Computing Vision – Industry Applications

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SCHOOL OF COMPUTING

Agenda

01

Introduction

Introduction

- **Background:**
  - Bsc Mechanical Engineering.
  - Production Intern, The Dow Chemical Company
  - KTP Associate Data Scientist .
- **Specialization:** Led the development and integration of AI solutions for automating remote inspection tasks in offshore environments, driving innovation and enhancing inspection accuracy.
- **Key skills:** Deep learning, Computer Vision, Data Engineering, 3D modelling, Statistics, and software development.

Industry Testimonial Session

- **Objective:** Share real-world experiences and insights on applying computer vision in the energy sector.
- **Topics:** Data acquisition, image pre-processing, computer vision models, and case studies.
- **Goals:** Provide practical knowledge and encourage discussion on the use of computer vision for offshore asset inspections.

02

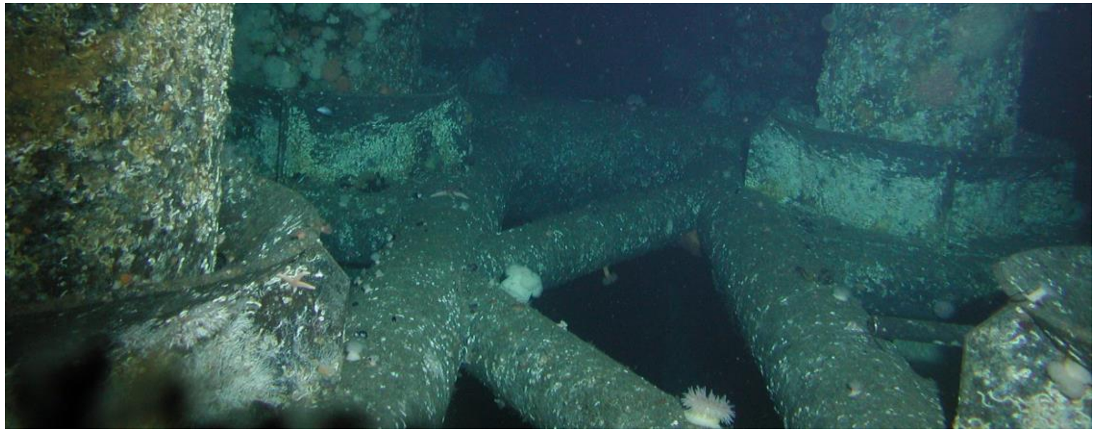
Offshore Asset Inspection: Challenges and Opportunities

Challenges

- **Harsh environment:** Challenging weather conditions, strong currents, and varying visibility in the North Sea and surrounding areas
- **Accessibility:** Remote locations of offshore assets often require specialized equipment and personnel for inspections
- **Safety:** Offshore inspection tasks can pose significant risks to human inspectors, especially in hazardous areas or during adverse weather
- **Regulatory compliance:** Adherence to regulations and guidelines set by the Health and Safety Executive (HSE) and other governing bodies

Traditional Inspection Methods

- **Manual inspections:** Visual inspection by engineers, divers, or rope access technicians
- **Remotely Operated Vehicles (ROVs):** Submersible robotic vehicles equipped with cameras for underwater inspections
- **Limitations:**
  - Time-consuming and labor-intensive processes
  - Inconsistent inspection results due to human error
  - Limited data capture and analysis capabilities



Opportunities for Computer Vision in Offshore Asset Inspections

- **Enhanced data analysis:** AI-powered algorithms can process and analyze vast amounts of inspection data, enabling better decision-making.
- **Improved accuracy:** Computer vision can help to detect defects and anomalies sometimes with greater precision than human inspectors.
- **Increased efficiency:** Automation of inspection processes reduces inspection time and resource requirements.
- **Enhanced safety:** Remote visual inspections minimize the need for human inspectors in hazardous environments.
- **Compliance:** Adherence to HSE regulations and guidelines through accurate and consistent inspection results.

03

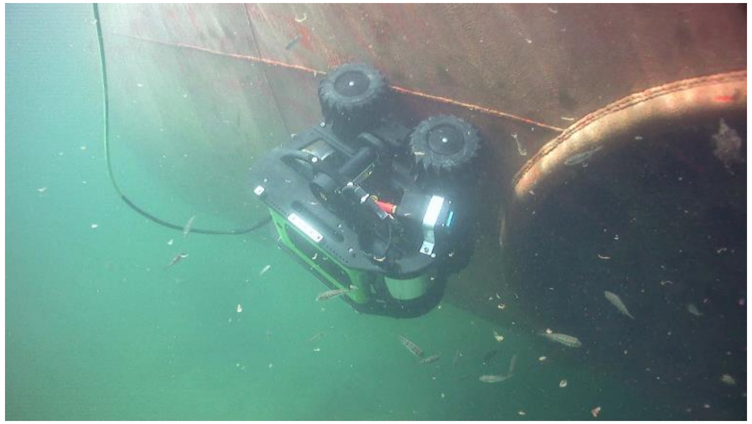
Data Acquisition for Remote Visual Inspections

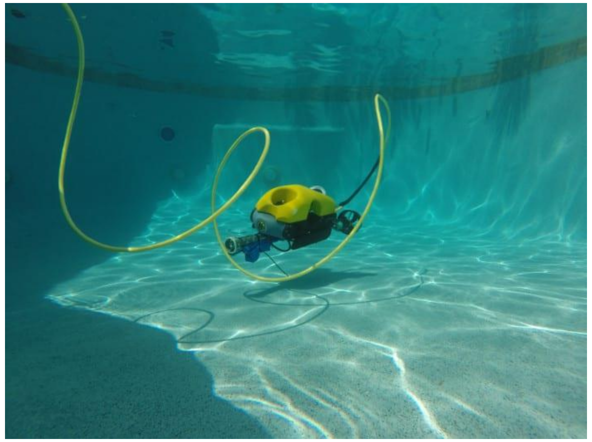
Data Sources for Remote Visual Inspections

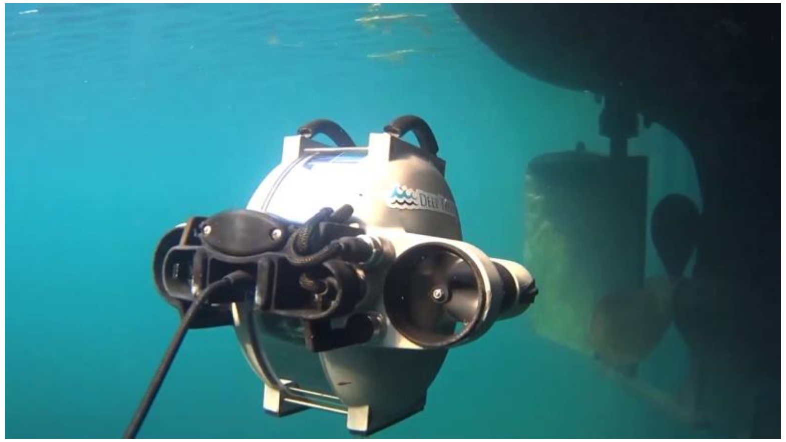
- **Drones:** Unmanned aerial vehicles equipped with high-resolution cameras for aerial inspections of offshore structures.

Data Sources for Remote Visual Inspections

- **ROVs:** Remotely operated underwater vehicles with cameras and sensors for subsea inspections.

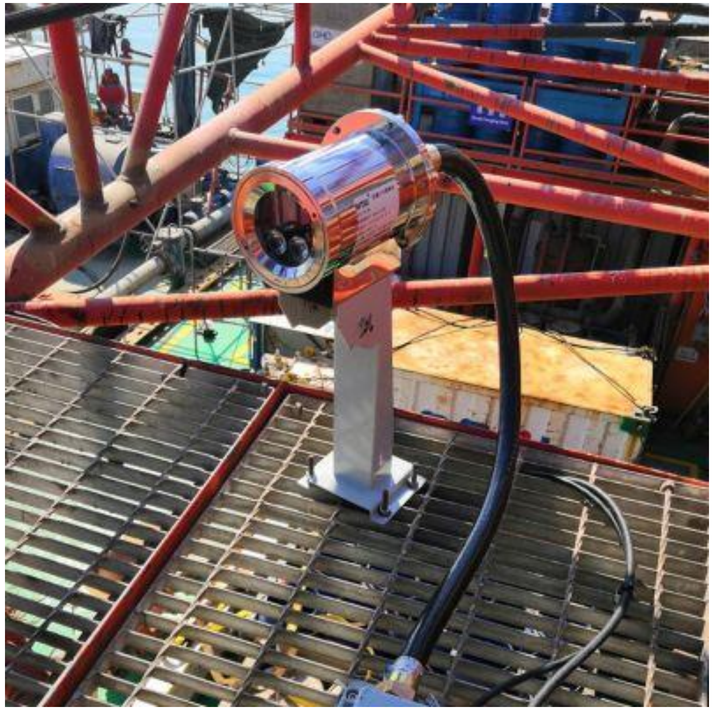






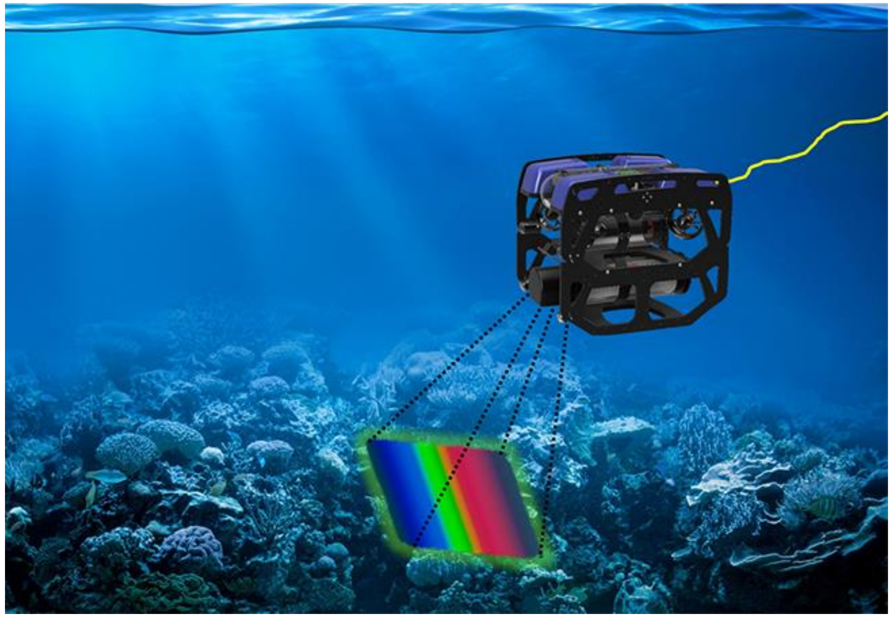
Data Sources for Remote Visual Inspections

- **Fixed cameras:** Stationary cameras installed on offshore assets for continuous monitoring and inspection.



Data Sources for Remote Visual Inspections

- **Multispectral and hyperspectral imaging:** Advanced imaging techniques for capturing a wide range of spectral information, useful for detecting specific defects or material properties.



Challenges in Data Acquisition

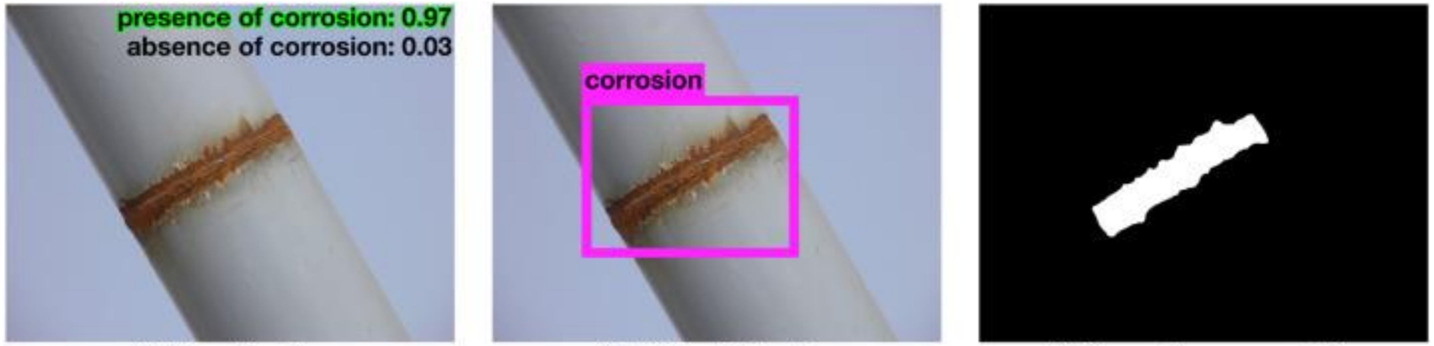
- Weather conditions.
- Lighting.
- Image quality.
- Underwater imagery: Water turbidity, Suspended Particles, Water motion.

04

Computer Vision Models and Techniques for Offshore Asset Inspections

Computer Vision Models and Techniques for Offshore Asset Inspections

- Object detection: Identifying and locating objects of interest within images (e.g., equipment, structural components)
- Segmentation: Partitioning images into regions or segments that correspond to different objects or features (e.g., defects, corrosion)
- Image classification: Categorizing identified defects or anomalies based on their characteristics (e.g., crack, corrosion, leak)

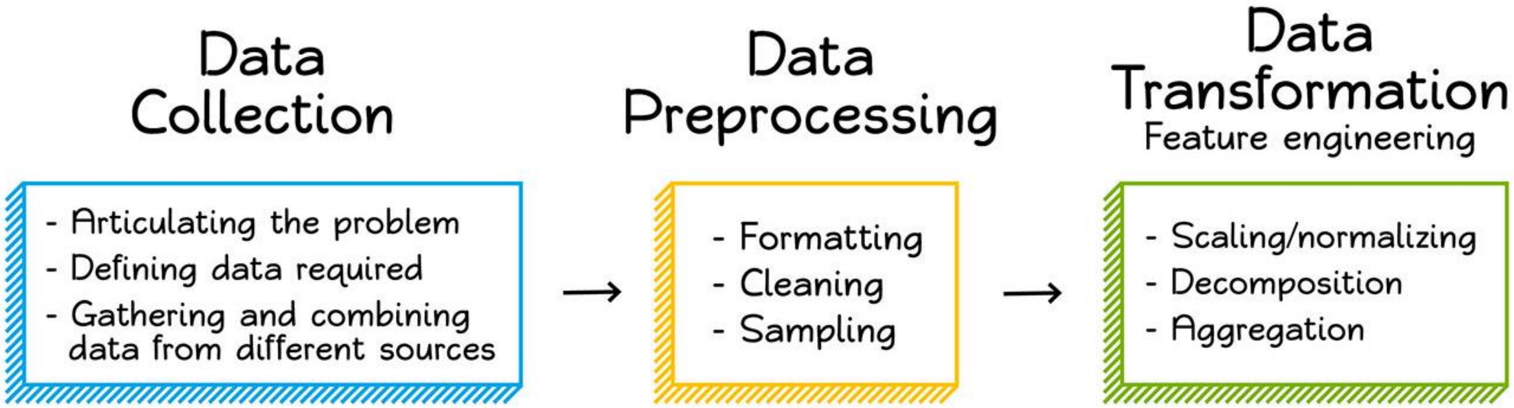


(a) Classification (b) Object detection (c) Semantic segmentation

https://www.sciencedirect.com/science/article/abs/pii/S0926580522000553

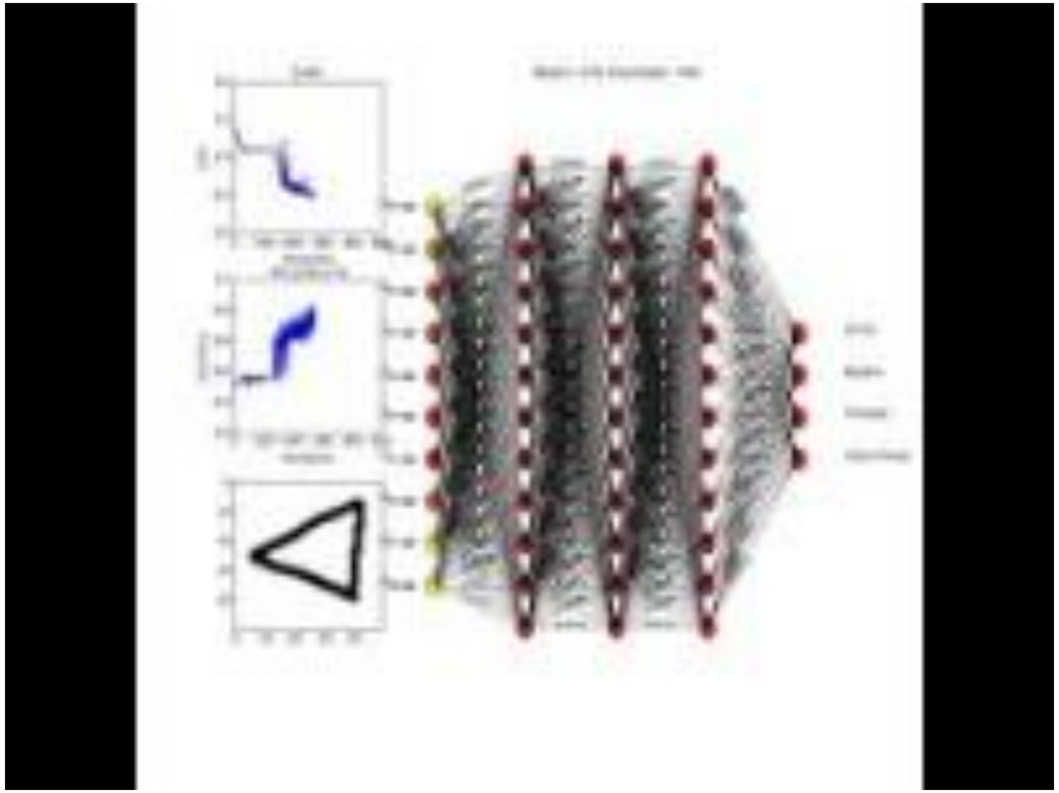
Customizing and Fine-tuning Models for Inspection Tasks

- **Data preparation:** Pre-processing and cleaning inspection data to create a suitable input format for model training



Customizing and Fine-tuning Models for Inspection Tasks

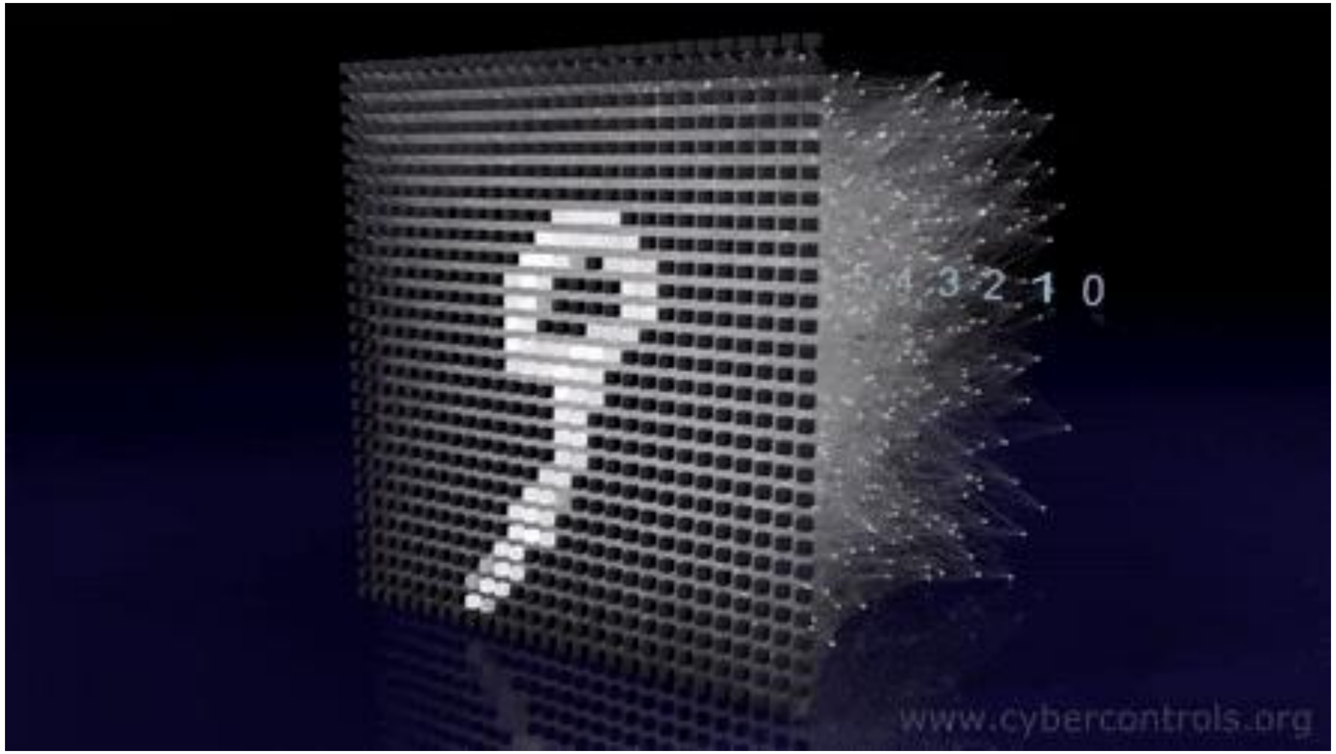
- **Model architecture:** Adapting the model architecture to address specific inspection requirements and challenges



Customizing and Fine-tuning Models for Inspection Tasks

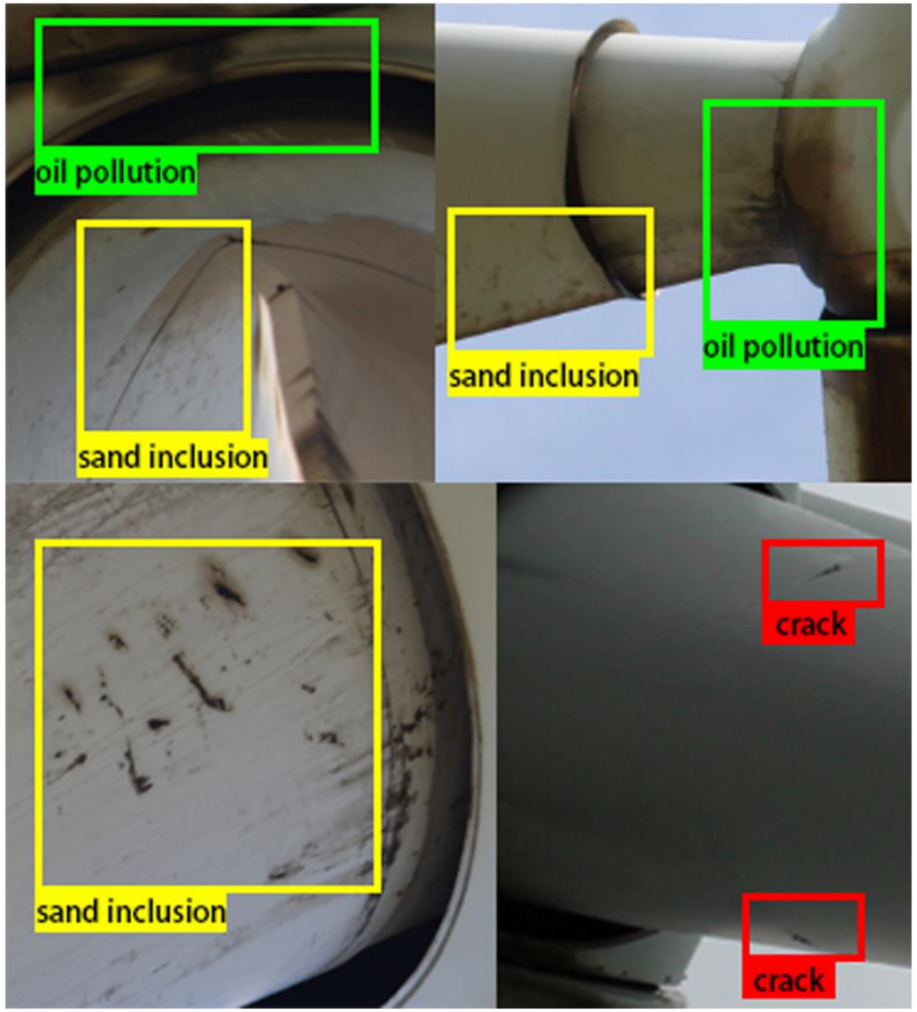
- **Hyperparameter tuning:** Adjusting model hyperparameters (e.g., learning rate, batch size, number of layers) to improve model performance and reduce overfitting

I. ***Learning Rate.***
II. ***Batch Size.***
III. ***Number of Epochs.***
IV. ***Weight Initialization.***
V. ***Regularization techniques.***
VI. ***Momentum and learning rate schedules.***



Real-World Example 1 - Autonomous Visual Inspection of Wind Turbine Blades (WTBs) Using Deep Learning

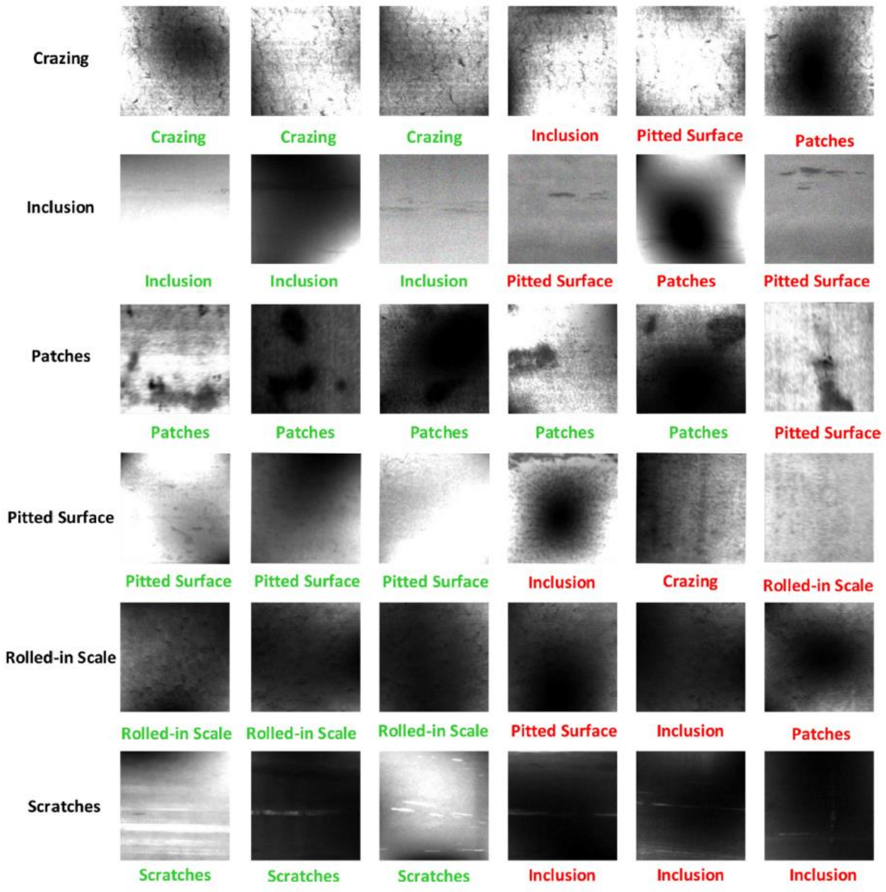
- **Objective:** Automate detection of small defects in wind turbine blades (WTBs) for efficient and safe operation.
- **Technique:** YOLO-based small object detection approach (YSODA) using multiscale feature pyramid.
- **Dataset:** 23,807 images labelled for three types of defect—crack, oil pollution, and sand inclusion.
- **Customization:** Modify YSODA architecture for detecting cracks, oil pollution, and sand inclusions in WTBs.
- **Results:** Improved inspection efficiency, reduced human intervention, and increased detection accuracy (average 91.3%).



Zifeng Qiu, Shuangxin Wang, Zhaoxi Zeng, and Dingli Yu "Automatic visual defects inspection of wind turbine blades via YOLO-based small object detection approach," Journal of Electronic Imaging 28(4), 043023 (6 August 2019). https://doi.org/10.1117/1.JEI.28.4.043023

Real-World Example 2 - Automate steel surface defect recognition for efficient quality control in steel strip production

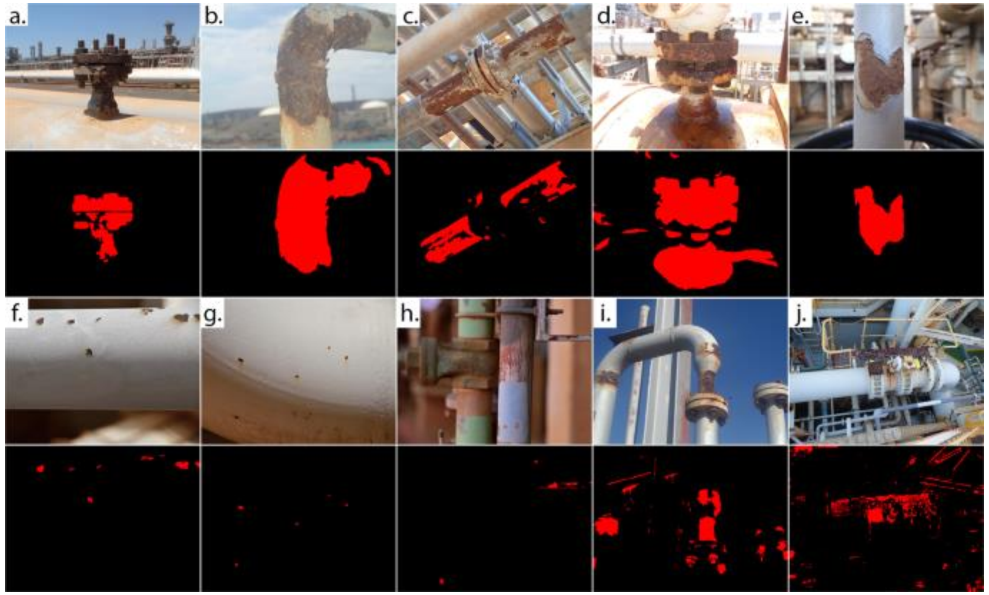
- **Objective:** Automate steel surface defect recognition for efficient quality control in steel strip production.
- **Technique:** Compact convolutional neural network (CNN) model with multiple receptive fields.
- **Dataset:** 1800 grayscale images (200x200) with 300 samples per defect category.
- **Customization:** Utilize pre-trained SqueezeNet as backbone architecture and require few defect-specific training samples.
- **Results:** High-accuracy recognition on diverse defect dataset, real-time online inspection (>100 fps) with a single NVIDIA TITAN X GPU.



Guizhong Fu, Peize Sun, Wenbin Zhu, Jiangxin Yang, Yanlong Cao, Michael Ying Yang, Yanpeng Cao, A deep-learning-based approach for fast and robust steel surface defects classification, Optics and Lasers in Engineering, Volume 121, 2019, Pages 397-405, ISSN 0143-8166, https://doi.org/10.1016/j.optlaseng.2019.05.005.

Real-World Example 3 - Advanced Corrosion Detection Model with Pixel-Level Segmentation

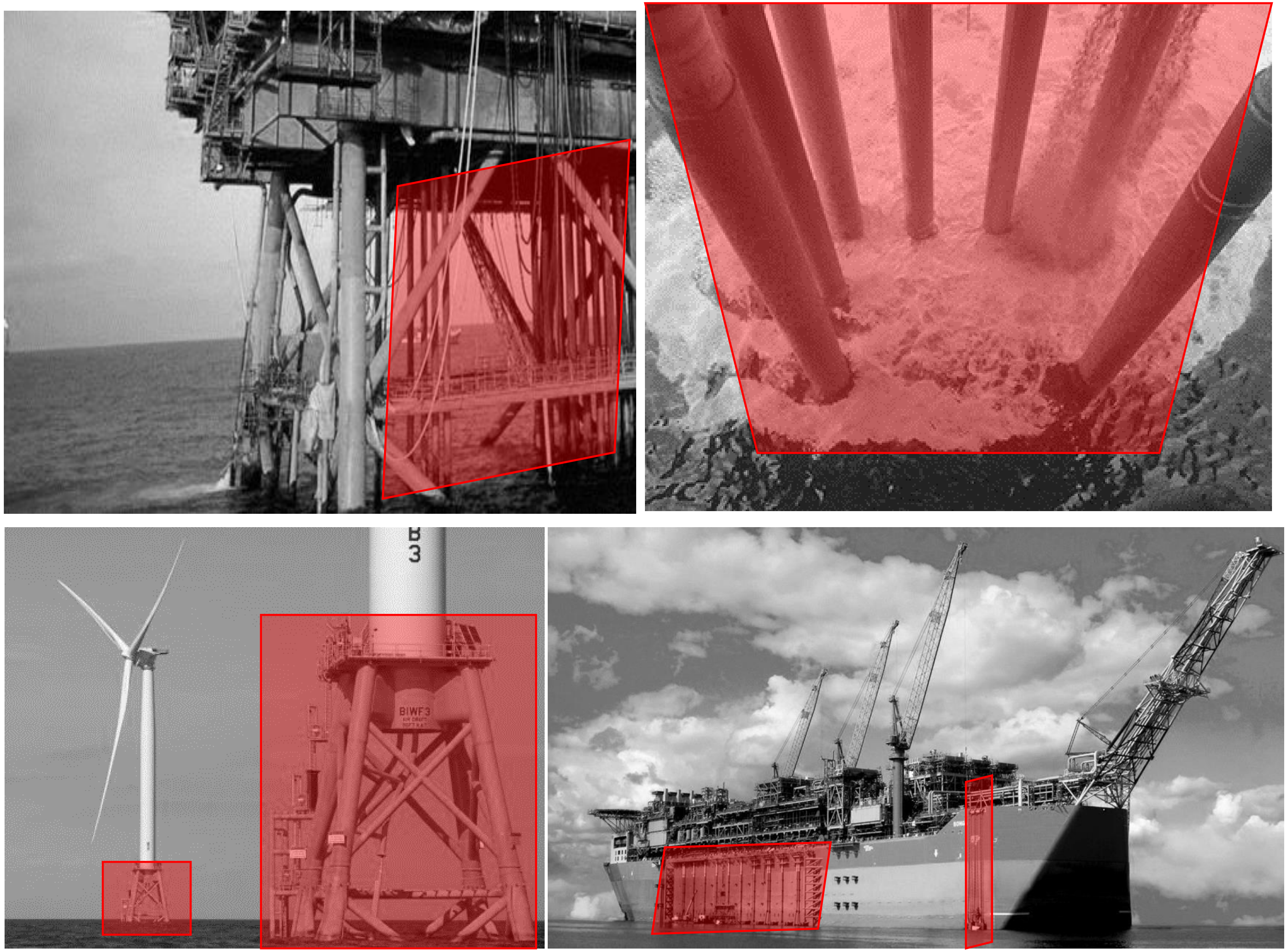
- **Objective:** Develop an automatic corrosion detection model with pixel-level segmentation and uncertainty estimates.
- **Technique:** Deep learning corrosion detector with three Bayesian variants for confidence levels.
- **Database:** Newly collected dataset of 225 images.
- **Challenges:** Lack of publicly available dataset leading to false positives and false negatives in field tests.
- **Solution:** Pixel-level segmentation and Bayesian uncertainty estimates to better inform decision makers.
- **Results:** Improved corrosion detection model with confidence levels for more accurate decision making.



Nash, W., Zheng, L. & Birbilis, N. Deep learning corrosion detection with confidence. *npj Mater Degrad* **6**, 26 (2022). https://doi.org/10.1038/s41529-022-00232-6

05

Case Study: Automating Offshore Asset Inspections.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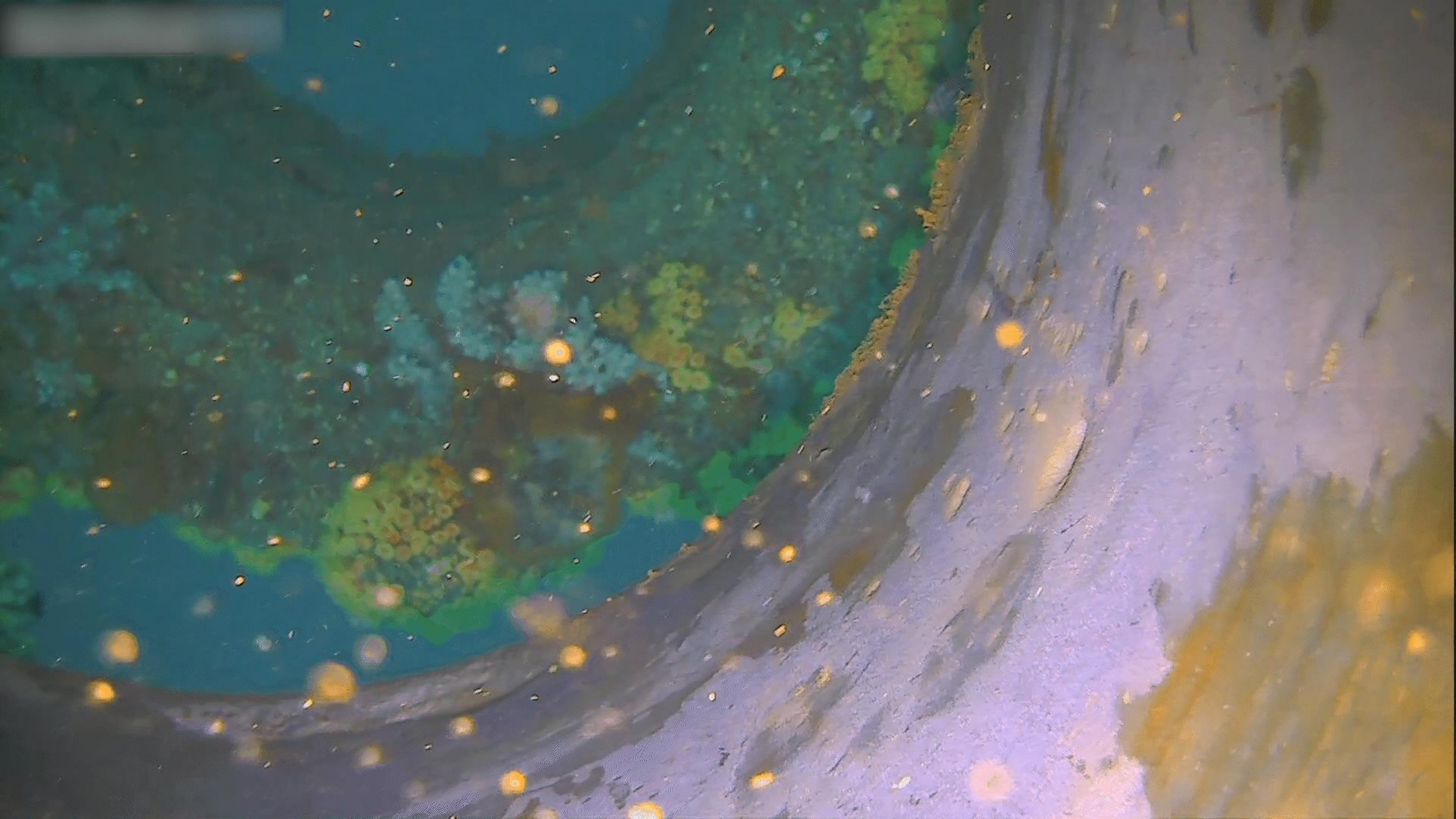
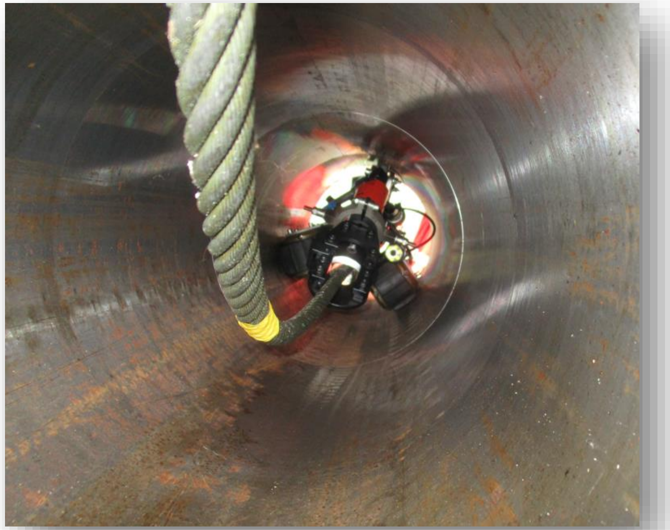
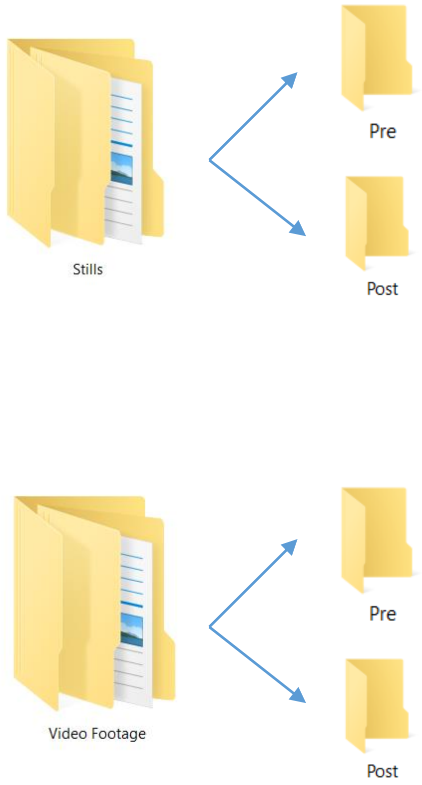


Current Practices – Remote Visual Inspection (RVI)

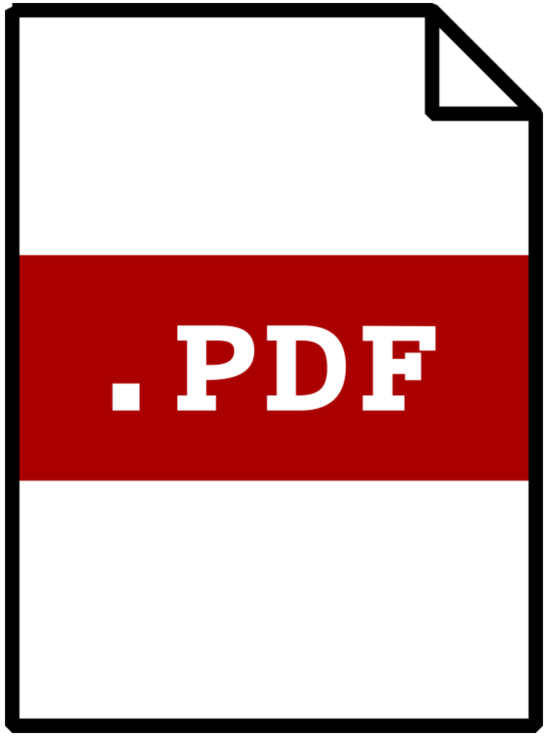
RVI



Classification



Final Report



Challenges

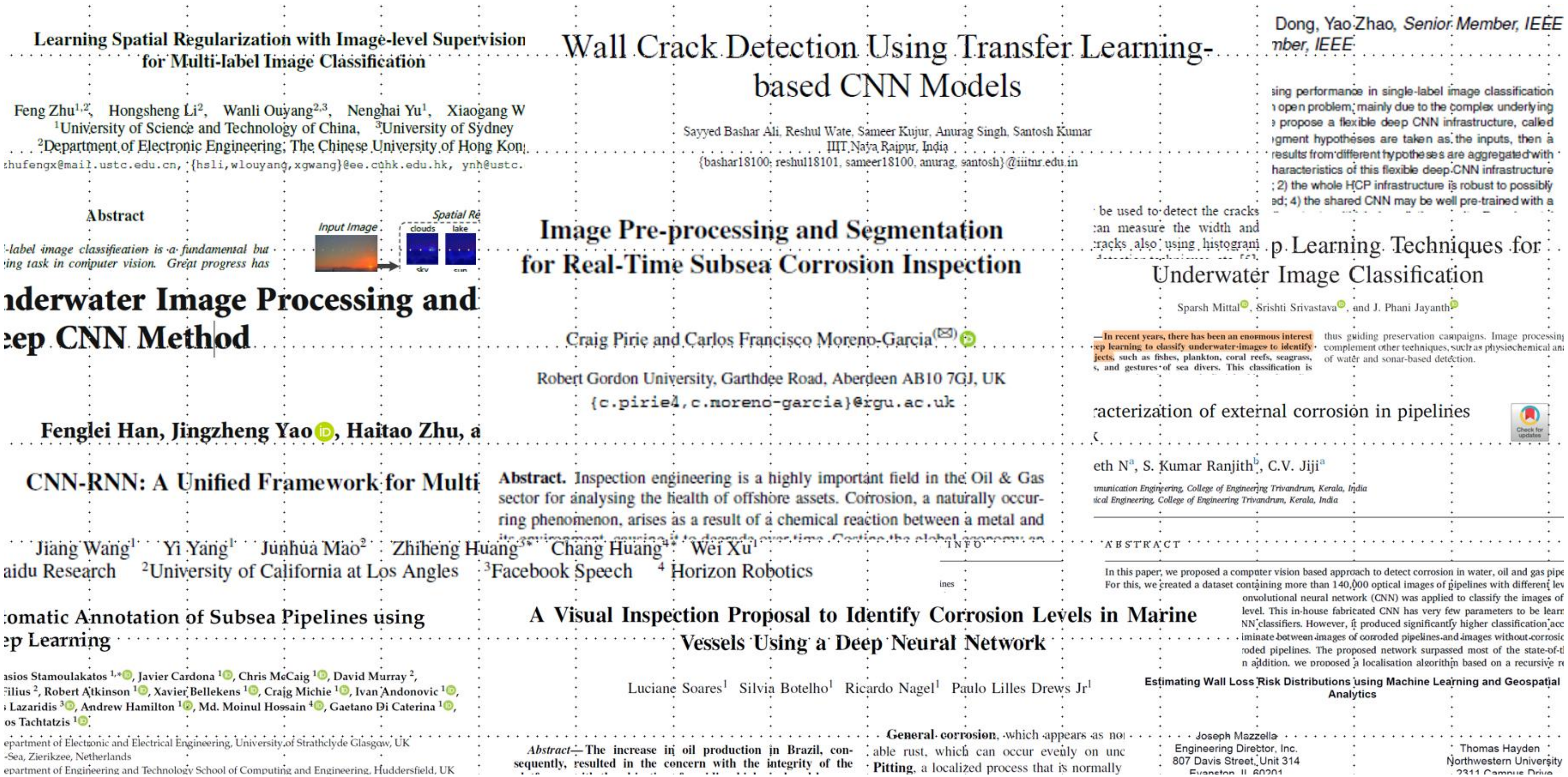
Standard Definition - 2014

Visual Inspection

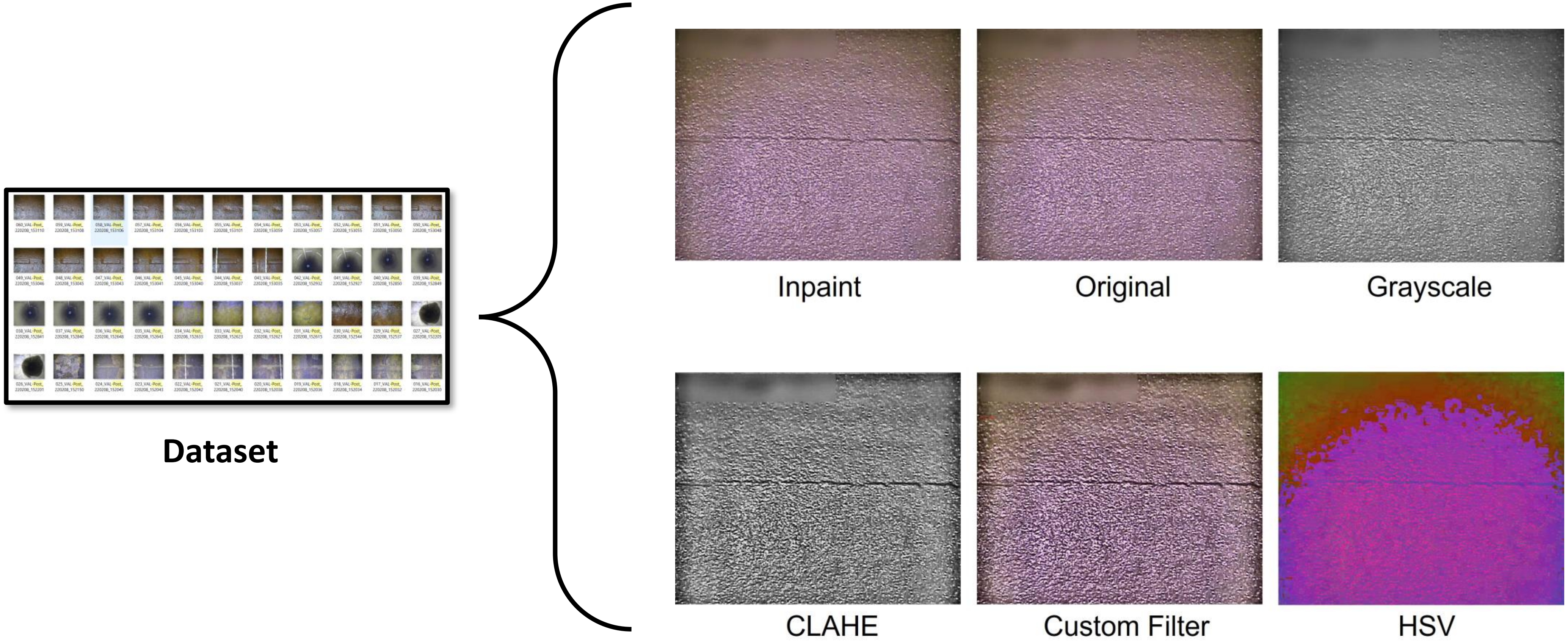
- Visibility
- Exposure
- Topside/Subsea
- Lighting
- Suspended particles
- Quality

High Definition - 2018

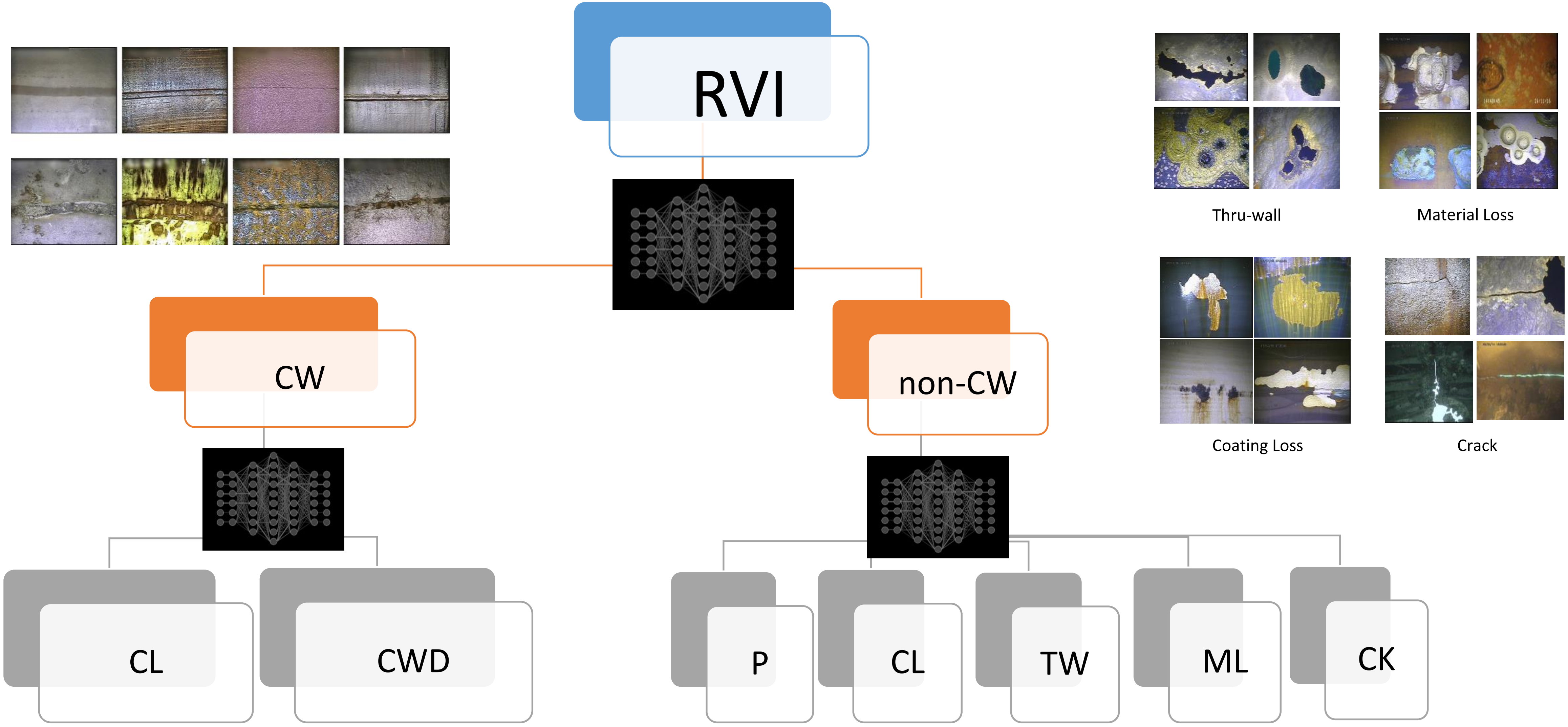
Stage 1 – Background Investigation



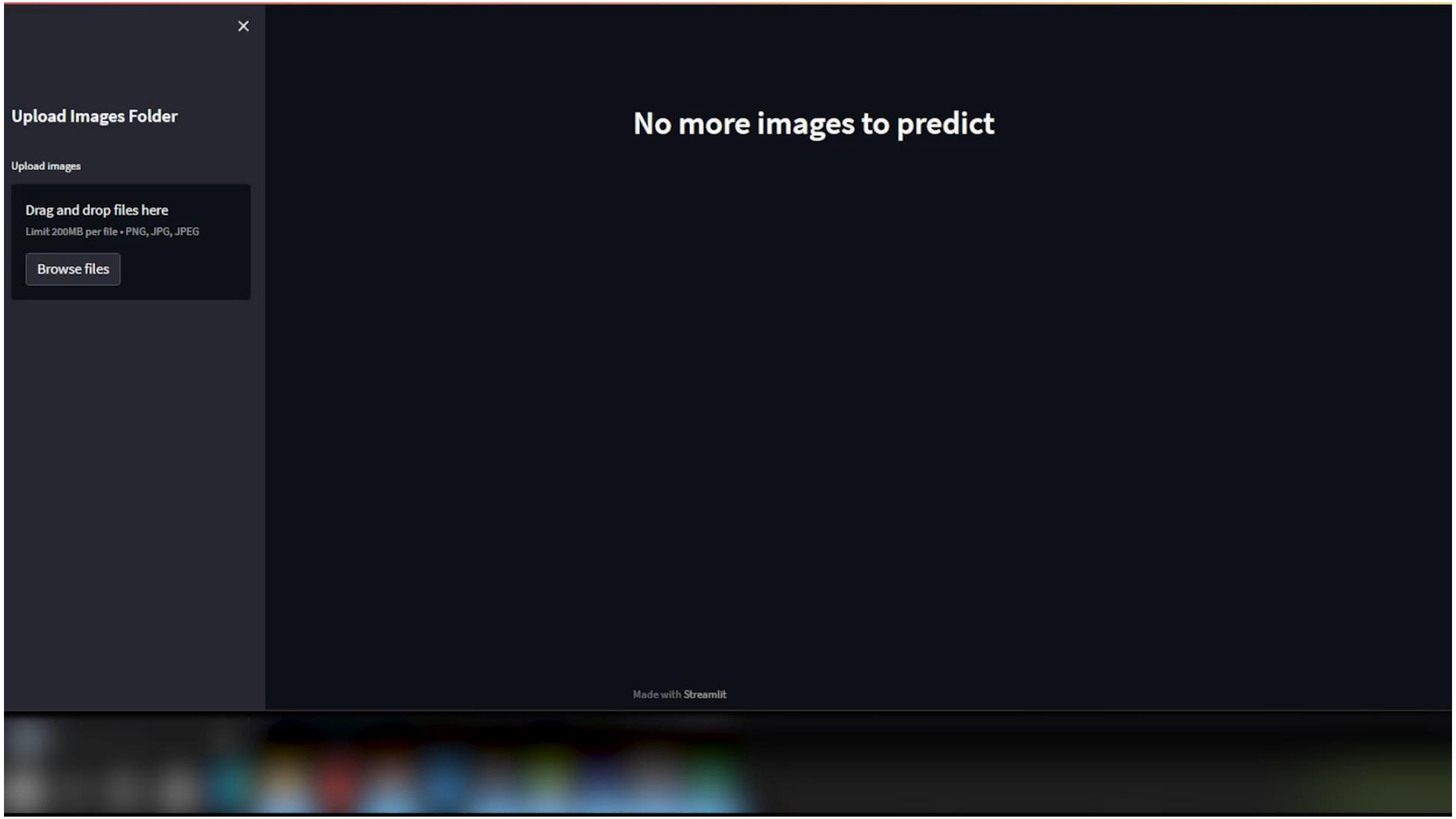
Stage 1 – Data Preparation



Stage 3 – Deep Learning Framework

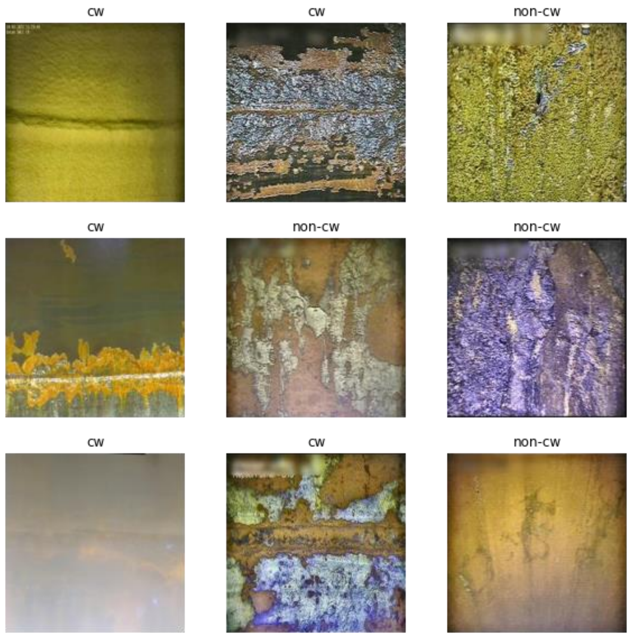


Stage 4 – Human in the loop



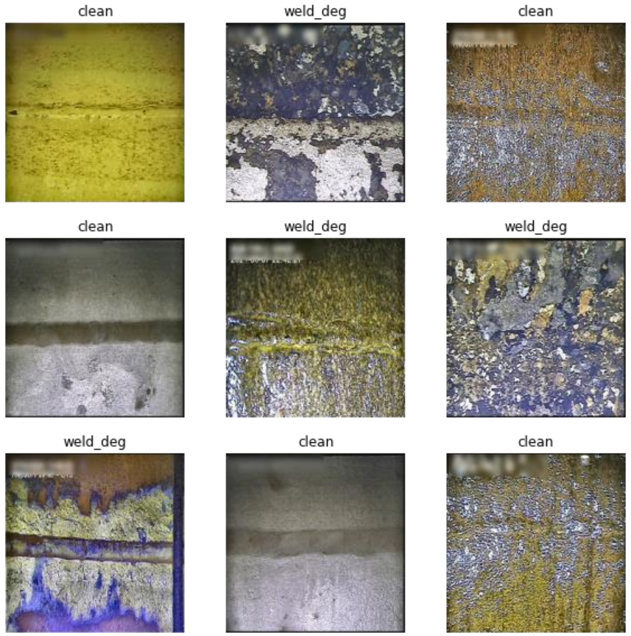
Stage 5 – Evaluation Results

GC



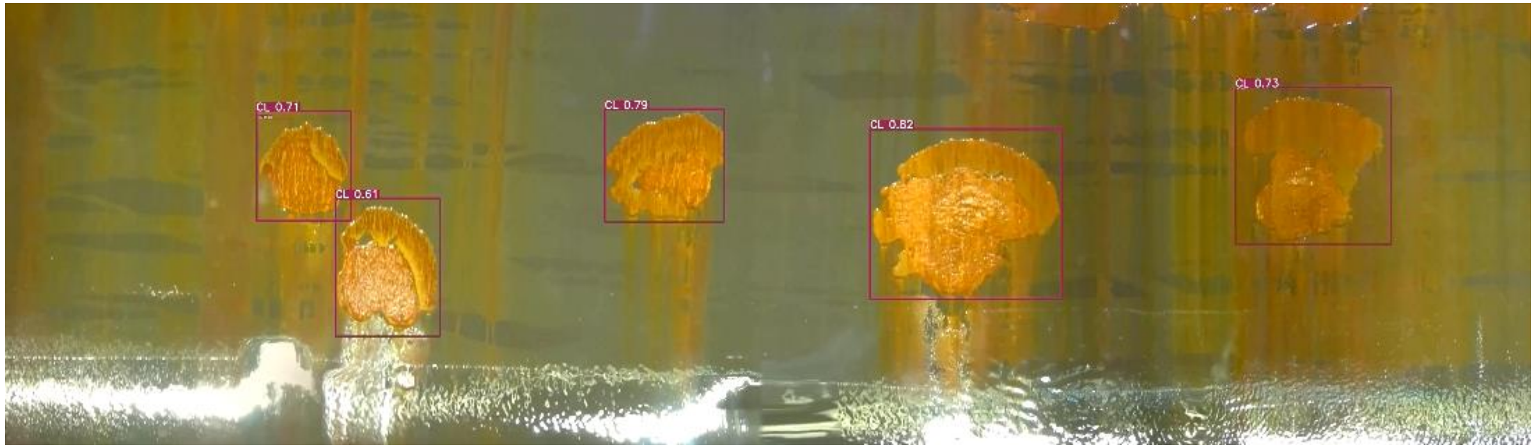
Precision	Recall	F1-Score
90% --> 96%	90% --> 94%	90% --> 96%

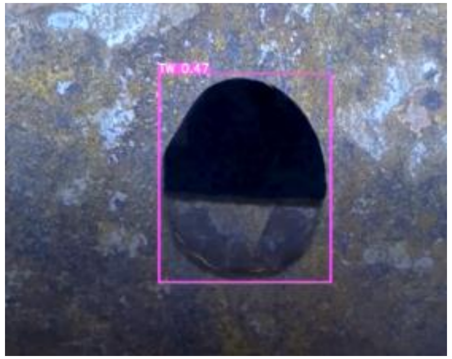
WC

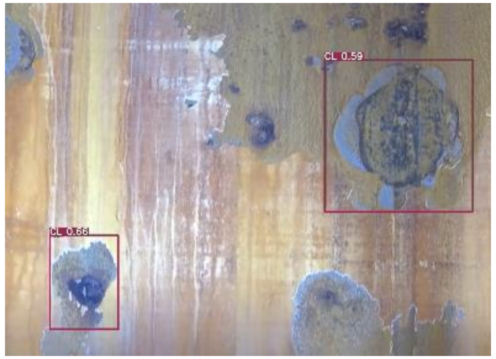


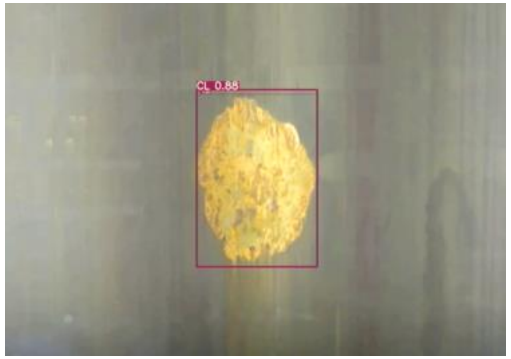
Precision	Recall	F1-Score
84% --> 92%	88% --> 94%	84% --> 92%

Stage 5 – Evaluation Results









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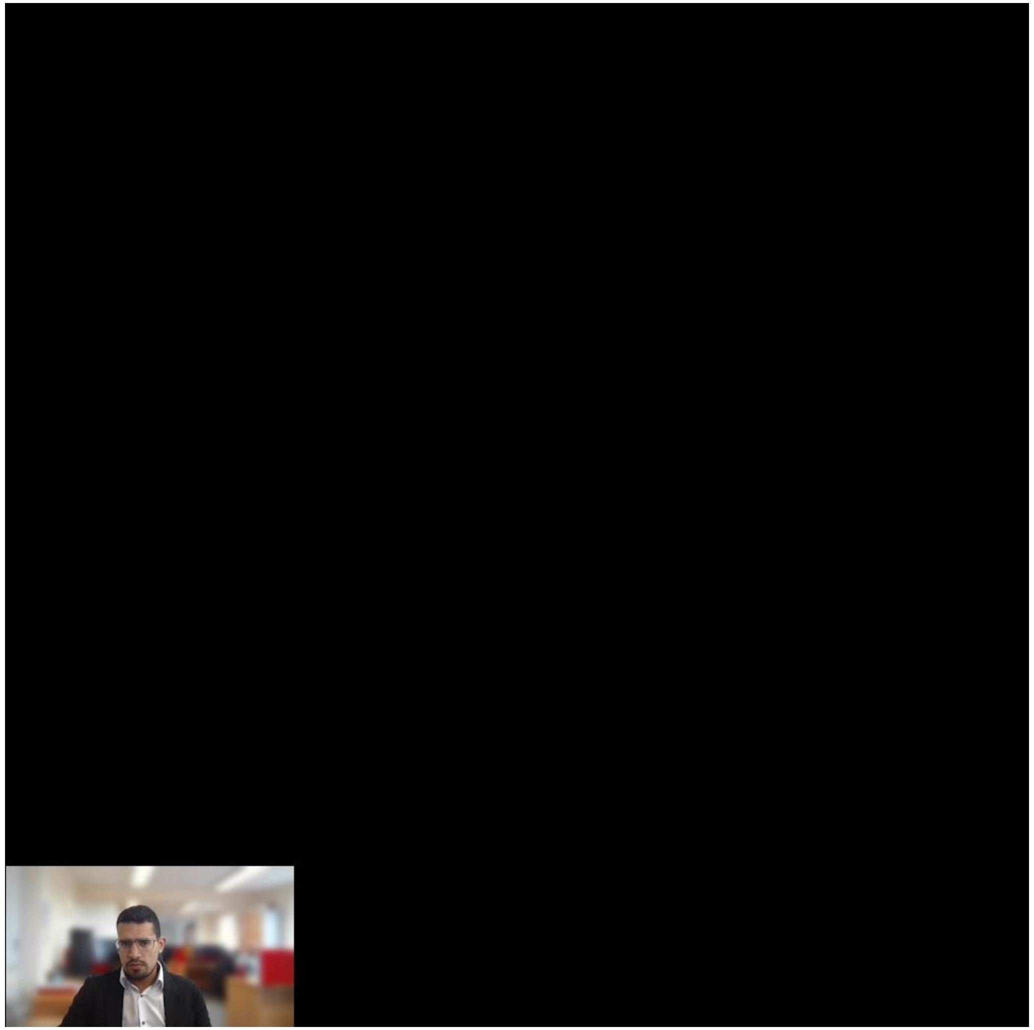
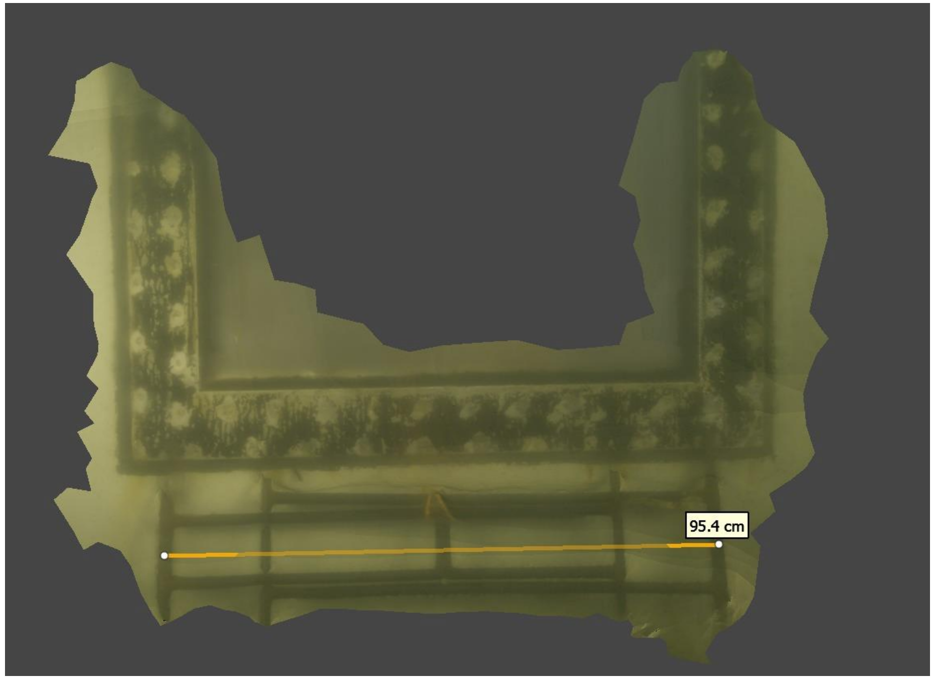


06

Other Aplications

Photogrammetry



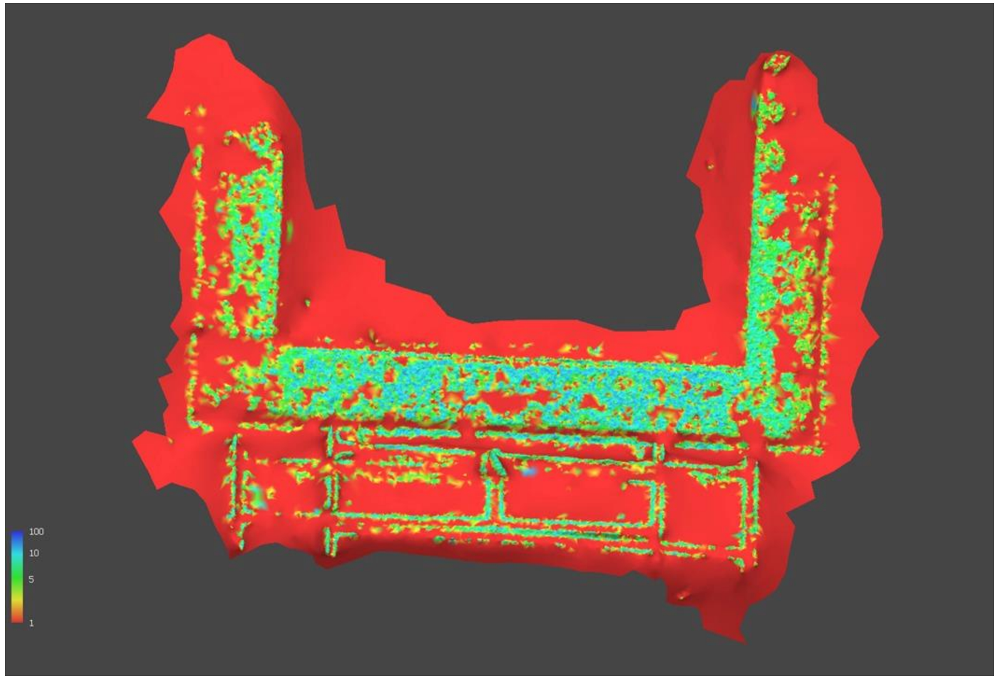
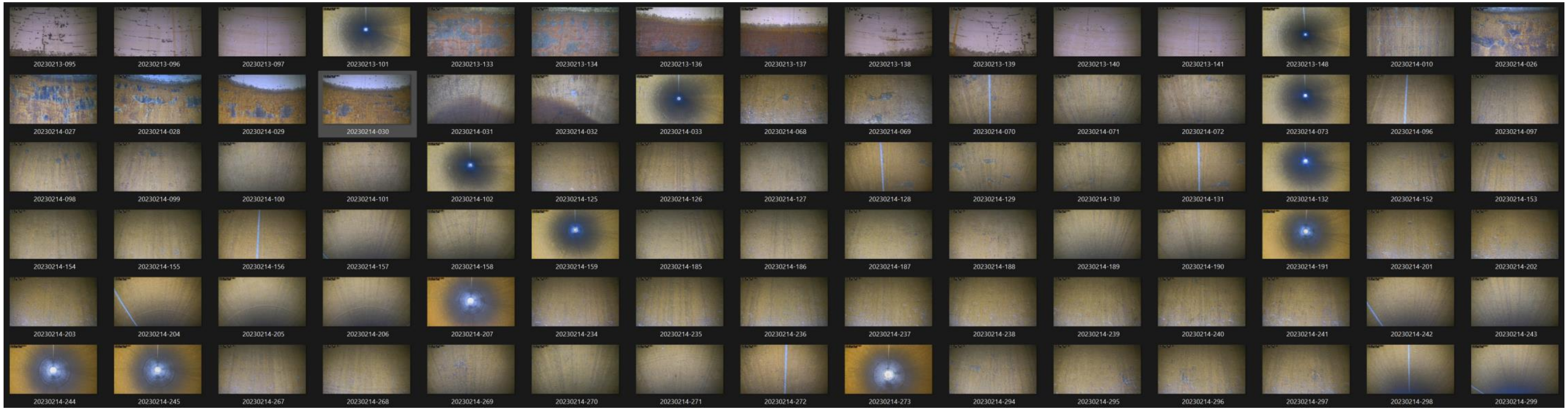
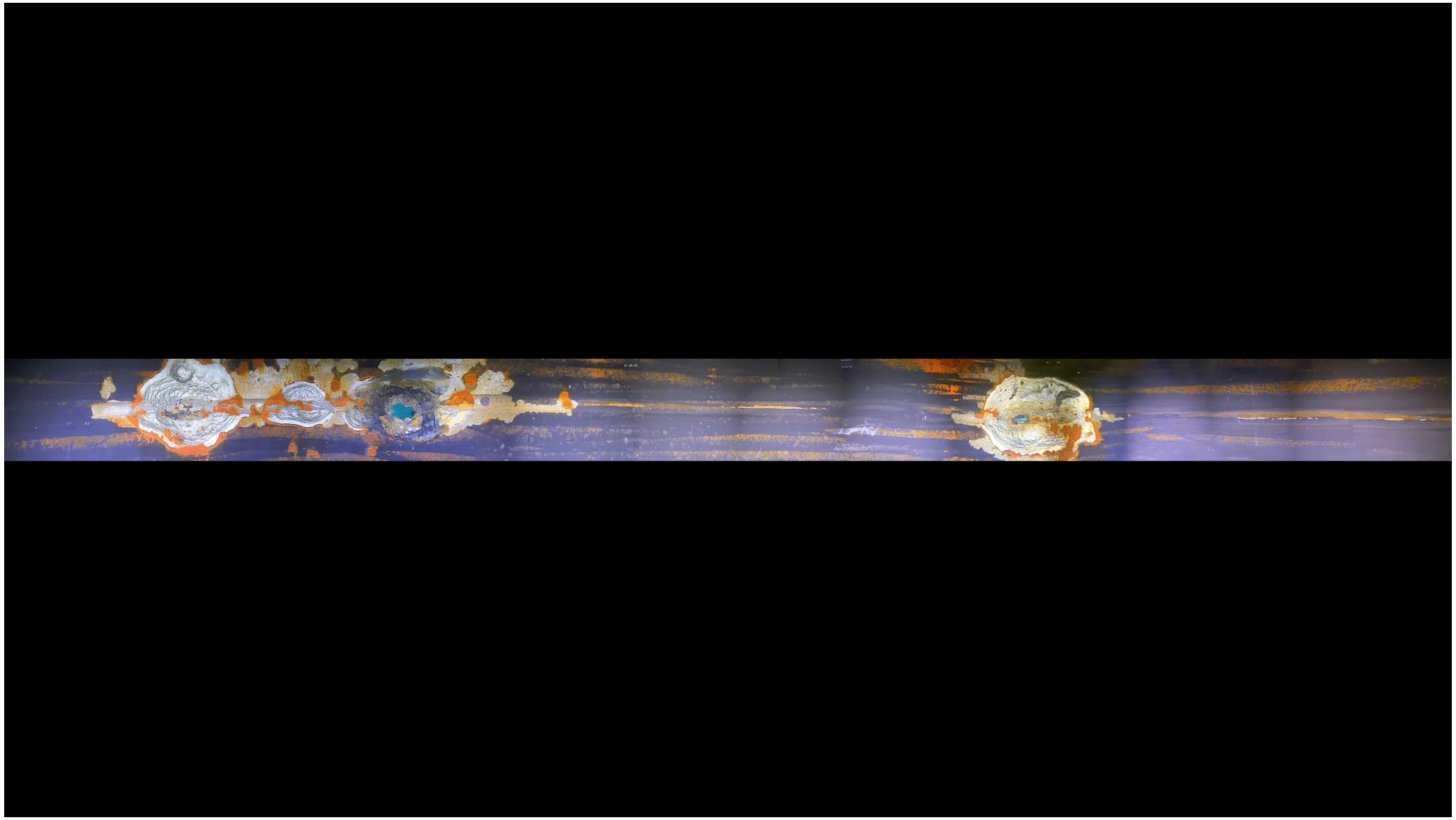


Image / Video Enhancement

Feature Frame Extraction



Data Inspection Overlay



07

Conclusion and Q&A

Future Trends and developments in computer vision for offshore asset inspection.

- **Enhanced 3D imaging:** Developing advanced 3D imaging techniques to provide more accurate and detailed representations of offshore assets, enabling precise damage detection and analysis.
- **Improved data fusion:** Combining data from multiple sensors (e.g., LiDAR, infrared, sonar, hyperspectral) to create comprehensive and holistic inspections for better decision-making.
- **Edge computing and real-time analysis:** Implementing edge computing to process computer vision data on-site, enabling real-time analysis and faster response to potential issues.
- **Augmented reality (AR) assistance:** Using AR to visualize inspection data and assist human operators in identifying defects, understanding asset conditions, and performing maintenance tasks.


Q & A