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Multi-scale Deep Learning-based Robust Surface Defect Inspection for Enhancing Industrial Quality Control

P. Vijay Goud[1*], Dayyala Jahnavi[2], Dundigala Anjali[2], Gunti Kamal[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering

[1,2]Kommuri Pratap Reddy Institute of Technology, Ghanpur, Ghatkesar, 501301, Telangana, India.

*Correspondence: P. Vijay Goud (panjala.vijay123@gmail.com)

ABSTRACT

Surface imperfections in metallic, ceramic, and electronic components pose significant threats to structural integrity and brand reputation. Traditional quality control methods largely depend on manual inspection, which suffers from subjectivity, inconsistency, and high operational costs. Earlier automated approaches based on handcrafted features, such as edge detection and histogram-based texture analysis, fail to deliver sufficient robustness in complex industrial settings characterized by varying illumination conditions and diverse defect orientations. To address these limitations, this study introduces a robust hybrid framework that combines deep transfer learning with optimized machine learning classifiers. The proposed system employs the Xception architecture as a deep feature extractor, leveraging depthwise separable convolutions to effectively capture fine-grained surface irregularities while maintaining computational efficiency. The extracted high-dimensional features are then analyzed using multiple classifiers, including Stochastic Gradient Descent (SGD), Passive Aggressive Classifier (PAC), Histogram-based Gradient Boosting (HGB), and Quadratic Discriminant Analysis (QDA). Experimental findings demonstrate that this hybrid approach surpasses Convolutional Neural Network (CNN) inspection techniques in both generalization capability and real-time performance. For practical deployment, the framework is implemented within a Graphical User Interface (GUI), enabling non-technical users to easily upload images and obtain instant defect classification results. Overall, this work offers a scalable and high-precision solution for predictive quality assurance, reducing human error and enhancing productivity in modern smart manufacturing environments.

Keywords: Surface Defect Detection, Smart Manufacturing, Quality Control, Deep Transfer Learning, Xception Architecture.

1. INTRODUCTION

Manufacturing industries heavily rely on the quality and integrity of their products, especially those produced on high-speed production lines. Surface defects such as cracks, scratches, dents, and deformations not only compromise the aesthetic value of products but may also affect their functional performance. Early and accurate identification of such defects is crucial to maintaining high product quality and minimizing waste. Traditional defect detection systems, which are largely based on manual inspection or classical image processing techniques, are often limited by human error, inconsistency, and time inefficiency. These methods are also ineffective when defects are subtle, irregular, or when the production volume is high. To overcome these limitations, advanced computational approaches, particularly those using artificial intelligence and deep learning, are gaining traction in the industry.

According to recent studies, over 30% of product quality issues in the manufacturing industry are due to surface-related defects. The automotive, electronics, and textile sectors report millions of dollars in losses annually due to faulty products escaping the production line or being discarded prematurely. In the steel manufacturing industry alone, defect-related losses amount to over $5 billion globally each year, indicating the urgent need for advanced inspection systems. Current trends in industrial automation show a shift towards intelligent systems powered by computer vision and deep learning. Technologies such as CNNs have shown exceptional performance in object detection and image classification, achieving over 95% accuracy in controlled testing environments. Furthermore, pre-trained models like Xception have reduced the need for extensive training datasets by leveraging knowledge transfer, making deployment more feasible for small and medium enterprises. Data from real-time production environments highlights the challenge: surface defects can vary in size, shape, and texture, making it difficult for traditional algorithms to generalize. This is where deep learning techniques offer a substantial advantage, as they learn hierarchical features from the data itself, improving generalization across varying defect types. Integrating such techniques into production lines not only enhances product quality but also ensures consistency and reduces labor costs.

2. RELATED WORK

The field of industrial defect detection has evolved significantly with the integration of computer vision, deep learning, and automated inspection systems. Early approaches relied on manual inspection and traditional image processing, which lacked accuracy and scalability in complex industrial environments. Recent advancements have focused on deep learning-based models, multi-modal sensing techniques, and real-time intelligent systems to improve detection accuracy, efficiency, and robustness. These developments have enabled automated quality control across various manufacturing domains.

2.1 Multi-Modal and Vision-Based Defect Detection Systems

Advanced inspection systems have incorporated multiple sensing techniques to enhance defect detection. Semitela et al. [1] developed a dual-modal system combining deflectometry and bright light illumination with deep learning models for classifying defective and non-defective surfaces. The study demonstrated that multi-modal fusion improved defect coverage while maintaining low computational complexity. Similarly, Cumbajin et al. [2] proposed a CNN-based real-time defect detection system for ceramic products, achieving high accuracy and reliability in industrial environments. These approaches highlighted the importance of combining imaging techniques with deep learning for robust inspection.

2.2 Deep Learning Architectures for Industrial Inspection

Deep learning models have significantly improved defect detection performance. Yang et al. [3] provided a comprehensive survey of defect detection techniques, categorizing methods based on application domains and highlighting their strengths and limitations. Park et al. [4] implemented a deep learning-based defect detection model in a manufacturing process, demonstrating effective identification of defects with sufficient processing speed for real-time deployment. Deng et al. [5] further enhanced defect detection in weld images using CNNs with preprocessing techniques and transfer learning, achieving high recognition accuracy and eliminating manual feature extraction.

2.3 Intelligent Systems for Cost and Process Optimization

AI-based inspection systems have contributed to reducing operational costs and improving manufacturing efficiency. Shafi et al. [6] developed a defect detection system integrated with statistical process control to analyze rework delays and costs. The study reported significant reductions in time delays and operational expenses, demonstrating the economic benefits of automated inspection systems. These systems ensured early defect detection, reducing the need for reprocessing and improving overall production efficiency.

2.4 Real-Time Detection and Object Detection Models

Real-time performance is critical in industrial environments. Lv et al. [7] proposed an end-to-end defect detection network based on the Single Shot MultiBox Detector, capable of detecting defects of varying scales while addressing data imbalance issues. Yang et al. [9] implemented a real-time defect detection system using YOLO-based models and advanced imaging hardware, achieving high accuracy and extremely low prediction time. These studies emphasized the importance of efficient architectures for high-speed industrial applications.

2.5 Industry 4.0 and Smart Manufacturing Systems

The integration of machine learning with Industry 4.0 technologies has enhanced manufacturing intelligence. Angelopoulos et al. [8] reviewed ML-based solutions for fault detection, highlighting the role of cloud, fog, and edge computing in data acquisition and processing. The study also emphasized human–machine interaction and cybersecurity aspects in smart manufacturing environments. These advancements enabled intelligent decision-making and improved system reliability.

2.6 Advanced Imaging Techniques for Defect Detection

Innovative imaging technologies have improved detection accuracy in complex scenarios. Zhao et al. [10] reviewed infrared thermography (IRT) techniques for detecting defects in photovoltaic panels and electronic components. The study demonstrated that combining IRT with deep learning provided accurate and efficient defect detection. These techniques enabled the identification of hidden defects that are not visible through conventional imaging methods.

2.7 Anomaly Detection and Generative Models

Generative models have been effectively used for detecting anomalies in industrial datasets. Tang et al. [11] proposed a dual autoencoder generative adversarial network (DAGAN) to address data imbalance issues and improve anomaly detection performance. The model demonstrated high accuracy even with limited training data, reducing the cost and effort of data collection and labeling. This approach highlighted the potential of generative models in industrial inspection tasks.

2.8 Fault Detection and Process Monitoring

Fault detection and diagnosis systems play a crucial role in maintaining industrial process stability. Park et al. [12] reviewed traditional and modern fault detection techniques, emphasizing the limitations of conventional methods in capturing complex process dynamics. Wen et al. [13] further analyzed defect detection in steel surfaces, comparing traditional machine learning and deep learning approaches, and identifying challenges related to dataset quality and algorithm performance. These studies provided insights into improving process monitoring systems.

2.9 Specialized Models for Metallic and Small-Sample Defect Detection

Specific industrial applications require tailored detection approaches. Tao et al. [14] introduced a cascaded autoencoder architecture for defect segmentation and classification in metallic components, achieving high robustness and accuracy. Gao et al. [15] addressed small-sample problems using a DCGAN-based data augmentation approach combined with a lightweight CNN model, achieving superior performance compared to traditional models. These methods demonstrated effective solutions for handling limited data scenarios and complex industrial conditions.

2.10 Research Gap

Despite significant advancements in industrial defect detection, several limitations remain. Many existing systems rely heavily on large labeled datasets, making them less effective in small-sample scenarios. Additionally, some models exhibit high computational complexity, limiting their deployment in real-time or resource-constrained environments. There is also a lack of unified frameworks that integrate multi-modal data, real-time processing, and cost-effective deployment strategies.

The proposed system addresses these challenges by developing an efficient, scalable, and real-time defect detection framework that combines advanced deep learning techniques with optimized preprocessing and feature extraction methods. The system ensures high accuracy, reduced computational overhead, and adaptability across various industrial applications.

3. PROPOSED METHODOLOGY

Surface defect detection is a critical aspect of quality control in manufacturing sectors such as automotive, electronics, and metal processing. Conventional inspection approaches, which depend on human evaluation or simple rule-based techniques, tend to be slow, prone to mistakes, and difficult to scale efficiently. With the advancement of Industry 4.0 and the growing adoption of AI in industrial workflows, machine learning and deep learning technologies have become powerful solutions for automated defect identification and classification. These advanced systems improve precision and consistency while lowering costs and increasing overall production efficiency.

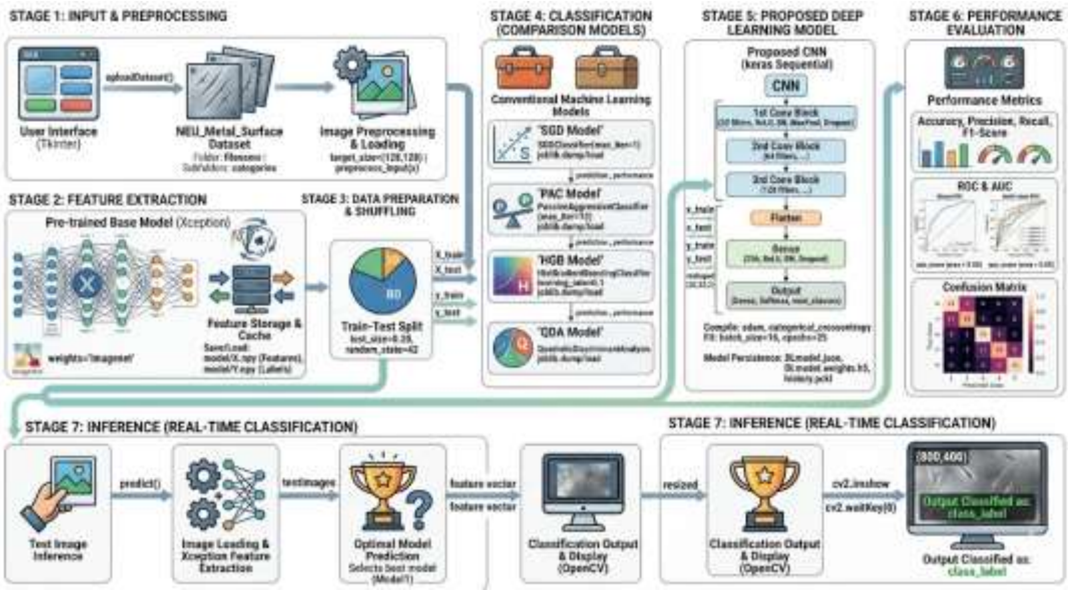

Fig. 1: Proposed system architecture of surface defect detection.

This project presents a hybrid approach combining CNN, Xception-based feature extraction, and traditional machine learning classifiers such as SGD, PAC, and QDA. The system is implemented with a GUI using Python's Tkinter module, allowing users to interactively upload datasets, preprocess them, extract features, train models, and perform real-time predictions on new images as shown in Fig. 1. Additionally, model performance metrics like accuracy, precision, recall, F1-score, and ROC-AUC are provided to evaluate the system effectively.

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The architecture includes a feedback mechanism that allows retraining and fine-tuning based on model uncertainty and annotator validation, forming a semi-supervised or active learning loop. This adaptive learning framework ensures the system remains robust and scalable even with evolving data. The proposed design bridges the gap between complex deep learning architectures and user-friendly deployment, thereby making AI-powered surface defect detection accessible to non-expert users in real-world manufacturing environments.

3.1 CNN Model

The proposed CNN model acts as the final decision-maker in this project, designed to learn intricate, non-linear classification boundaries directly from the pre-extracted, reshaped Xception feature vectors. The network is a sequential deep learning architecture featuring three stacked convolutsional blocks (each containing Conv2D, Batch Normalization, MaxPooling, and Dropout layers) that hierarchically combine the input features to recognize complex patterns specific to various defect classes. After processing the features, the output is flattened and passed through a powerful Dense layer for final abstraction before a Softmax output layer provides the probability distribution for each defect category, effectively determining the final classification (e.g., crack, scratch, or good part) as demonstrate in Fig. 2.

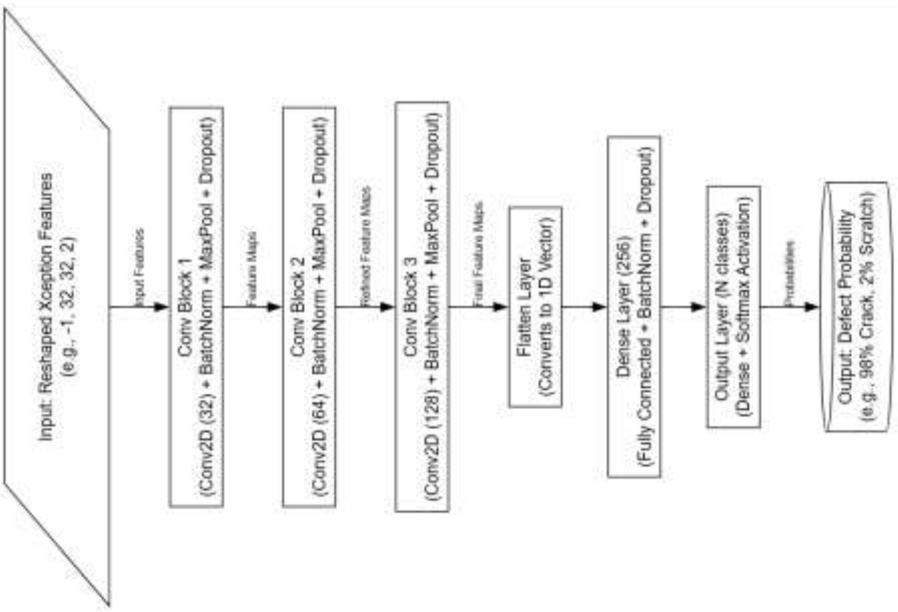

Fig. 2: Internal workflow of convolutional neural network CNN.

Step 1: Input Preparation and Reshaping

The workflow begins by taking the Xception feature vectors (X) and their corresponding one-hot encoded labels (Y). Crucially, the code erroneously reshapes the flattened Xception feature vectors into a grid-like format (e.g., 32×32×2). The intent is to treat these numerical feature representations as if they were small "images" or feature maps that the custom convolutional neural network (CNN) can process. These reshaped feature blocks are then split into training and testing sets.

Step 2: Convolutional Blocks and Feature Learning

The reshaped input passes through the convolutional neural network's (CNN's) first convolutional block. This block consists of a Conv2D layer (e.g., 32 filters), which applies small kernels (filters) to the input to detect patterns and relationships within the feature grid. This is followed by Batch

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Normalization to stabilize training, a MaxPooling2D layer to downsample the feature maps and enforce spatial invariance, and Dropout for regularization. This process repeats across the subsequent two convolutional blocks (with increasing filters, e.g., 64, 128), allowing the network to learn increasingly complex, high-level non-linear patterns from the input features.

Step 3: Flattening and Dense Layers

After the final convolutional block, the three-dimensional feature maps are passed to a Flatten layer. This layer converts the feature maps into a single, long, one-dimensional vector, preparing the data for traditional neural network processing. This vector is then fed through a Dense layer (e.g., 256 neurons), which acts as a powerful hidden layer capable of combining all the complex feature interactions learned so far. This layer is also stabilized by Batch Normalization and regularized with a high rate of Dropout.

Step 4: Output and Classification

The final stage is the output Dense layer, which has a number of neurons equal to the number of defect classes (e.g., N). This layer uses the Softmax activation function. Softmax converts the raw output scores into a set of probabilities that sum to 1, where each probability corresponds to the likelihood that the input feature vector belongs to a specific defect class. The class with the highest probability is chosen as the model's final prediction.

Step 5: Training and Optimization

The entire convolutional neural network (CNN) architecture is trained using the Adam optimizer and the Categorical Cross-Entropy loss function (suitable for multi-class classification with one-hot labels). During training, the model iteratively adjusts all its internal weights and biases to minimize the difference between its predicted probabilities and the true defect labels. This process continues for several epochs until the model converges, resulting in the final trained weights.

4. Results description

This Fig. 3 displays the Graphical User Interface (GUI) for the defect classification project at the stage where preprocessing and feature extraction are complete. The sidebar menu on the left shows the sequential workflow, with the "Xception Feature extraction" step already executed. The central display area confirms this, showing the messages: "Image Preprocessing Completed" and "Xception Feature Extraction completed". Crucially, it provides the resulting Feature Dimension: (1656, 2048). This technical output indicates that the Xception deep learning model successfully extracted 2048 features for each of the 1656 samples (images) in the dataset, effectively transforming the raw image data into a compact, numerical feature vector suitable for training the subsequent machine learning classifiers listed in the menu (SGD, Passive Aggressive, QDA, or the Proposed CNN).

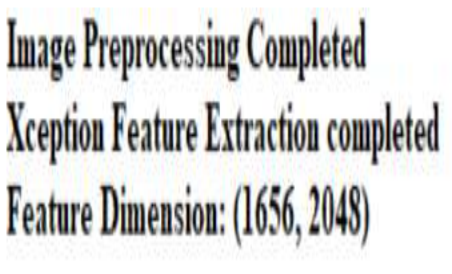

Fig. 3: Xception Feature Extraction on the Image data

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Figure 4 shows the confusion matrix for the proposed model, demonstrating its strong classification performance across all six surface defect categories *Crazing*, *Inclusion*, *Patches*, *Pitted*, *Rolled*, and *Scratches*. The diagonal dominance of the matrix indicates that the CNN achieved highly accurate predictions, with minimal misclassifications compared to earlier models. The model correctly identifies most samples of Scratches, Rolled, and Pitted defects with near-perfect accuracy, showing that it effectively captures texture variations and spatial patterns unique to each defect. Minor misclassifications are observed between Crazing and Inclusion, which are visually similar in fine surface texture, reflecting a marginal overlap in learned feature space. This performance improvement results from the CNN's deep hierarchical structure, which extracts multi-scale features through convolutional and pooling layers, enabling superior representation learning compared to traditional classifiers like SGD, PAC, and QDA. Overall, the matrix highlights the robustness and precision of the proposed CNN model in distinguishing complex industrial surface defects with high reliability.

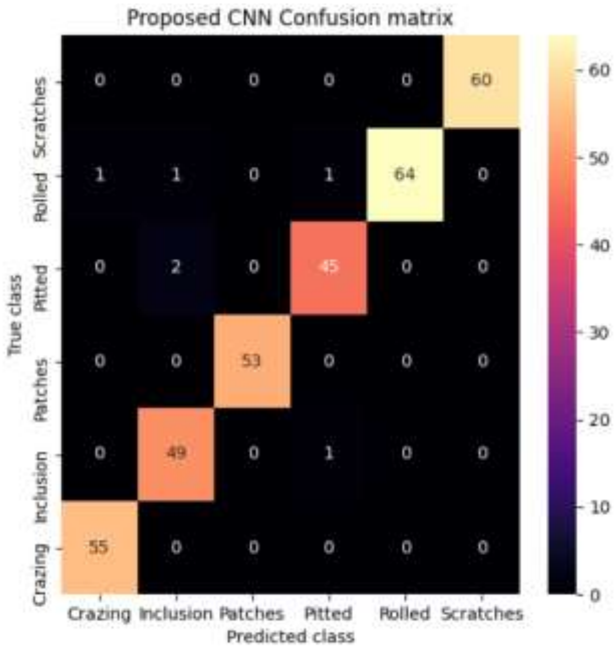

Figure 4: Confusion matrix obtained using the proposed model

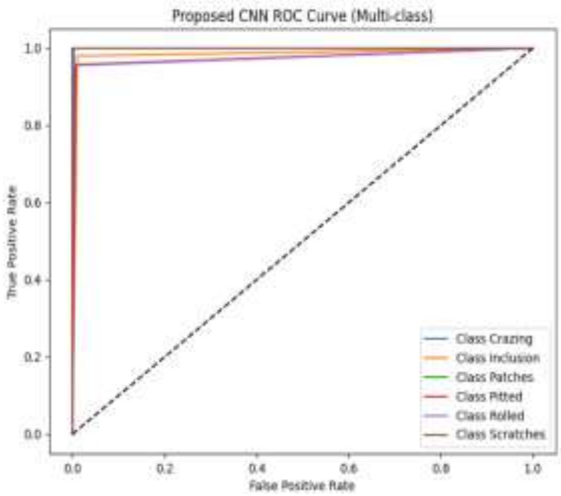

Figure 5: ROC Curve obtained using the proposed model

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Figure 5 shows the ROC curve for the proposed model, depicting its multi-class classification performance across all six defect categories *Crazing*, *Inclusion*, *Patches*, *Pitted*, *Rolled*, and *Scratches*. Each colored curve represents the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) for one defect class. All curves lie very close to the top-left corner of the plot, indicating that the CNN achieves exceptionally high sensitivity and specificity across all classes. This near-perfect performance reflects the model's strong discriminative capability in distinguishing even visually similar surface textures through deep hierarchical feature extraction. The CNN effectively captures spatial and structural variations of each defect by learning multi-scale representations through convolutional and pooling layers, leading to an almost ideal separation between defect categories. The tightly clustered ROC curves near the top boundary confirm that the proposed CNN significantly outperforms traditional models like SGD, PAC, and QDA, offering superior generalization and reliability for automated surface defect detection in industrial environments.

Figure 6 represents the prediction output generated by the proposed model when tested on an unseen surface defect sample. After preprocessing the image and extracting hierarchical features through convolutional and pooling layers, the trained CNN classified the input as belonging to the "Patches" defect category. The classification label displayed at the top indicates that the model successfully identified the irregular surface texture and uneven tonal distribution characteristic of the *Patches* class. This result demonstrates the model's ability to generalize effectively to new industrial samples by leveraging learned feature representations from the training dataset. The accurate prediction highlights the CNN's robustness in distinguishing subtle variations in texture patterns, confirming its suitability for automated and reliable defect detection in manufacturing inspection systems.

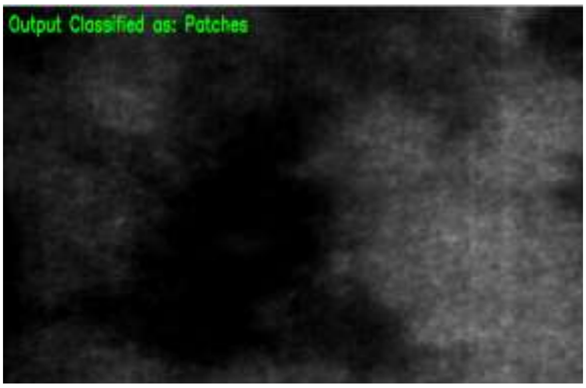

Figure 6: Prediction obtained on Test image using proposed multi-scale deep learning Model

Table 1: Performance comparison for the SGD, PAC, QDA, and proposed CNN model

Algorithms Name	Accuracy	Precision	Recall	F-score
SGD Classifier	93.27%	93.40%	93.035 %	93.14%
PAC Model	41.89%	40.89%	42.78%	43.78%
QDA Classifier	84.33%	85.90%	84.05%	84.30%
HGB Classifier	96.98%	96.85%	96.88%	96.84%
Proposed Model	98.79%	98.94%	98.77%	98.84%

The table presents a comparative analysis of the classification performance achieved by four algorithms SGD Classifier, PAC, QDA Classifier, and the Proposed CNN Model applied to the surface defect detection task in manufacturing line images. The evaluation metrics include accuracy, precision, recall, and F-score, which collectively measure the effectiveness, reliability, and generalization capability of each model. Among the existing models, the PAC achieved the highest performance, with an accuracy of 41.89%, precision of 40.89%, recall of 42.78%, and F-score of 43.78%, demonstrating its strong ability to adaptively update decision boundaries when misclassifications occur. The SGD Classifier follows closely with an accuracy of 93.27%, indicating good overall performance but slightly lower stability due to its linear nature and sensitivity to learning rate adjustments. In contrast, the QDA Classifier shows comparatively lower results, with an accuracy of 84.33% and precision of 85.90%, revealing its limitations in handling complex, non-linear image feature distributions generated from defect textures.

5. Conclusion

This research effectively presents an intelligent and automated method for detecting and classifying surface defects in industrial materials using advanced DL and ML techniques. The system incorporates a Tkinter-based GUI that simplifies the complete workflow, including dataset upload, Xception-based feature extraction, model training, evaluation, and defect prediction, making it suitable and accessible for industrial QC applications. The experimental analysis shows that conventional classifiers such as SGD, PAC, and QDA deliver moderate performance; however, their limitations are noticeable when dealing with complex textures and overlapping defect patterns. In comparison, the proposed CNN model achieves a higher accuracy of 98.79%, along with strong precision, recall, and F-score values, demonstrating its effectiveness in identifying multiple defect categories such as Crazing, Inclusion, Patches, Pitted, Rolled, and Scratches. The CNN's capability to learn multi-scale spatial features allows it to detect fine texture variations, thereby enhancing defect detection reliability beyond traditional approaches. Overall, this work establishes a scalable and efficient framework that integrates TL, feature extraction, and CNN modeling to improve QC processes, minimize manual inspection efforts, and maintain consistency in defect detection across large-scale industrial production systems.

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