An Interpretable and Data-Efficient Learning Paradigm for Defect Classification in Industrial Visual Inspection Systems

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ABSTRACT

Industrial components are continuously exposed to demanding operational environments, making them vulnerable to defects such as cracks, corrosion, weld imperfections, overheating, and surface degradation. Early and accurate defect detection is essential for ensuring operational reliability, improving safety, and reducing maintenance costs. Traditional inspection methods rely heavily on manual assessment, which is often time-consuming, labor-intensive, and prone to inconsistencies. To address these limitations, the proposed framework introduces an intelligent industrial defect detection system that combines Deep Learning (DL) and Machine Learning (ML) techniques for automated defect identification and classification. The framework initially employs a hybrid ConvLogiDefect (CLD) model that integrates Convolutional Neural Networks (CNN) for deep feature extraction and Logistic Regression (LR) for defect classification. In addition, conventional ML models, including K-Nearest Neighbors (KNN) and Decision Tree (DT), are implemented to provide comparative performance evaluation. To further enhance detection accuracy, the framework incorporates an advanced TransForestDefectNet (TFD-Net) model based on Data-efficient Image Transformer (DeiT) and Random Forest Classifier (RFC). The DeiT architecture captures high-level transformer-based visual representations, while RFC improves classification robustness and multi-class defect prediction. The system is implemented using a Tkinter-based Graphical User Interface (GUI) that supports dataset upload, preprocessing, model training, visualization, and real-time prediction. Furthermore, a secure authentication mechanism is integrated to restrict unauthorized access. Experimental results demonstrate that the proposed TFD-Net model significantly outperforms CLD, KNN, and DT models, providing a scalable, accurate, and efficient solution for automated industrial defect detection in smart manufacturing environments.

Keywords: Industrial Defect Detection, Deep Learning, Machine Learning, Convolutional Neural Network (CNN), Vision Transformer (DeiT), Smart Manufacturing.

1. INTRODUCTION

The rapid growth of internet technologies, digital platforms, and intelligent sensing systems has resulted in an unprecedented increase in the volume of image data generated and shared across various domains. Consequently, image classification has become a fundamental task in computer vision, enabling the automatic categorization and interpretation of visual information for decision-making and analysis. Traditional image classification approaches largely depend on manual inspection and human expertise, which are often time-consuming, labor-intensive, and prone to inconsistencies when dealing with large-scale image repositories. As image datasets continue to expand in size and complexity, manual methods become increasingly inefficient and unsuitable for real-time processing requirements.

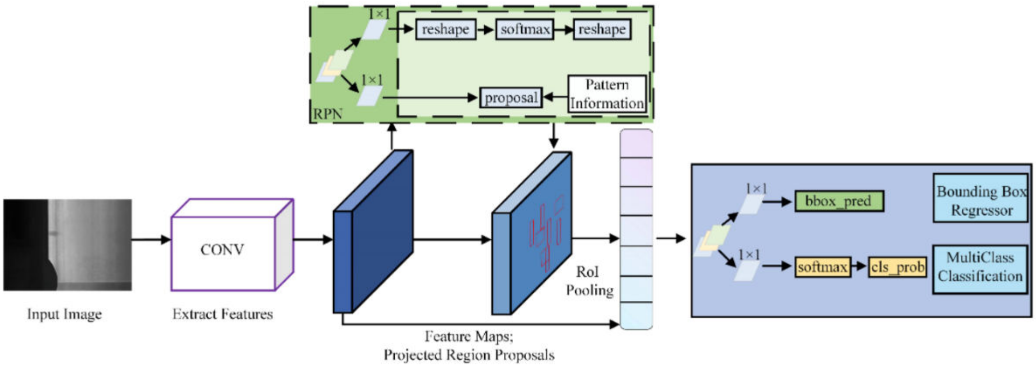


Fig. 1: Defect classification in industrial components

Therefore, automated image classification techniques have emerged as essential solutions for extracting meaningful information from vast collections of visual data while improving efficiency, consistency, and scalability [1]. In industrial environments, image classification plays a critical role in quality assurance and defect inspection processes. Manufacturing components are frequently exposed to harsh operational conditions that can lead to defects such as cracks, corrosion, surface damage, weld imperfections, and structural abnormalities. Accurate identification and classification of such defects are essential for maintaining product quality, ensuring operational reliability, and reducing maintenance costs [2]. However, conventional manual inspection methods are often limited by human fatigue, subjective judgment, and processing delays, making them unsuitable for modern high-volume production systems. Automated defect detection systems provide a more reliable and efficient alternative by enabling rapid analysis of large numbers of component images while minimizing human intervention [3].

Recent advancements in Artificial Intelligence (AI), ML, and DL have significantly transformed image classification and defect detection applications. Advanced learning models are capable of automatically extracting complex visual features, identifying subtle defect patterns, and achieving high classification accuracy across diverse industrial scenarios [4]. These intelligent approaches have demonstrated superior performance compared to traditional techniques and are increasingly adopted in engineering, manufacturing, healthcare, transportation, and quality control applications. As industries continue to embrace smart manufacturing and Industry 4.0 technologies, the development of accurate, scalable, and automated image classification systems has become increasingly important for improving productivity, reducing inspection time, and enhancing overall operational efficiency [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.

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

3. PROPOSED METHODOLOGY

The proposed methodology presents a structured and data-driven framework for detecting defects in industrial component images, with the objective of improving accuracy, efficiency, and reliability in quality assessment. The study follows a comprehensive processing pipeline that begins with image acquisition and progresses through preprocessing, feature extraction, model training, evaluation, and prediction stages. The overall architecture is designed to integrate both DL and ML techniques, as shown Fig. 2 enabling robust analysis of complex visual patterns present in industrial environments. By combining multiple models and evaluation strategies, the framework ensures consistency and reliability in defect classification. The system is capable of handling large-scale image data and supports both real-time prediction and offline analysis, making it suitable for modern industrial applications.

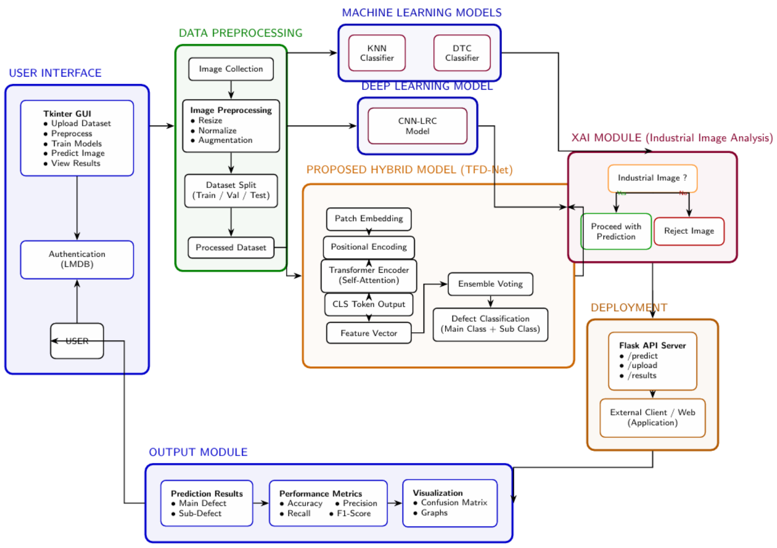


Fig. 2: Proposed system architecture of industrial defect detection system

User Interface (Image Input / Dataset Upload)

- Users provide industrial component images through a graphical interface, supporting both bulk dataset folder uploads and individual test image selection.
- The interface serves as the primary control center for executing preprocessing, model training, and prediction operations.
- All user interactions are transmitted to the backend as structured requests for further processing and analysis.

Backend Processing Environment

- This environment acts as the orchestration layer, controlling the flow of data across the preprocessing, feature extraction, and training modules.
- It manages the lifecycle of the models, including loading weights, executing inference, and generating results.
- The backend ensures seamless communication between the input interface and the analytical output components.

Raw Image Data

- The primary input consists of unstructured images of industrial components collected from various manufacturing sources.
- The data includes both defective and non-defective samples, featuring significant variations in lighting, surface texture, and component orientation.
- This raw data forms the foundational training and testing sets for the analytical pipeline.

Image Preprocessing Module

- To ensure consistency, raw images undergo resizing, normalization, and noise handling.
- All images are standardized to a fixed resolution (e.g., 224x224 or 128x128) to maintain a uniform input shape for the neural network.
- This module converts raw pixel data into normalized tensors suitable for deep feature extraction.

Feature Extraction using Deep Learning

- The system utilizes DieT model to automatically learn and extract high-level visual features.
- The network captures critical patterns such as edges, surface textures, and defect-specific characteristics (e.g., cracks, pits, or discolorations).
- These layers generate compact, high-dimensional feature representations that enable efficient and accurate classification.

Classification and Learning Models

The system employs a multi-model strategy to ensure optimal performance:

- **Hybrid Approach:** Combines DieT-based feature extraction with a RFC head for the final classification task.
- **Baseline Comparison:** Implements traditional models such as KNN, DT and CLD to provide performance benchmarks.

- **Multi-Output Classification:** The models are trained to predict both the primary defect category and specific subcategories, offering a more granular diagnostic report.

Prediction Output and Defect Interpretation

- The system assigns definitive defect labels to the input images at multiple hierarchical levels.
- Prediction results are displayed alongside confidence scores, indicating the model's certainty in its diagnosis.
- Real-time visualization allows operators to immediately see the classification outcome on the user interface.

Model Evaluation and Performance Analysis

- The framework computes rigorous metrics to assess reliability, including:
  - **Accuracy and Precision**
  - **Recall and F1-score**
- Confusion matrices and Receiver Operating Characteristic (ROC) curves are generated to visualize the model's capability to distinguish between different defect types.
- This comparative analysis identifies the most effective algorithmic approach for industrial deployment.

System Integration and Deployment

- The architecture integrates the graphical interface with backend processing and API-based prediction services.
- Secure authentication mechanisms are included to ensure controlled system access within the manufacturing facility.
- The system is designed for scalability, allowing it to be integrated into high-volume production lines for real-world industrial use.

3.1 TFD-NET MODEL

TFD-Net is an advanced hybrid deep learning framework designed for intelligent industrial defect detection and multi-output classification. The model combines transformer-based visual feature extraction with ensemble-based machine learning classification to accurately identify industrial defect categories and their corresponding sub-defect types from component images. By leveraging deep transformer representations and robust classification capabilities, TFD-Net effectively captures complex defect patterns such as cracks, corrosion, weld imperfections, and surface degradations. The framework improves defect detection accuracy, enhances feature learning capability, and supports reliable automated inspection for smart industrial monitoring systems.

Internal working of TFD-Net

1. Industrial Image Acquisition: Industrial component images are collected from different defect categories and sub-defect classes. These images serve as the input data for the TFD-Net framework and contain various structural and surface-level defect patterns required for automated defect analysis.

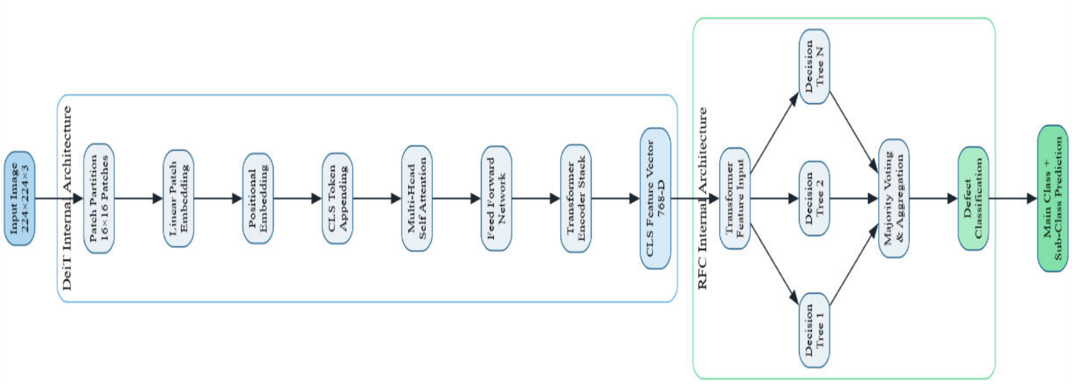


Fig. 3: Internal workflow of TFD-Net

2. Image Resizing and Normalization: The input images are resized into a fixed dimension compatible with transformer processing requirements. Pixel normalization is then applied to convert image intensity values into a standardized range, improving computational stability and helping the model learn features more effectively.

3. Patch Generation from Images: As shown in Fig. 3 the resized image is internally divided into multiple small image patches by the transformer architecture. Each patch represents a local visual region of the industrial component and helps the model analyze detailed defect structures independently.

4. Patch Embedding Conversion: Each image patch is transformed into numerical embedding vectors through linear projection operations. These embeddings convert visual image information into mathematical representations that can be processed by the transformer network for feature learning.

5. Positional Information Encoding: Positional embeddings are added to patch embeddings to preserve the spatial arrangement of image patches. This enables TFD-Net to understand the relative positions of defects and structural patterns present within the industrial image.

6. Self-Attention Feature Learning: The transformer applies multi-head self-attention mechanisms to analyze relationships between all image patches simultaneously. This process allows TFD-Net to focus on critical defect regions and learn both local and global defect characteristics effectively.

7. Deep Transformer Representation: Through multiple transformer encoder layers, the model gradually refines the learned feature representations. These deep representations capture highly discriminative industrial defect information such as texture abnormalities, crack structures, weld inconsistencies, and surface degradations.

8. CLS Token Extraction: After transformer processing, the CLS token representation is extracted from the final hidden layer. This token acts as a compact summary vector containing the overall visual understanding of the entire industrial image and its defect characteristics.

9. High-Dimensional Feature Vector Formation: The extracted CLS token is converted into a high-dimensional deep feature vector representing the industrial component image. This feature vector contains rich semantic information required for accurate defect classification.

10. Random Forest Ensemble Learning: The transformer-generated feature vectors are provided to the Random Forest classifier. Multiple decision trees are created internally, and each tree independently analyzes the extracted defect features to generate classification predictions.

11. Decision Aggregation and Voting: Predictions obtained from all decision trees are aggregated using majority voting and probability-based decision mechanisms. This ensemble strategy improves classification robustness and reduces the chances of incorrect predictions caused by individual tree variations.

12. Main Defect Category Prediction: TFD-Net first predicts the primary industrial defect category, such as machinery defect, paint defect, or weld defect. This high-level classification provides the overall defect type associated with the industrial component.

13. Fine-Grained Sub-Defect Prediction: After predicting the main defect class, the framework simultaneously predicts the detailed sub-defect category, including corrosion, crack, overheating, porous weld, blistering, faulty wiring, and other fine-grained defect conditions.

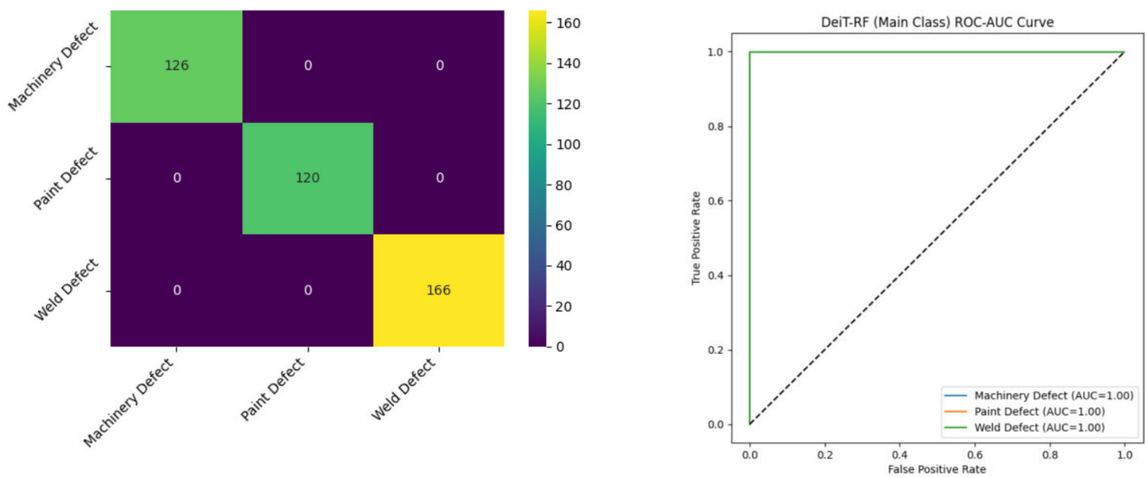
14. Confidence Score Computation: The framework computes probability confidence scores for predicted defect classes. These confidence values indicate the certainty level of the model prediction and help assess prediction reliability during industrial inspection.

15. Final Multi-Output Defect Analysis: The final output generated by TFD-Net includes both the primary defect category and detailed sub-defect classification results. This multi-output analysis provides accurate industrial defect diagnosis for automated quality inspection systems.

4. RESULTS DESCRIPTION

Fig. 9.7(a) presents the confusion matrix generated by the TFD-Net model for main defect classification. The model successfully classified all 126 Machinery Defect samples, 120 Paint Defect samples, and 166 Weld Defect samples into their respective categories. No misclassifications were observed, as all off-diagonal elements contain zero values. Out of the total 412 test samples, every sample was correctly predicted, demonstrating the model's ability to accurately distinguish among different defect classes and achieve perfect classification performance.

Fig. 9.7(b) illustrates the ROC-AUC curves obtained from the TFD-Net model for the three defect categories. The Machinery Defect, Paint Defect, and Weld Defect classes each achieved an AUC value of 1.00, indicating perfect class separability. The ROC curves closely follow the upper-left corner of the graph, corresponding to a True Positive Rate approaching 1.0 and a False Positive Rate close to 0.0. These results confirm the exceptional discriminative capability of the TFD-Net model and its effectiveness in accurately identifying industrial defects with maximum reliability and precision.



(a) (b)

Fig. 4: Obtained (a) confusion matrix and (b) ROC-AUC curve main class from TFD-Net model

Fig. 5 presents the confusion matrix obtained from the TFD-Net model for sub-class defect classification. The matrix demonstrates strong classification performance across most defect categories, with the majority of samples correctly classified along the diagonal. The model correctly identified 21 Corrosion samples, 21 Fracture and Cracks samples, 22 Lubrication Failures samples, 21 Overheating samples, 20 Adhesion Loss samples, 20 Blistering samples, 21 Chalking samples, 20 Crack samples, 41 Fading samples, 21 Sagging samples, 21 Bagging samples, 20 Burnthrough Weld samples, 20 Crack Weld samples, 21 Misalignment Weld samples, 21 Perfect Weld samples, and 20 Porous Weld samples. A small number of misclassifications were observed, particularly for the Defective Component class, where 14 samples were incorrectly classified as Corrosion and 7 samples were correctly identified. Similarly, the Slag Inclusion and Underfilled classes exhibited minor confusion, with 8 Slag Inclusion samples and 15 Underfilled samples correctly classified, while a few instances were misclassified between these two categories. Overall, the confusion matrix indicates that the proposed TFD-Net model achieves highly accurate fine-grained defect recognition while maintaining strong class discrimination across multiple industrial defect types.

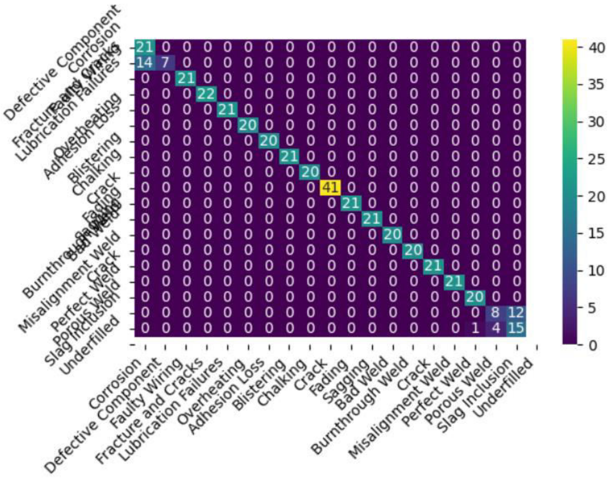


Fig. 5: Obtained confusion matrix of sub class from TFD-Net model

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.

(a)

(b)

(c)

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

The comparative analysis demonstrates the effectiveness of the implemented classification models, including KNN, DT, the hybrid CLD model, and the proposed TFD-Net model. Traditional ML models such as KNN and DT achieved lower performance due to their limited ability to capture complex defect patterns from industrial images. The hybrid CLD model significantly improved classification accuracy by combining CNN-based feature extraction with LR classification, achieving strong performance across all defect categories. However, the proposed TFD-Net model delivered the best overall results by integrating DeiT with RFC for advanced feature learning and robust classification. The model achieved perfect performance in main-class classification and superior results in sub-class classification. These findings highlight the capability of transformer-based feature extraction in capturing discriminative defect characteristics. The TFD-Net outperformed all baseline models and proved to be a reliable solution for automated industrial defect detection.

Table. 3: 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
TFD-Net Model	1.0000	1.0000	1.0000	1.0000

Table 3 presents the performance comparison of different models for main-class defect classification. The KNN model achieved an accuracy of 74.76%, with precision, recall, and F1-score values of 77.57%, 72.97%, and 69.62%, respectively. The DTC model demonstrated improved classification capability, attaining an accuracy of 96.84% and achieving precision, recall, and F1-score values above 96%. The hybrid CLD model further enhanced the classification performance by obtaining perfect scores of 100.00% for accuracy, precision, recall, and F1-score. Similarly, the proposed TFD-Net model achieved 100.00% across all evaluation metrics, indicating flawless classification of the main defect categories. These results confirm that the proposed TFD-Net model provides highly reliable and accurate defect classification, outperforming conventional ML models and matching the performance of the hybrid CLD model.

Table. 4: 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
TFD-Net Model	0.9248	0.9355	0.9202	0.9139

Table 4 presents the performance comparison of different models for sub-class defect classification. The KNN model achieved an accuracy of 42.72%, with precision, recall, and F1-score values of 48.05%, 41.73%, and 39.00%, respectively. Similarly, the DTC model attained an accuracy of 42.72%, while recording precision, recall, and F1-score values of 49.25%, 40.14%, and 38.59%, respectively. The hybrid CLD model significantly improved the classification performance, achieving an accuracy of 91.26%, precision of 91.95%, recall of 90.70%, and F1-score of 90.14%. The proposed TFD-Net model further enhanced the results, attaining the highest accuracy of 92.48%, precision of 93.55%, recall of 92.02%, and F1-score of 91.39%. These findings demonstrate that the transformer-based TFD-Net model provides superior fine-grained defect classification capability, outperforming both conventional ML models and the hybrid CLD model in identifying sub-class defect categories.

5. CONCLUSION

This research presented an intelligent industrial defect detection system that combines DL and ML techniques for accurate defect classification. The framework incorporates KNN, DTC, the hybrid CLD model, and the proposed TFD-Net model for comprehensive performance evaluation. The proposed TFD-Net model, which integrates DeiT and RFC, achieved superior results in both main-class and sub-class defect classification tasks. Experimental findings demonstrated higher accuracy, precision, recall, and F1-score compared to conventional ML models and the baseline CLD model. The Tkinter-based GUI enabled efficient dataset management, model training, and real-time prediction. The proposed TFD-Net framework provides a reliable, scalable, and efficient solution for automated industrial defect detection, supporting smart manufacturing and industrial automation applications.

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