Proceedings of the 6th South American Conference on Industrial Engineering and Operations Management
Sorocaba, Sao Paulo, Brazil, May 12-15, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/SA6.20250175
Published: May 12, 2025

Automated Visual Inspection Using Artificial Intelligence for Quote and Quality Analysis in Electrolyzer Renovation

Guilherme Luques, Alex Silva, Nadilson Souza, Denis Borg and Daniel Ohata
Postgraduate School of Industrial Automation and Control Engineering.
FACENS University, Brazil
guilhermeluques@hotmail.com, alexjulio99@outlook.com, nadilsonsouza12@gmail.com, denis.borg@facens.br, daniel.ohata@facens.br

Abstract

This paper presents the development of an automated visual inspection system based on artificial intelligence (AI), designed for quality assessment and cost estimation in the refurbishment processes of industrial electrolyzers. The proposed solution integrates high-resolution cameras, computer vision algorithms, and machine learning models to identify defects and standardize the technical evaluation of components. The methodology involves image acquisition and annotation, training of convolutional neural networks (CNNs), and integration with industrial control systems. Expected outcomes include improved operational efficiency, reduction of human errors, faster cost estimation processes, and enhanced traceability of quality control. The study also discusses technical limitations, implementation costs, and the requirements for integration in real industrial environments.

Keywords
Automated Inspection, Artificial Intelligence, Computer Vision, Quality Control, Electrolyzers.

1. Introduction
The constant pursuit of greater efficiency, quality, and standardization in industrial processes has driven the adoption of emerging technologies such as artificial intelligence (AI) and computer vision. These tools have become established as effective solutions to challenges related to visual inspection and quality control in complex industrial environments (Lee et al., 2018; Zhou et al., 2017). In the context of the digital transformation promoted by Industry 4.0, the integration of physical and digital systems has enabled the automation of critical processes, enhancing diagnostic capacity, traceability, and data-driven decision-making (Lasi et al., 2014).

In specific cases of maintenance and refurbishment of industrial equipment, such as electrolyzers, visual inspection is a fundamental step in identifying defects and supporting technical decisions related to budgeting and quality. Traditionally carried out by human operators, this activity is susceptible to judgment errors, operator fatigue, and inconsistencies in analysis. With the evolution of machine learning models and deep neural networks, it has become feasible to automate this inspection process, thereby increasing precision, repeatability, and processing speed (Zhang et al., 2021; Sivaraman & Sankaran, 2020).

This paper originated from a practical project developed within the postgraduate program in Control and Automation at FACENS University, based on real challenges faced by the company. The proposal involves applying AI and computer vision as technical support tools for the automated inspection of refurbished electrolyzers, aiming to reduce human error, increase analytical precision, and accelerate the technical evaluation process.

Studies such as those by Galati (2023) and Bueno (2000) demonstrate that applying AI to industrial inspection tasks can significantly increase defect detection accuracy when compared to human inspection. Furthermore, the proposed approach aligns with the principles of Industry 4.0, fostering data-driven decision-making, improved traceability, and intelligent automation (Silva et al., 2023; Lee et al., 2018).

This study aims to demonstrate how the integration of inspection hardware and AI algorithms can offer innovative and economically viable solutions for industrial sectors that rely on precise and standardized visual analyses.

2. Theoretical Background

The application of artificial intelligence (AI) to visual inspection has advanced significantly in recent years, driven by the growing demand in the industry for automated, accurate, and repeatable systems. Computer vision, when combined with deep learning algorithms such as convolutional neural networks (CNNs), has demonstrated high effectiveness in defect detection, component measurement, and pattern comparison against predefined standards (Zhang et al., 2021; LeCun et al., 2015; Szeliski, 2022).

According to Sivaraman and Sankaran (2020), AI-based automated inspection systems are capable of overcoming the limitations of manual inspection, such as subjective variability among operators, physical fatigue, and inconsistent decision-making. Furthermore, these systems allow for the continuous collection and real-time analysis of data, yielding substantial gains in quality and operational efficiency. The use of CNNs for visual classification tasks was propelled by influential studies such as those by Krizhevsky et al. (2017) and He et al. (2016), which demonstrated significant performance improvements in benchmarks like ImageNet. Architectures such as YOLO (Redmon et al., 2016) and Faster R-CNN (Ren et al., 2017) are also prominent for enabling high-accuracy and real-time object detection.

In the Brazilian context, studies like that of Torres (2019) highlight the increasing use of automated visual inspection in industrial processes, particularly in the analysis of cast parts and metallic structures. Galati (2023) reinforces this trend by showing that, with a robust image dataset, it is possible to train models capable of identifying anomalies in recycled materials with accuracy rates exceeding 95%.

The literature emphasizes that implementing AI in industrial environments is fully aligned with Industry 4.0 guidelines, which promote the integration of physical and digital systems, the analysis of large data volumes, and autonomous decision-making (Silva et al., 2023; Lee et al., 2018). Moreover, references such as Goodfellow et al. (2016) and Szeliski (2022) reinforce that model robustness directly depends on the diversity, quality, and volume of data used during supervised training, thereby justifying the effort invested in building well-structured and annotated datasets.

Therefore, the theoretical foundation demonstrates that adopting AI-based systems for visual inspection is not only viable but also necessary to meet current demands for productivity, traceability, and quality control in complex industrial processes.

3. Methods

The methodology adopted in this study was structured to develop an automated visual inspection system based on computer vision and convolutional neural networks (CNNs). The system was designed for operation in industrial environments, with a focus on the inspection of refurbished electrolyzers, and it followed principles of modularity, scalability, and real-world applicability, as recommended by Chollet (2021) and Abadi et al. (2016).

The process began with the acquisition of images using high-resolution industrial cameras mounted on adjustable supports, which enabled image capture from various angles and lighting conditions. This step was essential to ensure dataset diversity and robustness, a factor emphasized by Russakovsky et al. (2015). The images were collected directly on the shop floor of the company refurbishment unit, simulating actual inspection conditions. Figures 1, 2, and 3 illustrate the environment and objects involved in the inspection process.

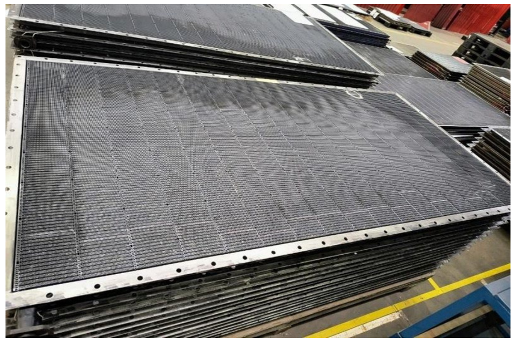

Figure 1. Refurbished electrolyzer plates stored for final inspection

Figure 1 shows the refurbished electrolyzer plates awaiting inspection. Figure 2 highlights a surface defect manually marked on one of the plates, used as a visual reference during data labeling. Figure 3 presents the layout of the industrial workspace where the automated inspection system is intended to operate.

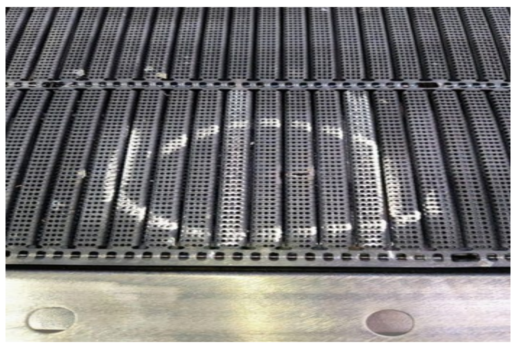

Figure 2. Visible defect marked on one of the plates, used as a reference for annotation in the dataset.

Figure 3. Industrial environment designed for visual inspections, with benches and structure for integrating the automated system.

The collected images underwent a pre-processing phase that included scale normalization, noise removal using median filters, and contrast enhancement through histogram equalization techniques. These procedures aimed to standardize image inputs and improve the performance of the CNN model, as discussed by Deng et al. (2009) and Szeliski (2022). Following pre-processing, the images were manually annotated by company specialists to identify regions containing defects such as cracks, corrosion, deformations, and surface contamination. The annotation process was conducted using tools like LabelImg, resulting in a supervised dataset built according to technical consistency and validation criteria, as recommended by Li et al. (2020).

With the annotated dataset prepared, the CNN model was trained using TensorFlow and Keras libraries. The training process included cross-validation techniques and hyperparameter tuning, along with regularization strategies such as batch normalization and data augmentation to improve generalization. Modern architecture such as ResNet and EfficientNet were tested, as they have shown high accuracy and computational efficiency in similar contexts (He et al., 2016; Tan & Le, 2019).

The final model was integrated into a real-time classification system capable of analyzing input images and automatically determining whether the inspected parts should be approved or rejected. The system's performance was evaluated using metrics such as accuracy, precision, recall, and F1-score, and results were validated on unseen data to ensure external generalization, in line with the practices discussed by Redmon et al. (2016).

Finally, the system was designed to operate in two formats: a fixed inspection station integrated into the refurbishment line and a mobile setup mounted on a portable bench. The choice of infrastructure depends on the layout of each industrial plant and the inspection volume. This dual deployment approach aligns with Morik et al. (2021), who emphasize the importance of adaptable AI implementations in dynamic manufacturing environments.

This methodology ensures the technical feasibility of applying convolutional neural networks to industrial visual inspections, while meeting the requirements for robustness, replicability, and integration in real-world operational settings.

4. Expected Results

The implementation of the proposed automated visual inspection system using artificial intelligence is expected to generate significant advancements in the electrolyzer refurbishment process, particularly in terms of inspection quality and operational efficiency. One of the primary anticipated outcomes is a substantial reduction in inspection time, as diagnostics are generated in real time, eliminating repetitive manual tasks and streamlining the workflow. Furthermore, replacing subjective human evaluation with a model trained on standardized historical data contributes to reducing human errors and increasing the consistency of inspection outcomes, as evidenced in similar applications throughout the literature (Li et al., 2020; Redmon et al., 2016).

Another expected result is a considerable increase in the accuracy of defect detection. By training the model with a well-annotated and diverse image dataset, the system is projected to achieve accuracy levels above 95% in key performance metrics such as precision and sensitivity, as reported by Galati (2023) and Zhang et al. (2021). This improvement will directly enhance the reliability of inspections, enabling the identification of subtle defects that are often missed during human analysis, especially under variable lighting or positioning conditions.

The system is also expected to standardize inspection criteria by eliminating variations in judgment among human operators and ensuring that consistent evaluation rules are applied across all inspected units. This standardization is essential for maintaining product quality levels and supporting traceability in audits and industrial certifications. Additionally, the automation process enables the real-time generation of digital reports containing not only the classification results but also annotated images and aggregated data per batch or operator, thus expanding the company's quality management capabilities.

Another important expectation is the system's scalability across different types of industrial parts and use cases. Due to the modular architecture and reusable computational infrastructure, the solution can be adapted to new inspection scenarios simply by retraining the model with a new dataset. This adaptability is particularly relevant in dynamic industrial settings, where product lifecycles and quality requirements may change frequently, as highlighted by Morik et al. (2021).

In summary, the expected outcomes of this study span multiple dimensions: increased productivity, enhanced reliability of inspection reports, standardized quality control criteria, faster reporting, and the potential for deployment across various production lines. Together, these contributions position the proposed system as a strategic tool for manufacturers seeking competitiveness and technological alignment with Industry 4.0 principles.

5. Discussion and Limitations

Although the proposed automated visual inspection system based on artificial intelligence offers promising prospects for the manufacturing industry, its practical implementation still faces several technical, operational, and ethical challenges. One of the most critical obstacles is the high initial investment required for implementation, which includes not only the acquisition of specialized hardware—such as industrial cameras, graphic processing units (GPUs), and sensors, but also the development or adaptation of computational systems capable of supporting deep learning algorithms in real time. Recent studies have shown that this cost can be prohibitive for small and medium-sized enterprises, particularly in cases where a short-term return on investment (ROI) is not evident (Zhang et al., 2021; Makridakis et al., 2017).

In addition to infrastructure requirements, there is a significant demand for technical expertise. The operation, maintenance, and evolution of AI-based systems require professionals skilled in data science, software engineering, and industrial automation. A lack of qualified personnel may compromise the sustainability of the system and increase its dependence on external providers, which can limit operational autonomy (Silva et al., 2023; Morik et al., 2021). Even though user-friendly solutions are being developed, the interpretation of models, handling of exceptions, and management of sensitive data still demand specialized technical knowledge.

From a methodological standpoint, a critical limitation lies in the quality and representativeness of the data used to train the models. To achieve acceptable levels of accuracy and generalization, it is essential to have robust, well-annotated image datasets that reflect the diversity of real-world scenarios. Creating such datasets is a time-consuming and resource-intensive task that requires qualified personnel and strict control of environmental variables (Russakovsky et al., 2015; Galati, 2023). Models trained on biased or homogeneous data tend to underperform when exposed to unfamiliar conditions, thereby compromising system reliability.

Another relevant issue involves the legal and ethical implications of AI systems operating in industrial environments. The continuous collection of images and operational data, especially in areas with human presence, raises concerns regarding privacy, surveillance, and the potential misuse of sensitive information. Compliance with regulatory frameworks such as the Brazilian General Data Protection Law (LGPD) and the European Union's guidelines for trustworthy AI (European Commission, 2019) is essential to avoid legal risks and maintain worker trust. Floridi and Cowls (2019) also emphasize that intelligent systems must be guided by principles of fairness, transparency, and inclusiveness, which means that organizations must be ethically accountable, not just technically compliant.

Finally, cultural and organizational acceptance plays a crucial role in the successful adoption of AI-based technologies. The replacement of manual processes with automated systems may be perceived as a threat by workers, particularly when job security is at stake. Overcoming this resistance requires thoughtful change management strategies, including training programs, transparent communication about project goals, and recognition of the human role in supervising and interpreting automated results. As highlighted by Sivaraman and Sankaran (2020), organizational acceptance is just as important as technical feasibility in ensuring the success of industrial AI deployments.

Therefore, although the potential benefits of AI-based visual inspection systems are well established, their effective implementation demands a strategic approach that considers not only technical and economic factors but also legal, ethical, and human dimensions. A successful deployment depends on the balanced integration of these elements to ensure both system effectiveness and long-term sustainability within the production environment.

6. Conclusion

This study presented the development and proposed implementation of an automated visual inspection system based on artificial intelligence, aimed at supporting quality assessment and cost estimation processes in the refurbishment of industrial electrolyzers. Grounded in well-established concepts from computer vision and deep learning, the project demonstrated how convolutional neural networks trained on real operational data can perform highly accurate and reliable technical diagnostics. The proposed system offers an innovative solution to a recurrent issue in the industrial sector: the subjectivity and inefficiency of manual visual inspection. By structuring data collection, pre-processing, supervised annotation, and training of optimized models, the system was designed to operate in both fixed and mobile environments, with potential for direct integration into production lines.

The expected benefits include a significant reduction in inspection time, improved accuracy in defect detection, standardization of evaluation criteria, and the automatic generation of technical reports to support auditing, continuous improvement, and traceability. The proposal aligns with Industry 4.0 principles by enabling intelligent automation, data-driven decisions, and cyber-physical integration within manufacturing systems. Additionally, the model demonstrated potential for replication in other industrial scenarios through retraining with application-specific datasets, thus extending its relevance across different contexts.

Nevertheless, the practical deployment of the system requires careful consideration of existing limitations, such as initial infrastructure investments, the need for technical training, and compliance with data protection and ethical standards. The long-term success of the system also depends on cultural acceptance within organizations, highlighting the importance of engaging stakeholders and fostering trust in AI-based technologies.

As future work, we recommend conducting real-world pilot studies to evaluate the system in operational settings, expanding the image database with additional defect classes, and benchmarking different neural network architectures in terms of efficiency and robustness. Moreover, exploring the use of unsupervised learning techniques and generative models may enhance the system's adaptability to complex or previously unseen patterns. With continued development, the proposed solution has the potential to become a strategic asset for modern industry, driving improvements in quality control and reinforcing competitiveness in the digital age.

References

Abadi, M., Agarwal, A., Barham, P. and Brevdo, E., TensorFlow: Large-scale machine learning on heterogeneous systems, Available: https://www.tensorflow.org/, 2016.
Bueno, M., Inspeção visual de peças cerâmicas via inteligência artificial, Relatório Técnico, Instituto de Pesquisas Tecnológicas (IPT), São Paulo, Brasil, 2000.
Chollet, F., Deep Learning with Python, 2nd ed., Manning Publications, 2021.
Deng, J., Dong, W., Socher, R., Li, L. J., Li, K. and Fei-Fei, L., ImageNet: A large-scale hierarchical image database, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 248–255, 2009.
European Commission, Ethics guidelines for trustworthy AI, European Union, 2019.
Floridi, L. and Cowls, J., A unified framework of five principles for AI in society, Harvard Data Science Review, 2019.
Galati, G., Sistema de inspeção automatizada utilizando inteligência artificial na reciclagem de garrafas de vidro, Trabalho de Conclusão de Curso – Centro Universitário SENAI, São Caetano do Sul, SP, Brasil, 2023.
Goodfellow, I., Bengio, Y. and Courville, A., Deep Learning, MIT Press, 2016.
He, K., Zhang, X., Ren, S. and Sun, J., Deep residual learning for image recognition, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778, 2016.
Krizhevsky, A., Sutskever, I. and Hinton, G. E., ImageNet classification with deep convolutional neural networks, Communications of the ACM, vol. 60, no. 6, pp. 84–90, 2017.
Lasi, H., Fettke, P., Kemper, H. G., Feld, T. and Hoffmann, M., Industry 4.0, Business & Information Systems Engineering, vol. 6, no. 4, pp. 239–242, 2014.
Lee, J., Bagheri, B. and Kao, H. A., A cyber-physical systems architecture for industry 4.0-based manufacturing systems, Manufacturing Letters, vol. 3, pp. 18–23, 2018.
Li, Y., He, Y. and Wang, K., A review of machine vision-based defect detection for industrial surfaces, Journal of Manufacturing Systems, vol. 56, pp. 760–777, 2020.
Makridakis, S., Spiliotis, E. and Assimakopoulos, V., Forecasting the impact of artificial intelligence, Futures, vol. 90, pp. 46–60, 2017.
Morik, K., Brockhausen, P., Schäfermeier, E. and Schmid, U., Towards an open AI lifecycle: Lessons from industrial use cases, Proceedings of the IEEE, vol. 109, no. 5, pp. 640–659, 2021.
Redmon, J., Divvala, S., Girshick, R. and Farhadi, A., You Only Look Once: Unified, real-time object detection, Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 779–788, 2016.
Ren, S., He, K., Girshick, R. and Sun, J., Faster R-CNN: Towards real-time object detection with region proposal networks, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017.

Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., Huang, Z., Karpathy, A., Khosla, A., Bernstein, M., Berg, A. C. and Fei-Fei, L., ImageNet Large Scale Visual Recognition Challenge, International Journal of Computer Vision, vol. 115, no. 3, pp. 211–252, 2015.
Silva, L. S., Costa, F. and Pereira, A. L., Oportunidades e desafios para implementação de projetos da Indústria 4.0 na indústria farmacêutica, Revista de Engenharia e Pesquisa Aplicada, vol. 8, no. 1, pp. 32–47, 2023.
Sivaraman, S. and Sankaran, S., Automated visual inspection in manufacturing using deep learning: A review, Procedia Computer Science, vol. 172, pp. 192–199, 2020.
Szeliski, R., Computer Vision: Algorithms and Applications, 2nd ed., Springer, 2022.
Tan, M. and Le, Q., EfficientNet: Rethinking model scaling for convolutional neural networks, Proceedings of the 36th International Conference on Machine Learning, PMLR, pp. 6105–6114, 2019.
Torres, C., Inspeção visual automática de peças fundidas, Dissertação de Mestrado, Instituto Politécnico do Porto, Portugal, 2019.
Zhang, Y., Wang, H., Zhang, M. and Ma, Y., Deep learning-based object detection techniques for industrial applications: A review, Engineering Applications of Artificial Intelligence, vol. 97, 104000, 2021.

Biographies

Daniel Ohata is PhD in electrical and computer engineering (2024), master's in electrical and computer engineering (2019) and bachelor's in information systems (2017), all titles obtained from Universidade Presbiteriana Mackenzie, training in game design from HAL College of Technology Design in Japan (2014) and technician in Industrial Computing from Colégio Radial (1998). Researcher at the JAS3 Laboratory (Laboratory of Games, Learning, Simulation, Systems and Signals) and the digital TV laboratory, both at Universidade Presbiteriana Mackenzie. He holds the position of university professor of technology and postgraduate courses at Universidade Facens, in addition to participating in the structuring teaching core of the university's Digital Games course. In addition to having the role of consultant and development analyst in digital systems and games.

Denis Borg degree in Electrical Engineering from the School of Engineering of São Carlos - University of São Paulo (1998) and a master's degree in electrical engineering from the University of São Paulo (2011). PhD from the same institution (2016). He was a professor at Unilins in the discipline of Supervisory Systems (2005). He worked as an Applications Engineer at Smar Equipamentos Industriais (1999 - 2005) and in the same position at Emerson Process Management (2005-2007). He managed the company Engeserve de Prestação de Serviços e Consultoria in PLC configuration, fieldbus systems, supervisory systems and asset management (2007-2008). He returned to work with Emerson Process Management in 2008 as an Applications Engineering and Sales Consultant until November 2015. His main areas of activity are Industrial Instrumentation for pressure, temperature, level and flow measurements, Automation and Control, Intelligent Systems, and Training. He is currently a Postgraduate Coordinator and PIII Professor of Mechatronics/Electrical Engineering.

Guilherme Luques With 19 years of experience in the maintenance area, I am an electromechanic passionate about innovative and sustainable solutions for the treatment of industrial, drinking water and effluents. I currently work at De Nora, a world leader in electrochemical and water treatment technologies, where I assemble, maintain and test special machines, such as softeners, electrolyzers and water treatment solutions for various clients and segments. I am always seeking to update and improve myself in my field, which is why I am studying for a postgraduate degree in Industrial Control and Automation Engineering and Industrial Electrical Engineering with the aim of expanding my knowledge and skills in projects, systems and automated processes.

Alex Silva is a specialist in Industrial Automation and Control Engineering, graduated from Centro Universitário Facens. His training qualifies him to work in the development of automated systems and innovative industrial solutions. With a solid technical base, he demonstrates a commitment to excellence and continuous improvement in the engineering field.

Nadilson Souza is a mechanical engineer with a specialization in Industrial Automation and Control Engineering. He is currently a partner and owner of NS Ferramentaria e Usinagem Ltda, located in Sorocaba, São Paulo. With solid experience in the industrial sector, he stands out for his work in automation and precision machining projects. His career combines technical knowledge and entrepreneurial spirit, contributing to the development of innovative solutions in the metalworking industry.