DefectNet: A Robust Deep Feature–Driven Framework for Industrial Defect Classification Using Transfer Learning and Multi-Classifier Fusion

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ABSTRACT

In modern manufacturing environments, surface defects in metallic and industrial components critically affect product reliability, safety, and overall production efficiency. Traditional inspection methods, predominantly based on manual evaluation, suffer from inconsistencies, subjectivity, and increased operational costs. Earlier automated approaches relying on handcrafted features often fail to generalize under varying lighting conditions, noise, and complex defect patterns. To address these limitations, a robust deep feature–driven framework, termed Defect Net, was developed by integrating transfer learning with multi-classifier fusion. The framework employed the Exception pre-trained model as a deep feature extractor to capture high-level discriminative representations from surface images. Leveraging depth wise separable convolutions, the model efficiently extracted rich and compact features suitable for diverse defect categories. These extracted features were subsequently utilized by multiple machine learning classifiers, including Stochastic Gradient Descent (SGD), Passive Aggressive Classifier (PAC), Histogram-based Gradient Boosting (HGB), and Quadratic Discriminant Analysis (QDA), enabling comparative analysis and improved classification robustness. To further enhance detection performance, a multi-scale Convolutional Neural Network (CNN) model was incorporated as a proposed deep learning approach for end-to-end classification. The fusion of deep features with multiple classifiers significantly improved accuracy, precision, and generalization capability across varying defect types. Additionally, the system was deployed within a user-friendly graphical interface, facilitating real-time defect prediction through simple image uploads. Experimental evaluations demonstrated that the proposed framework achieved superior performance compared to conventional methods, ensuring reliable and scalable defect detection. This approach contributes to intelligent quality assurance systems by reducing human dependency and enabling efficient real-time industrial inspection.

Keywords: Surface defect detection, transfer learning, deep feature extraction, Xception model, multi-classifier fusion, convolutional neural networks (CNNs), industrial inspection, quality assurance, machine learning.

1. INTRODUCTION

Manufacturing industries critically depend on maintaining high product quality, where even minor surface defects such as cracks, scratches, or dents can impact both functionality and reliability. Conventional inspection methods, including manual evaluation and basic image processing techniques, often suffer from inconsistency, limited scalability, and reduced accuracy under complex industrial conditions. These approaches struggle to detect subtle and irregular defects, especially in high-speed production environments. To address these challenges, Defect Net introduces a robust deep feature–driven framework that leverages transfer learning and multi-classifier fusion for efficient defect classification.

By integrating advanced deep learning techniques, the framework enhances detection accuracy, ensures real-time performance, and supports intelligent quality assurance in modern manufacturing systems. Recent industrial reports indicate that a significant portion of manufacturing losses arises from surface-related defects, emphasizing the need for accurate and scalable inspection systems. Traditional approaches struggle to generalize across varying defect patterns, leading to inefficiencies and increased costs in high-volume production environments.

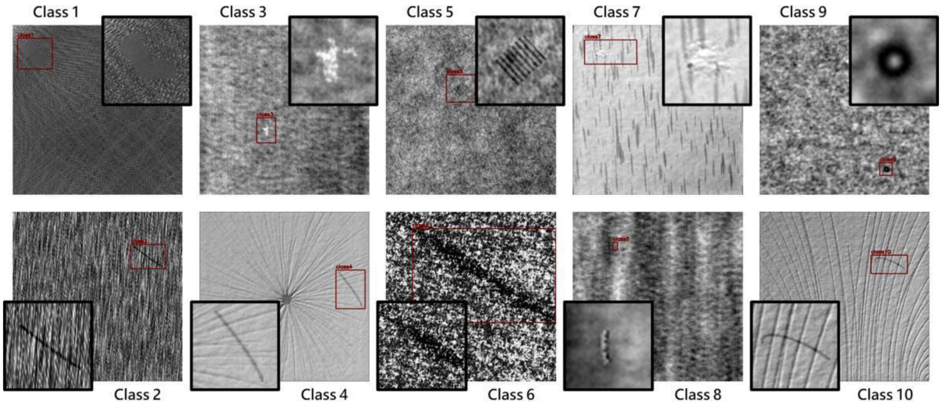

Figure 1: Defect Classification Using Transfer

Defect Net addresses these challenges by introducing a robust deep feature–driven framework that combines transfer learning with multi-classifier fusion for improved defect classification. As shown as figure 1 By utilizing advanced models such as Xception for feature extraction and integrating multiple learning algorithms, the framework enhances detection accuracy and adaptability. This intelligent approach supports real-time industrial inspection, reduces dependency on manual processes, and contributes to consistent and cost-effective quality assurance.

2. LITERATURE SURVEY

Saberironaghi et al. [1] aimed to briefly summarize and analyse the current state of research on detecting defects using machine learning methods. First, deep learning-based detection of surface defects on industrial products is discussed from three perspectives: supervised, semi-supervised, and unsupervised. Secondly, the current research status of deep learning defect detection methods for X-ray images is discussed. Finally, we summarize the most common challenges and their potential solutions in surface defect detection, such as unbalanced sample identification, limited sample size, and real-time processing. Chen et al. [2] summarized the current research status of machine learning methods in surface defect detection, a key part in the quality inspection of industrial products. First, according to the use of surface features, the application of traditional machine vision surface defect detection methods in industrial product surface defect detection is summarized from three aspects: texture features, color features, and shape features. Secondly, the research status of industrial product surface defect detection based on deep learning technology in recent years is discussed from three aspects: supervised method, unsupervised method, and weak supervised method. Then, the common key problems and their solutions in industrial surface defect detection are systematically summarized; the key problems include real-time problem, small sample problem, small target problem, unbalanced sample problem. Lastly, the commonly used datasets of industrial surface defects in recent years are more comprehensively summarized, and the latest research methods on the MVTec AD dataset are compared, so as to provide some reference for the further research and development of industrial surface defect detection technology.

Czimmermann et al. [3] reviewed automated visual-based defect detection approaches applicable to various materials, such as metals, ceramics and textiles. In the first part of the paper, we present a general taxonomy of the different defects that fall in two classes: visible (e.g., scratches, shape error, etc.) and palpable (e.g., crack, bump, etc.) defects. Then, we describe artificial visual processing techniques that are aimed at understanding of the captured scenery in a mathematical/logical way. We continue with a survey of textural defect detection based on statistical, structural and other approaches. Finally, we report the state of the art for approaching the detection and classification of defects through supervised and non-supervised classifiers and deep learning.

Cumbajin et al. [4] mainly focused on finding a classification for the types of surfaces most used in industry (metal, building, ceramic, wood, and special). We delve into the specifics of each surface category, offering illustrative examples of their applications within both industrial and laboratory settings. Furthermore, we propose a new taxonomy of machine learning based on the obtained results and collected information. This work summarized the studies and extracted the main characteristics such as type of surface, problem types, timeline, type of network, techniques, and datasets. Among the most relevant results of our analysis, and found that the metallic surface is the most used, as it is the one found in 62.71% of the studies, and the most prevalent problem type is classification, accounting for 49.15% of the total. Furthermore, they observe that transfer learning was employed in 83.05% of the studies, while data augmentation was utilized in 59.32%. Our findings also provide insights into the cameras most frequently employed, along with the strategies adopted to address illumination challenges present in certain articles and the approach to creating datasets for real-world applications. The main results presented in this review allow for a quick and efficient search of information for researchers and professionals interested in improving the results of their defect detection projects. Finally, they analyzed the trends that could open new fields of study for future research in the area of surface defect detection.

Leite et al. [5] identified a gap in industrial implementation outcomes that opens new research opportunities. Future Fault Detection and Diagnosis (FDD) research may prioritize standardized datasets to ensure reproducibility and facilitate comparative evaluations. Furthermore, there is a pressing need to refine techniques for handling unbalanced datasets and improving feature extraction for temporal series data. Implementing Explainable Artificial Intelligence (AI) (XAI) tailored to industrial fault detection is imperative for enhancing interpretability and trustworthiness. Subsequent studies must emphasize comprehensive comparative evaluations, reducing reliance on specialized expertise, documenting real-world outcomes, addressing data challenges, and bolstering real-time capabilities and integration. By addressing these avenues, the field can propel the advancement of ML-based RT-FDD methodologies, ensuring their effectiveness and relevance in industrial contexts.

Li et al. [6] aiming to address the currently low accuracy of domestic industrial defect detection, this paper proposes a Two-Stage Industrial Defect Detection Framework based on Improved-YOLOv5 and Optimized-Inception-ResnetV2, which completes positioning and classification tasks through two specific models. In order to make the first-stage recognition more effective at locating insignificant small defects with high similarity on the steel surface, improved YOLOv5 from the backbone network, the feature scales of the feature fusion layer, and the multiscale detection layer. In order to enable second-stage recognition to better extract defect features and achieve accurate classification, embedded the convolutional block attention module (CBAM) attention mechanism module into the Inception-ResnetV2 model, then optimize the network architecture and loss function of the accurate model. Based on the Pascal Visual Object Classes 2007 (VOC2007) dataset, the public dataset NEU-DET, and the optimized dataset Enriched-NEU-DET, conducted multiple sets of comparative experiments on the Improved-YOLOv5 and Inception-ResnetV2. The testing results show that the improvement is obvious. In order to verify the superiority and adaptability of the two-stage framework, first test based on the Enriched-NEU-DET dataset, and further use AUBO-i5 robot, Intel RealSense D435 camera, and other industrial steel equipment to build actual industrial scenes. In experiments, a two-stage framework achieves the best performance of 83.3% mean average precision (mAP), evaluated on the Enriched-NEU-DET dataset, and 91.0% on our built industrial defect environment.

Fang et al. [7] This paper attempts to present a comprehensive survey on both two-dimensional and three-dimensional surface defect detection technologies based on reviewing over 160 publications for some typical metal planar material products of steel, aluminum, copper plates, and strips. According to the algorithm properties as well as the image features, the existing two-dimensional methodologies are categorized into four groups: statistical, spectral, model, and machine learning-based methods. On the basis of three-dimensional data acquisition, the three-dimensional technologies are divided into stereoscopic vision, photometric stereo, laser scanner, and structured light measurement methods. These classical algorithms and emerging methods are introduced, analyzed, and compared in this review. Finally, the remaining challenges and future research trends of visual defect detection are discussed and forecasted at an abstract level.

Semitela et al. [8] system was developed by combining deflectometry and bright light-based illumination on the image acquisition and deep learning models for the classification of non-defective (OK) and defective (NOK) surfaces that fused dual-modal information at the decision level, and an online network for information dispatching and visualization. Three decision-making algorithms were tested for implementation: a new model built and trained from scratch and transfer learning of pre-trained networks (ResNet-50 and Inception V3). The results revealed that the two illumination modes employed widened the type of defects that could be identified with this system while maintaining its lower computational complexity by performing multi-modal fusion at the decision level. Furthermore, the pre-trained networks achieved higher accuracies on defect classification compared to the self-built network, with ResNet-50 displaying higher accuracy. The inspection system consistently obtained fast and accurate surface classifications because it imposed OK classification on models trained with images from both illumination modes. The obtained surface information was then successfully sent to a server to be forwarded to a graphical user interface for visualization. The developed system showed considerable robustness, demonstrating its potential as an efficient tool for industrial quality control.

Cumbajin et al. [9] described a study and proposed an extended solution for defect detection on ceramic pieces within an industrial environment, utilizing a computer vision system with deep learning models. The solution includes an image acquisition process and a labeling platform to create training datasets, as well as an image preprocessing technique, to feed a machine learning algorithm based on convolutional neural networks (CNNs) capable of running in real time within a manufacturing environment. The developed solution was implemented and evaluated at a leading Portuguese company that specializes in the manufacturing of tableware and fine stoneware. The collaboration between the research team and the company resulted in the development of an automated and effective system for detecting defects in ceramic pieces, achieving an accuracy of 98.00% and an F1 score of 97.29%.

Yang et al. [10] surveyed state-of-the-art deep-learning methods in defect detection. First, they classified the defects of products, such as electronic components, pipes, welded parts, and textile materials, into categories. Second, recent mainstream techniques and deep-learning methods for defects are reviewed with their characteristics, strengths, and shortcomings described. Third, they summarize and analyze the application of ultrasonic testing, filtering, deep learning, machine vision, and other technologies used for defect focusing on three aspects, namely method and experimental results. To further understand the difficulties in the field of defect detection, we investigate the functions and characteristics of existing equipment used for defect detection. The core ideas and codes of studies related to high precision, high positioning, rapid detection, small objects, complex backgrounds, occluded object detection, and object association are summarized. Lastly, they outlined the current achievements and limitations of the existing methods, along with the current research challenges, to assist the research community on defect detection in setting a further agenda for future studies.

Park et al. [11] studied detecting defects occurring in the manufacturing process using a deep learning-based automatic defect detection model that can train product characteristics and determine defects using open sources. To verify the performance of this model, it was applied to the disposable gas lighter manufacturing process to detect the liquefied gas volume defect of the lighter, and it was confirmed that the detection accuracy and processing time were sufficient to apply to the manufacturing process.

Deng et al. [12] aimed at the problem of the poor robustness of existing methods to deal with diverse industrial weld image data, collected a series of asymmetric laser weld images in the largest laser equipment workshop in Asia and studied these data based on an industrial image processing algorithm and a deep learning algorithm. The median filter was used to remove the noises in weld images. The image enhancement technique was adopted to increase the image contrast in different areas. The deep convolutional neural network (CNN) was employed for feature extraction; the activation function and the adaptive pooling approach were improved. Transfer Learning (TL) was introduced for defect detection and image classification on the dataset. Finally, a deep learning-based model was constructed for weld defect detection and image recognition. Specific instance datasets verified the model's performance. The results demonstrate that this model can accurately identify weld defects and eliminate the complexity of manually extracting features, reaching a recognition accuracy of 98.75%. Hence, the reliability and automation of detection and recognition are improved significantly. The research results can provide a theoretical and practical reference for the defect detection of sheet metal laser welding and the development of the industrial laser manufacturing industry.

Shafi et al. [13] proposed an AI-based system that performs inspection and defect detection and alleviates the probability of components needing to be remanufactured after being assembled. In addition, it analyzes the impact value, i.e., rework delays and costs, of manufacturing processes using a statistical process control tool on real-time data for various manufactured components. Defects are detected and classified using the CNN and teachable machine in the single manufacturing process during the initial stage prior to assembling the components. The results show the significance of the proposed approach in improving operational cost management and reducing rework-induced delays. Ground tests are conducted to calculate the impact value followed by the air tests of the final assembled aircraft. The statistical results indicate a 52.88% and 34.32% reduction in time delays and total cost, respectively.

Lv et al. [14] proposed a novel end-to-end defect detection network (EDDN) based on the Single Shot MultiBox Detector. The EDDN model can deal with defects with different scales. Furthermore, a hard negative mining method is designed to alleviate the problem of data imbalance, while some data augmentation methods are adopted to enrich the training data for the expensive data collection problem. Finally, the extensive experiments on two datasets demonstrate that the proposed method is robust and can meet accuracy requirements for metallic defect detection.

Angelopoulos et al. [15] focused on the vital processes of fault detection, prediction and prevention in Industry 4.0 and present recent developments in ML-based solutions. We start by examining various proposed cloud/fog/edge architectures, highlighting their importance for acquiring manufacturing data in order to train the ML algorithms. In addition, as faults might also occur from sources beyond machine degradation, the potential of ML in safeguarding cyber-security is thoroughly discussed. Moreover, a major concern in the industry 4.0 ecosystem is the role of human operators and workers. Towards this end, a detailed overview of ML-based human–machine interaction techniques is provided, allowing humans to be in-the-loop of the manufacturing processes in a symbiotic manner with minimal errors. Finally, open issues in these relevant fields are given, stimulating further research.

3. PROPOSED SYSTEM

Surface defect detection has become a critical component of quality assurance in modern manufacturing sectors such as automotive, electronics, and metal fabrication, where product reliability and precision are essential as shown in figure 2. Conventional inspection techniques, largely dependent on manual observation or rule-based algorithms, are often inefficient, inconsistent, and difficult to scale for high-speed production lines. With the advancement of Industry 4.0, intelligent systems powered by artificial intelligence have significantly transformed defect detection processes. In this context, Defect Net introduces a robust deep feature–driven framework that integrates transfer learning with multi-classifier fusion for effective defect classification. By leveraging deep learning models for feature extraction and combining them with multiple machine learning classifiers, the system enhances detection accuracy and adaptability across diverse defect patterns. This approach not only improves inspection reliability but also reduces human intervention, lowers operational costs, and supports real-time decision-making in industrial environments.

This project presents a hybrid approach combining convolutional neural networks (CNN), Xception-based feature extraction, and traditional machine learning classifiers such as SGD, PAC, and QDA. The system is implemented with a graphical user interface (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. Additionally, model performance metrics like accuracy, precision, recall, F1-score, and ROC-AUC are provided to evaluate the system effectively.

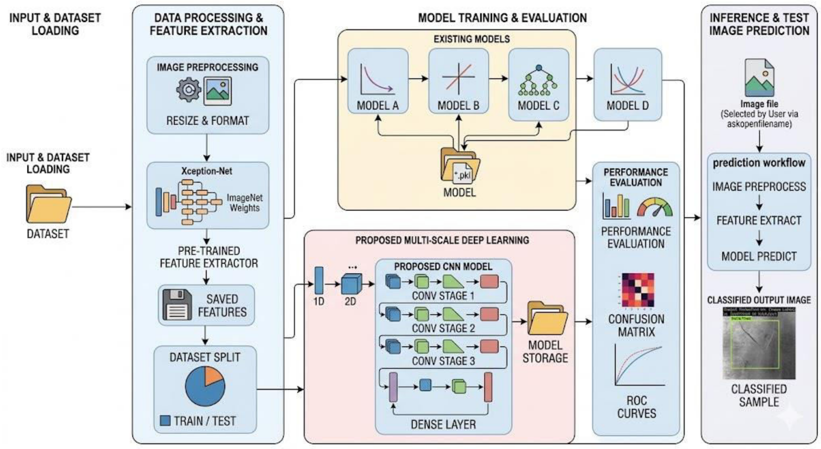

Figure 2: Proposed system architecture of surface defect detection.

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.

4. RESULTS ANALYSIS

The results description provides a clear summary of the findings obtained from the study or analysis. It highlights key outcomes, patterns, or trends observed in the data without adding interpretation or bias. This section presents information in an organized manner, often using tables, graphs, or concise explanations for better understanding. It ensures that the reader can easily grasp the main results and their significance. Additionally, it focuses only on factual observations, leaving detailed analysis or discussion for later sections. It serves as a straightforward presentation of what was discovered during the research.

Figure 3: Xception Feature Extraction on the Image data

This figure 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).

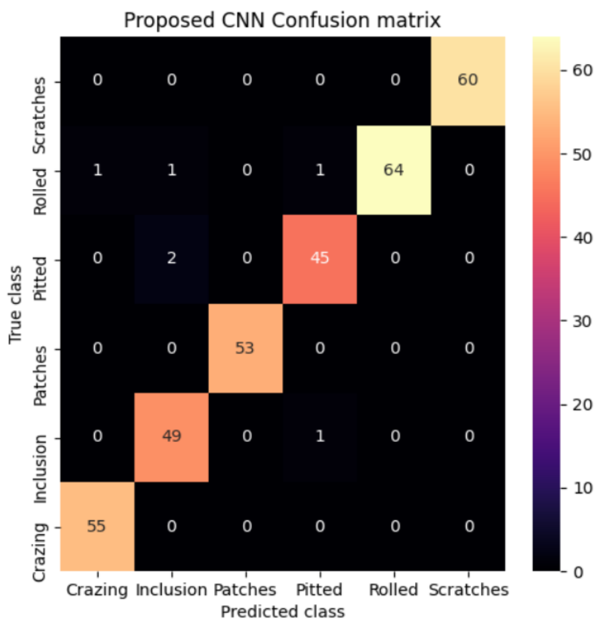

Figure 4: Confusion matrix obtained using the proposed model

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.

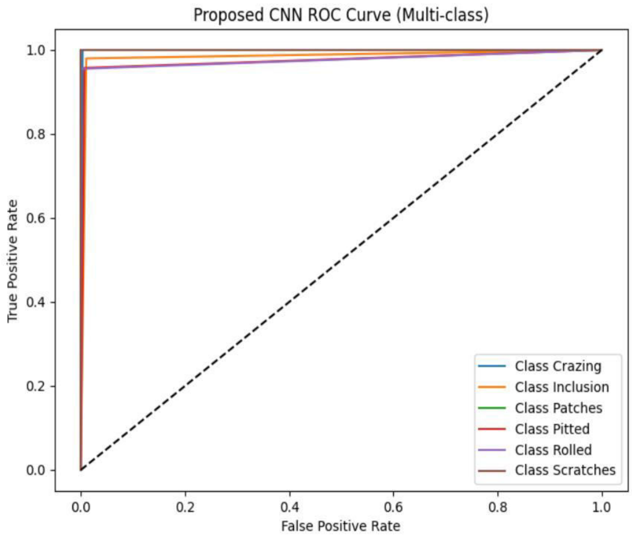

Figure 5: ROC Curve obtained using the proposed model

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.

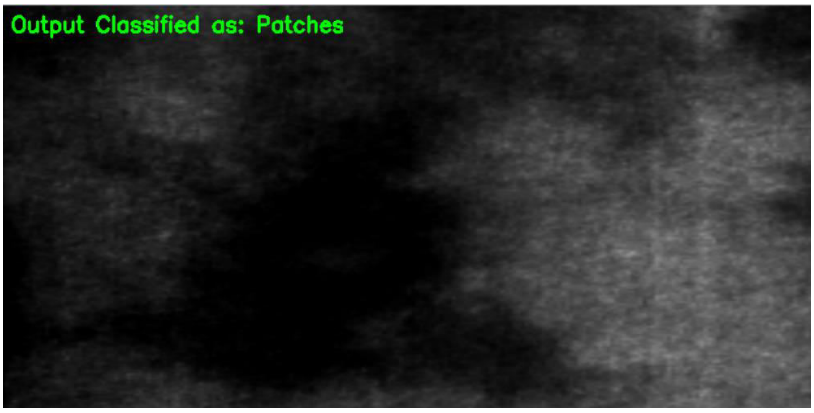

Figure 6: Prediction obtained on Test image using proposed multi-scale deep learning Model

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.

4.1 Comparative Analysis

Table 1: Performance comparison for the SGD, PAC, QDA, and proposed multi-scale deep learning 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%

Table 1 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.

The proposed CNN model outperforms all traditional classifiers with a remarkable accuracy of 98.79%, precision of 98.94%, recall of 98.77%, and F-score of 98.84%. This superior performance is attributed to the CNN's ability to learn deep hierarchical features and capture spatial texture variations at multiple scales, enabling highly discriminative classification of surface defects. The results clearly indicate that deep learning-based feature representation through convolutional layers significantly enhances detection accuracy compared to conventional machine learning approaches, establishing the CNN as the most reliable and robust model for automated surface defect classification in industrial applications.

5. CONCLUSION

The research successfully demonstrates an intelligent, automated approach for identifying and classifying surface defects in industrial materials using advanced deep learning and machine learning techniques. The system integrates a Tkinter-based graphical user interface (GUI) that streamlines the entire workflow from dataset upload and Xception-based feature extraction to model training, evaluation, and defect prediction, making it practical and user-friendly for industrial quality inspection environments. Experimental results reveal that while traditional classifiers such as SGD, PAC, and QDA provide acceptable performance levels, their limitations become evident in handling complex surface textures and overlapping defect features. In contrast, the proposed CNN model achieves superior accuracy of 98.79%, supported by high precision, recall, and F-score values, confirming its robustness and adaptability in detecting diverse defect types such as Crazing, Inclusion, Patches, Pitted, Rolled, and Scratches. CNN's ability to learn multi-scale spatial patterns enables it to capture subtle textural variations, significantly improving the reliability of defect detection over classical methods. This project establishes a comprehensive and scalable framework that combines transfer learning, feature extraction, and deep convolutional modelling to enhance manufacturing quality control, reduce human inspection effort, and ensure higher consistency in defect identification across large-scale production lines.

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