A Case Study of Anomaly Detection in Tinplate Lids: Supervised vs Unsupervised approaches

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***Abstract*—This research presents a comparative study of deep learning-based anomaly detection methods, both supervised and unsupervised, applied to industrial systems for detecting product defects in manufacturing. The study implements the OPC-UA protocol for data communication and algorithm execution using finite state machines, demonstrating its practical application in a tinplate lid system. Integration with OPC-UA ensures real-time data access, interoperability, and scalability across various industrial environments. The experimental results, evaluated using metrics such as Average Precision, Mean AUROC, Mean Pixel AUROC, and Execution Time (CPU and GPU), reveal the strengths and limitations of each approach, providing valuable insights for addressing modern challenges in industrial anomaly detection.**

***Index Terms*—anomaly detection, industry 4.0, deep learning, unsupervised techniques, supervised techniques, YOLO v8, DRAEM, MMR, OPC-UA**

I. Introduction

Industrial systems form the foundation of modern manufacturing, driving efficiency across diverse sectors while facing increasing complexity and operational challenges. The ability to detect anomalies early has become crucial for maintaining operational stability and preventing costly unplanned downtimes, making anomaly detection systems an essential component of industrial operations.

Statistical and traditional machine learning approaches have established a strong foundation in industrial anomaly detection. Statistical methods like z-score analysis and control charts remain fundamental tools for identifying deviations from expected behavior ([1], [2]). Support Vector Machines (SVM) have proven particularly effective, as demonstrated by Schölkopf et al. [3] in their work on anomaly boundary detection. Real-time condition-based maintenance, utilizing sensor data and machine learning algorithms, has revolutionized industrial monitoring [4]. While rule-based systems offer straightforward implementation [5], they often struggle with dynamic industrial environments, requiring significant maintenance effort ([6], [7]).

Deep learning has emerged as a transformative technology for industrial anomaly detection, offering superior pattern recognition capabilities in complex datasets. Autoencoders have demonstrated remarkable success in identifying anomalies through reconstruction error analysis [8], particularly in complex industrial settings [9]. Recurrent Neural Networks (RNNs) and LSTM networks have proven especially effective for time-series anomaly detection [10], enabling sophisticated monitoring of dynamic industrial processes [11].

This research compares supervised and unsupervised deep learning methods for industrial anomaly detection, integrated with OPC-UA protocol. As demonstrated by Lee and Kim [12], OPC-UA's communication framework enables effective integration across diverse industrial systems. The study validates these approaches through practical implementation in a tinplate lid classification system.

To address this work, the manuscript is organized as follows. Section II presents works related to supervised and unsupervised deep learning based approaches and also introduces OPC-UA. Section III presents the proposed pipeline to carry out the classification of *"good"/"defective"* lids. Then, Section IV shows the experimental results taking as a reference a case study for anomaly detection in tinplate lids using both approaches. Also, OPC-UA Server and Vision Finite State Machine are implemented. Finally, conclusions are presented in Section V.

II. Related Work

This research evaluates supervised and unsupervised deep learning approaches for industrial anomaly detection, integrating OPC-UA as the communication backbone. Before delving into this methodology, it present a comprehensive review of relevant literature in three key areas: industrial anomaly detection techniques, deep learning applications in manufacturing, and OPC-UA implementations for industrial control systems. This review establishes the theoretical foundation for our comparative analysis and highlights the current state of the art in industrial process monitoring and control.

A. Supervised Approaches

Deep learning has revolutionized industrial inspection through its capacity to extract complex patterns from extensive datasets. Recent implementations showcase significant advances in this field. For instance, Pham et al. [13] developed a

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real-time detection system using YOLO v5, achieving remarkable speed and accuracy in industrial settings, despite some limitations in varying lighting conditions. Building on this foundation, Beak et al. [14] implemented YOLO v7 for cosmetic manufacturing inspection, though noting the challenges of maintaining updated training datasets. Further advancing the field, Klarak et al. [15] enhanced anomaly detection capabilities by incorporating defect classification, while Kim et al. [16] demonstrated the effectiveness of supervised learning in food packaging inspection through X-ray image analysis, though both approaches highlight the ongoing challenge of requiring substantial labeled training data.

B. Unsupervised Approaches

On the other hand, unsupervised approaches have emerged as powerful alternatives to traditional supervised methods. DRAEM [17] pioneered an unsupervised technique for surface anomaly detection using discriminative embeddings, demonstrating exceptional precision in detecting subtle anomalies, despite its computational demands. A significant advancement in this field is MMR [18] which is an advanced method for industrial anomaly detection that uses a masked multi-scale reconstruction approach. Its main innovation lies in the ability to handle domain changes between training and test data, a common problem in real industrial environments where lighting conditions, view angles and scales can vary significantly. The method introduces the AeBAD dataset (specific for aero engine blades) and employs an architecture that improves causality inference between patches in normal samples using a masked reconstruction task.

C. OPC-UA Overview

OPC-UA serves as a key technology in modern industrial systems, providing comprehensive functionality beyond basic communication. It supports historical data access, alarms, program execution, and finite state machines, making it essential for data collection and model deployment. Lee and Kim [12] demonstrated its effectiveness in integrating machine learning for anomaly detection, while Vogel-Heuser et al. [19] showed its capability in early fault detection for automated production systems, leading to improved maintenance efficiency and reduced downtime. Recent advancements in industrial automation have demonstrated powerful integrations of OPC-UA with modern analytics. Velesaca et al. [20] developed a comprehensive anomaly detection system that combines OPC-UA's standardized communication capabilities with deep learning algorithms, enabling real-time defect detection.In a complementary study, Velesaca et al. [21] introduced a systematic 11-step methodology for implementing industrial systems, providing a structured approach to server implementation and system integration.

III. Proposed Approach

The system architecture implements deep learning methods across three industrial tiers: control (PLC subsystem for plant operations), supervision (OPC-UA subsystem for data collection, image acquisition, and model implementation), and visualization (operator dashboard). Both supervised and unsupervised approaches are integrated within this hierarchical structure, as illustrated in Fig.1 and Fig.2.

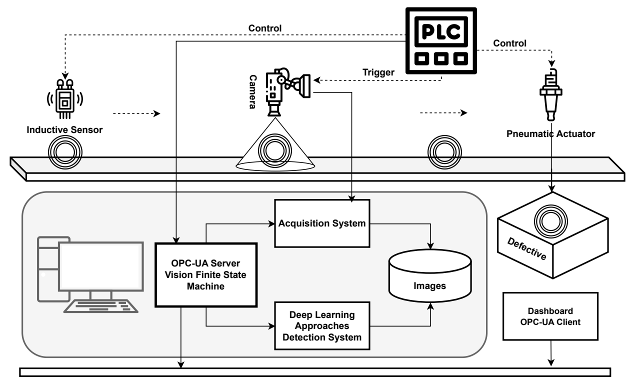


Fig. 1. General outline of the system architecture proposed in this paper.

A. Pre-processing

The initial preprocessing stage involves segmenting the tinplate lid area utilizing the Hough Transform [22]. By removing the background through this segmentation, we ensure that the subsequent classification task concentrates exclusively on analyzing the pertinent features of the object of interest.

B. Supervised Technique

For the anomaly detection task's image recognition component, we implement YOLOv8 [23] as our deep neural network architecture. This selection is driven by its proven efficiency and rapid object detection capabilities, which are essential for industrial applications requiring real-time response. The versatile and deep architecture of YOLOv8 facilitates straightforward modifications and optimizations, enabling adaptation to varying conditions such as lighting changes, different viewing angles, and diverse defect types. These characteristics make it particularly suitable for addressing the complex and varied challenges of industrial defect detection. Additionally, its open-source nature and robust developer community support ensure straightforward implementation and sustainable long-term maintenance. For our specific implementation, this work utilize the *"yolov8m-cls.pt"* model propose by [20], selected based on resource constraints and the need for minimal processing times that align with our industrial application requirements.

C. Unsupervised Techniques

For surface defect detection, this work employ DRAEM [17] and MMR [18] as unsupervised anomaly detection method. This selection is supported by its demonstrated state-of-the-art (SOTA) performance on MVTec AD datasets [24]. DRAEM and MMR represent two innovative approaches in industrial surface anomaly detection. DRAEM combines a reconstructive and discriminative approach, simultaneously

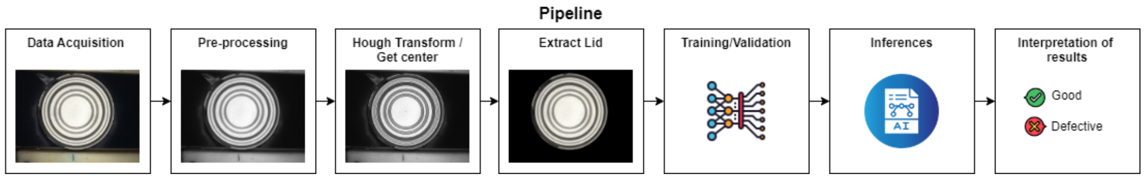


Fig. 2. Overall pipelines of the proposed approaches

learning to reconstruct normal images while establishing a decision boundary to identify anomalies, using simple defect simulations during training to improve its detection ability. For its part, MMR focuses on addressing domain changes through a multi-scale reconstruction architecture that employs patch masking, allowing it to learn more robust representations of normal features and better adapt to variations in illumination, view and typical scale in real industrial environments. Both techniques stand out for their ability to operate efficiently with limited data sets and their adaptability to different industrial scenarios, although they differ in their main focus: DRAEM focuses on accurate discrimination of anomalies, while MMR prioritizes robustness to changes in conditions of operation.

D. OPC-UA Vision Specification

The OPC-UA companion specification for machine vision (OPC 40100-1) [25] provides a standardized framework for integrating vision systems into production control and IT infrastructures. This specification extends beyond traditional interface replacement, enabling both horizontal and vertical integration capabilities that facilitate authorized data communication across all enterprise levels. The OPC-UA Vision interface enables seamless information exchange between diverse machine vision systems, PLCs, and control-level software systems. In our implementation, we leverage this standard by developing a server incorporating a Vision Finite State Machine Type, where both supervised and semi-supervised models operate within the "ContinuousExecution" state. This architecture ensures standardized communication while maintaining the flexibility needed for advanced computer vision applications.

E. Metric Evaluation

The framework's performance evaluation encompasses multiple metrics. The primary measure of effectiveness is established through Average Accuracy calculations over the test dataset. To assess computational efficiency, we analyze execution times across both CPU and GPU implementations. Additionally, this work evaluate network performance of unsupervised approaches through two metrics: Mean AUROC and Mean Pixel AUROC.

IV. Case Study

This section examines the practical implementation of our anomaly detection framework in a manufacturing environment, where both supervised and semi-supervised deep learning approaches operate concurrently. The system integrates with the production line through OPC-UA, which facilitates the collection and processing of sensor and equipment data. Performance evaluation is conducted through multiple metrics: Average Accuracy for detection reliability, Execution Time on both CPU and GPU platforms for processing efficiency. A critical operational constraint of the system is its requirement to process 500 tinplate lids per minute, establishing a maximum allowable Execution Time threshold of 75ms per inspection to maintain production throughput.

A. System Implementation

The propose implementation focuses on detecting manufacturing defects in tinplate lids within an industrial environment. The system architecture comprises multiple layers: the control layer features a Siemens S7 1200 PLC, complemented by a vision system that includes an industrial visible spectrum camera, lighting equipment, and an inductive sensor for lid detection on the conveyor belt. The supervision layer operates on a high-performance workstation equipped with an Intel Core I9 3.3GHz CPU and NVIDIA Titan XP GPU, which handles multiple tasks: image acquisition, OPC-UA server operation, YOLOv8-based image recognition, DRAEM-based, and MMR-based anomaly segmentation. The key components of this system architecture are illustrated in Figure3.

B. Dataset Acquisition

The initial phase involves acquiring images of tinplate lids categorized as either *"good"* or *"defective"*, with the latter category encompassing common defects such as interior peeling, paint imperfections, and missing rubber along the inside edge. The total number of images is 1026, with $Good = 512$ and $Defective = 514$.

Fig. 3. *(1st)* Siemens S7 1200 PLC. *(2nd)* Conveyor belt. *(3rd)* Industrial camera and lighting system.

C. YOLO v8

The implementation process begins with dataset enhancement using the Albumentations library, which applies various transformations (cropping, rotations, brightness/contrast adjustments) to create realistic variations in the training data. The YOLOv8 model (*"yolov8m-cls.pt"*) is trained for classification using specific parameters: *epochs=500, imgsz=640, batch=18, patience=20, auto_augment=autoaugment, optimizer=SGD*. Performance evaluation is conducted through normalized confusion matrices (Fig.4) and Average Accuracy percentages (TableI). To provide insights into the models' decision-making process, this work employ the EigenCAM technique [26], implemented via GitHub[1], with the resulting activation maps from the last three layers shown in Fig. 5.

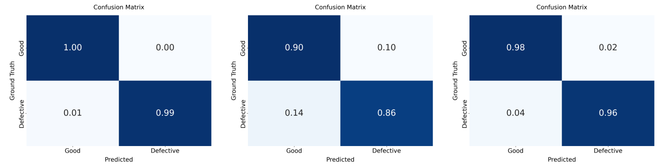
D. DRAEM

The DRAEM implementation utilizes a dual-branch architecture, consisting of a reconstructive sub-network and a discriminative sub-network working in parallel. The training process involves generating synthetic anomalies through a specialized simulator that creates just-out-of-distribution patterns, enabling the model to learn both normal surface reconstruction and anomaly detection capabilities. The reconstructive sub-network aims to restore normal patterns while the discriminative sub-network learns a joint reconstruction-anomaly embedding for accurate anomaly localization. Performance evaluation encompasses multiple metrics: AUROC scores, Average Precision percentages, and pixel-wise accuracy, collectively quantifying the model's discrimination capabilities between defective and non-defective samples. The system's decision-making process is made transparent through attention-guided mask visualizations that highlight detected anomaly regions, providing valuable insights into the model's detection patterns and validating its effectiveness across different surface conditions without requiring real anomaly samples during training.

E. MMR

The MMR implementation utilizes a dual-model architecture, consisting of a Vision Transformer (ViT) with a simple Feature Pyramid Network (FPN) and a frozen pre-trained hierarchical encoder. The training process involves masking random patches of input images and reconstructing multi-scale features, enabling the model to establish robust causal relationships among different parts of normal samples. The model enhances its perception of spatial dependencies through a masked reconstruction task that completely hides selected patches rather than sharing features with visible regions. Performance evaluation encompasses multiple metrics: AUROC scores, PRO (Per-Region-Overlap) percentages, and pixel-level accuracy, collectively quantifying the model's discrimination capabilities between defective and non-defective samples, particularly under domain shifts. The system's decision-making process is made transparent through attention-guided anomaly maps that highlight detected anomaly regions, providing valuable insights into the model's detection patterns and validating its effectiveness across different illumination conditions, views, and backgrounds.

[1]https://github.com/rigvedrs/YOLO-V8-CAM



YOLOv8 [20] *DRAEM* [17] MMR [18]

Fig. 4. Normalized confusion matrix of each technique calculated on the test set.

F. OPC-UA Vision Server Implementation

The OPC-UA companion specification for machine vision facilitates seamless integration between vision systems, production control, and IT infrastructure, enabling comprehensive data communication across all enterprise levels. Within this framework, our implementation leverages the "ContinuousExecution" state for algorithm deployment, as opposed to "SingleExecution", due to the continuous nature of the conveyor belt operation and the constant monitoring requirement for tinplate lid inspection. While other states fulfill standard OPC-UA vision system specifications, our focus remains on the continuous processing mode.

TABLE I
PERFORMANCE EVALUATION PER EACH APPROACH AND METRICS. MEAN AUROC (M1), MEAN PIXEL AUROC (M2).

Technique	**Parm. (M)**	**Exec. Time (ms) CPU**	**GPU**	**Avg Acc.**	**M1**	**M2**
YOLOv8 [20]	42.70	218.90	67.50	**0.995**	-	-
DRAEM [17]	69.00	236.70	70.80	0.880	87.60	75.40
MMR [18]	126.90	410.30	115.60	0.969	94.40	84.83

G. Experimental Results

The framework's performance evaluation encompasses multiple metrics: Average Accuracy, Mean AUROC, Mean Pixel AUROC, Execution Time (CPU and GPU). As shown in Table I, the YOLOv8 model achieves optimal Average Accuracy with a high score of 0.995. Regarding Execution Time, the same YOLOv8 model demonstrates the best CPU and GPU performance at 218.90ms and 67.50ms respectively. The confusion matrices presented in Fig.4 reveal that YOLOv8 show exceptional ability to distinguish between *"good"* and *"defective"* classes. While DRAEM shows the lowest performance of the evaluated techniques with an Average Accuracy of 0.880 and MMR shows acceptable performance with an Average Accuracy of 0.969. Also, DRAEM's performance is further validated through AUROC metrics, achieving 87.60% for image-level and 75.40% for pixel-level detection on the test dataset. On the other hand, MMR's performance AUROC metrics, achieving 94.40% for image-level and 84.83% for pixel-level detection on the test dataset.

V. CONCLUSION

This article presents an integrated system combining OPC-UA protocol with deep learning for industrial anomaly detection. Experimental results show YOLOv8 models, specifically

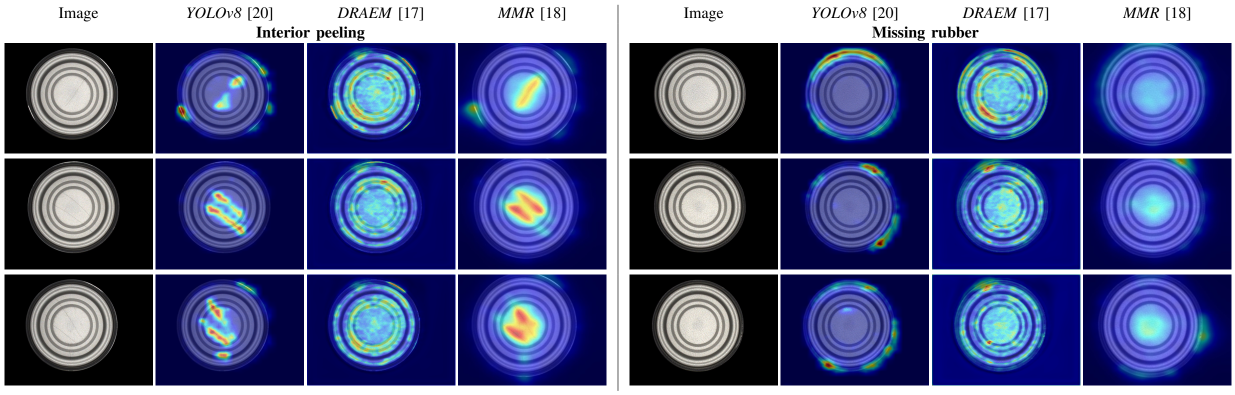


Fig. 5. Qualitative evaluation of YOLO v8, DRAEM and MMR prediction results on defective images of the testing set.

”yolov8m-cls.pt”, achieved superior performance with 0.995 accuracy and fastest execution time (67.50ms), compared to DRAEM (0.880) and MMR (0.969). The system implements OPC-UA through a Vision Finite State Machine, with model execution in the ”ContinuousExecution” state. While YOLOv8 leads in accuracy, MMR provides valuable capabilities for detecting novel anomalies, with only a 3% performance difference. The framework successfully combines OPC-UA's secure communication infrastructure with efficient anomaly detection, enabling automated visual inspection while meeting industrial requirements for real-time processing and security.

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References

[1] E. M. Ferragut, J. Laska, and R. A. Bridges, “A new, principled approach to anomaly detection,” in *Int. Conf. on Machine Learning and Applications*, vol. 2. IEEE, 2012, pp. 210–215.

[2] N. B. Chikodili, M. D. Abdulmalik, O. A. Abisoye, and S. A. Bashir, “Outlier detection in multivariate time series data using a fusion of K-medoid, standardized euclidean distance and Z-score,” in *Int. Conf. on Information and Communication Technology and Applications*. Springer, 2020, pp. 259–271.

[3] B. Schölkopf, J. C. Platt, J. Shawe-Taylor, A. J. Smola, and R. C. Williamson, “Estimating the support of a high-dimensional distribution,” *Neural Computation*, vol. 13, no. 7, pp. 1443–1471, 2001.

[4] R. Ahmad and S. Kamaruddin, “An overview of time-based and condition-based maintenance in industrial application,” *Computers & industrial engineering*, vol. 63, no. 1, pp. 135–149, 2012.

[5] W.-K. Wong, A. Moore, G. Cooper, and M. Wagner, “Rule-based anomaly pattern detection for detecting disease outbreaks,” in *AAAI/IAAI*, 2002, pp. 217–223.

[6] M. Peña, F. Biscarri, J. I. Guerrero, I. Monedero, and C. León, “Rule-based system to detect energy efficiency anomalies in smart buildings, a data mining approach,” *Expert Systems with Applications*, vol. 56, pp. 242–255, 2016.

[7] V. Chandola, A. Banerjee, and V. Kumar, “Anomaly detection: A survey,” *ACM computing surveys*, vol. 41, no. 3, pp. 1–58, 2009.

[8] G. E. Hinton and R. R. Salakhutdinov, “Reducing the dimensionality of data with neural networks,” in *Science*, vol. 313, no. 5786. American Association for the Advancement of Science, 2006, pp. 504–507.

[9] G. Pang, C. Shen, L. Cao, and A. v. d. Hengel, “Deep learning for anomaly detection: A review,” *ACM Computing Surveys*, vol. 54, no. 2, pp. 1–38, 2021.

[10] M. Canizo, I. Triguero, A. Conde, and E. Onieva, “Multi-head CNN–RNN for multi-time series anomaly detection: An industrial case study,” *Neurocomputing*, vol. 363, pp. 246–260, 2019.

[11] T. Ergen and S. S. Kozat, “Unsupervised anomaly detection with LSTM neural networks,” *Transactions on Neural Networks and Learning Systems*, vol. 31, no. 8, pp. 3127–3141, 2019.

[12] J. Lee and Y. Kim, “Application of OPC-UA based on IoT for monitoring and controlling manufacturing processes,” *Procedia Computer Science*, vol. 155, pp. 154–161, 2019.

[13] D.-L. Pham, T.-W. Chang *et al.*, “A YOLO-based real-time packaging defect detection system,” *Procedia Computer Science*, vol. 217, pp. 886–894, 2023.

[14] S. Beak, Y.-H. Han, Y. Moon, J. Lee, and J. Jeong, “YOLOv7-Based Anomaly Detection Using Intensity and NG Types in Labeling in Cosmetic Manufacturing Processes,” *Processes*, vol. 11, no. 8, p. 2266, 2023.

[15] J. Klarák, R. Andok, P. Malík, I. Kuric, M. Ritomskỳ, I. Klačková, and H.-Y. Tsai, “From anomaly detection to defect classification,” *Sensors*, vol. 24, no. 2, p. 429, 2024.

[16] K. Kim, H. Kim, J. Chun, M. Kang, M. Hong, and B. Min, “Real-time anomaly detection in packaged food x-ray images using supervised learning,” *Comput. Mater. Contin*, vol. 67, no. 2, pp. 2547–2568, 2021.

[17] V. Zavrtanik, M. Kristan, and D. Skočaj, “Draem-a discriminatively trained reconstruction embedding for surface anomaly detection,” in *Int. Conf. on Computer Vision and Pattern Recognition*, 2021, pp. 8330–8339.

[18] Z. Zhang, Z. Zhao, X. Zhang, C. Sun, and X. Chen, “Industrial anomaly detection with domain shift: A real-world dataset and masked multi-scale reconstruction,” *Computers in Industry*, vol. 151, p. 103990, 2023.

[19] B. Vogel-Heuser, A. Fay, I. Schaefer, M. Tichy, A. Trächtler, and C. Legat, “Architectural design of multi-agent systems in the context of OPC UA and automationML,” *Proceedings of the IEEE*, vol. 104, no. 5, pp. 947–967, 2016.

[20] H. Velesaca., D. Carrasco., D. Carpio., J. A. Holgado-Terriza., J. Gutierrez-Guerrero., T. Toscano., and A. Sappa., “Anomaly detection in industrial production products using opc-ua and deep learning,” in *Int. Conf. on Data Science, Technology and Applications*, INSTICC. SciTePress, 2024, pp. 505–512.

[21] H. O. Velesaca, J. A. Holgado-Terriza, and J. M. G. Guerrero, “Optimizing Smart Factory Operations: A Methodological Approach to Industrial System Implementation based on OPC-UA,” in *E3S Web of Conferences*, vol. 532. EDP Sciences, 2024, pp. 1–15.

[22] V. Leavers, “Which hough transform?” *CVGIP: Image understanding*, vol. 58, no. 2, pp. 250–264, 1993.

[23] G. Jocher, A. Chaurasia, and J. Qiu, “Ultralytics yolov8,” 2023. [Online]. Available: https://github.com/ultralytics/ultralytics

[24] J. Liu, G. Xie, J. Wang, S. Li, C. Wang, F. Zheng, and Y. Jin, “Deep industrial image anomaly detection: A survey,” *Machine Intelligence Research*, vol. 21, no. 1, pp. 104–135, 2024.

[25] O. Foundation, “OPC 40100-1 Machine Vision - Control, Configuration management, recipe management, result management,” OPC Foundation, Tech. Rep., 2024. [Online]. Available: https://opcfoundation.org/developer-tools/documents/view/217

[26] M. B. Muhammad and M. Yeasin, “Eigen-cam: Class activation map using principal components,” in *Int. Joint Conference on Neural Networks*. IEEE, 2020, pp. 1–7.