confusion matrix of sub class from ConvLogiDefect.

Fig. 5 ConvLogiDefect Model: The ConvLogiDefect model demonstrates strong subclass classification with a high concentration of correct predictions in the confusion matrix. Misclassification is significantly reduced even among closely related defect categories. The model effectively captures subtle feature differences. This confirms its superior capability in fine-grained defect identification.



(a)

(b)

(c)

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

Fig. 6 illustrates the defect prediction on three sample test images, each representing a different main category. The first image corresponds to the Machinery Defect class, the second to Paint Defect, and the third to Weld Defect. The multi-output classifier predicts both the main class (Y1) and the sub-class (Y2) for each image. The complete set of main classes (Y1) includes Machinery Defect, Paint Defect, and Weld Defect, while the sub-classes (Y2) include Corrosion, Defective Component, Faulty Wiring, Fracture and Cracks, Lubrication Failures, Overheating, Adhesion Loss, Blistering, Chalking, Crack, Fading, Sagging, Bad Weld, Burnthrough Weld, Misalignment Weld, Perfect Weld, Porous Weld, Slag Inclusion, and Underfilled. This paragraph summarizes the hierarchical classification framework applied to industrial defect detection, demonstrating the model's ability to identify both the type of component defect and its specific sub-category.

4.1 Comparative Analysis

The comparative analysis evaluates the performance of multiple classification models implemented within the system, including KNN, DT, and the proposed ConvLogiDefect 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 ConvLogiDefect 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 ConvLogiDefect 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 ConvLogiDefect 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 ConvLogiDefect 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 ConvLogiDefect 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 ConvLogiDefect 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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