Advanced AI-Based Solutions for Visual Inspection: A Systematic Literature Review

Angelo Corallo[a], Vito Del Vecchio[b] and Alberto Di Prizio[c]
Department of Innovation Engineering, University of Salento, Lecce, Italy

Keywords: Visual Inspection, Artificial Intelligence, Machine Learning, Deep Learning, Manufacturing, Industry.

Abstract: Artificial Intelligence (AI)-based solutions, including Machine Learning (ML) and Deep Learning (DL), are ever more implemented in industry for assisting advanced Visual Inspection (VI) systems. They support companies in a more effective identification of product defects, enhancing the performance of humans and avoiding the risks of product incompliance. However, companies often struggle in considering the most appropriate AI-based solutions for VI and for a specific manufacturing domain. Also, an extensive literature study focused on this topic seems to lack. On the basis of a Systematic Literature Review, this paper aims to map the main advanced AI-based VI system solutions (including methods, technologies, techniques, algorithms) thus helping companies in considering the most appropriate solutions for their needs.

1 INTRODUCTION

In recent years, the adoption of Artificial Intelligence (AI), including Machine Learning (ML) and Deep Learning (DL), has significantly improved the efficiency of industrial solutions in Computer Vision (CV) and Visual Inspection (VI) activities (Kitaguchi et al., 2022). This is particularly relevant for manufacturing companies. These technologies have transformed the roles and relationships between machines, humans, automated processes. Traditional manual VI processes have been replaced by advanced AI solutions, aiming to enhance the accuracy and speed through the integrated use of enabling technologies. Advanced technologies not only improve the accuracy and speed of analysis, but also address issues such as defect control. CV emerges as a discipline for supporting production processes and high product quality. While traditional techniques still find integration challenges in data processing, monitoring, time, quality, and input data (Paneru & Jeelani, 2021), modern and complex systems need the implementation of advanced AI solutions for more efficient and reactive production processes. Despite several studies are availbale on CV and AI in the scientific literature (Zhou et al., 2019), a comprehensive map of AI solutions for VI seems to lack. Through a Systematic Literature Review (SLR), the paper maps all the AI-based technologies for VI, including methods, techniques, algorithms and enabling technologies. An in-depth analysis reveals several sectors where advanced AI-based solutions are crucial. The study contributes to the literature by providing a comprehensive analysis of AI for VI. It also serves as a practical guide for industrial companies for a clear view of AI-VI applications.

[a] https://orcid.org/0000-0001-5216-5366
[b] https://orcid.org/0000-0001-9040-783X
[c] https://orcid.org/0009-0003-4818-4718

2 THEORETICAL BACKGROUND

2.1 Advanced Visual Inspection Solutions

VI represents a methodological and technological approach to detect component defects and control their quality (Cottrell, 2019). To date, the human eye is the main tool to ensure product compliance, but in this scenario, inspection activities can only be carried out if humans are close to the products. Advanced VI solutions include not only the use of technologies to

Corallo, A., Del Vecchio, V. and Di Prizio, A.
Advanced AI-Based Solutions for Visual Inspection: A Systematic Literature Review.
DOI: 10.5220/0012618000003690

In *Proceedings of the 26th International Conference on Enterprise Information Systems (ICEIS 2024) - Volume 1*, pages 656-664
ISBN: 978-989-758-692-7; ISSN: 2184-4992

support and improve inspection results, but also the ability to remote sensing (American Bureau of Shipping, 2022). Traditional inspections include repetitive tasks that can reduce workers' attention, increasing the risk of misidentification. Such issues are critical within manufacturing industries, especially in sectors such as aerospace and automotive where product quality must be high (Brandoli et al., 2021).

Technological advances, associated with the digitization of industrial processes, assets and information, and the adoption of enabling technologies such as the Internet of Things (IoT), have pushed companies to rely on data and collect images and videos from their production assets to perform VI. The availability of digital data is a relevant factor for performing real-time inspections (Yang et al., 2021). In this context, automated VI, also known as Smart VI (El Zant et al., 2021), represents the most innovative inspection activity, which involves the use of integrated hardware and software systems based on AI. In the field of AI, CV aims to study how computers can interpret and understand the visual world through the use of specific learning methods and algorithms (Brownlee, 2022). By training algorithms, companies can automate the inspection process, saving time and improving the accuracy and quality of results. Regardless of the type of algorithms, defect identification activities and the related systems solution require knowledge of some critical issues, such as signal acquisition, signal pre-processing, feature selection and extraction, fusion and classification of the data (Piuri et al., 2005). In manufacturing scenarios, advanced VI solutions are usually implemented to identify defects such as corrosion (Brandoli et al., 2021) and scratches (Zhou et al., 2019) on the surface of components. In the aerospace sector, identifying defects on turbine blades is relevant to understand and ensure their functional compliance (Aust et al., 2021).

By adopting advanced AI-based technology solutions, organizations can conduct inspections more quickly and accurately across a wider range of environments, while also saving costs and keeping people out of critical areas while improving safety (IBM, 2023). VI has become a crucial methodological and technological approach to detect defects from components and ensure quality control (Cottrell, 2019). It is the technological progress that has occurred in the digitalization of services and the adoption of the IoT that drives the collection of data for VI, facilitating real-time assessments (Yang et al., 2021). Training algorithms to read images improves inspection automation, saving time and improving accuracy. Regardless of the type of algorithm, defect identification involves critical aspects such as signal acquisition, preprocessing, feature selection, data fusion and classification (Piuri et al., 2005).

2.2 Artificial Intelligence for Visual Inspection

In the context of advanced AI-based VI, the integration of ML and DL models is critical for software and hardware systems (Mueller & Massaron, 2021; Voulodimos et al., 2018). Emulating human intelligence to analyze unknown data, AI shows adaptive improvement as the learning sample size increases (Mueller & Massaron, 2021). DL, distinct from ML, usually operates on unstructured data with or without preprocessing, enabling automatic extraction of components and reducing dependence on human experts (Voulodimos et al., 2018).

Moreover, among supervised, unsupervised and reinforcing learning models, supervised ML is commonly employed in defect detection algorithms, which use structured input-output pairs labelled with expected values. They are mainly composed of (Mujeeb et al., 2019): i) algorithm, as a set of rules, often rooted in statistical methods, that extract recurring patterns from data; ii) model, a representation of the real context with appropriate parameters and constraints; iii) training dataset, that includes data for feeding the learning algorithm with the association of known output values assigned by human; iv) test datasets, that after the training phase allows for evaluating the quality of the model in terms of precision and accuracy. In particular, supervised learning algorithms, such as classification and regression models are commonly used (Yang et al., 2021; Zaidi et al., 2021). While classification models return analytical labels associated with binary or nominal qualitative variables, regression models identify outputs with continuous numerical values.

The integration of ML and DL represents a challenge for the development of robust AI solutions for VI, contributing to advance defect identification (Mueller & Massaron, 2021; Voulodimos et al., 2018).

3 RESEARCH METHODOLOGY

This article relies on a robust review methodology, the systematic literature review (SLR), to explore the scientific literature and consider diverse research contributions (Xiao & Watson, 2019). Therefore, based on the SLR procedure suggested by (Corallo et al., 2023) this article explores the scientific body regarding advanced AI solutions, including ML, to perform automated VI in manufacturing. The adopted SLR protocol consist of four steps (Figure 1).

3.1 Step 1 - Review Planning

This article aims to map AI-based solutions for VI and answer the Research Question (RQ): "What are the main AI-based solutions to support VI in manufacturing?" Scopus (https://www.scopus.com) has been selected as source of reference (Mishra et al., 2016). The relevant search keywords ("Automated Visual Inspection" OR "Visual Inspection") AND ("Artificial Intelligence" OR "Machine Learning") AND ("Manufacturing" OR "Industry 4.0") have been combined. The inclusion and exclusion criteria were set to refine the review, selecting documents in line with the SLR objective, which are in English and belong to the engineering or computer science fields.

3.2 Step 2 - Review Execution

This step consists of implementing the search query on Scopus and filtering the results. Articles were retrieved if the planned keywords appeared in the title, keywords, or abstract. The query returned 98 papers which were downloaded to allow content analysis. However, 13 articles were unavailable, so the final sample was reduced to 85 papers.

3.3 Step 3 - Analysis

The first analysis of papers allowed a preliminary screening of the sample based on their title and abstract. The sample was reduced to 73. The second phase was based on a qualitative full content analysis to systematically analyse and organize all key information in terms of AI technologies, algorithms and methods.

3.4 Step 4 - Reporting

This step focused on presenting the findings. The most relevant information has been mapped to provide an answer to the aforementioned RQ. Several contributions have been identified in terms of AI-ML algorithms, software and hardware systems, typical types of defect inspection, flexible VI solutions, VI architectures. Furthermore, the reporting phase was structured by organizing the results based on different industrial fields of application.

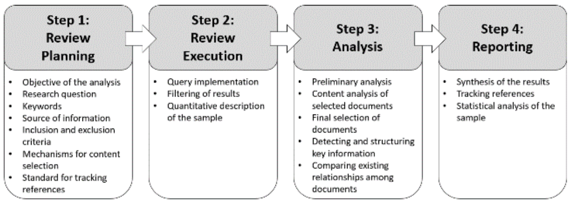

Figure 1: SLR protocol.

4 BODY OF LITERATURE: AI-BASED SOLUTIONS FOR VI

4.1 Electronic Industry

AI-based solutions for VI play a crucial role in controlling and testing advanced materials within the electronic industry, with a primary focus on semiconductors and Printed Circuit Boards (PCBs). Recent studies highlight various AI algorithms for defect detection and classification. (Buckermann et al., 2021) propose a ResNet50-based Convolutional Neural Network (CNN) for semiconductor defect classification, utilizing digital image segmentation. (Beuth et al., 2020; Chu et al., 2022) introduce an embedded algorithm for clustering high-dimensional features of Wafer Container Map (WBM) models, employing multi-objective optimization. (Hou et al., 2019) use pre-trained DL and CNN models for wafer quality analysis, employing the GoogLeNet tool. (Schlosser et al., 2019, 2022) develop a Stacked Deep Neural Network (SH-DNN) for fault detection, evaluating performance based on the F1-score. (Chan et al., 2021; Saqlain et al., 2020) propose a framework combining ML and human judgment for weld inspections, recommending real-time implementation with CNN-Hough and CNN-Wafer Defect Identification (CNN-WDI) algorithms. (Weiss, 2020) explores Deep VI for welding tasks, achieving a classification accuracy of over 97% in real-time. (Schwebig & Tutsch, 2020) combine DL with an optical inspection system for enhanced recognition accuracy of production errors in power packs. (Dorf et al., 2018) adopt VI algorithm in mechatronics and micro electro mechanical systems (MEMS). (Raveendran & Chandrasekhar, 2022) use light image processing and DL models for defect detection in semiconductor and polymeric MEMS substrates. (Koppe & Schatz, 2021) introduce a ML-based VI process consisting in image acquisition, labeling and model development, by leveraging ML as a Service

(MLaaS) platforms. Chen and Shiu (2022) combine YOLO technology versions with an automatic optical inspection platform for quality detection, showcasing YOLOv3 and YOLOv5 with an accuracy rate exceeding 70%, while other versions like YOLOv2 and YOLOv4 exhibit lower performance.

4.2 Automotive Industry

The automotive industry faces a critical challenge in ensuring vehicle manufacturing and quality compliance. Recent literature introduces various CV systems addressing this issue. (el Wahabi et al., 2020) develop a three-layer CNN specifically for vehicle analysis from images. Their system demonstrates a 99% accuracy during the testing phase of product development and 84% accuracy during algorithm training, considering multiple parameters. (Zhou et al., 2019) propose an automatic inspection system for defect identification, particularly focusing on scratch classification. The integrated system includes hardware and software components such as image acquisition subsystems, processing subsystems, and LED light sources. (Chouchene et al., 2020) explore automated CV systems for analyzing and identifying non-compliant vehicles. The authors emphasize the importance of considering five influencing factors (activity, individual, environmental, organizational, and social) for effective classification techniques in inspection performance.

4.3 Ceramic Industry

In (Karangwa et al., 2020), a Fast Region Convolutional Neural Network (R-CNN) is proposed to automate the detection of ceramic surface defects on specular materials. The model adopts the VGG16 architecture for the feature extraction and applies the selective search algorithm to extract the proposed regions. By aggregating the features into a matrix, a 92.7% of accuracy was achieved on ImageNet during the testing activities. After that, the model demonstrated an average accuracy of more than 94% in detecting, recognizing and identifying six different types of defects: breaks (physical damages), cracks (thin and long signs), dirt (small particles of materials on the surface), spots (discontinuity of the surface), pits (reliefs of the glazed surface), pinholes (small holes on the surface). In (Andrei-Alexandru et al., 2021), a new iteration of YOLOv4 is deployed to improve the accuracy and speed of detection within a ceramic manufacturing environment. YOLOv4 modifies the structure of standard YOLO by adjusting the depth, width, resolution, and network structure to accommodate scaling. It also uses a CSPDarknet53 backbone and implements a cross-stage pooling principles for reducing computational costs. Finally, (Kadar & Onita, 2019) introduces a CNN solution to enhance a machine vision system, providing additional information on the types of product, the production stage and the detected defects. The system, equipped with a 10 Mpixel black-and-white camera, uses image pre-processing techniques within Vision Builder for Automated Inspection software.

4.4 Aerospace Industry

The aerospace industry, characterised by strong quality standards and considerations for safety and security (Brandoli et al., 2021), is a critical sector for VI. (Brandoli et al., 2021) present a Deep Neural Network (DNN)-based methodology for automatic detection of aircraft fuselage corrosion using the D-Sight aircraft inspection system. Leveraging a pre-trained CNN model, the system achieves 90.2% accuracy with InceptionV3 and 92.2% with DenseNet, supporting aircraft maintenance activities. (Aust et al., 2021) develop a system for automated defect detection on engine blades, achieving high accuracy and recall to aid maintenance decisions. (Meister et al., 2021) propose a novel classification approach, integrating CNN and support vector machine (SVM) models to visualize regions of interest and compare feature maps with geometric attributes, enhancing VI. (Beltrán-González et al., 2020) study a ML-based VI system for aerospace component defect detection, combining CNN with long/short-term memory networks (LSTMs) for improved performance, achieving an average accuracy of 90.7%. (Aust & Pons, 2022) compare human operators, image processing algorithms, AI software, and 3D scanning for various inspections and defects in the aerospace industry. In approaching Additive Manufacturing (AM) technology, aerospace industry supports process engineers in data modelling for quality assurance of AM welding operations, proposing the use of Random Forest algorithms with polar transformation and local binary model for defect classification (Dasari et al., 2020). (Finney et al., 2019) collaborate with NASA to develop a system for inspecting metal components additively produced with multi-material technologies.

4.5 Additive Manufacturing Industry

Due to increasing product complexity, the demand for mass customization and technological advancements in production, AM emerges as a pivotal technology for ensuring high-quality products with intricate geometries. It not only replaces traditional manufacturing methods but also demonstrates improved performance in terms of time and costs (Dilberoglua & Gharehpapagh, 2017). In various manufacturing domains like biomedical and aerospace, where VI systems are essential for ensuring product quality compliance, AM finds several applications in the literature. (Sivabalakrishnan et al., 2020) introduce an AM system based on IoT to facilitate the customization of customer orders through mobile or web applications. The system includes a cloud-based platform that tracks order and product status, integrating a VI application to ensure correctness and quality through image detection and processing. (Gobert et al., 2018) present a defect detection strategy for melting AM powder beds, employing supervised ML. This approach enables real-time defect correction during production processes through the use of a multi-level VI system. Visual features are extracted using a Digital Single Lens Reflex (DSLR) camera and evaluated with a linear support vector machine (LSVM) algorithm.

4.6 Textile Industry

In the textile industry, (Sandhya et al., 2021) propose an AI-based system for automatically detecting tissue defects. Employing various levels of pre-processing, tissue images are enhanced using CNN processing techniques. The Deep Convolutional Neural Network (DCNN) and a pre-trained network (AlexNet) are used for training and classifying defects such as color, cut, hole, thread, and metal contamination. The system demonstrates a 92.6% accuracy in defect detection. (Voronin et al., 2021) introduce a two-step approach that combines novel and traditional algorithms to enhance image and defect detection. Their CNN-based defect detection method improves defect localization compared to traditional methods, with the analysis showing high method efficiency. Utilizing the carrier machine as a post-processing technique significantly it reduces the likelihood of false alarms. (Tayeh et al., 2020) tackle the challenge of training CNNs for texture analysis to detect anomalies and defects based on distance analysis. They adopt the Triplet Network Model (TNM), allowing the inclusion of three different images (anchor, positive, negative) in the CNN algorithm, which is based on the Euclidean distances.

4.7 Metallurgy Industry

Metallurgy, as an applied science focused on understanding metal structures and properties, demands advanced technological systems for performance and quality monitoring (Cottrell, 2019). (Thalagala & Walgampaya, 2021) propose a VI system based on AlexNet CNN architecture and transfer learning to recognize casting surface defects. The proposed three-step approach involves dataset definition, image augmentation and nonparametric classification, using the k-nearest neighbor algorithm. The system utilizes a pre-trained model feature extractor and fine-tuning of hyper-parameters. (Damacharla et al., 2021) introduce the Transfer Learning-based U-Net (TLU-Net) framework for steel surface defect detection, exploring ResNet and DenseNet encoders. Transfer learning outperforms random initialization in segmentation and defect classification, with an 81% improvement for ResNet and 63% for DenseNet. (Fang et al., 2020) conduct a comprehensive investigation into 2D and 3D surface defect detection for flat metal products, emphasizing the critical link between defect classification accuracy and detection accuracy in automated VI systems. Similarly, (Luo et al., 2020) focus on defect detection in flat steel products by adopting ML approaches with wavelets and contourlets.

4.8 Smart Manufacturing Industry

This section highlights diverse applications of VI systems within the broad manufacturing landscape. (Babic et al., 2021) delve into 3D image-based VI systems in Smart Manufacturing Systems (SMSs) for product quality assessment. They acknowledge the benefits of AI but underscore challenges related to reflective surfaces, high investment costs for image analysis software and achieving accuracy with flexible materials like rubber. (Robotyshyn et al., 2021) use ML and advocate for binary segmentation models over multiclass models in product quality inspection. DL techniques are also considered in (Li et al., 2020) who develop an Optical Inspection (OPICA) system using a combination of CNN and rules-based classification models for edge defect detection on hard disk recording heads. (Tabernik et al., 2020) present a segmentation-based DL architecture for surface anomaly detection, outperforming DeepLab v3+ and UNet. (El Zant et al., 2021) integrate intelligent VI into Manufacturing Execution Systems (MES) for real-time monitoring and anomaly detection. (Jeong et al., 2021) leverage ML for controlling chipping defects in display production, introducing an automatic VI system with a DNN. They use TensorFlow v1.13 and Keras v2.2, evaluating accuracy against U-Net, YOLOv2, and commercial tools. A conditionally coupled generative network provides synthetic defect images under various lighting conditions.

5 DISCUSSION & CONCLUSION

The results of the literature analysis show a comprehensive overview of AI-based VI solutions based on ML and DL algorithms. Indeed, the study allowed for providing an answer to the aforementioned research question, thus identifying the most important methodological and technological solutions for supporting industries in VI activities.

The study showed how such AI-VI solutions are useful independently from the specific industrial sector. Indeed, the need to ensure high quality standards of products or machines and to identify defects is pivotal in any scenario. Also, the literature contributions highlighted the importance and effectiveness of integrating ML and DL techniques for achieving a more accurate classification of defects, such as of images. The use of supervised learning algorithm is fundamental for training systems and obtaining reliable results.

In addition, among the several algorithm solutions for VI, Convolutional Neural Networks seem to be the most used technique, often associated with the use of other models such as Random Forest, and Support Vector Machine. Also, the use of different evaluation metrics such as F-score, accuracy, precision and recall is suggested.

Furthermore, the study highlighted some issues in the field of available AI-VI solutions. No ready-to-use solutions emerge and effective solutions need to be ad-hoc developed or configured. Also, challenges emerge in terms of data availability and quality, as well as training datasets, and the need of important computational resources for CNN and DNN models.

Despite the paper contribute in extending the literature and proving suggestions to industrial companies on AI-based solutions for VI, it suffers from some limitations in terms of qualitative approach and industrial validation, which leave future directions for improvement.

ACKNOWLEDGEMENTS

This study comes form AVIS (Advanced Visual InSpection) project, RIPARTI (assegni di Ricerca per riPARTire con le imprese) framework funded by the Puglia Region, Italy - FESRT-FSE 2014/2020.

REFERENCES

American Bureau of Shipping. (2022, dicembre). *The use of remote inspection technologies*. https://ww2.eagle.org/content/dam/eagle/rules-and-guides/current/other/242-gn-remote-inspection-tech-dec-2022/rit-gn-dec22.pdf

Andrei-Alexandru, T., Cosmin, C., Bogdan, P., & Adrian-Alexandru, T. (2021). Automated ceramic plate defect detection using ScaledYOLOv4-large. *2021 13th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, 1–6. https://doi.org/10.1109/ECAI52376.2021.9515185

Aust, J., & Pons, D. (2022). Comparative Analysis of Human Operators and Advanced Technologies in the Visual Inspection of Aero Engine Blades. *Applied Sciences*, *12*(4), Articolo 4. https://doi.org/10.3390/app12042250

Aust, J., Shankland, S., Pons, D., Mukundan, R., & Mitrovic, A. (2021). Automated Defect Detection and Decision-Support in Gas Turbine Blade Inspection. *Aerospace*, *8*(2), Articolo 2. https://doi.org/10.3390/aerospace8020030

Babic, M., Farahani, M. A., & Wuest, T. (2021). Image Based Quality Inspection in Smart Manufacturing Systems: A Literature Review. *Procedia CIRP*, *103*, 262–267. https://doi.org/10.1016/j.procir.2021.10.042

Beltrán-González, C., Bustreo, M., & Del Bue, A. (2020). External and internal quality inspection of aerospace components. *2020 IEEE 7th International Workshop on Metrology for AeroSpace (MetroAeroSpace)*, 351–355. https://doi.org/10.1109/MetroAeroSpace48742.2020.9160103

Beuth, F., Schlosser, T., Friedrich, M., & Kowerko, D. (2020). Improving Automated Visual Fault Detection by Combining a Biologically Plausible Model of Visual Attention with Deep Learning. *IECON 2020 The 46th Annual Conference of the IEEE Industrial Electronics Society*, 5323–5330. https://doi.org/10.1109/IECON43393.2020.9255234

Borangiu, T. (2006). Interactive learning of scene-robot models based on AI techniques. In *IFAC Proceedings Volumes* (Vol. 39, p. 210). https://doi.org/10.3182/20060517-3-FR-2903.00120

Brandoli, B., de Geus, A. R., Souza, J. R., Spadon, G., Soares, A., Rodrigues, J. F., Komorowski, J., & Matwin, S. (2021). Aircraft Fuselage Corrosion Detection Using Artificial Intelligence. *Sensors*, *21*(12), Articolo 12. https://doi.org/10.3390/s21124026

Brownlee, J. (2022, aprile 4). *Deep Learning for Computer Vision: Image Classification, Object Detection, and Face Recognition in Python*. https://b.eruditor.link/file/3706194/

Buckermann, F., Klement, N., Beyer, O., Hütten, A., & Hammer, B. (2021). Automating the optical identification of abrasive wear on electrical contact pins. *At - Automatisierungstechnik*, *69*(10), 903–914. https://doi.org/10.1515/auto-2021-0021

Chan, K. Y., Yiu, K. F. C., Lam, H.-K., & Wong, B. W. (2021). Ball bonding inspections using a conjoint framework with machine learning and human judgement. *Applied Soft Computing*, *102*, 107115. https://doi.org/10.1016/j.asoc.2021.107115

Chouchene, A., Carvalho, A., Lima, T. M., Charrua-Santos, F., Osório, G. J., & Barhoumi, W. (2020). Artificial Intelligence for Product Quality Inspection toward Smart Industries: Quality Control of Vehicle Non-Conformities. *2020 9th International Conference on Industrial Technology and Management (ICITM)*, 127–131. https://doi.org/10.1109/ICITM48982.2020.9080396

Chu, M., Park, S., Jeong, J., Joo, K., Lee, Y., & Kang, J. (2022). Recognition of unknown wafer defect via optimal bin embedding technique. *The International Journal of Advanced Manufacturing Technology*, *121*, 1–13. https://doi.org/10.1007/s00170-022-09447-y

Corallo, A., Crespino, A. M., Vecchio, V. D., Lazoi, M., & Marra, M. (2023). Understanding and Defining Dark Data for the Manufacturing Industry. *IEEE Transactions on Engineering Management*, *70*(2), 700–712. https://doi.org/10.1109/TEM.2021.3051981

Cottrell, S. A. (2019). *An Introduction to Metallurgy, Second Edition* (2ª ed.). CRC Press. https://doi.org/10.1201/9780429293917

Damacharla, P., M. V., A. R., Ringenberg, J., & Javaid, A. Y. (2021). TLU-Net: A Deep Learning Approach for Automatic Steel Surface Defect Detection. *2021 International Conference on Applied Artificial Intelligence (ICAPAI)*, 1–6. https://doi.org/10.1109/ICAPAI49758.2021.9462060

Dasari, S. K., Cheddad, A., & Palmquist, J. (2020). Melt-Pool Defects Classification for Additive Manufactured Components in Aerospace Use-Case. *2020 7th International Conference on Soft Computing & Machine Intelligence (ISCMI)*, 249–254. https://doi.org/10.1109/ISCMI51676.2020.9311555

Dilberoglua, U. M., & Gharehpapagh, B. (2017). *The Role of Additive Manufacturing in the Era of Industry 4.0 | Elsevier Enhanced Reader*. https://doi.org/10.1016/j.promfg.2017.07.148

Dorf, R. C., Murakami, A., Lyshevski, S. E., & Grigsby, L. L. (2018). *Electromechanical Systems, Electric Machines, and Applied Mechatronics*. CRC Press. https://doi.org/10.1201/9780203758687

el Wahabi, A., Hadj Baraka, I., Hamdoune, S., & El Mokhtari, K. (2020). *Detection and Control System for Automotive Products Applications by Artificial Vision Using Deep Learning* (pp. 224–241). https://doi.org/10.1007/978-3-030-36671-1_20

El Zant, C., Charrier, Q., Benfriha, K., & Le Men, P. (2021). Enhanced Manufacturing Execution System "MES" Through a Smart Vision System. In L. Roucoules, M. Paredes, B. Eynard, P. Morer Camo, & C. Rizzi (A c. Di), *Advances on Mechanics, Design Engineering and Manufacturing III* (pp. 329–334). Springer International Publishing. https://doi.org/10.1007/978-3-030-70566-4_52

Fang, X., Luo, Q., Zhou, B., Li, C., & Tian, L. (2020). Research Progress of Automated Visual Surface Defect Detection for Industrial Metal Planar Materials. *Sensors (Basel, Switzerland)*, *20*. https://doi.org/10.3390/s20185136

Finney, G. A., Persons, C. M., Whitten, J. R., Centamore, A. A., & Trevithick, C. P. M. (2019). Evaluation of technologies for autonomous visual inspection of additive manufacturing (AM). *Dimensional Optical Metrology and Inspection for Practical Applications VIII*, *10991*, 172–183. https://doi.org/10.1117/12.2520279

Gobert, C., Reutzel, E. W., Petrich, J., Nassar, A. R., & Phoha, S. (2018). Application of supervised machine learning for defect detection during metallic powder bed fusion additive manufacturing using high resolution imaging. *Additive Manufacturing*, *21*, 517–528. https://doi.org/10.1016/j.addma.2018.04.005

Hou, D., Liu, T., Pan, Y.-T., & Hou, J. (2019). AI on edge device for laser chip defect detection. *2019 IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC)*, 0247–0251. https://doi.org/10.1109/CCWC.2019.8666503

IBM. (2023, luglio 6). *AI vs. Machine Learning vs. Deep Learning vs. Neural Networks: What's the difference?* IBM Blog. https://www.ibm.com/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks/www.ibm.com/blog/ai-vs-machine-learning-vs-deep-learning-vs-neural-networks

Jeong, E.-Y., Kim, J., Jang, W.-H., Lim, H.-C., Noh, H., & Choi, J.-M. (2021). A more reliable defect detection and performance improvement method for panel inspection based on artificial intelligence. *Journal of Information Display*, *22*(3), 127–136. https://doi.org/10.1080/15980316.2021.1876174

Kadar, M., & Onita, D. (2019). A deep CNN for Image Analytics in Automated Manufacturing Process Control. *2019 11th International Conference on Electronics, Computers and Artificial Intelligence (ECAI)*, 1–5. https://doi.org/10.1109/ECAI46879.2019.9042159

Karangwa, J., Kong, L., You, T., & Zheng, J. (2020). Automated Surface Defects Detection on Mirrorlike Materials by using Faster R-CNN. *2020 7th International Conference on Information Science and Control Engineering (ICISCE)*, 2288–2294. https://doi.org/10.1109/ICISCE50968.2020.00341

Kitaguchi, D., Takeshita, N., Hasegawa, H., & Ito, M. (2022). Artificial intelligence-based computer vision in surgery: Recent advances and future perspectives. *Annals of Gastroenterological Surgery*, *6*(1), 29–36. https://doi.org/10.1002/ags3.12513

Koppe, T., & Schatz, J. (2021). *Cloud-based ML Technologies for Visual Inspection: A Case Study in Manufacturing*. http://hdl.handle.net/10125/70736

Li, G., Feng, C., Woldesenbet, A., King, B., Hadavi, H., Moku, V., Loken, K., & Kunkel, G. (2020). Deep Learning based Optical Inspection with Centralized Analysis for High Volume Smart Manufacturing. *Annual Conference of the PHM Society*, *12*(1), Articolo 1. https://doi.org/10.36001/phmconf.2020.v12i1.1282

Luo, Q., Fang, X., Liu, L., Yang, C., & Sun, Y. (2020). Automated Visual Defect Detection for Flat Steel Surface: A Survey. *IEEE Transactions on Instrumentation and Measurement*, *69*(3), 626–644. https://doi.org/10.1109/TIM.2019.2963555

Meister, S., Wermes, M., Stüve, J., & Groves, R. M. (2021). Cross-evaluation of a parallel operating SVM – CNN classifier for reliable internal decision-making processes in composite inspection. *Journal of Manufacturing Systems*, *60*, 620–639. https://doi.org/10.1016/j.jmsy.2021.07.022

Mishra, D., Gunasekaran, A., Childe, S. J., Papadopoulos, T., Dubey, R., & Wamba, S. (2016). Vision, applications and future challenges of Internet of Things: A bibliometric study of the recent literature. *Industrial Management & Data Systems*, *116*(7), 1331–1355. https://doi.org/10.1108/IMDS-11-2015-0478

Mueller, J. P., & Massaron, L. (2021). *Machine learning for dummies* (2nd edition). John Wiley & Sons, Inc.

Mujeeb, A., Dai, W., Erdt, M., & Sourin, A. (2019). One class based feature learning approach for defect detection using deep autoencoders. *Advanced Engineering Informatics*, *42*, 100933. https://doi.org/10.1016/j.aei.2019.100933

Paneru, S., & Jeelani, I. (2021). Computer vision applications in construction: Current state, opportunities & challenges. *Automation in Construction*, *132*, 103940. https://doi.org/10.1016/j.autcon.2021.103940

Piuri, V., Scotti, F., & Roveri, M. (2005). Computational intelligence in industrial quality control. *IEEE International Workshop on Intelligent Signal Processing, 2005.*, 4–9. https://doi.org/10.1109/WISP.2005.1531623

Raveendran, S., & Chandrasekhar, A. (2022). Inspecting and classifying physical failures in MEMS substrates during fabrication using computer vision. *Microelectronic Engineering*, *254*, 111696. https://doi.org/10.1016/j.mee.2021.111696

Robotyshyn, M., Sharkadi, M., & Malyar, M. (2021). *Surface Defect Detection Based on Deep Learning Approach*. 13.

Sandhya, N., Sashikumar, N. M., Priyanka, M., Wenisch, S. M., & Kumarasamy, K. (2021). Automated Fabric Defect Detection and Classification: A Deep Learning Approach. *Textile & Leather Review*, *4*, 315–335. https://doi.org/10.31881/TLR.2021.24

Saqlain, M., Abbas, Q., & Lee, J. Y. (2020). A Deep Convolutional Neural Network for Wafer Defect Identification on an Imbalanced Dataset in Semiconductor Manufacturing Processes. *IEEE Transactions on Semiconductor Manufacturing*, *33*(3), 436–444. https://doi.org/10.1109/TSM.2020.2994357

Schlosser, T., Beuth, F., Friedrich, M., & Kowerko, D. (2019). A Novel Visual Fault Detection and Classification System for Semiconductor Manufacturing Using Stacked Hybrid Convolutional Neural Networks. *2019 24th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA)*, 1511–1514. https://doi.org/10.1109/ETFA.2019.8869311

Schlosser, T., Friedrich, M., Beuth, F., & Kowerko, D. (2022). Improving automated visual fault inspection for semiconductor manufacturing using a hybrid multistage system of deep neural networks. *Journal of Intelligent Manufacturing*, *33*(4), 1099–1123. https://doi.org/10.1007/s10845-021-01906-9

Schwebig, A. I. M., & Tutsch, R. (2020). Intelligent fault detection of electrical assemblies using hierarchical convolutional networks for supporting automatic optical inspection systems. *Journal of Sensors and Sensor Systems*, *9*(2), 363–374. https://doi.org/10.5194/jsss-9-363-2020

Sivabalakrishnan, R., Kalaiarasan, A., Ajithvishva, M. S., Hemsri, M., Oorappan, G. M., & Yasodharan, R. (2020). IoT visualization of Smart Factory for Additive Manufacturing System (ISFAMS) with visual inspection and material handling processes. *IOP Conference Series: Materials Science and Engineering*, *995*(1), 012027. https://doi.org/10.1088/1757-899X/995/1/012027

Tabernik, D., Šela, S., Skvarč, J., & Skočaj, D. (2020). Segmentation-based deep-learning approach for surface-defect detection. *Journal of Intelligent Manufacturing*, *31*. https://doi.org/10.1007/s10845-019-01476-x

Tayeh, T., Aburakhia, S., Myers, R., & Shami, A. (2020). Distance-Based Anomaly Detection for Industrial Surfaces Using Triplet Networks. *2020 11th IEEE Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, 0372–0377. https://doi.org/10.1109/IEMCON51383.2020.9284921

Thalagala, S., & Walgampaya, C. (2021). Application of AlexNet convolutional neural network architecture-based transfer learning for automated recognition of casting surface defects. *2021 International Research Conference on Smart Computing and Systems Engineering (SCSE)*, *4*, 129–136. https://doi.org/10.1109/SCSE53661.2021.9568315

Voronin, V. V., Sizyakin, R., Zhdanova, M., Semenishchev, E. A., Bezuglov, D., & Zelemskii, A. A. (2021). Automated visual inspection of fabric image using deep learning approach for defect detection. *Automated Visual Inspection and Machine Vision IV*, *11787*. https://doi.org/10.1117/12.2592872

Voulodimos, A., Doulamis, N., Doulamis, A., & Protopapadakis, E. (2018). Deep Learning for Computer Vision: A Brief Review. *Computational Intelligence and Neuroscience*, *2018*, e7068349. https://doi.org/10.1155/2018/7068349

Weiss, E. (2020). Electronic component solderability assessment algorithm by deep external visual inspection. *2020 IEEE Physical Assurance and*

Inspection of Electronics (PAINE), 1–6. https://doi.org/10.1109/PAINE49178.2020.9337565

Xiao, Y., & Watson, M. (2019). Guidance on conducting a systematic literature review. *Journal of planning education and research*, *39*(1), 93–112.

Yang, J., Xu, R., Qi, Z., & Shi, Y. (2021). *Visual Anomaly Detection for Images: A Survey* (arXiv:2109.13157). arXiv. https://doi.org/10.48550/arXiv.2109.13157

Zaidi, S. S. A., Ansari, M. S., Aslam, A., Kanwal, N., Asghar, M., & Lee, B. (2021). *A Survey of Modern Deep Learning based Object Detection Models* (arXiv:2104.11892). arXiv. https://doi.org/10.48550/arXiv.2104.11892

Zhou, Q., Chen, R., Huang, B., Liu, C., Yu, J., & Yu, X. (2019). An Automatic Surface Defect Inspection System for Automobiles Using Machine Vision Methods. *Sensors*, *19*(3), Articolo 3. https://doi.org/10.3390/s19030644