INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 2, February 2026 | ISSN: 2456-4184 | IJNRD.ORG

# Automated Defect Detection in Aerospace Engine Using YOLO v8

Mr J Jeya Ganesan
*Department of Artificial Intelligence and Data Science*
*Sri Sai Ram Insitute of Technology*
Chennai, India
jeyaganesan.ai@sairamit.edu.in

Dr A Rajasekar
*Department of Artificial Intelligence and Data Science*
*Sri Sai Ram Institute of Technology*
Chennai, India
rajasekar.ai@sairamit.edu.in

Jagajanani S D
*Department of Artificial Intelligence and Data Science*
*Sri Sai Ram Insitute of Technology*
Chennai, India
sit22ad039@sairamtap.edu.in

Tharuunika T
*Department of Artificial Intelligence and Data Science*
*Sri Sai Ram Institute of Technology*
Chennai, India
sit22ad035@sairamtap.edu.in

Karthika H
*Department of Artificial Intelligence and Data Science*
*Sri Sai Ram Institute of Technology*
Chennai, India
sit22ad044@sairamtap.edu.in

***Abstract*—AI-powered visual inspection systems, like YOLOv8, are transforming how defects are detected in aerospace engine manufacturing. By automating the process, these systems can quickly and accurately identify flaws in real time, using carefully curated datasets to improve their pattern recognition capabilities. This not only boosts quality control but also reduces costs and ensures the reliability and safety of aerospace components. By combining the power of computer vision and deep learning technologies, these systems minimize human error and make inspections faster and more efficient, ultimately advancing the entire manufacturing process.**

**Keywords—Defect Detection, Yolo v8, Deep Learning, Aerospace Industries**

## I. INTRODUCTION

Manufacturing processes are essential across industries like electronics, automotive, and aerospace, where the quality of final products is critical for customer satisfaction and compliance with rigorous industry standards. In sectors such as aerospace and automotive, even minor defects can lead to catastrophic outcomes, making robust quality control systems indispensable. High-quality manufacturing ensures not only product reliability but also safeguards brand reputation and operational efficiency in an increasingly competitive market.

Traditionally, quality control has relied on manual inspection, with skilled workers visually assessing products for defects. However, this approach is inherently limited by its time-consuming nature, subjectivity, and vulnerability to human error. Results can vary due to fatigue, differing levels of expertise, or the repetitive nature of the task. As production volumes increase to meet growing demand, traditional methods struggle to keep pace with the speed and precision required. Detecting subtle defects or recognizing intricate patterns becomes even more challenging in complex manufacturing environments, leading to inefficiencies and potential quality compromises.

To address these challenges, industries are turning to artificial intelligence (AI)-driven visual inspection systems. These systems use advanced machine learning algorithms, particularly deep learning, to analyse visual data such as images and videos captured during production. Unlike manual inspection, AI systems excel in processing large datasets, identifying complex patterns, and delivering consistent results in real time. Deep learning models like convolutional neural networks (CNNs) are trained on vast collections of defect images, enabling them to recognize anomalies ranging from surface irregularities to critical structural flaws. This automation improves inspection accuracy, reduces time, and enhances scalability in high-volume production settings.

To overcome the limitations of manual inspection, many industries now employ artificial intelligence (AI)-based visual inspection systems. These systems rely on deep learning techniques to process images and videos collected during manufacturing. Unlike human inspectors, AI can handle large volumes of data, recognize intricate patterns, and deliver reliable results consistently in real time. Convolutional neural networks (CNNs), a core deep learning approach, are trained using extensive datasets of defective and non-defective samples, allowing them to detect both minor surface flaws and critical structural defects. By automating the inspection process, such systems achieve higher accuracy, reduce inspection time, and scale efficiently for large-scale production environments.

## II. BACKGROUND

### *A. YOLOv8*

The YOLO (You Only Look Once) series of algorithms, introduced in 2016, has become widely adopted across multiple industries. The first version, YOLOv1, was primarily used in manufacturing, while YOLOv2 found applications in the electrical and electronics sectors. Later iterations, YOLOv3 and YOLOv4, were implemented in aerospace applications. This paper focuses on YOLOv8, the latest advancement in the series, which excels not only in object detection but also in image segmentation. YOLOv8 supports the full lifecycle of machine learning models, including training, validation, prediction, exporting, tracking, and deployment. Its versatility allows it to handle tasks such as detection, segmentation, classification, and even pose estimation.

YOLOv8's architecture is built around two main components: the backbone and the head. The backbone is responsible for feature extraction, utilizing modules such as C2f, Bottlenecks, and CSP blocks. These modules help optimize spatial resolution, increase depth, and capture both local and global features effectively. The head, on the other hand, focuses on object detection and classification. It employs convolutional layers, detection layers, and spatial pyramid pooling layers (SPPF) to extract features at multiple scales. These refined features are then used to generate bounding boxes, predict class probabilities, and assign confidence scores to each detected object.

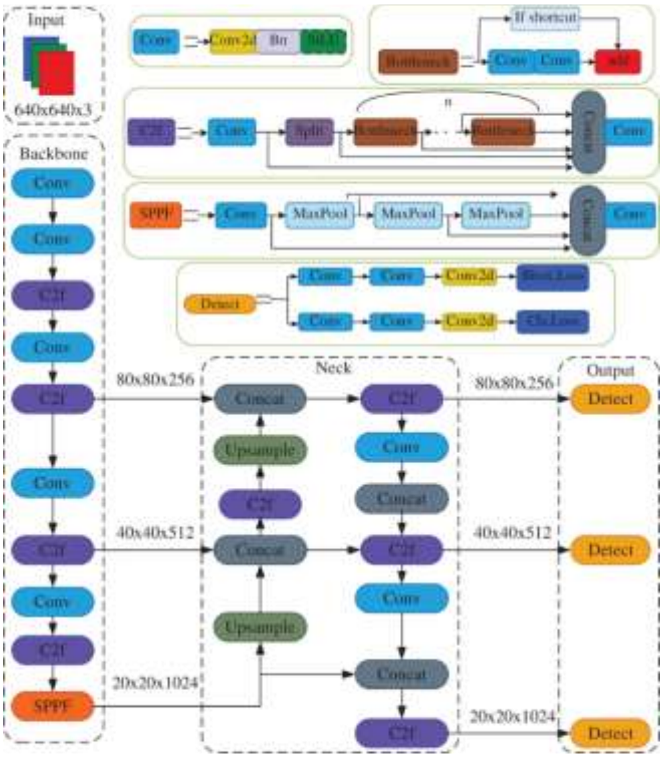

Fig. 1. Structure Of Yolo v8

## B. *Focused Image Analysis through Segmentation*

Image segmentation involves breaking an image into distinct, meaningful regions, which allows for more focused analysis of specific areas. For instance, in defect detection, segmentation helps isolate surfaces or components where flaws are more likely to occur. This targeted approach not only improves the focus of the algorithm but also enhances the accuracy of defect identification, making it an essential technique in computer vision tasks.

## C. *Retrieval-Augmented Generation(RAG)*

By integrating Retrieval-Augmented Generation (RAG) with YOLOv8, defect detection systems can be significantly enhanced. RAG leverages a knowledge base of historical defect data to improve classification accuracy and adaptability. When YOLOv8 identifies a potential defect, RAG retrieves similar images and metadata, aiding in the accurate classification of even rare or unique cases. This integration reduces the likelihood of misclassification, enables the system to adapt to new defects without retraining, and generates detailed reports vital for quality assurance. Together, YOLOv8 and RAG form a robust, adaptive defect detection system that aligns with the goals of Industry 4.0, driving innovation in high-stakes industries.

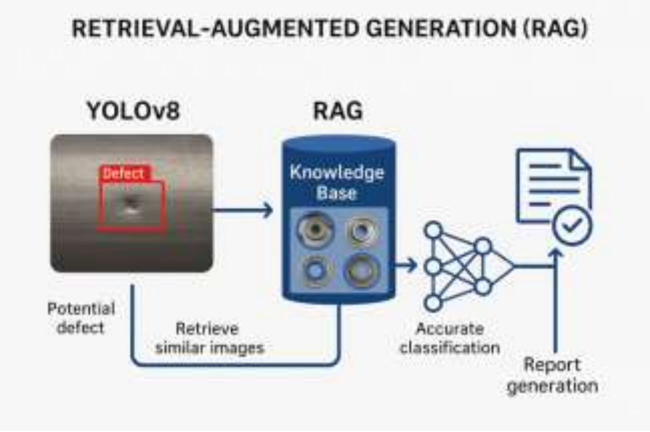

Fig. 2. Architectural Diagram of Retrieval Augmented Generation

## III. METHODOLOGY

The proposed system leverages advanced artificial intelligence and imaging technologies to revolutionize defect detection in aerospace engine manufacturing. By combining high-resolution imaging with deep learning techniques, the system ensures accurate, real-time identification of defects, optimizing safety and efficiency in production. The architecture integrates the YOLOv8 model, known for its precision and speed, with automated workflows for streamlined inspections. Below is an in-depth discussion of the system's components and implementation strategies.

## A. *AI-Driven Defect Detection System*

This system employs state-of-the-art AI algorithms integrated with high-resolution imaging to analyze aerospace engine components. The YOLOv8 convolutional neural network (CNN) is highly effective at detecting even small and intricate defects in real time. Its combination of accuracy and speed makes it especially well-suited for the strict safety and quality requirements of the aerospace sector. By automating defect detection and classification, the system significantly enhances inspection reliability and reduces human error.

## B. *Data Acquisition and Preprocessing*

The foundation of accurate defect detection lies in high-quality data. Images of engine components are captured using a Basler ace 2 pro industrial camera, which ensures sharp, unobstructed visuals. To make detection more accurate, the images are first processed using techniques like noise reduction, normalization, and contrast enhancement. These methods ensure uniformity across the dataset, minimize image artifacts, and highlight subtle features, enabling the model to perform at its best.

## C. *Defect Detection Model*

The YOLOv8 model architecture is optimized for aerospace-specific applications. Feature extraction, localization layers, and customized anchor boxes are fine-tuned to detect minute and complex defects. The model is trained on a comprehensive dataset encompassing diverse defect types, augmented with techniques like rotation, scaling, and brightness adjustments to enhance its generalizability. Transfer learning, leveraging pre-trained YOLOv8 weights, further boosts detection accuracy by tailoring the model to aerospace-specific defect patterns. The model’s performance is carefully assessed using metrics like accuracy, precision, and recall to ensure it meets industry standards.

### D. Image Analysis Techniques

The system is adept at recognizing defect-specific features such as textures, edges, and patterns. Using YOLOv8's advanced bounding box localization and segmentation capabilities, it isolates defect regions with precision. By identifying deviations from normal patterns, the system flags potential anomalies, allowing for proactive interventions. This nuanced analysis supports high-stakes quality control processes in aerospace manufacturing.

### E. Post-Processing and Classification

To make the system more reliable, post-processing is used to remove false positives and refine the segmentation results. These refined outputs improve detection accuracy and ensure minimal disruption due to erroneous classifications. The classification process assesses defect severity, aiding operators in prioritizing maintenance tasks. This approach optimizes repair schedules, reduces operational downtime, and ensures smooth production workflows.

### F. Real-Time Inspection and Integration

The defect detection system operates seamlessly in real-time, enabling immediate identification of anomalies during production. This capability reduces inspection times while maintaining high accuracy. Integration with automated tools like robotic arms and visual inspection systems facilitates comprehensive quality control. By embedding the system into the production line, it creates a holistic solution for maintaining the safety and integrity of aerospace engines.

### G. Feedback and Continuous Learning

To maintain its efficacy over time, the system incorporates a feedback loop that monitors performance and collects new data. The model is periodically retrained using images of newly discovered defects, allowing it to adapt to changing patterns and conditions. This continuous learning approach improves the system's ability to identify rare or emerging defects, keeping it prepared for future challenges.

### H. Validation and Evaluation

The system's performance is carefully validated using a ground truth dataset annotated by industry experts. Key metrics including accuracy, sensitivity, specificity, and F1 score are employed to assess and benchmark the model's effectiveness. Robustness is tested under diverse conditions, including varying lighting and defect types, ensuring consistent performance across all aerospace engine components. These evaluations guarantee compliance with stringent industry standards.

### I. Implementation and Deployment

The deployment of the system requires high-performance GPUs and cloud infrastructure to support real-time processing. Software frameworks like TensorFlow and PyTorch are utilized for model training and inference. Designed for seamless integration into manufacturing and maintenance workflows, the system operates efficiently in both centralized production facilities and distributed maintenance sites.

### J. Future Improvements and Challenges

To address challenges such as imbalanced datasets, the system employs synthetic data generation and oversampling techniques to improve model generalization. Scalability remains a key focus, with the system being adaptable to various engine types and defect conditions. To ensure reliable performance, the system is validated against a ground truth dataset annotated by industry experts. Metrics such as accuracy, sensitivity, specificity, and F1 score are then used to evaluate and benchmark the model's effectiveness. These advancements aim to push the boundaries of what is possible in aerospace manufacturing quality control.

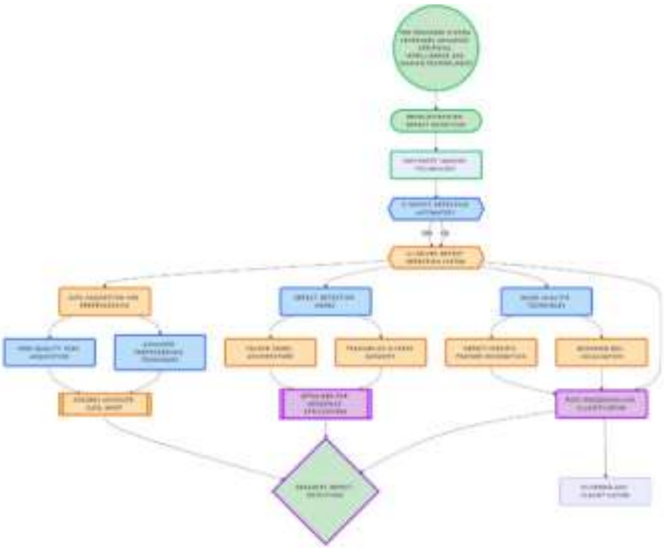

Fig. 3. Work-Flow of Defect Detection

## IV. MODEL DEVELOPMENT

Industry experts annotate a ground truth dataset, which serves as the basis for evaluating the system's performance. The model is then measured using indicators like accuracy, sensitivity, specificity, and F1 score to determine how effectively it performs.

### A. Dataset Description and Preprocessing

The dataset, titled Aero-Engine Defect Detection, consists of high-resolution images designed to highlight defects in aerospace engine components. It is meticulously organized into directories for training and validation purposes, with each image labeled to indicate specific transformations applied during preprocessing (e.g., flips, rotations). Applying these transformations increases the variety within the dataset, allowing the model to encounter defects in different orientations and scenarios.

Annotations are provided in YOLO format, where each defect is represented with a bounding box defined by normalized coordinates for the box's center, width, and height. This annotation format ensures seamless scalability across various image resolutions, enabling precise defect localization regardless of the image size. By incorporating bounding box annotations with corresponding class IDs, the dataset is primed for training object detection models with a high degree of accuracy, making it ideal for aerospace inspection tasks.

### B. Model Selection and Configuration

The defect detection process begins with the selection of a pretrained YOLOv8 model, specifically the "nano" version (yolov8n.pt). This variant of YOLOv8 is designed for resource-constrained environments, offering an optimal balance of speed and efficiency. Its streamlined architecture allows for quick prototyping and deployment, making it particularly useful in environments with limited computational resources.

Model configuration is managed through a YAML file, which serves as a blueprint for the dataset structure. This file specifies the paths to training and validation datasets, defines the mapping of class IDs to defect categories, and outlines essential training parameters. Critical parameters such as the number of epochs, input image resolution (imgsz), and batch size are fine-tuned to maximize performance while maintaining compatibility with the available computational resources.

Precision measures how many of the model's positive predictions are correct, while recall evaluates its ability to identify all actual defects. The mean Average Precision (mAP) score combines these metrics to give a complete assessment of the model's detection performance.

The model version with the highest validation scores is saved as 'best_yolov8_model.pt,' preserving the most accurate and dependable version for future use. This iterative refinement process not only tracks the model's progress but also optimizes its performance for defect detection tasks.

### C. Inference and Defect Detection

After training, the Yolo v8 model is deployed for inference. Users can specify either a single image or a directory of images for analysis. During inference, the model Processes each image and identifies potential defects, drawing bounding boxes around detected areas and labeling them with predicted defect classes along with their confidence scores.

The output images complete with visual annotations that are saved for further review and verification. This enables quality inspectors to validate the model's predictions and reapidly identify any discrepancies, significantly reducing manual inspection time.

### D. A Comprehensive and Scalable Solution

This comprehensive defect detection pipeline uses deep learning to automate and improve the quality control process in aerospace manufacturing. By integrating a carefully prepared dataset with the YOLOv8 architecture and a structured training approach, the system attains high accuracy and reliability. Its scalability and adaptability to new datasets or emerging defect types ensure long-term effectiveness, making it a valuable tool in high-stakes environments where precision and efficiency are critical.

### E. Training and Validation

During training, yolov8 iteratively learns to recognize and localize defects by comparing its predicted outputs against the ground truth labels. With each passing epoch, the model refines its internal parameters to enhance precision and minimize prediction errors.

At the end of each epoch, the model's performance is evaluated using key metrics: precision, which measures the proportion of correct positive predictions; recall, which reflects the model's ability to detect all actual defects; and mean Average Precision (mAP), which provides an overall assessment of detection quality across all defect classes.

The performance of the defect detection model is quantitatively measured using three standard metrics: Precision, Recall, and mean Average Precision (mAP), each providing insight into different aspects of the model's effectiveness.

$$Precision = \frac{TP}{TP+FP} \qquad (1)$$

$$Recall = \frac{TP}{TP+FN} \qquad (2)$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \qquad (3)$$

Two mAP thresholds are used:

- **mAP@0.5**: Average Precision computed at an Intersection over Union (IoU) threshold of 0.5.
- **mAP@0.5:0.95**: Average over multiple IoU thresholds from 0.5 to 0.95 with a step size of 0.05, providing a stricter and more comprehensive assessment of model performance.

In equations (1) and (2), TPTPTP (True Positives) denotes the number of correctly identified defect instances, FPFPFP (False Positives) denotes incorrectly predicted defects, and FNFNFN (False Negatives) represents missed defect instances. Precision evaluates how accurate the model's positive predictions are, while recall reflects its ability to detect all relevant defect instances.

Equation (3) defines the Mean Average Precision (mAP), where APiAP_iAPi represents the Average Precision of the i-th class, and NNN is the total number of defect classes. mAP is computed as the mean of AP values across all classes and is widely used to evaluate object detection models.

These metrics collectively help in understanding the model's accuracy, coverage, and consistency. Training continues iteratively until the model converges, and the best-performing version based on validation results is saved as the final checkpoint for deployment.

Fig. 4. Work Flow of Model Development

## V. RESULT AND EVALUATION

The YOLOv8n model for aerospace defect detection was trained on a custom dataset containing 42 validation images, covering three defect classes: crack, dent, and corrosion. The training of the model took 50 epochs, optimized through the Ultralytics framework (v8.3.170), on a Tesla T4 GPU acceleration. The model used light architecture with 3 million parameters and 8.2 GFLOPs, fine-tuned through augmentation techniques like Rand Augment, color jittering (HSV), and flipping. Prediction results, visualized over 25 sample images, show the model's confidence bounding box scores per class, with explicit annotation overlays confirming detection accuracy.

During evaluation, the model produced a mean average precision (mAP@0.5) of 0.245 and a mAP@0.5:0.95 of 0.224 for all classes. The dent class showed high detection performance with 0.734 mAP@0.5 and 0.673 mAP@0.5:0.95, reflecting strong spatial localisation and confidence. On the other hand, the corrosion and crack classes achieved lower precision-recall values, likely because of their relative paucity in the training set and difficulty in recognizing visual patterns with changing illumination. The confusion matrix also shows a considerable class-wise performance imbalance, highlighting the necessity for richer data diversity and sampling techniques for underrepresented types of defects.

In general, the model demonstrates robust real-time detection with negligible computational overhead, justifying its applicability for onboard or edge-level aerospace inspection systems. Although the recall is limited for minor types of defects, the strong performance for detecting dents and the seamless post-processing pipeline justify the efficiency of YOLOv8n for real-world non-destructive testing applications. Subsequent versions will include class-balanced augmentation, attention-based refinement, and multi-view temporal data integration to enhance recognition of fine-grained surface anomalies such as corrosion and cracks.

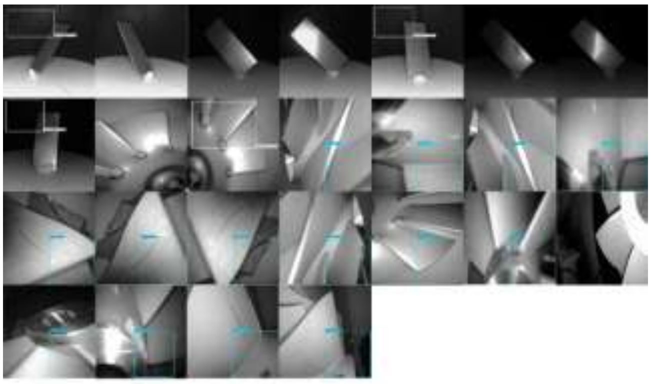

Fig. 5. Predicted images using Yolo v8

## CONCLUSION

This research successfully showcases how YOLOv8 can be applied for real-time defect detection in aerospace engine manufacturing. Using high-resolution imaging alongside deep learning, the system can automatically detect and classify complex defects while adhering to the stringent standards of the aerospace industry. This automated approach not only improves quality control but also reduces the likelihood of human error and enhances production efficiency. Looking ahead, future efforts will focus on incorporating additional AI techniques to further refine detection accuracy, paving the way for a scalable solution that an adapt to the evolving quality requirements of the aerospace sector.

## REFERENCE

[1] D. Li, Y. Li, Q. Xie, Y. Wu, Z. Yu, and J. Wang, “Tiny defect detection in high-resolution aero-engine blade images via a coarse-tofine framework,” IEEE Trans.Instrum.Meas., vol.70, pp.1-12,2021.

[2] Du, S., Pan, W., Li, N., Dai, S., Xu, B., Liu, H., Xu, C. and Li, X., 2024. TSD-YOLO: Small traffic sign detection based on improved YOLO v8. *IET Image Processing*, *18*(11), pp.2884-2898.

[3] Bao, Zhu. "The UAV target detection algorithm based on improved YOLO V8." In *Proceedings of the International Conference on Image Processing, Machine Learning and Pattern Recognition*, pp. 264-269. 2024.

[4] Patel, K., Patel, V., Prajapati, V., Chauhan, D., Haji, A. and Degadwala, S., 2023, June. Safety helmet detection using YOLO v8. In *2023 3rd international conference on pervasive computing and social networking (ICPCSN)* (pp. 22-26). IEEE.

[5] Gebrehiwet, L., Chimido, A., Melaku, W. and Tesfaye, E., 2023. A review of common aerospace composite defects detection methodologies. Int. J. Res. Publ. Rev, 4(8), pp.1829-1846.

[6] Wang, J., Meng, R., Huang, Y., Zhou, L., Huo, L., Qiao, Z. and Niu, C., 2024. Road defect detection based on improved YOLOv8s model. Scientific reports, 14(1), p.16758.

[7] Hussain, Muhammad. "YOLO-v1 to YOLO-v8, the rise of YOLO and its complementary nature toward digital manufacturing and industrial defect detection." Machines 11, no. 7 (2023): 677.

[8] Karthika, B., M. Dharssinee, V. Reshma, R. Venkatesan, and R. Sujarani. "Object detection using yolo-v8." In 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), pp. 1-4. IEEE, 2024.

[9] Safaldin M, Zaghden N, Mejdoub M. An improved YOLOv8 to detect moving objects. IEEE Access. 2024 Apr 25;12:59782-806.

[10] Arslan, M., Ghanem, H., Munawar, S. and Cruz, C., 2024. A Survey on RAG with LLMs. Procedia computer science, 246, pp.3781-3790.

[11] Jha SB, Babiceanu RF. Deep CNN-based visual defect detection: Survey of current literature. Computers in Industry. 2023 Jun 1;148:103911.

[12] Vaghela, R., Vaishnani, D., Sarda, J., Thakkar, A., Nasit, Y., Brahma, B. and Bhoi, A.K., 2025. Optimizing object detection for autonomous robots: A comparative analysis of YOLO models. Measurement, p.118676.

[13] Varghese, Rejin, and M. Sambath. "Yolov8: A novel object detection algorithm with enhanced performance and robustness." In 2024 International conference on advances in data engineering and intelligent computing systems (ADICS), pp. 1-6. IEEE, 2024.

[14] Nimma, Divya, Omaia Al-Omari, Rahul Pradhan, Zoirov Ulmas, R. V. V. Krishna, Ts Yousef A. Baker El-Ebiary, and Vuda Sreenivasa Rao. "Object detection in real-time video surveillance using attention based transformer-

YOLOv8 model." Alexandria Engineering Journal 118 (2025): 482-495.

[15] Ali ML, Zhang Z. The YOLO framework: A comprehensive review of evolution, applications, and benchmarks in object detection. Computers. 2024 Dec 14;13(12):336.

[16] Tu, Yiteng, Weihang Su, Yujia Zhou, Yiqun Liu, and Qingyao Ai. "Robust Fine-tuning for Retrieval Augmented Generation against Retrieval Defects." In Proceedings of the 48th International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 1272-1282. 2025.

[17] Zhang, Mei, Jinglan Wu, Huifeng Lin, Peng Yuan, and Yanan Song. "The application of one-class classifier based on CNN in image defect detection." Procedia computer science 114 (2017): 341-348..

[18] Zhou, Chuande, Zhenyu Lu, Zhongliang Lv, Minghui Meng, Yonghu Tan, Kewen Xia, Kang Liu, and Hailun Zuo. "Metal surface defect detection based on improved YOLOv5." Scientific Reports 13, no. 1 (2023): 20803.

[19] Qiao, Q., Hu, H., Ahmad, A. and Wang, K., 2025. A Review of Metal Surface Defect Detection Technologies in Industrial Applications. IEEE Access.

[20] Álvaro, José Antonio Heredia, and Javier González Barreda. "An advanced retrieval-augmented generation system for manufacturing quality control." Advanced Engineering Informatics 64 (2025): 103007.