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Extending Asset Lifespan Through Data Augmentation Assisted Quality Control

Ruben Alonso **Guido Noce** **Vincenzo Cutrona** **Diego Reforgiato Recupero** †

R2M Solution Srl, Pavia, Italy (e-mail: ruben.alonso@r2msolution.com)
Programa de Doctorado, Centro de Automática y Robótica, Universidad Politécnica de Madrid-CSIC, Madrid, Spain
DIMAC Srl, Tortona, Italy
University of Applied Sciences and Arts of Southern Switzerland, Lugano-Viganello, Switzerland
† *Department of Mathematics and Computer Science, University of Cagliari, Cagliari, Italy*

Abstract: Quality control is essential for the life cycle of components and has an impact on the costs and maintenance time of the entire production chain. In modern quality control, AI power could be unleashed if enough information for training AI models is always available. In this work, an approach based on data augmentation has been applied to oil plug quality control to mitigate the lack of images of defective parts, which hinders the training of classification models. The proposed approach has demonstrated a positive impact on quality inspection by maintaining or reducing the percentage of classification errors with respect to a baseline trained with images of real oil plugs.

Keywords: Quality Assurance, Quality Maintenance, Industry 4.0, Machine Learning, Sorting Machines, Artificial Intelligence

1. INTRODUCTION

Although the ideas of Industry 5.0 are on the agendas of the automotive industry, e.g., sustainability and human-centricity, some key points of what came to be called Industry 4.0 are still being addressed, including the integration of the supply chain and interoperability (Frederico et al., 2023). Both approaches are not mutually exclusive; in fact, a solid foundation in cyber-physical systems facilitates the new paradigm of Industry 5.0, where more emphasis is placed on human-machine cooperation, customization, and long-term sustainability (Ahelero et al., 2022).

Moreover, both paradigms emphasize the crucial integration of supply chains and the maintenance of high-quality standards throughout the production process. This integration underscores the significance of quality control across all components, materials, and parts involved in assembly and production. Ensuring quality throughout the integrated chain is paramount for optimizing the lifespan of each part or component, consequently impacting overall production costs and maintenance timelines. For instance, premature failure of any of these assets not only undermines reliability but also tarnishes the brand image indirectly.

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In this paper, we approach asset reliability from the perspective of upstream quality control. We assume that thorough and accurate quality control of assets can impact the maintenance of machines in the production process and even improve the predictability of failures and downtime. In particular, starting from the assumption that the purpose of maintenance is *"to ensure equipment functions to its original optimal level and this can be accomplished by eliminating losses that a ect the equipment"* (Mansor et al., 2012), our article focuses on the elimination of *breakdown losses* and *scrap and rework losses*.

In our investigation, we delve into the potential integration of machine learning techniques for data augmentation and classification within the realm of quality control for manufactured parts. Our primary objective is to ascertain the viability of these advanced methodologies in enhancing the overall quality and predictability across the entirety of the production chain. Furthermore, by leveraging the power of machine learning in conjunction with traditional quality control methodologies, we endeavor to pave the way for more agile, adaptive, and predictive manufacturing processes.

The implementation of the quality control plan is based on the customer's specifications. These specifications define the conformance characteristics that each part will have. These characteristics can be defined by variables, such as dimensions specified by a nominal value and a tolerance range. Additionally, there are features defined as discrete attributes, such as the presence of burrs or even color-

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based attributes. In terms of dimensions, these values and tolerances can be used to carry out efficient control. However, when the challenge is to detect other types of defects, such as the presence of stains or scratches, this detection becomes more challenging. It is in these cases that new approaches based on computer vision, machine learning, and artificial intelligence(AI) are proliferating (Fahle et al., 2020).

Aligned with these challenges and the idea that quality a ects the entire process, the main objective of this paper is to present the approach and the results of improving quality control within an automotive assembly, focusing on oil plugs.

In our inquiry, we pose a fundamental question: in scenarios where images of defective parts are limited, can data augmentation serve as a viable strategy to enrich the dataset utilized for training oil plug quality inspection models? This question underscores a critical challenge faced by many in the realm of quality control: the scarcity of diverse and representative data. In such circumstances, traditional machine learning approaches may falter, hindered by the lack of sufficient training examples to effectively discern between acceptable and defective components. By leveraging data augmentation, a technique that addresses data scarcity by artificially expanding the dataset through various transformations such as rotation, scaling, and flipping, our goal is to introduce a broader spectrum of variations. This enables the model to generalize more e ectively, accurately identifying defects even when authentic samples are limited.

To tackle one of the primary challenges in quality inspection—specifically, the scarcity of images depicting defective parts and the absence of references—we have developed an approach centered on synthesized image generation (data augmentation). We hypothesize that synthetic images could be used as a replacement or supplement to real images in environments where there are not enough defective parts to train an AI, and validated this idea in the specific case mentioned above by empirically evaluating the quality control results with a commercial-grade classification solution, demonstrating the e ectiveness of the augmentation technique. We do not focus on the specific machine learning algorithm but rather on the analysis of the augmented dataset with synthetic images and how they a ect the overall accuracy. Moreover, the methodology tailored for the intricacies of oil plug manufacturing presents a robust framework transferrable to various domains. Its adaptability extends beyond the confines of its original application, o ering insights and strategies that can be e ectively implemented across a spectrum of industries and scenarios. By embracing this methodology, organizations can unlock new avenues for problem-solving and efficiency improvements, fostering continuous advancement and competitive advantage in diverse fields.

These challenges and results are presented in the subsequent sections. Specifically, Section 2 summarises the state of the art. Section 3 presents the augmentation technique we have adopted in the proposed use case. Section 4 discusses the results. Finally, Section 5 presents conclusions and outlines future activities where we are headed.

2. STATE OF THE ART

Quality control and product life cycle management are very related to each other (Brettel et al., 2016). Specifically, the well-known Sand Cone Model (Ferdows and De Meyer, 1990) is already positioned as a reference element in the framework, as reduced rework and waste directly impact cost, efficiency, and dependability.

One of the benefits of an optimal quality control process is the reduction of waste generation, which in turn brings sustainability improvements and cost savings to industries. The future of asset management will be characterized, among other aspects, by extended asset lifespan, cost-e ectiveness, and improved sustainable performance, adhering to the concepts of Quality 5.0 and Maintenance 5.0, which are closely related to Industry 5.0 (Frick, 2023). Asset life cycle management, besides being key to this Industry 5.0 approach, is fully in line with the ideas of sustainability and environmental improvement. A life cycle management approach focused on these aspects will result in a *"practical, and integrated, approach to minimize the environmental burdens associated with a product over its life cycle"* (Hunkeler et al., 2003).

Therefore, improvements in quality control can have a significant impact on the product life cycle and the entire production chain, and contribute to achieving the objectives of Industry 5.0. AI may represent a game changer for quality control, leading to outstanding improvements. While modern quality control approaches are embracing AI more and more, a huge uptake is hindered by the scarcity of a crucial piece of information needed to train powerful AI models, i.e., information about defective parts enabling balanced training for optimal results. This is especially true when the manufacturing process has not started yet, thus it is not possible to collect data about defective parts (Volkau et al., 2022).

When dealing with a data-lacking issue, data augmentation represents a powerful solution, as demonstrated by its application in di erent fields (Li et al., 2022; Mikołajczyk and Grochowski, 2018). Apart from expanding and balancing datasets, data augmentation capabilities provide the needed flexibility to adapt existing datasets to the requirements of new product families in initial phases or even to adapt to newly detected defects. This flexibility enables iterative improvement in the classification and quality control of the parts, showing appreciable performance boosts when compared with non-augmented datasets (Yang et al., 2022; Singh and Bruzzone, 2022). Similar augmentation techniques have been applied to the automotive industry, currently in full transition to Industry 5.0, where consistent improvements have been achieved on quality inspection of automobile parts (Lee et al., 2021) and structural adhesives for automotive part application (Peres et al., 2021).

In their comprehensive survey, Shorten and Khoshgoftaar (2019) o er a taxonomy that encapsulates these diverse strategies of data augmentation techniques, spanning from traditional image manipulation methods to more sophisticated deep learning approaches. Within the realm of image manipulation, techniques encompass a spectrum of transformations. Geometric alterations, such as rotation, translation, and scaling, alongside image blending methods, a ord simple yet e ective means of augmenting datasets. Additionally, kernel filters for sharpening or blurring images provide further avenues for enhancing dataset variability and model robustness. On the other end of the spectrum lie techniques rooted in deep learning paradigms, which operate within the feature space rather than directly on the images themselves (Nanni et al., 2022). These methods leverage the intrinsic characteristics of the data to enact transformations that transcend mere pixel-level modifications, thereby enriching the dataset with more nuanced variations. Moreover, advancements in adversarial training and generative modeling have propelled the development of cutting-edge augmentation techniques, exemplified by the emergence of Generative Adversarial Networks (GANs) (Antoniou et al., 2018). These models employ a game-theoretic framework to generate synthetic data samples that closely mimic real-world instances, thereby expanding the dataset while preserving its underlying statistical properties.

3. DATA AUGMENTATION ASSISTED QUALITY CONTROL CASE

The sorting operation is the quality control step where defective parts are recognized and separated from non-defective parts. Nowadays, some sorting methods do exist and are also implemented in automatic sorting machines; however, these methods are traditionally limited and not extremely powerful, require a delicate fine-tuning of image analysis algorithms, and depend considerably on the stability/uniformity of lighting and stability of the position of the part under the lighting, the image quality and the variability of the reflective characteristics of the surfaces. To solve this issue, recent advancements in AI, especially in object detection and recognition, are increasingly employed for sorting operations. Unfortunately, and despite the sector's extensive knowledge about the possible defects that may occur, due to experiences with other similar parts, a critical requirement for the adoption of AI models for image recognition and detection of defections is the availability of large datasets of images for training models. In the context of quality control, in mechanical series production, this requirement could represent a big barrier, due to the shortage of images depicting representative defective parts. Indeed, defective parts may occur very rarely (defective parts are usually described using the unit "parts per million"), and randomly. Also, this challenge is compounded by the costs of e ort, time, and waste required to generate such data.

The use case presented in this work fits into these circumstances. Specifically, our use case is focused on the sorting of oil plugs used in the automotive industry. These plugs constitute small elements of a specific component, yet they wield a significant influence on the overall quality of the final product. For this reason, having a quality process for these plugs is essential to correctly manage the life cycle of the final product. An oil plug is assembled with an O-ring to ensure sealing. However, the seal is only guaranteed if the outer metal surface of the plug as well as the O-ring grove are perfectly flat, to ensure the O-ring fits the plug perfectly and prevent O-ring damage. It follows that the quality of the outer metal surface and the O-ring groove are key decision points for sorting. Figure 1 exemplifies typical defects occurring on these two plug components. Figure 1 (left) depicts a defective O-ring groove, possibly due to the absence of surface coating or the formation of lumps due to excessive coating. Figure 1 (right) shows a plug with an irregular outer metal surface. Both defects, which the human eye can easily detect, are difficult to detect with conventional testing tools. In this scenario, AI image classification algorithms could be a viable solution if reference images of the defects were available for quality classification.

In this work, we propose an application of data augmentation techniques based on computer vision and image manipulation to generate artificial images of defective parts. Starting from images depicting non-defective plugs, the proposed solution artificially generates images of defective plugs, which can be in turn exploited for training classification algorithms. Expert knowledge is required however to identify which are the regions of interest where defects may occur (i.e., the outer metal surface and the O-ring groove), as well as how the defects may appear (in terms of shapes and sizes). This information is needed to prevent the solution from generating non-realistic defects.

Given an image of a non-defective plug, the region of interest can be described in two ways: i) through user interaction, where the user selects the area where the defect may appear; and ii) through the automatic generation of a mask that detects the surfaces of the reference part, for example by background removal. Once the region of interest is defined, we can employ one of two di erent techniques to introduce defects. The first one is based on image manipulation and blending (Zhang et al., 2020). This technique exploits di erent pixel combination functions to merge two distinct images into a new one. These operations enable the attainment of distinct e ects, making them applicable to various use cases depending on di erent contexts. E ects may include integrating the defect region of interest into the original image while maintaining, darkening, or lightening the area. Another option is the subtraction of the e ect representation from the reference image, for instance, to represent cracks or grooves. Figure 2 shows two examples of synthetic images of defective plugs generated by using the image manipulation and blending technique. In particular, the image on the left is generated with the dodge blending mode, whereas within the image on the right, the defect was blended by multiplying the defect data on the reference image. The second technique involves the automatic generation of spots or stains (Buslaev et al., 2020), allowing the creation of blemishes with varying numbers or sizes on the reference image.

Through the application of these two techniques, we managed to generate synthetic images depicting defective parts, starting from real images of similar parts containing correct parts and defects. The new synthetic images enable us to generate a new training dataset, with balanced samples of good and defective parts. The balanced dataset, in turn, allows us to train and validate di erent classification models, which can be exploited to automatize the sampling operation. Additionally, it facilitates the comparison of di erent o -the-shelf models, enabling the selection of the most suitable one for each family of parts. Finally, it streamlines the fine-tuning of these algorithms and models,

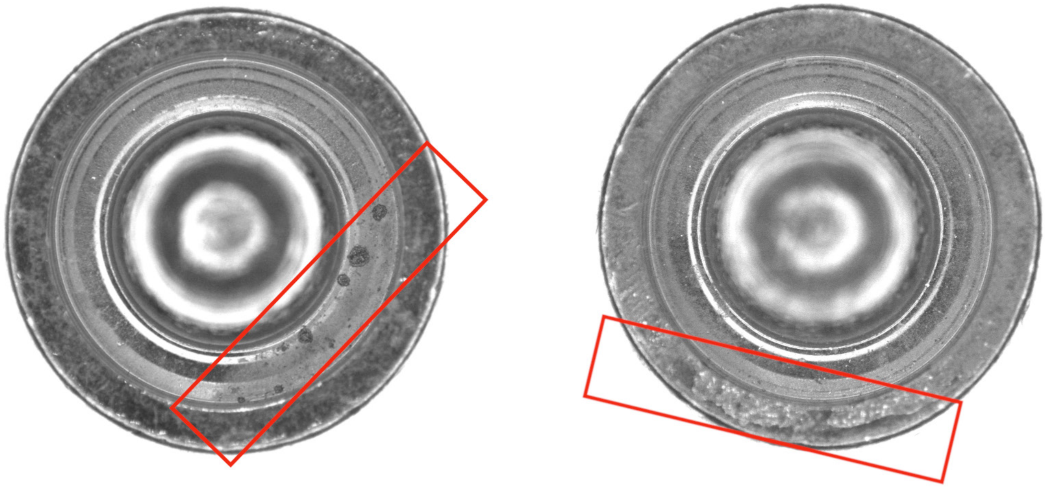

Fig. 1. Defects in the oil plug. On the left, a type of defect a ecting the groove housing the O-ring. On the right, the defect is located on the outer metal surface, which is irregular.

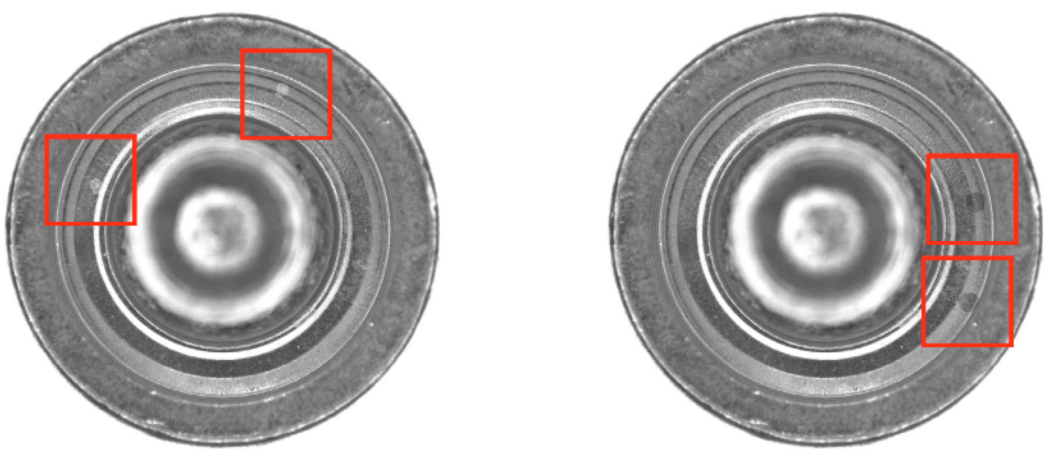

Fig. 2. Two images of defective plugs generated by applying the image manipulation and blending technique to an image of a good plug.

making them easily adaptable to newly identified defects within di erent product families.

4. VALIDATION AND RESULTS

To validate the quality of the generated images, as well as the performance of classification models for solving the sorting problem, we set up an experiment in the context of the KITT4SME project . Within the experiment, DIMAC, a company of the KITT4SME consortium, adopted the solution by envisioning potential applications for its automatic sorting machines. An unbalanced dataset of real images (showing both non-defective and defective plugs) has been provided by DIMAC. This dataset has been augmented with new synthetic images of defective parts generated with the proposed solution. Then, an AI classification model was trained to solve a binary classification problem, i.e., to classify non-defective products (OK - positive class) and defective parts (NOK - negative class). For this experiment, we selected as a classification model a commercial product widely employed in inspection and quality control, i.e., Zebra Aurora Vision Deep Learning [2]. This solution is hardware-agnostic. It provides a dual Deep Learning and traditional machine vision system, thus addressing tasks from surface inspection to dimensional measurements or presence/absence checks. After some trials with di erent libraries that yielded comparable results, the final choice was mainly driven by the tool's versatility and ease of integration into DIMAC software.

To evaluate the utility of the augmented dataset, the proposed solution is compared against a baseline solution, where the same classification model is trained using the original dataset with real images only.

The proposed solution is evaluated concerning the following key performance indicators (KPI):

https://kitt4sme.eu/

[2] https://www.zebra.com/gb/en/products/oem/software/aurora deep learning.html

KPI #1 - False positives: the number of pieces classified as correct (OK) when they have a defect (NOK). This indicator is crucial as it has a direct impact on the life cycle of the assets that include the part and may lead to safety issues. The target value is set to not more than 100 parts per million (ppm) compared to the baseline[3], a threshold that is ten times the residual typical value for a mature commercial solution (ISO 16426). This is measured as a result of a comparison between classification algorithms trained with synthetically generated defective parts versus algorithms trained with only real images of defective parts.

KPI #2 - False negatives: the percentage of pieces incorrectly classified as defective (NOK). This indicator is relevant from a business perspective (process inefficiencies and waste generation), even if it is not as critical as the previous one (related to safety). Based on DIMAC's experience in the field and the technological maturity level of the solution, the target value is set to a maximum increment of 3% when comparing the proposed solution against the baseline.

Table 1. Training and Test sets

Use	Set name	Number of images
Training	Real OK set	200
Training	Real NOK set	3
Training	Arti cial NOK set	30
Test	Control Set, Real OK images	968
Test	Control Set, Real NOK images	920

To support our experiment, we created di erent image training and test sets, as reported in Table 1. We started with sets featuring images of defective (NOK) and non-defective (OK) oil plugs, both from real production processes or crafted deliberately. Then, due to the difficulty of obtaining samples of defective pieces, some defective parts have been artificially generated using image manipulation and blending techniques.

We proceeded to train three distinct models, each utilizing a training set comprised of both authentic and synthetic images, as illustrated in Table 2.

After training, each of the three models underwent testing using an identical set of 1888 control images, comprising 968 "OK" and 920 "NOK" images. The control set of NOK images has been generated from a small sample with about 40 real defective parts by running the 40 pieces through the sorting machine several times, changing the light and the angle slightly each time. The obtained results are detailed in Table 3.

The first model (baseline) has been trained on a dataset combining the OK set (200 real images of parts without defects) and the real NOK set (3 parts with defects). In this baseline scenario, no artificial defects are introduced. False-negative results were significant (10%) with one case of false positive. The second model (CF1) has been trained on a dataset combining the OK set (200 real OK images) and the artificial NOK set (30 artificially generated images of defective parts shown in the Synthetic NOK columnof Table 2). In this case, the images of real NOK images have been excluded. CF1 performance is better than the baseline mode, with a significant reduction in false negatives (4%), and no cases of false positives. Finally, a third model (CF2) has been trained on a dataset combining all the training sets (200 real OK images, 3 real NOK images, and 30 artificially generated NOK images). The performance of CF2 is identical to CF1, with 4% false negatives and no false positives.

[3] We used the ppm unit rather than a percentage because the number of defective parts among those classi ed as OK should be as low as possible (also for safety reasons).

Table 2. Model data composition

Method/Model	Real OK	Real NOK	Synthetic NOK
Baseline	200	3	0
CF1	200	0	30
CF2	200	3	30

Table 3. Results in terms of false negatives (FN) and false positives (FP).

Method	False Negatives	False Positives
Baseline	10%	1
CF1	4%	0
CF2	4%	0

Our results suggest that extending the training dataset with artificial images of defects leads to significant improvements (both with CF1 and CF2). More specifically, within the mentioned KPIs, the already minimal number of false positives is further decreased. Additionally, the percentage of false negatives not only remains below the 3% increase mentioned in KPI #2, but also decreases when considering images with artificial defects. Hence, training with a larger number of images containing artificial defects is preferable to training with a limited number of images depicting real defects.

5. CONCLUSION

This paper presents a case study on the quality control of automotive parts, focusing specifically on the quality of oil plugs. The scarcity of images depicting defective parts complicated the training of classification models. Consequently, data augmentation techniques were employed to generate synthetic images. Our approach has demonstrated a positive impact on quality inspection by either reducing or, at the very least, maintaining the number of classification errors, thus suggesting that artificially generated images with defects could replace or complement real images of defective pieces.

In our opinion, these results have a positive impact on maintenance engineering and lifecycle management of the assets where the evaluated parts are used. The potential reductions in costs and waste generation align the solution with the ideas of Industry 5.0. This enhanced control over part quality facilitates data-driven decision-making. It enables the selection of the most suitable quality inspection method and ensures the availability of quality data in subsequent stages of product assembly.On the other hand, it enables adaptation to changes. Upon detecting previously unidentified defects, these new findings can be utilized to synthetically generate images of parts from the same or other families, subsequently training the classification models accordingly. This ultimately a ects the volume and requirement for spare parts, and, significantly, the consistency of these parts and, consequently, the overall consistency of production.

The results obtained and the advancements in the state of the art suggest continuing the research by applying other data augmentation techniques. Techniques based on Generative Adversarial Networks, Di usion Models, and Variational Autoencoders are regarded as possible improvements over the more traditional techniques focused on image manipulation that we have applied. As classification algorithms, we aim to enhance efficiency by utilizing Large Language Models (LLMs) for classification once we successfully generate larger artificial datasets.

Furthermore, we are interested in applying the approach to other use cases within the automotive sector, such as di erent types of fasteners. We would also like to compare other KPIs, such as performance and the impact on sorting times. This data would give us a more comprehensive view and move toward the possible exploitation of a solution based on the presented approach.

Finally, we believe that further research into software platforms that can simplify the deployment of data documentation tools and their interoperability with classification models may be of interest. This will allow SMEs, in particular, to compose their solutions and adapt to the needs of quality control and asset management as they arise.

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REFERENCES

Ahelero , S., Huang, H., Xu, X., and Zhong, R.Y. (2022). Toward sustainability and resilience with industry 4.0 and industry 5.0. *Frontiers in Manufacturing Technology*, 2, 951643.

Antoniou, A., Storkey, A., and Edwards, H. (2018). Augmenting image classifiers using data augmentation generative adversarial networks. In *Artificial Neural Networks and Machine Learning–ICANN 2018: 27th International Conference on Artificial Neural Networks, Rhodes, Greece, October 4-7, 2018, Proceedings, Part III 27*, 594–603. Springer.

Brettel, M., Klein, M., and Friederichsen, N. (2016). The relevance of manufacturing flexibility in the context of industrie 4.0. *Procedia Cirp*, 41, 105–110.

Buslaev, A., Iglovikov, V.I., Khvedchenya, E., Parinov, A., Druzhinin, M., and Kalinin, A.A. (2020). Albumentations: Fast and flexible image augmentations. *Information*, 11(2). doi:10.3390/info11020125. URL `https://www.mdpi.com/2078 2489/11/2/125`.

Fahle, S., Prinz, C., and Kuhlenkötter, B. (2020). Systematic review on machine learning (ml) methods for manufacturing processes–identifying artificial intelligence (ai) methods for field application. *Procedia CIRP*, 93, 413–418.

Ferdows, K. and De Meyer, A. (1990). Lasting improvements in manufacturing performance: in search of a new theory. *Journal of Operations management*, 9(2), 168–184.

Frederico, G.F., Kumar, V., Garza-Reyes, J.A., Kumar, A., and Agrawal, R. (2023). Impact of i4. 0 technologies and their interoperability on performance: future pathways for supply chain resilience post-covid-19. *The International Journal of Logistics Management*, 34(4), 1020–1049.

Frick, J. (2023). Future of industrial asset management: A synergy of digitalization, digital twins, maintenance 5.0/quality 5.0, industry 5.0 and iso55000. *International Journal of Business Marketing and Management (IJBMM)*, 8(4), 93–99.

Hunkeler, D., Saur, K., Stranddorf, H., Rebitzer, G., Schmidt, W., Jensen, A.A., and Christiansen, K. (2003). Life cycle management. *SETAC*.

ISO 16426 (2002). Fasteners — quality assurance system. Standard, International Organization for Standardization, Geneva, CH.

Lee, K.J., Kwon, J.W., Min, S., and Yoon, J. (2021). Deploying an artificial intelligence-based defect finder for manufacturing quality management. *AI Magazine*, 42(2), 5–18.

Li, W., Chen, J., Cao, J., Ma, C., Wang, J., Cui, X., and Chen, P. (2022). Eid-gan: Generative adversarial nets for extremely imbalanced data augmentation. *IEEE Transactions on Industrial Informatics*, 19(3).

Mansor, M.A., Ohsato, A., and Sulaiman, S. (2012). Knowledge management for maintenance activities in the manufacturing sector. *International Journal of Automotive and Mechanical Engineering*, 5, 612–621.

Mikołajczyk, A. and Grochowski, M. (2018). Data augmentation for improving deep learning in image classification problem. In *2018 international interdisciplinary PhD workshop (IIPhDW)*, 117–122. IEEE.

Nanni, L., Paci, M., Brahnam, S., and Lumini, A. (2022). Feature transforms for image data augmentation. *Neural Computing and Applications*, 34(24), 22345–22356.

Peres, R.S., Guedes, M., Miranda, F., and Barata, J. (2021). Simulation-based data augmentation for the quality inspection of structural adhesive with deep learning. *IEEE Access*, 9, 76532–76541.

Shorten, C. and Khoshgoftaar, T.M. (2019). A survey on image data augmentation for deep learning. *Journal of big data*, 6(1), 1–48.

Singh, A. and Bruzzone, L. (2022). Data augmentation through spectrally controlled adversarial networks for classification of multispectral remote sensing images. In *IGARSS 2022-2022 IEEE International Geoscience and Remote Sensing Symposium*, 651–654. IEEE.

Volkau, I., Mujeeb, A., Dai, W., Erdt, M., and Sourin, A. (2022). The impact of a number of samples on unsupervised feature extraction, based on deep learning for detection defects in printed circuit boards. *Future Internet*, 14(1), 8.

Yang, S., Xiao, W., Zhang, M., Guo, S., Zhao, J., and Shen, F. (2022). Image data augmentation for deep learning: A survey. *arXiv preprint arXiv:2204.08610*.

Zhang, L., Wen, T., and Shi, J. (2020). Deep image blending. In *Proceedings of the IEEE/CVF winter conference on applications of computer vision*, 231–240.