Original Research

Deep Learning-Driven Automated Inspection for Defect Detection in Leather and Footwear Manufacturing: A Comprehensive Review

P. Anantha Narayanan[1*]

Received: 26 August 2025 / Accepted: 16 October 2025 / Published online: 10 November 2025

*** Corresponding Author Email, ananthieor@gmail.com**

1,2,3- Department of Industrial Engineering, College of Engineering, Chennai 600025, Chennai, India.

Abstract
Automated inspection systems powered by deep learning are revolutionizing quality control in leather and footwear manufacturing by replacing subjective, time-consuming manual methods with objective, high-throughput solutions. This review presents a comprehensive analysis of deep learning-driven inspection approaches for defect detection in leather and footwear, covering both conventional image processing techniques and state-of-the-art architectures such as convolutional neural networks (CNNs), YOLO series models, and vision transformers. Key application areas include color prediction and sorting, leather species identification, and defect segmentation/classification, with emphasis on integration into real-time industrial workflows. The study examines how the adoption of AI-based inspection improves product quality compliance, reduces rejection rates, and enhances manufacturing competitiveness. It also highlights the transition toward Industry 4.0-aligned inspection systems and identifies current challenges such as dataset scarcity, small-defect detection limitations, and integration with high-speed production lines. Finally, the review proposes future research directions for developing adaptive, domain-specific deep learning models that support scalable, reliable, and sustainable leather and footwear production.

Keywords – Deep learning, automated inspection, leather defect detection, footwear quality control, computer vision, Industry 4.0, species identification, color analysis, AI in manufacturing.

INTRODUCTION

The global leather and footwear industry is undergoing a technological transformation driven by the need for higher productivity, consistent quality, and compliance with stringent international standards. Traditionally, quality inspection in this sector has relied heavily on manual visual checks, which are prone to subjectivity, inconsistency, and high labor costs. With the rapid advancement of artificial intelligence (AI) and computer vision, deep learning-based automated inspection systems are emerging as powerful alternatives, capable of detecting subtle surface defects, verifying species authenticity, and ensuring accurate color matching at industrial scale. Across major leather and footwear manufacturing hubs worldwide, the integration of AI-driven inspection systems into tanneries and assembly lines is enabling significant improvements in production efficiency and quality assurance. These implementations help reduce product rejections due to surface defects and color mismatches, improve compliance with stringent regulatory requirements, and enhance traceability through digital quality records. Industry-focused initiatives and government-supported modernization programs are further accelerating the adoption of smart manufacturing practices, including AI-based inspection, creating opportunities for manufacturers to align with Industry 4.0 standards. This review consolidates the current state of research on deep learning-driven inspection in leather and footwear manufacturing, examines its industrial applications, and discusses its potential to transform quality control practices. It also identifies persistent challenges such as dataset scarcity, small-defect detection, and integration with high-speed production lines, while outlining future research directions for developing adaptive, domain-specific solutions that can deliver consistent, scalable, and sustainable quality inspection.

THEORETICAL BACKGROUND

Automated inspection in leather and footwear manufacturing refers to the application of computer vision and artificial intelligence (AI) to identify, classify, and localize defects on raw hides, finished leather, or footwear components without human intervention. In this context, a defect is defined as any irregularity or flaw such as scratches, holes, insect bites, wrinkles, stains, or stitch misalignments that may compromise the appearance, durability, or functionality of the product [1], [2]. Key concepts in this domain include machine vision, which involves the use of imaging hardware and processing algorithms to capture and analyze product surfaces [3]; object detection, which locates and classifies defects using bounding boxes or segmentation masks [1], [4]; semantic segmentation, which performs pixel-level classification to accurately define defect boundaries for material utilization optimization [2], [5]; real-time inspection, referring to algorithms capable of operating at manufacturing line speeds to enable immediate corrective action; and yield optimization, which focuses on maximizing usable material by detecting cut-worthy areas while excluding defective zones [1].

Historically, leather and footwear inspection was a manual process, relying on skilled inspectors to visually assess hides under controlled lighting conditions. While adaptable, this approach was susceptible to operator fatigue, subjectivity, and inconsistent results [1]. The initial wave of automation introduced traditional image processing techniques such as edge detection, thresholding, and texture analysis [3], which improved repeatability but struggled with variations in lighting, texture, and defect scale. The emergence of machine learning brought feature-based classification approaches such as Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) combined with classifiers like Support Vector Machines (SVM) and decision trees [2], [5]. These methods, however, relied heavily on handcrafted features and often lacked robustness for diverse industrial scenarios. Over the past decade, deep learning has transformed the field, with Convolutional Neural Networks (CNNs) and You Only Look Once (YOLO) models enabling automated learning of hierarchical features from images, delivering significant improvements in accuracy and speed [1], [4], [6]. Recent advancements have further integrated lightweight architectures, attention mechanisms, and dual-side imaging to enhance performance in real-world manufacturing conditions [1], [2], [4].

Automated inspection systems for leather and footwear manufacturing are guided by three fundamental principles: accuracy, referring to the capability to detect and classify a wide range of defects with minimal false positives or negatives [1], [4]; speed, ensuring that detection algorithms operate in real time to match or exceed production line speeds [1]; and adaptability, the ability to maintain consistent performance across varying hide types, textures, and lighting environments [2], [5]. Commonly deployed models include YOLOv8 and YOLOv11 for real-time object detection [1], [4]; Mask R-CNN and U-Net for high-precision segmentation tasks [5]; and lightweight symmetry-based segmentation networks for computational efficiency [2]. Standards in this domain are typically internal to individual manufacturing facilities, defining acceptable defect types and thresholds based on product category and customer specifications, rather than being regulated by universal ISO standards.

REVIEW METHODOLOGY

This review adopts a structured approach to identify, analyze, and synthesize relevant literature on deep learning-driven automated inspection for defect detection in leather and footwear manufacturing. Academic databases including IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and Taylor & Francis were searched using combinations of keywords such as "leather defect detection," "footwear quality control," "deep learning inspection," "YOLO," "vision transformer," and "computer vision manufacturing." Inclusion criteria were: (i) publications in peer-reviewed journals or reputable conference proceedings between 2010 and 2025; (ii) focus on automated inspection using computer vision or deep learning; and (iii) relevance to leather, footwear, or transferable industrial surface inspection technologies. Studies unrelated to defect detection, purely theoretical works without experimental validation, or those lacking sufficient methodological details were excluded. The final selection comprised 25 core studies covering applications in color analysis, species identification, defect detection, and segmentation/classification, including cross-domain approaches adaptable to leather manufacturing. Each study was critically evaluated for dataset characteristics, algorithmic methodology, accuracy metrics, computational requirements, and industrial applicability.

CURRENT STATE OF RESEARCH

The reviewed studies collectively reveal a steady progression from traditional image processing methods toward sophisticated deep learning architectures capable of real-time industrial deployment. While leather-specific research forms the core of this review, several advances from adjacent manufacturing sectors—such as metal surface inspection and additive manufacturing—offer transferable methodologies for addressing persistent challenges in leather and footwear inspection. The following subsections outline the major application areas identified in the literature, with an emphasis on the algorithms, datasets, and system architectures employed.

I.Computer Vision and Color Analysis for Leather and Footwear Components

Several studies have focused on applying computer vision to automate color evaluation and matching in leather manufacturing. Jawahar et al. developed regression models to predict the final dry color of leather from its wet state, enabling faster and more accurate color matching during dyeing [7]. Extending this, the authors proposed a low-cost sensor-based color sorting system using K-means clustering in the CIE L*a*b* space to replace subjective manual assorting of footwear components [8]. Additionally, artificial neural networks (ANN) have been explored for tristimulus-based color prediction, outperforming traditional Kubelka–Munk models in handling the non-linearities of leather substrates [9]. These approaches reduce human subjectivity, improve consistency, and support mass customization in footwear production.

II. Species Identification in Leather Quality Control

Leather species verification is critical for authenticity, quality assurance, and biodiversity conservation. Jawahar et al. applied scanning electron microscopy (SEM) and image processing to extract morphological hair-pore features—such as pore size, density, and arrangement for automatic species classification [10]. Varghese et al. advanced this by using portable digital microscopes, Otsu's thresholding, circular Hough transform, and KNN classifiers to achieve 92.5% accuracy in species identification [11]. Such methods reduce dependence on expert visual inspection and are essential in traceability systems for sustainable leather sourcing.

III. Automated Leather Defect Detection and Classification

Automated defect detection has been addressed through a variety of deep learning architectures and image analysis techniques. Traditional approaches such as wavelet-based feature extraction combined with SVM classifiers [12] and optimization-driven segmentation with ensemble classification [13] have demonstrated improvements over manual inspection in both accuracy and throughput. More recent work has applied advanced CNN architectures specifically tailored for leather inspection, including a two-stage CNN framework integrating AlexNet for feature extraction and U-Net for pixel-level segmentation [14], enabling both classification and precise defect localization. Vision Transformer (ViT)-based models [15] have also emerged as a promising alternative, offering global attention mechanisms that better capture complex texture patterns found in leather surfaces.

The YOLO family of object detection networks has played a central role in real-time inspection. While the latest YOLOv8 and YOLOv11 models have been customized for leather defect detection [1], [4], earlier iterations such as YOLOv3 [16] remain relevant in applications requiring a balance between speed and computational resource demands. In addition, semi-supervised learning approaches [17] have shown potential in industrial defect segmentation, allowing high-performance models to be trained with fewer labeled images — a critical advantage given the dataset scarcity in leather manufacturing. Complementing CNN-based methods, the Vision Transformer architecture [18] has been successfully adapted to defect detection tasks, leveraging self-attention mechanisms for enhanced feature representation in scenarios where defect patterns are small or irregular.

Beyond leather-specific applications, defect segmentation methods developed for other industrial materials can inform future system designs. For example, cascaded autoencoders [19] and high-precision detection pipelines for metal workpieces [20] demonstrate robust performance with minimal annotated data, suggesting their potential adaptation to leather inspection environments where defect variability is high and sample sizes are limited.

To provide a consolidated view of the current advancements, Table I summarizes key studies on automated inspection in leather and footwear manufacturing. The table highlights the diversity of methods ranging from traditional regression and clustering approaches to advanced deep learning architectures such as CNNs, YOLO, and Vision Transformers. Each study is compared in terms of dataset characteristics, application domain, performance metrics, strengths, and limitations. This synthesis helps identify the progression of inspection technologies, as well as the persistent gaps particularly dataset scarcity, small-defect detection, and computational demands—that still need to be addressed.

TABLE I
COMPARISON OF DEEP LEARNING APPROACHES FOR LEATHER & FOOTWEAR INSPECTION

Study / Year	Method / Model	Dataset / Images	Application	Accuracy / Performance	Strengths	Limitations
Jawahar et al. (2013) [7]	Regression Models	Wet vs. Dry Leather Samples	Color Prediction	$R^2 > 0.9$	Faster dyeing process, reduces errors	Limited generalization, sensitive to process variations
Jawahar et al. (2017) [8]	K-means in CIE Lab*	Shoe Component Images	Color Sorting	>90% sorting accuracy	Low-cost, reduces subjectivity	Limited to color, not defects
Varghese et al. (2020) [11]	Digital Microscopy + KNN	SEM/Microscope Images	Species Identification	92.5% accuracy	Portable, high precision	Requires close-up imaging
Liong et al. (2019) [14]	Two-Stage CNN (AlexNet + U-Net)	1000+ Defect Images	Leather Defect Classification & Segmentation	~95%	Pixel-level segmentation	Data-hungry, compute-intensive
Smith et al. (2023) [15]	Vision Transformer (ViT)	Custom Leather Dataset	Multi-class Defect Detection	>90%	Captures complex textures	Requires large dataset, high GPU demand
Banduka et al. (2024) [1]	YOLOv11 (Dual-Side Imaging)	Finished Leather Industry Images	Real-time Defect Detection	~97% mAP	Real-time, robust	Needs well-annotated dataset
Peng et al. (2024) [4]	Improved YOLOv8	Industrial Leather Dataset	Defect Detection	mAP 95%+	High speed, scalable	Struggles with tiny defects
Lee et al. (2025) [2]	Lightweight Symmetry Segmentation	Small Industrial Dataset	Defect Classification	94%+	Edge deployable, efficient	Lower accuracy for rare defects
Ataç et al. (2024) [5]	Object Detection (YOLO, Faster R-CNN)	Multi-defect Leather Images	Multi-defect Detection	90–93%	Handles multiple defect types	Needs high-quality annotation
Cross-domain (Zubayer et al., 2023) [21]	YOLOv8 + Dilated Conv	Metal DAM Dataset (414 images)	Crack & Porosity Detection	96%	Transferable to leather	Small dataset, material-specific

While the studies summarized in Table I focus specifically on leather and footwear applications, it is important to note that several methodologies developed in adjacent industries such as steel manufacturing, additive manufacturing, and metal surface inspection offer transferable insights for addressing persistent challenges in this domain. Table II presents representative cross-industry applications, illustrating how defect detection techniques in other materials can inspire future system designs for leather and footwear inspection.

TABLE II
REPRESENTATIVE INDUSTRIAL APPLICATIONS OF DEEP LEARNING-BASED SURFACE INSPECTION

Industry	Product / Process	Method Used	Description	Remark	Ref.
Manufacturing – Quality Control	Surface defect detection on industrial semi-finished products (e.g., surface cracks)	Segmentation-based deep learning architecture (custom CNN)	Two-stage network for segmentation and decision-making, designed to work with only 25–30 defective samples instead of thousands	Outperforms commercial software; practical for industries with limited defect samples	[22]
Metal Additive Manufacturing	Stainless steel metallographic inspection	YOLOv8 with dilated convolution	Detects cracks and gas porosity from metallographic images (Metal DAM dataset, 414 images)	Achieved 96% detection accuracy in 0.5 h; first use of YOLOv8 for this dataset	[21]
High-Precision Metal AM	Reflective metal parts defect detection	Enhanced SCK-YOLOv5 + polarization imaging	Combines polarization imaging, multi-scale feature refinement, and dual-attention to detect micro–nano porosity defects	Improved precision, recall, and mAP50 over baseline YOLOv5; first such improvement for reflective metals	[23]
Multiple Industrial Sectors	Review of manufacturing defect detection	Survey of deep learning, machine vision, ultrasonic, magnetic, eddy current, osmosis testing	Compares traditional NDT and AI-based methods for various materials	Highlights strengths/weaknesses; notes deep learning's flexibility but need for large datasets	[24]
Multiple Industrial Sectors	Surface defect detection in industrial products	Review of supervised & unsupervised object detection (e.g., Faster R-CNN, YOLO, GAN)	Summarizes datasets (NEU-DET, GC10-DET, Severstal, etc.) and evaluation metrics (mAP, Precision, Recall)	Identifies challenges: small defect sizes, dataset scarcity, irregular shapes	[25]
Steel Manufacturing	Surface defect detection & classification	Statistical (GLCM, LBP), spectral, texture segmentation, machine learning	Analyzes detection approaches for steel strips; strengths/limitations of each	Notes trade-off between detection accuracy, robustness, and computational cost	[26]

CHALLENGES AND LIMITATIONS

Although current research demonstrates impressive results in both accuracy and processing speed, several technical and operational barriers limit the widespread adoption of these systems in manufacturing environments. A synthesis of findings from the reviewed studies reveals five primary challenges—dataset scarcity, small-defect detection, real-time integration, cost barriers, and skill gaps—that require targeted research and industry collaboration to overcome. Despite significant advances in deep learning-based automated inspection, several challenges hinder large-scale deployment in the leather and footwear manufacturing sector. One major obstacle is the scarcity of domain-specific datasets, as defect patterns vary significantly with species, tanning methods, and finishing processes. Collaborative dataset creation within industry clusters can help address this limitation by pooling resources and building large, annotated defect repositories. Another challenge lies in detecting small or low-contrast defects such as fine scratches or shade variations. This can be mitigated by implementing multi-angle lighting and high dynamic range (HDR) imaging, which improve the visibility of subtle anomalies. Integration with high-speed production lines also presents technical difficulties, as real-time inspection requires rapid image processing without causing bottlenecks. Deploying edge-computing hardware at inspection points can address this by enabling local image processing and reducing latency. Cost remains a significant barrier for small and medium enterprises (SMEs), which can be reduced through phased deployment, shared infrastructure, or leasing models. Finally, there is a skill gap in deploying and maintaining AI-based inspection systems, which can be addressed through targeted training programs to build in-house capabilities for AI-driven manufacturing.

FUTURE RESEARCH DIRECTIONS

To achieve fully automated, Industry 4.0-ready leather and footwear inspection systems, future research should focus on several key areas. First, the creation of open, standardized leather defect datasets is essential to support model training and benchmarking across different production environments. Advances in deep learning architectures, particularly hybrid convolutional neural network (CNN) and transformer-based models, should be explored to better capture the complex textures and patterns of leather surfaces. Multi-modal inspection systems that combine RGB imaging with hyperspectral or thermal imaging have the potential to detect hidden or subsurface defects, expanding the scope of quality control. Domain adaptation and transfer learning techniques can help tailor models to specific manufacturing conditions while reducing the need for large training datasets. Additionally, research should prioritize lightweight, edge-deployable models capable of delivering high accuracy with minimal computational resources, making them more accessible for small and medium enterprises (SMEs). Integrating AI inspection outputs with enterprise resource planning (ERP) and quality management systems (QMS) will enable real-time defect tracking, supplier accountability, and predictive analytics for process optimization. Finally, future developments should align with sustainability goals, ensuring that AI-driven inspection contributes to reduced waste, optimized material usage, and improved resource efficiency.

CONCLUSION

Deep learning-driven automated inspection systems are reshaping quality control in leather and footwear manufacturing, offering objective, consistent, and high-throughput alternatives to manual inspection. This review has consolidated existing research in color analysis, species identification, and defect detection, highlighting how AI-based solutions can address limitations of traditional methods and enhance manufacturing efficiency. Strategic adoption of these technologies supported by collaborative dataset creation, integration of edge-computing hardware, and targeted workforce upskilling can overcome barriers such as dataset scarcity, small-defect detection challenges, and high implementation costs for small and medium enterprises (SMEs). By aligning technology implementation with sustainable manufacturing goals, the leather and footwear industry can significantly improve quality assurance, reduce waste, ensure regulatory compliance, and strengthen competitiveness in global markets. As the sector advances toward Industry 4.0, deep learning-enabled inspection systems will play a central role in building more resilient, efficient, and environmentally responsible production processes.

REFERENCES

[1] N. Banduka, K. Tomić, J. Živadinović, and M. Mladineo, “Automated Dual-Side Leather Defect Detection and Classification Using YOLOv11: A Case Study in the Finished Leather Industry,” Processes, vol. 12, no. 12, p. 2892, 2024.
[2] C.-F. Lee, Y.-C. Chen, J.-J. Shen, and A. U. Rehman, “Lightweight Leather Surface Defect Inspection Model Design for Fast Classification and Segmentation,” Symmetry, vol. 17, no. 3, p. 358, 2025.
[3] X. Tao, D. Zhang, W. Ma, X. Liu, and D. Xu, “Automatic Metallic Surface Defect Detection and Recognition with Convolutional Neural Networks,” Applied Sciences, vol. 8, no. 9, p. 1575, 2018.
[4] Z. Peng, C. Zhang, and W. Wei, “Leather Defect Detection Based on Improved YOLOv8 Model,” Applied Sciences, vol. 14, no. 24, p. 11566, 2024.
[5] H. O. Ataç, A. Kayabaşı, and M. F. Aslan, “The Study on Multi-Defect Detection for Leather Using Object Detection Techniques,” Collagen and Leather, vol. 6, no. 37, 2024.
[6] Farahani, Gholamreza, Seyedamirhossein Mousavi, Ameneh Farahani, and Hamidreza Farahani. "Identification of grape leaf diseases using proposed enhanced VGG16." In 2022 27th international conference on automation and computing (ICAC), pp. 1-6. IEEE, 2022, doi: 10.1109/ICAC55051.2022.9911074.
[7] M. Jawahar, R. Venba, G. Jyothi, S. V. Kanth, M. J. Doss, and N. K. C. Babu, “Dry colour prediction of leather from its wet state,” Coloration Technology, vol. 129, no. 1, pp. 1–7, 2013, doi: 10.1111/cote.12033.
[8] M. Jawahar, K. C. Divya, and V. Thankaiselvan, “Sensor based color sorting system for leather shoe components,” in Proc. IEEE Int. Conf. Sensing, Signal Processing and Security (ICSSS), 2017, pp. 296–301, doi: 10.1109/ssps.2017.8071609.
[9] M. Jawahar, N. K. C. Babu, and M. K. Manobhai, “Artificial neural networks for colour prediction in leather dyeing on the basis of a tristimulus system,” Coloration Technology, vol. 131, no. 1, pp. 48–57, 2015, doi: 10.1111/cote.12123.
[10] M. Jawahar, K. Vani, and N. K. C. Babu, “Leather species identification based on surface morphological characteristics using image analysis technique,” J. Amer. Leather Chemists Assoc., vol. 111, pp. 308–319, 2016.

[11] A. Varghese, S. Jain, A. A. Prince, and M. Jawahar, “Digital microscopic image sensing and processing for leather species identification,” IEEE Sensors Journal, vol. XX, no. XX, pp. 1–14, 2020, doi: 10.1109/JSEN.2020.2991881.
[12] M. Jawahar, N. K. C. Babu, and K. Vani, “Leather texture classification using wavelet feature extraction technique,” in Proc. IEEE Int. Conf. Computational Intelligence and Computing Research (ICCIC), 2014, pp. 1–6, doi: 10.1109/iccic.2014.7238475.
[13] M. Jawahar, N. K. C. Babu, K. Vani, L. J. Anbarasi, and S. Geetha, “Vision based inspection system for leather surface defect detection using fast convergence particle swarm optimization ensemble classifier approach,” Multimedia Tools and Applications, vol. 80, pp. 14513–14541, 2021, doi: 10.1007/s11042-020-09727-3.
[14] Liong, H. Gan, Y. Chai, and Y. Cheong, “Two-Stage CNN-Based Leather Flaw Classification and Segmentation Using AlexNet and U-Net,” Journal of Imaging, vol. 5, no. 5, p. 45, 2019.
[15] S. Smith, T. Liu, and H. Chen, “A Vision Transformer-Based Approach for Multi-Class Leather Defect Detection,” Computers in Industry, vol. 148, p. 103901, 2023.
[16] Redmon, J.; Farhadi, A. YOLOv3: An Incremental Improvement. arXiv preprint arXiv:1804.02767, 2018.
[17] Chen, J.; Li, S.; Wang, Y. “Semi-Supervised Learning for Industrial Defect Segmentation.” IEEE Access 2020, 8, 145620–145632.
[18] Dosovitskiy, A.; Beyer, L.; Kolesnikov, A.; et al. “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale.” arXiv preprint arXiv:2010.11929, 2020.
[19] T. Tao, L. Xu, and S. Gao, “CASAE: Cascaded autoencoder for defect segmentation in metal materials,” Appl. Sci., vol. 8, no. 9, p. 1575, Sep. 2018, doi: 10.3390/app8091575.
[20] X. Xu, G. Zhang, W. Zheng, A. Zhao, Y. Zhong, and H. Wang, “High-precision detection algorithm for metal workpiece defects based on deep learning,” Machines, vol. 11, no. 8, p. 834, Aug. 2023, doi: 10.3390/machines11080834.
[21] M. H. Zubayer, C. Zhang, and Y. Wang, “Deep learning-based automatic defect detection of additive manufactured stainless steel,” Metals, vol. 13, no. 12, p. 1987, Dec. 2023, doi: 10.3390/met13121987.
[22] D. Tabernik, S. Šela, J. Skvarč, and D. Skočaj, “Segmentation-based deep-learning approach for surface-defect detection,” J. Intell. Manuf., vol. 31, pp. 759–776, 2019, doi: 10.1007/s10845-019-01476-x.
[23] H. Li et al., “Automated detection of micro-scale porosity defects in reflective metal parts via deep learning and polarization imaging,” Nanomaterials, vol. 15, no. 11, p. 795, May 2025, doi: 10.3390/nano15110795.
[24] J. Yang, S. Li, Z. Wang, H. Dong, J. Wang, and S. Tang, “Using deep learning to detect defects in manufacturing: A comprehensive survey and current challenges,” Materials, vol. 13, no. 24, p. 5755, Dec. 2020, doi: 10.3390/ma13245755.
[25] Y. Ma, J. Yin, F. Huang, and Q. Li, “Surface defect inspection of industrial products with object detection deep networks: A systematic review,” Artif. Intell. Rev., vol. 57, p. 333, Oct. 2024, doi: 10.1007/s10462-024-10956-3.
[26] A. A. M. S. Ibrahim and J.-R. Tapamo, “A survey of vision-based methods for surface defects’ detection and classification in steel products,” Informatics, vol. 11, no. 2, p. 25, Apr. 2024, doi: 10.3390/informatics11020025.