

AI-Powered Automated Defect Recognition for Weld Radiography: A Transformation to the Traditional approach in Oil & Gas Industry

Whitepaper

**SAUDI ARAMCO
ZULUF WATER INJECTION PROJECTS**

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1. Executive Summary

Weld inspection in the oil and gas industry is crucial for ensuring the integrity of infrastructure operating under harsh conditions, high pressures, and corrosive environments. Historically, this has relied on manual interpretation by certified inspectors, a process that is time-consuming and susceptible to human variability and inefficiencies such as fatigue-induced errors and inconsistent defect classification.

To address these limitations, the Zuluf Offshore Water Injection Project team successfully validated an innovative AI-driven Automated Defect Recognition (ADR) system. This solution leverages a hybrid approach, combining advanced machine learning models with rule-based algorithms to automate the weld radiography interpretation process.

The core of the technology is a multi-stage processing model that includes:

- A Preprocessing Module for image enhancement and standardization.
- An AI Detection Core trained on a large, annotated dataset to detect and classify defects. The IQI and defect detection models use YOLOv5, while the ROI model uses YOLOv8. The system utilizes both the YOLOv5 and YOLOv8 models for high-speed object detection and instance segmentation, enabling the identification of six key defect types: porosities, slag inclusions, lack of fusion (LOF), lack of penetration (LOP), and root/external undercuts.
- A Post-Processing Engine that applies a rule-based engine to automate compliance checks, perform measurements, and generate digital reports.
- Rigorous testing and validation, including a comparative field trial against manual inspectors, have demonstrated the system's superior performance. Key results include:
- Enhanced Accuracy: The ADR system achieved a defect detection accuracy in the range of 90~95%, a significant improvement from the 85-90% range of traditional manual methods. In a comparative field trial, ADR consistently outperformed manual inspection across all defect types, achieving 97% POD for porosity, >91% POD for lack of fusion and 90 % for lack of penetration, >90% POD for slag inclusions, and 98 % for IQI/ROI.
- Operational Efficiency: Inspection time was reduced to under 1 minute per radiograph, facilitating faster project timelines.
- Assured Compliance: The system ensures 100% automated and reliable adherence to critical industry standards, including ASME B31.3, API 1104, ASME Section V & AWS D1.1.

The deployment of this ADR solution represents a paradigm shift in Non-Destructive Testing (NDT), delivering tangible benefits such as cost savings through reduced manual labor and rework, as well as significant ESG impact by enhancing worker safety and protecting environment. As a testament to its success, the system was validated through Saudi Aramco's Zuluf Project, processing over 5,000 radiographs using scientific sampling with a 90-95% accuracy.

Looking ahead, the model is designed to be scalable and adaptable. Future work includes fine-tuning the model to handle Digital Radiography (DR) and Computed Radiography testing

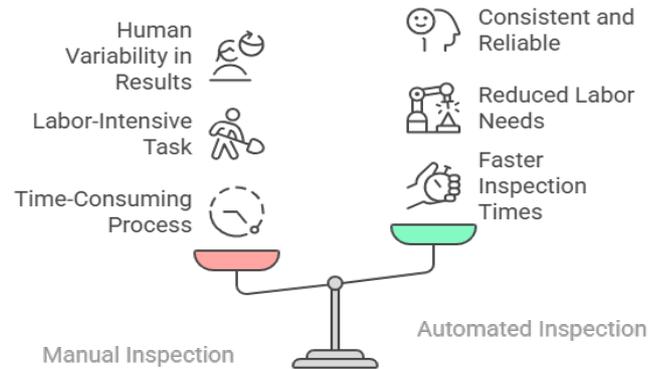
(CRT) images and integrating with cloud-based workflows for remote collaboration. This innovation sets a new benchmark for quality and efficiency, aligning with Saudi Aramco's strategic initiatives in digital transformation and sustainable practices.

2. The Challenge

2.1 The Criticality of Weld Quality

In oil & gas infrastructure, weld failures can lead to:

- Catastrophic safety incidents
- Environmental contamination
- Production losses

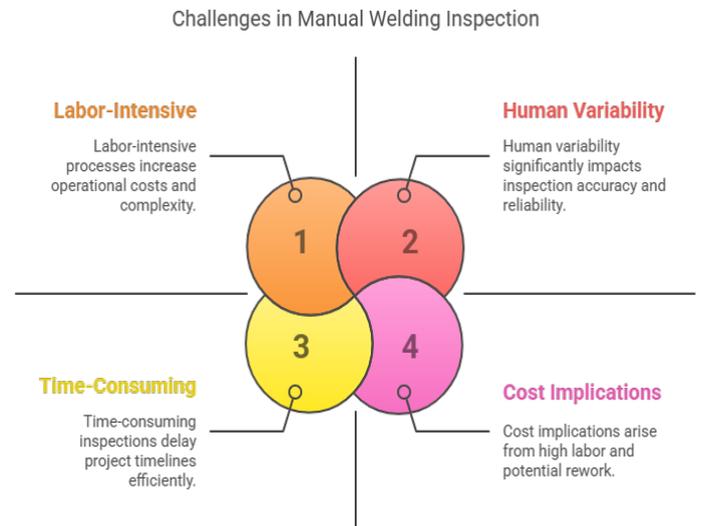


Comparing Manual and Automated Welding Inspection

2.2 Limitations of Conventional RT

Our analysis of manual inspections revealed:

1. **Time Constraints**
 - Elongated minutes; 500 min/ 100 radio graphs
 - 100 images/day minimum per inspector
2. **Human Factors**
 - Reproducibility error in defect classification; about 15% to 20% discrepancies
 - Fatigue-induced error rate increases
3. **Compliance Risks**
 - manual reports showed incomplete ASME Section V ARTICLE 2 checks



3. Methodology

The ADR system uses a three-layer processing model consisting of a preprocessing module, an AI detection core, and a post-processing engine. The core of the system relies on a multi-stage YOLO network architecture for defect detection and a rule-based engine for compliance checks

This Project utilized a pre-existing "Base Model" developed over six years, which was then updated with project-specific images to create a more "matured model".

The ADR solution leverages state-of-the-art deep learning frameworks, specifically YOLOv5 and YOLOv8, which have been widely studied in the context of industrial defect detection. Recent research (Khanam & Hussain, 2024) provides a comprehensive overview of YOLOv5's architecture and its applicability in real-world tasks. Comparative studies (Casas et al., 2024) highlight that YOLOv8 delivers measurable improvements over YOLOv5 in segmentation accuracy for industrial imaging, validating our dual-model approach for defect detection.

For deployment, the trained ADR models were exported into ONNX format to ensure hardware-independent inference acceleration. The ONNX runtime has been benchmarked as a reliable and high-performance inference engine across CPU and GPU architectures, providing flexibility for on-site and cloud-based ADR deployments (ONNX, 2024).

3.1 Solution Overview

The proposed ADR system integrates YOLOv5/YOLOv8 (You Only Look Once) object detection models with rule-based logic to identify and validate welding defects in radiographic images. It supports computed radiography (CR) and digital radiography (DR) formats and automates compliance checks against standards such as ASME Section V, API 1104, ASME B31.3, AWS D1.1 and ISO 17636.

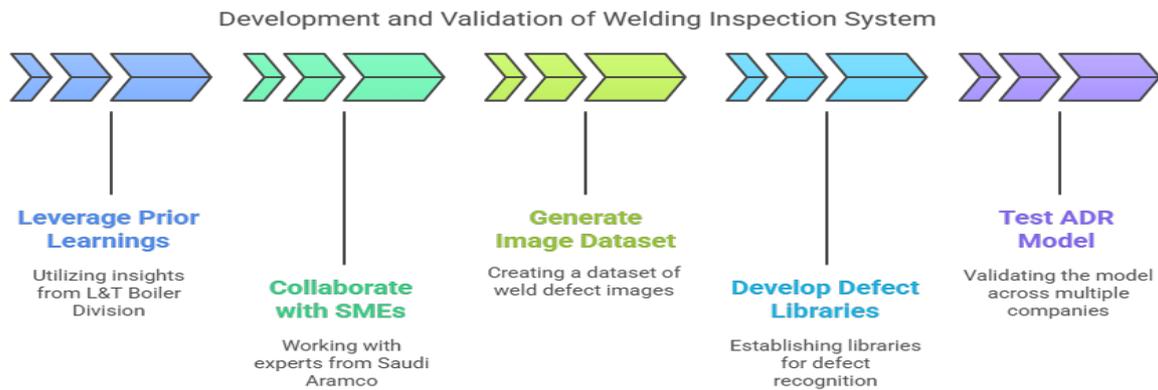
1. *Data Training:*

- The model was trained for '200 epochs' using a curated dataset of approximately 2,000 images, which were part of a larger collection of over 5,000+ images collected for the project.
- More than 80% of these collected images featured artificially induced defects.
- 3000 images out of 5000+ images were used for validation and testing the model
- 2500+ annotated CR images were with different defect types (AWS D1.1/API 1104&B31.3 standards)
- 80/10/10 train/validation/test split (ASTM E2862)

2. *Model Optimization:*

- Loss function: Composite CIoU + Focal Loss
- Hardware: NVIDIA RTX 2080 Ti
- Loss Function: Modified CIoU (Complete IoU)
- Learning Rate: Cyclic (0.01 → 0.0001)

Figure-1: Development and Validation of Welding Inspection System



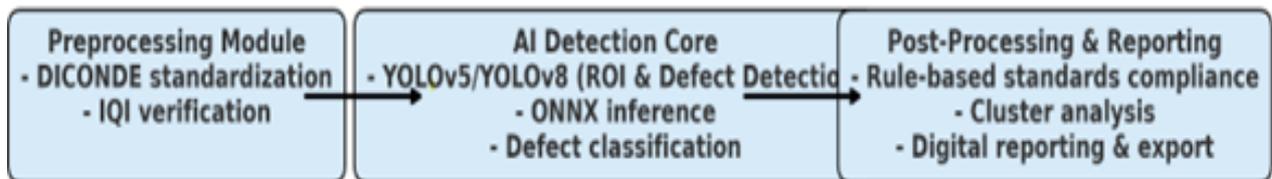
3.2 System Architecture and Training

The ADR system uses a three-layer processing model consisting of a pre-processing module, an AI detection core, and a post-processing engine. The core of the system relies on a multi-stage YOLO network architecture for defect detection and a rule-based engine for compliance checks.

3.2.1 System Architecture Diagram (3-Layer Processing Model):

shows the workflow: **Pre-processing** → **AI Detection Core** → **Post-Processing**.

Figure-2: Workflow



1. Preprocessing Module

- DICONDE-compliant image standardization
- IQI visibility verification (per ASTM E1742)

2. AI Detection Core

- Multi-stage YOLO network architecture
- Defect-specific feature extraction layers
- Confidence thresholding at 80-90% probability

3. Post-Processing Engine

- Automated length measurement.
- Cluster analysis for porosity quantification
- Digital report generation

3.2.2 Training

This model was trained with 2500+ CR annotated images, and "200 epochs" on an extensive, curated dataset. Here's a breakdown of the image counts used for training, validation, and testing for the various models:

Table-1: Dataset distribution:

<i>Model</i>	<i>Training Images</i>	<i>Validation Images</i>	<i>Testing Images</i>
<i>Structural IQI</i>	946	95	95
<i>Piping IQI</i>	489	49	49
<i>ROI Detection</i>	670	85	83
<i>Porosity, Slag, LOF</i>	1015	101	101
<i>LOP</i>	833	82	82

4. Technical Breakthroughs

The system architecture combines convolutional neural networks (CNNs) for image pre-processing, defect classification, and standards validation. Training was conducted on a large, annotated dataset curated in collaboration with subject matter experts (SMEs).

Key components include:

- YOLOv5 / YOLOv8 / ONNX for the inferencing of ROI, IQI, and defect detection models
- Rule-based engine for standards compliance
- Agile development methodology
- Integration with enterprise quality systems

Relevant standards include ASME Section V, API 1104, AWS D1.1, ASME B31.3 and ISO 17636.

5. Case Study: Real-World Validation of ADR Technology

To validate the ADR system's performance in a real-world environment, a rigorous comparative field trial was conducted. This trial involved evaluating minimum **1000 individual artificial defects** using both the ADR system and Team consists of 4 members (Level III inspector; Coordinator & PCN L-II Interpreter). This approach allowed for a direct, quantitative comparison of the automated system against the industry's established manual method. The results, detailed in the following table, demonstrate the system's superior and consistent accuracy across all key defect types, while also highlighting the inherent variability and time-consuming nature of manual inspection

5.1 Comparative Field Trial

- Trial Scope: 500 weld images independently interpreted by Level III inspector & certified PCN L-II interpreter and the ADR system.
- Processing Speed: Manual inspection required ~3–5 minutes per radiograph, whereas ADR consistently processed images in <1 minute.
- Inspector Variability: Discrepancies were observed in defect sizing and acceptance interpretation among human inspectors, while ADR provided consistent rule-based evaluations.

5.2 Manual vs ADR Metrics (Comparison Table)

Table-2: Manual vs ADR Performance Comparison

<i>Metric</i>	<i>Manual Inspection</i>	<i>ADR System</i>
<i>Overall Accuracy</i>	85–90%	90-95%
<i>Porosity Detection</i>	90%	96%
<i>Slag Detection</i>	88%	90%
<i>Lack of Fusion (LOF)</i>	90%	95%
<i>Lack of Penetration (LOP)</i>	85%	94%
<i>Avg. Time per Image</i>	~3-5 min	<1 min

5.3 Key Takeaways

The validation results underscore several critical takeaways from the field trial:

- The ADR system consistently maintained an accuracy of 90-95% in defect detection, proving its reliability.
- The technology demonstrated seamless adaptability to diverse industry standards, including API, ASME, AWS and naval specifications.
- All validations were conducted in strict accordance with ASME Section V, API 1104, AWS D1.1, ASME B31.3
- The system has potential to deliver return on investment in less than six months across all implementations; this could be a testament to its operational efficiency and cost-effectiveness.

6. Impact and Benefits

The implementation of the ADR system has delivered significant benefits during the validation phase, both quantitative and qualitative, for operations, cost, and quality.

Quantitative Advantages:

1. Operational Efficiency

- Faster inspections; <1 min/ image vs 3-5 mins/image using manual method

- Reduction in manual labor hours; 70-80 % manhours saving for image review
- Enable the processing of more radiographs daily; >400 images vs <100 images using manual method

2. Cost Savings

- Reduction in labor costs and rework expenses
- Reduction in rework expenses
- ROI potential <6 months for most implementations.

3. Quality Improvement

- 90%-95 %defect detection accuracy a notable increase from manual methods
- Reduction in false positives
- It also ensures 100% compliance with ASME/API/AWS standards

Table-3: Industry Benchmark Comparison

<i>Metric</i>	<i>Traditional RT</i>	<i>ADR System</i>	<i>Improvement</i>
<i>Accuracy</i>	85-90%	90-95 %	+5-10%
<i>Compliance</i>	Manual checks	Automated	100% reliable

Qualitative Advantages:

1. ESG Impact

Beyond operational efficiency, ADR contributes directly to ESG objectives. By reducing unnecessary weld repairs, thus, reducing radiation exposure, associated material wastage, and carbon footprint. The automation of compliance and image quality checks reduces radiation exposure for inspectors by limiting retakes, thereby enhancing occupational safety. Energy consumption per inspection cycle is also lowered, contributing to organization's broader net-zero commitments and sustainable infrastructure goals.

2. Workforce Enhancement

- Reduces inspector fatigue and human error
- Allowing the workforce to develop new skills in AI-assisted NDT methods
- Enables 24/7 inspection capabilities without quality degradation

7. Project Achievements: Quantifiable Results and Success Stories

The ADR system on the Zuluf AH South & North Water Injection Project delivered significant, measurable achievements that underscore its value and technical maturity. This section summarizes the key results and success stories that validate technology’s effectiveness in a real-world, large-scale application.

7.1 Key Outcomes

The Automated Defect Recognition (ADR) initiative for weld inspection under the Zuluf Offshore Water Injection Project (ZOWIP) is First-of-its-kind deployment in Aramco Offshore Project. It has demonstrated measurable success across technical, operational, and compliance dimensions, that underscore its value and technical maturity. This section summarizes the key outcomes and success stories that validate the technology's effectiveness in a real-world, large-scale application.

The following summarizes the key outcomes:

- **Enhanced Accuracy:** The system achieved an overall **defect detection accuracy of 90-95 %**, a notable increase over the 85–90% typically seen in traditional manual methods.
- **Operational Efficiency:** Reduced inspection time from ~3 minutes/manual per image to **<1 minute per radiograph** (~66% faster), contributing to a significant overall reduction in project timelines.
- **Total Images Processed:** The system successfully processed over 5,000 radiographs throughout the project lifecycle. A total 2500 images were manually annotated to create a robust ground-truth dataset for training and validation.
- **Reduced False Positives:** The system operated with a false-call rate of approximately 5%, significantly reducing unnecessary rework and costs.
- **Assured Compliance:** It ensured 100% automated and reliable adherence to critical industry standards, including ASME Section V, API 1104, ASME B31.3 and AWS D1.1.
- **Defect Coverage:** Successful AI-driven detection of six defect types: porosity, slag, lack of fusion (LOF), lack of penetration (LOP)
- **Consistency:** Delivered **>90-95% standards compliance** in alignment with ASME Section V, ASME B31.3; API 1104, and AWS D1.1 codes.
- **Operational Deployment:** Deployed at Saudi Aramco **Zuluf Offshore Water Injection Project** for structures, and piping welds.

7.2 Summary of Achievements

- First-of-its-kind deployment in Saudi Aramco's Zuluf Increment Program for CR weld inspection automation.
- Demonstrated the feasibility and scalability of YOLOv5/YOLOv8-based ADR in offshore NDT workflows.
- Successfully processed 5,000+ radiographs with 1000+ artificial defects with 90-95 % accuracy
- Marked reduction in inspection bottlenecks, enabling higher throughput without compromising accuracy.
- Established a foundation for future scalability into Digital Radiography (DR) and Computed Radiography (CR)

8. ADR Scope and Limitations

The Automated Defect Recognition (ADR) system developed under the Zuluf Offshore Water Injection Project was designed with defined application boundaries to ensure compliance, reliability, and traceability. This section provides a clear overview of the current scope and operational limitations of the AI-powered ADR system. This helps to contextualize the technology's capabilities and serves as a roadmap for future development. The following outlines the system's scope of capability and its current limitations.

8.1 Scope of the ADR System

The current version of the ADR software is engineered to address the core challenges of weld inspection within a well-defined set of parameters.

- **Imaging Modalities:** The system supports Computed Radiography (CR) images, including single-wall, single-image (SWSI), double-wall, single-image (DWSI), and double-wall, double-image (DWDI) techniques.
- **Defect Detection:** The AI model is trained to detect and classify six primary defect types: porosities, slag inclusions, lack of fusion (LOF), lack of penetration (LOP).
- **Training and Data:** The models were trained on an extensive, curated dataset of over 5,000 images, which included 2500 manually annotated ground-truth images.
- **Compliance:** The software automates compliance checks with applicable standards, including ASME Section V, API 1104, ASME B31.3, and AWS D1.1.
- **Minimum Defect Size:** The system is capable of detecting porosities as small as 0.4 mm, in line with ASME standards.

8.2 Operational Limitations

While robust, the current ADR system has specific operational limitations that define its current application profile.

Table-4: Technology Limitation

<i>Area</i>	<i>Current Limitation</i>	<i>Notes / Mitigation</i>
<i>Processing Mode</i>	Batch processing only (not real-time)	Real-time integration under future scope.
<i>Defect Coverage</i>	Reduced accuracy for Root Undercut due to limited real-world training data	Requires collection of more field samples.
<i>Noise Sensitivity</i>	Accuracy drops in noisy or low-contrast images	Pre-processing enhancements and source optimization recommended.
<i>Minimum Defect Size</i>	Detects porosities ≥ 0.4 mm (per ASME standard)	Below 0.4 mm not supported.
<i>Image Dependency</i>	Performance dependent on IQI visibility, image contrast, and SNR	

9. Conclusion: The Future of AI-Driven Weld Inspection

The implementation of AI-powered Automated Defect Recognition (ADR) has fundamentally transformed radiographic testing in the oil & gas industry. The solution has brought about an efficiency revolution, reducing inspection time while improving accuracy. It has potential to deliver annual savings per facility through labor reduction and rework avoidance, all while ensuring compliance with key standards. From an ESG perspective, the technology has advanced sustainability by minimizing material waste and enhanced worker safety through remote analysis.

The success of this solution is underscored by its reception in the field:

- **Efficiency Revolution:** Reduced our interpretation time by 50% while improving accuracy to 90-95 %
- **Cost & Compliance:** During validation it has shown promising results for cost savings through labor reduction and rework avoidance, while ensuring 100% compliance with ASME Section V, AWS D1.1; ASME B31.3; API 1104, and ISO 3834.
- **ESG Leadership:** Advanced sustainability through less material waste and enhanced worker safety via remote analysis.

While the ADR system marks a significant advancement, its full potential is contingent on overcoming specific technical limitations. Furthermore, its application to new modalities like Digital Radiography (DR) will necessitate further training to account for inherent differences in image characteristics. Moving forward, a focused strategy of continuous model refinement using real-time field data and optimizing the system for varied operational conditions will be essential to mature the technology and broaden its applicability across the industry

"This AI solution has redefined our inspection capabilities, setting a new benchmark for quality and efficiency in oil & Gas industry."

9.1 Key Validation Milestones

The ADR system has been rigorously validated through:

1. **Saudi Aramco's Zuluf Offshore Water Injection Project:** Processed 5,000+ radiographs with 90~95 % accuracy.

9.2 The Road Ahead

The ADR framework is inherently designed for scalability. While the current deployment addresses Computed Radiography (CR) images, the architecture supports extension to Digital Radiography (DR) and conventional film with a modular design leveraging YOLOv5/YOLOv8 and ONNX, the system can be adapted to different imaging techniques (SWSI, DWSI, DWDI). Planned integration with cloud-based workflows will enable multi-site collaboration and centralized data governance, ensuring enterprise-wide adoption. In addition, the system can be extended to other NDT modalities such as Phased Array Ultrasonic Testing (PAUT).

Together, these dimensions highlight ADR not just as a technical breakthrough but as a scalable, sustainable, and ROI-driven innovation for weld quality assurance in the oil & gas industry.

The success of the ADR system paves the way for a broader set of applications. Our future goals include:

2025 Goal:

- Expanding the technology to include digital radiography (DR) and computed films and enhancing the model maturity to identify "Artefacts, Root Undercut and Crack".
- Fine-tuning the Model for Conventional films and DR images of welds.

2026 Vision:

- Integration with cloud-based NDT workflows for remote collaboration, especially for CR/DR application at offshore.
- Development of Statistical Analysis tool to measure the accuracy of the model and distribution of defects per material, process, and thickness etc.

Long Term:

- Extending AI platform to other NDT method-(PAUT)
- Integrating the system with autonomous UT inspection drones for fully automated asset integrity management for downstream business.

10. References

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