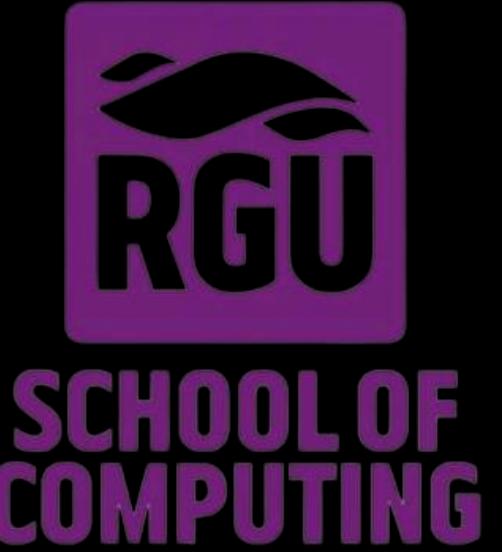




Computing Vision – Industry Applications

*Luis Toral – Digital Transformation
Lead*



Agenda

-
- 01** Intro
 - 02** Offshore Asset Inspection: Challenges and Opportunities
 - 03** Data Acquisition for Remote Visual Inspections
 - 04** Computer Vision Models and Techniques for Offshore Asset Inspections
 - 05** Case Study: Automating Offshore Asset Inspections
 - 06** Other Applications
 - 07** Conclusion and Q&A
-

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

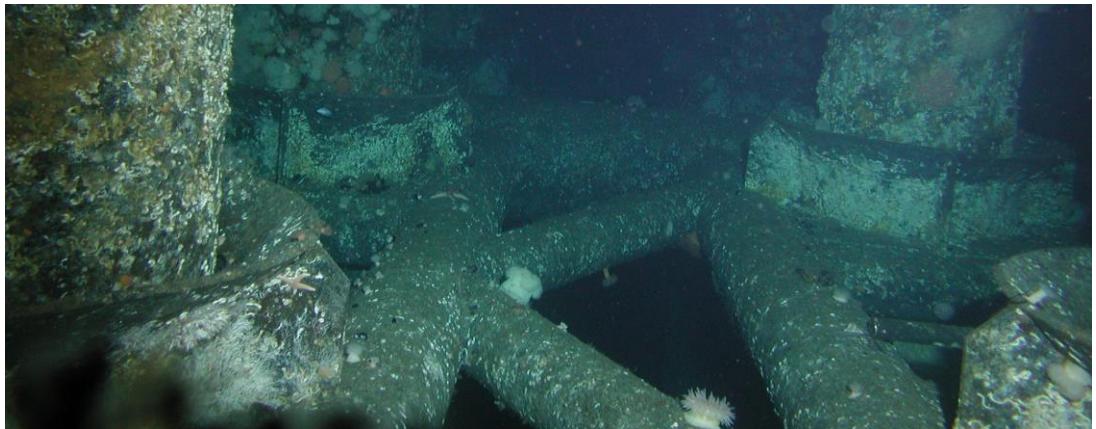
Challenges

- **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

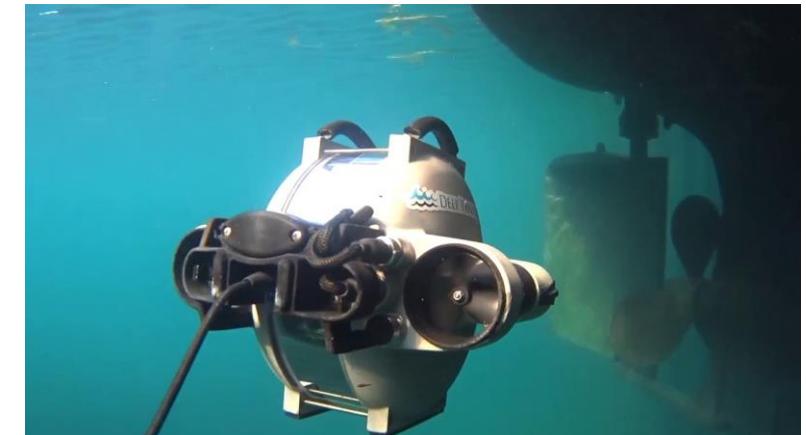
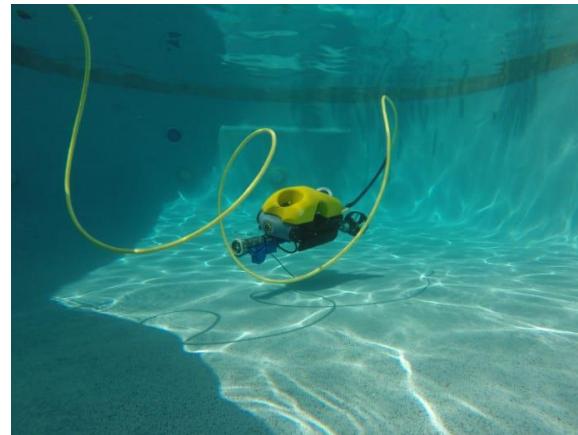
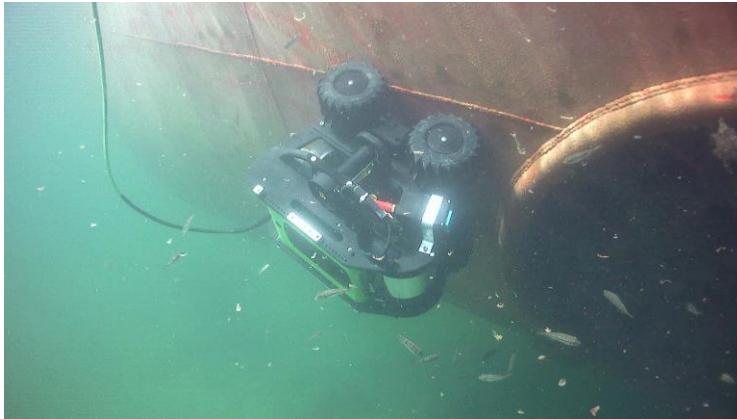
Data Sources for Remote Visual Inspections

- **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.



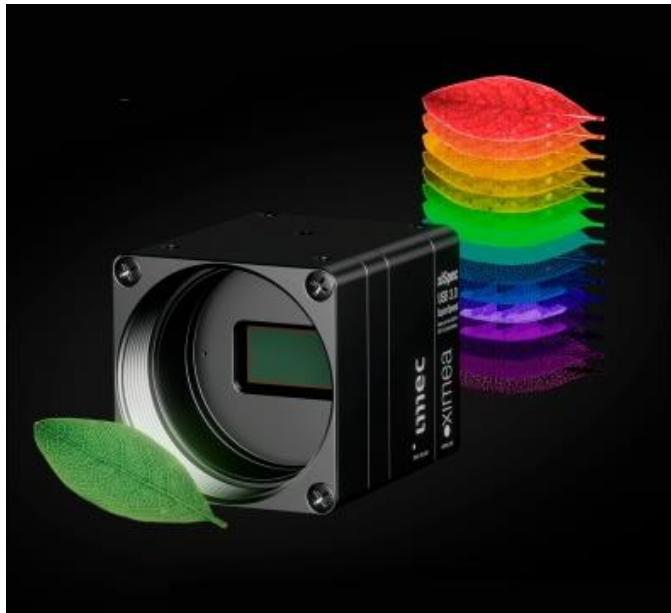
Data Sources for Remote Visual Inspections

- **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.

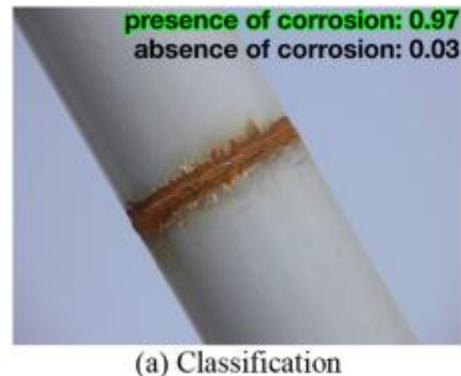


04

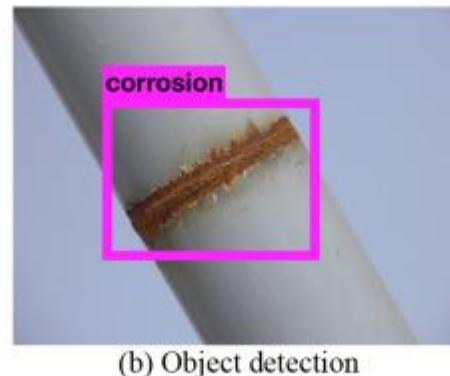
Computer Vision Models and Techniques for Offshore Asset Inspections

Computer Vision Models and Techniques for Offshore Asset Inspections

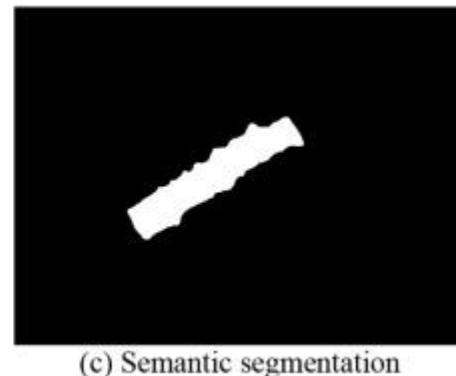
- Object detection: Identifying and locating objects of interest within images (e.g., equipment, structural components)
- Segmentation: Partitioning images into regions or segments that correspond to different objects or features (e.g., defects, corrosion)
- Image classification: Categorizing identified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



(a) Classification



(b) Object detection

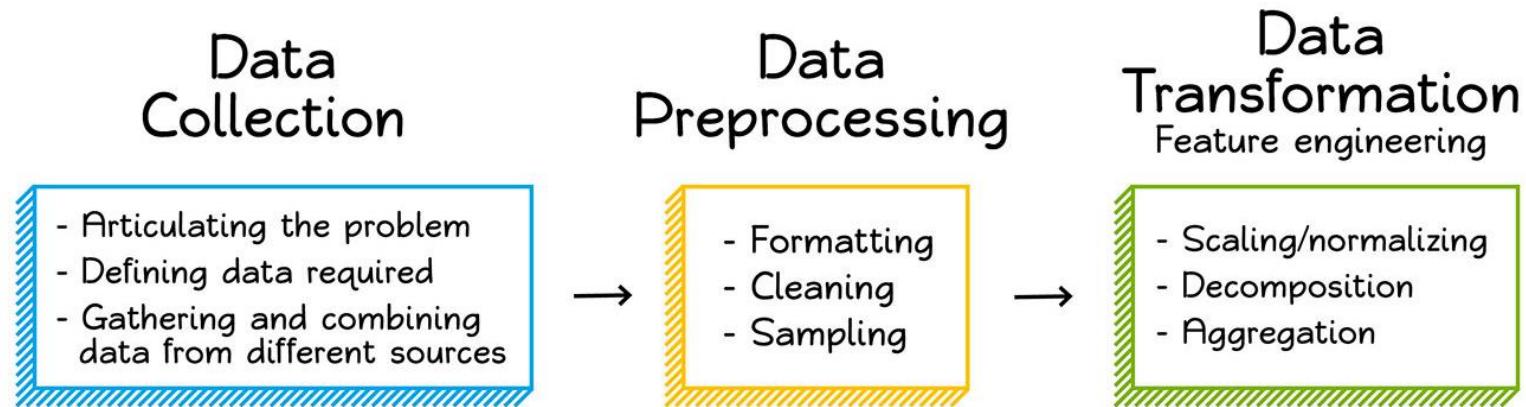


(c) Semantic segmentation

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

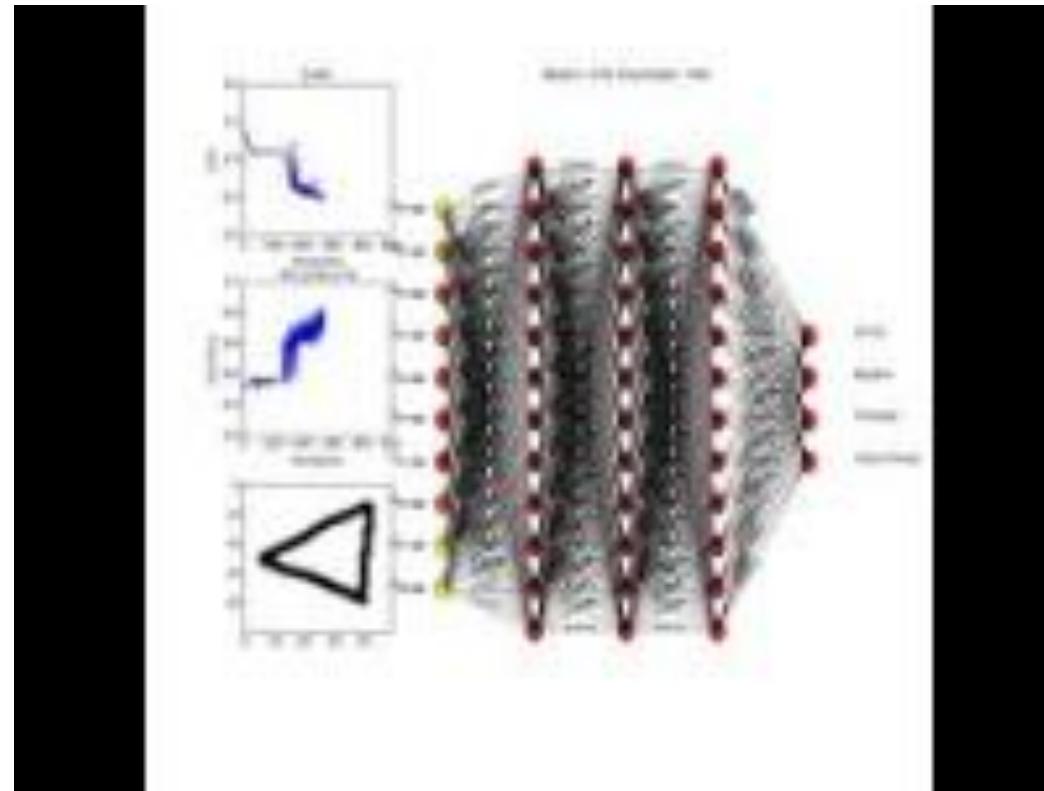
Customizing and Fine-tuning Models for Inspection Tasks

- **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.

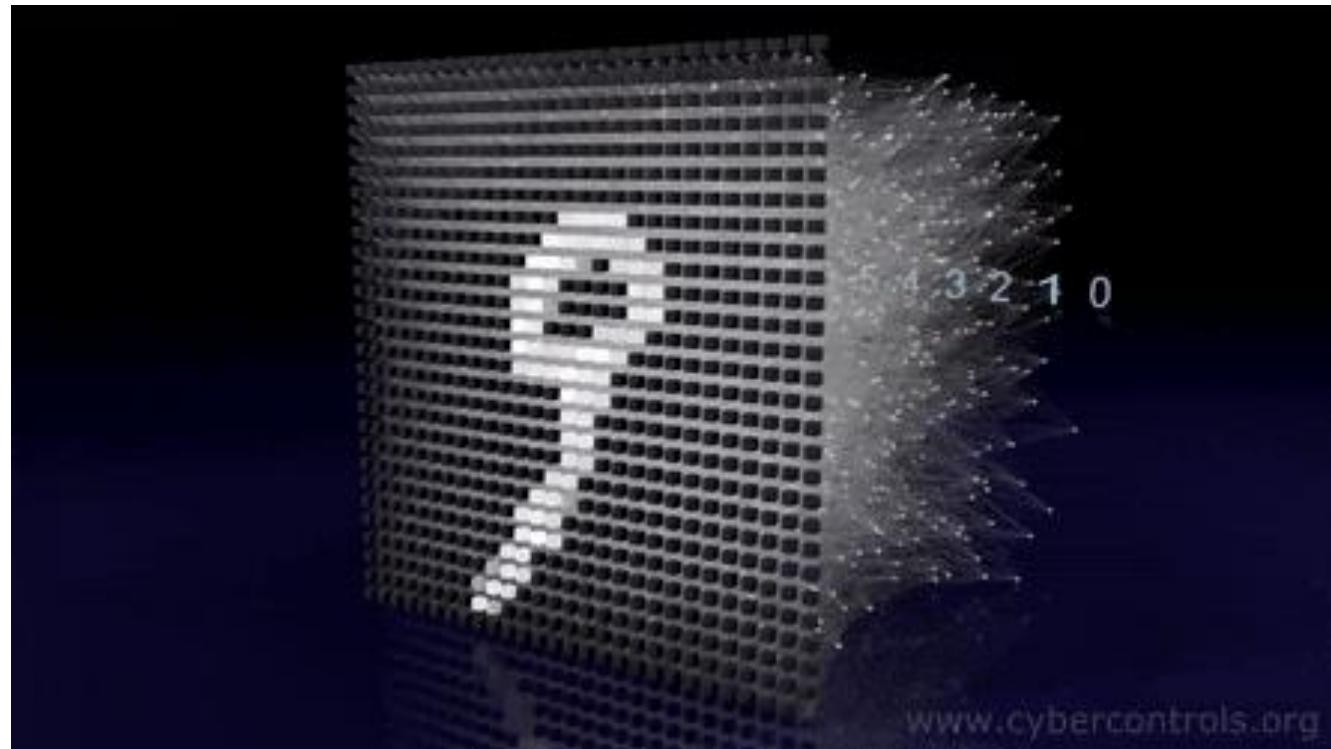
II. Batch Size.

III. Number of Epochs.

IV. Weight Initialization.

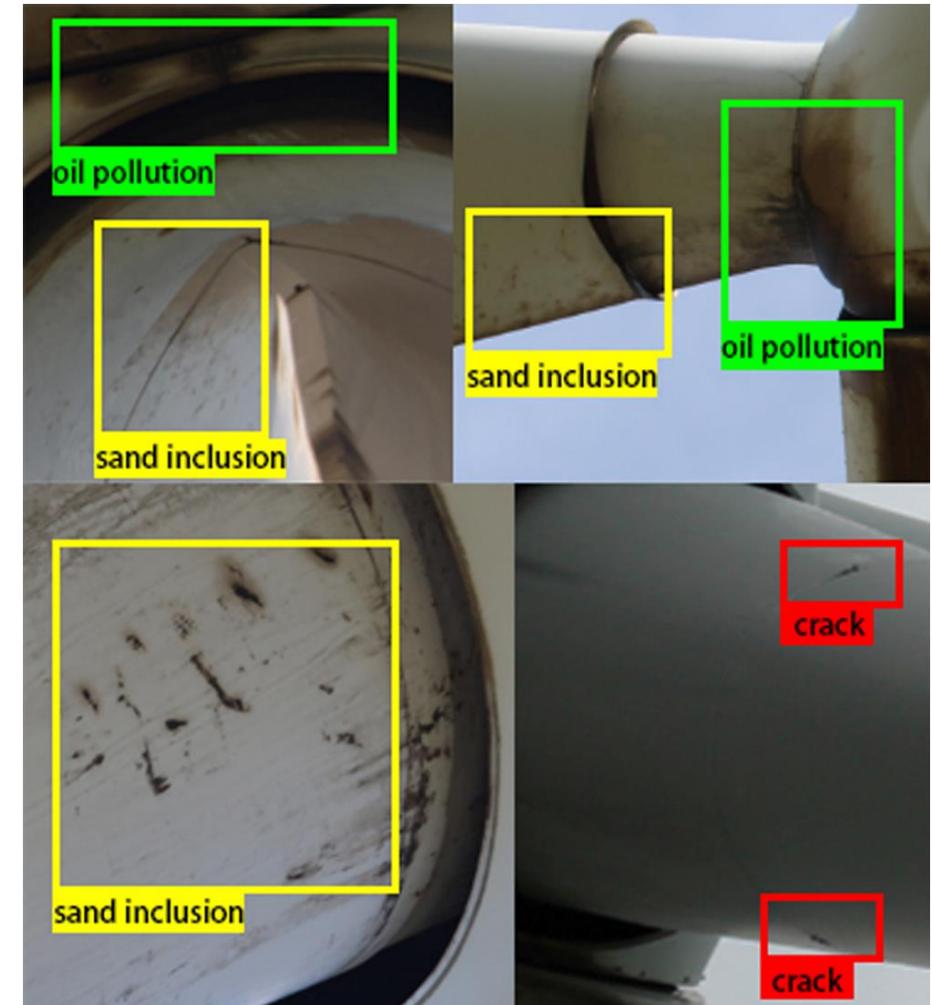
V. Regularization techniques.

VI. Momentum and learning rate schedules.



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

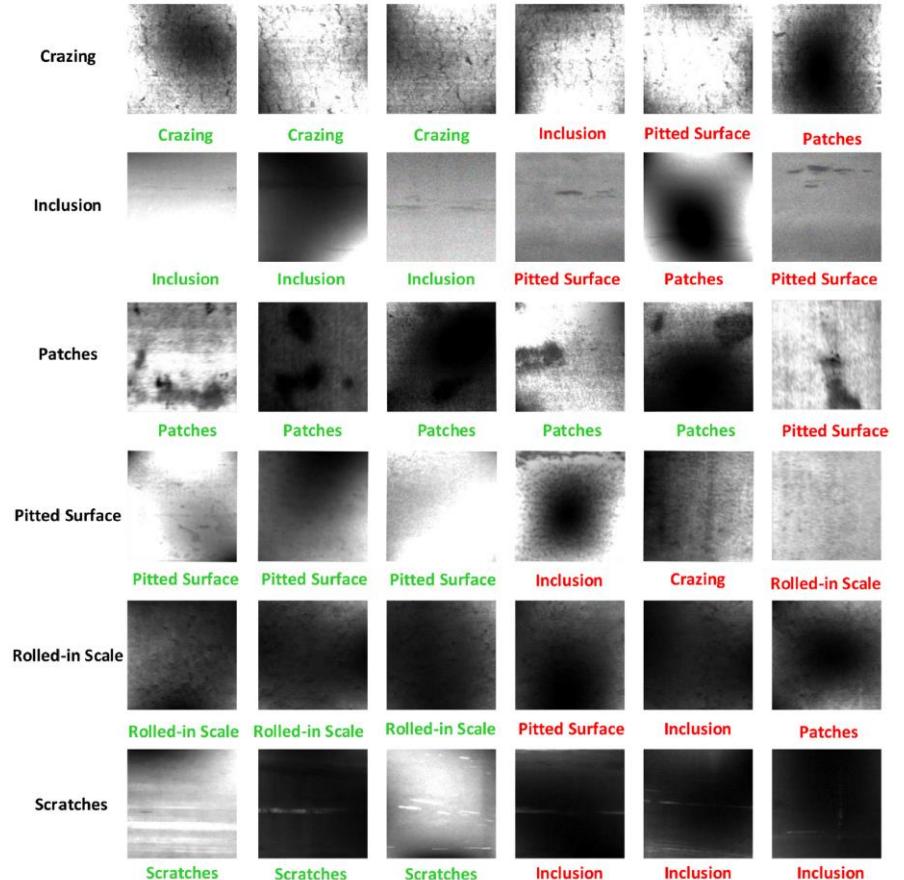
- **Objective:** Automate detection of small defects in wind turbine blades (WTBs) for efficient and safe operation.
- **Technique:** YOLO-based small object detection approach (YSODA) using multiscale feature pyramid.
- **Dataset:** 23,807 images labelled for three types of defect—crack, oil pollution, 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

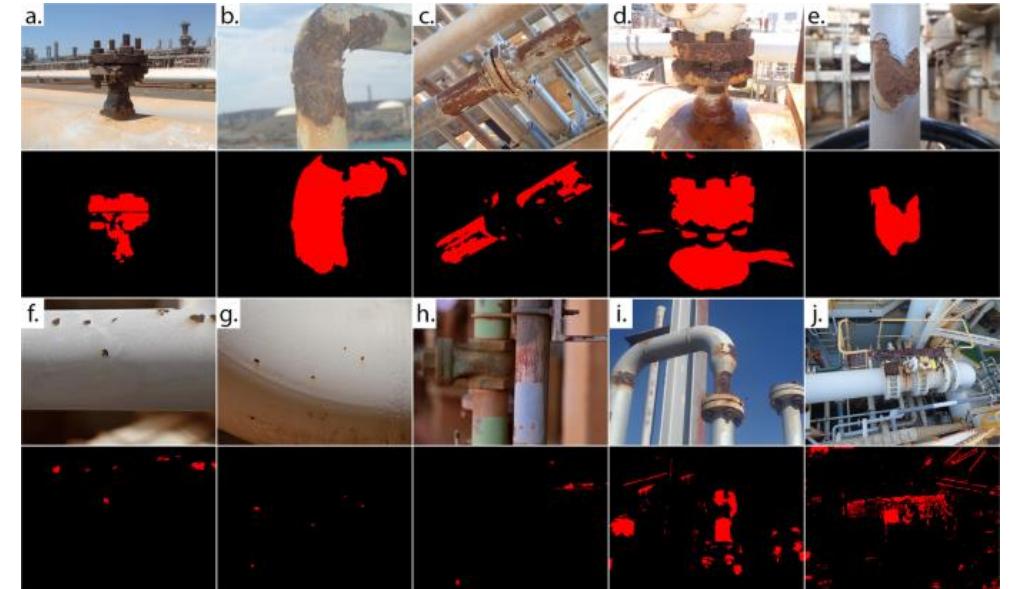
- **Objective:** Automate steel surface defect recognition for efficient quality control in steel strip production.
- **Technique:** Compact convolutional neural network (CNN) model with multiple receptive fields.
- **Dataset:** 1800 grayscale images (200x200) with 300 samples per defect category.
- **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

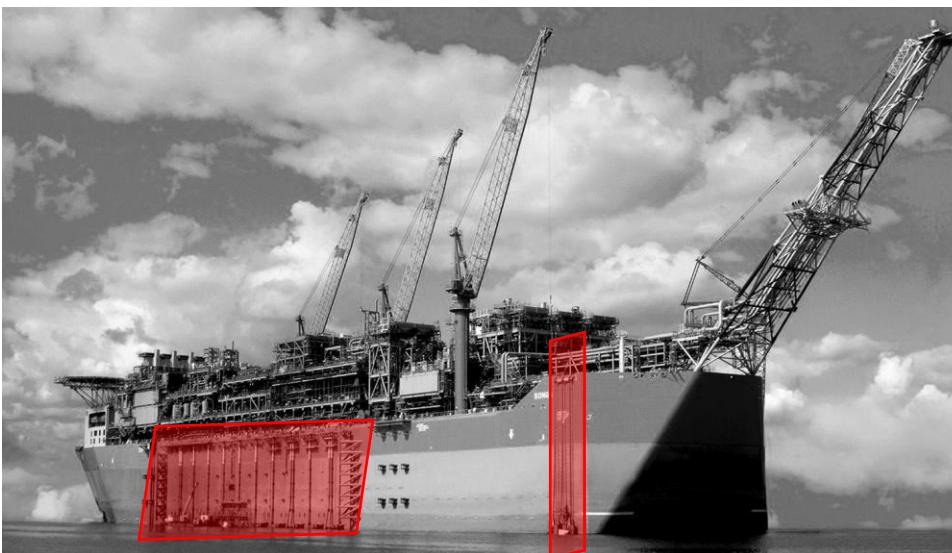
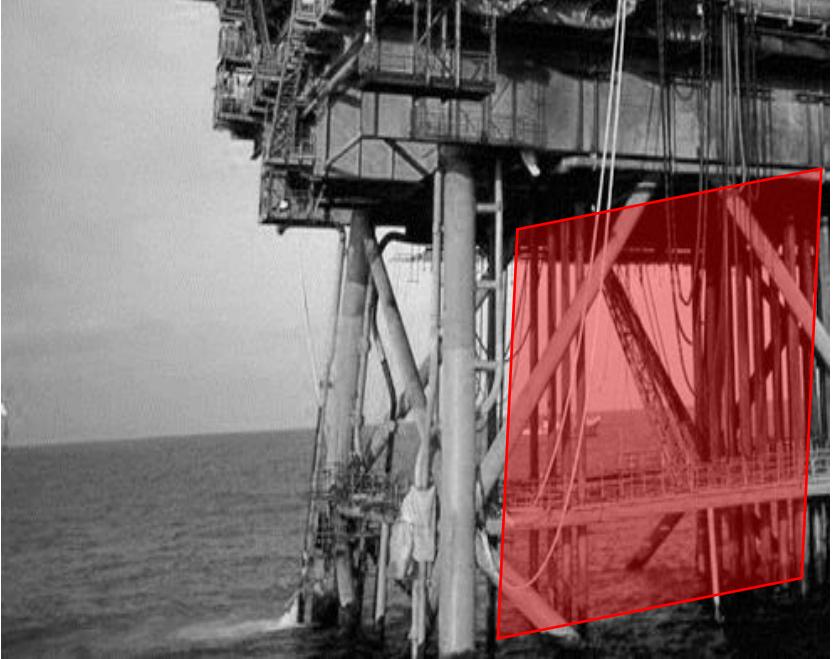
- **Objective:** Develop an automatic corrosion detection model with pixel-level segmentation and uncertainty estimates.
- **Technique:** Deep learning corrosion detector with three Bayesian variants for confidence levels.
- **Database:** Newly collected dataset of 225 images.
- **Challenges:** Lack 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.

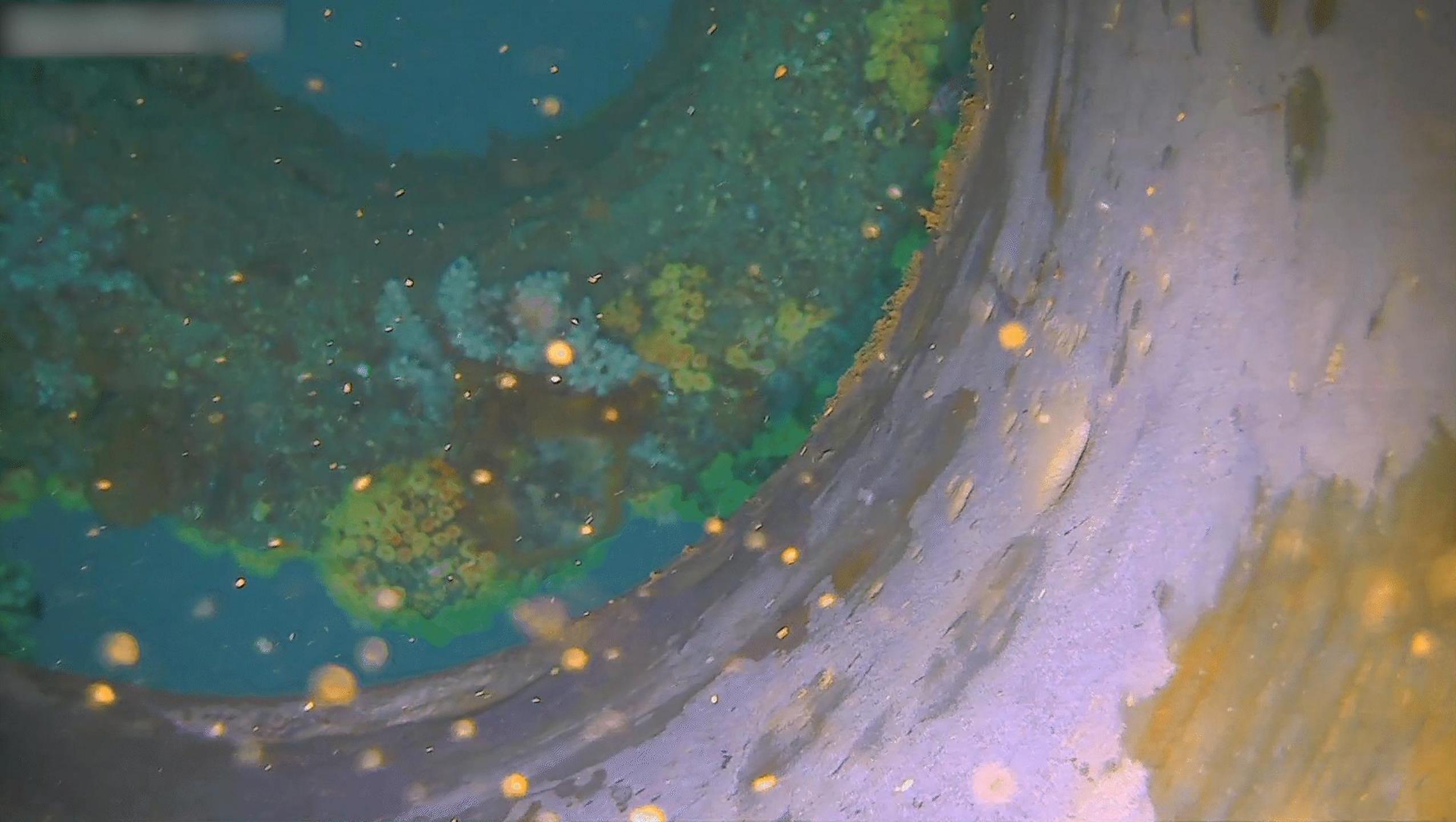


Nash, W., Zheng, L. & Birbilis, N. Deep learning corrosion detection with confidence. *npj Mater Degrad* **6**, 26 (2022). <https://doi.org/10.1038/s41529-022-00232-6>

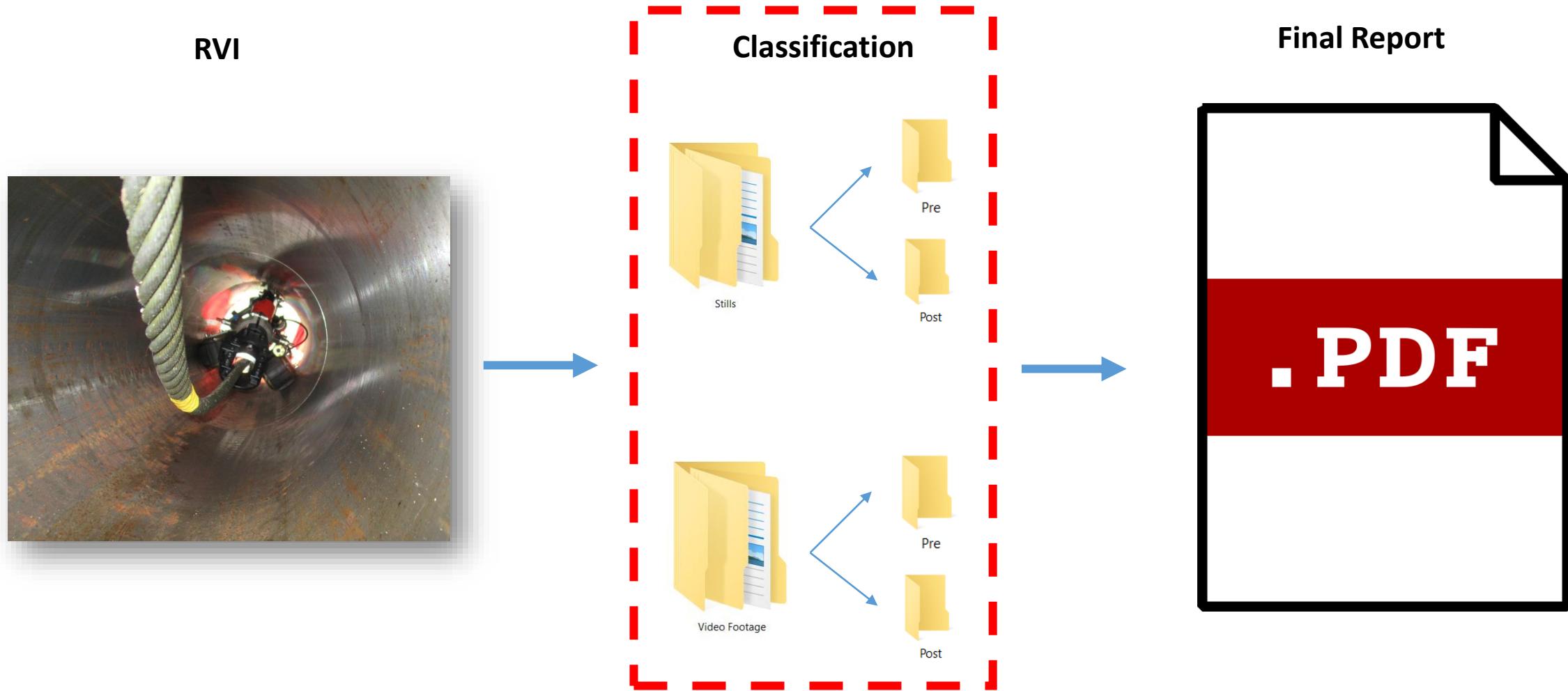
05

Case Study: Automating Offshore Asset Inspections.





Current Practices – Remote Visual Inspection (RVI)



Challenges

Standard Definition - 2014



Visual Inspection

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

High Definition - 2018



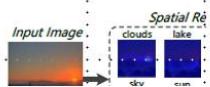
Stage 1 – Background Investigation

Learning Spatial Regularization with Image-level Supervision for Multi-label Image Classification

Feng Zhu^{1,2}, Hongsheng Li², Wanli Ouyang^{2,3}, Nenghai Yu¹, Xiaogang Wang¹
¹University of Science and Technology of China, ²University of Sydney
²Department of Electronic Engineering, The Chinese University of Hong Kong,
zhufengx@mail.ustc.edu.cn, {hsli, wlouyang, xgwang}@ee.cuhk.edu.hk, ynh@ustc.edu.hk

Abstract

Multi-label image classification is a fundamental but challenging task in computer vision. Great progress has



Underwater Image Processing and Deep CNN Method

Fenglei Han, Jingzheng Yao¹, Haitao Zhu, a

CNN-RNN: A Unified Framework for Multi-

Jiang Wang¹, Yi Yang¹, Juhua Mao², Zhiheng Huang^{3*}, Chang Huang⁴, Wei Xu¹
¹aidu Research ²University of California at Los Angeles ³Facebook Speech ⁴Horizon Robotics

Automatic Annotation of Subsea Pipelines using Deep Learning

ios Stamoulakatos^{1,*}, Javier Cardona¹, Chris McCaig¹, David Murray²,
illius², Robert Atkinson¹, Xavier Bellekens¹, Craig Michie¹, Ivan Andonovic¹,
Lazaridis³, Andrew Hamilton¹, Md. Moinul Hossain⁴, Gaetano Di Caterina¹,
os Tachtatzis¹.

Department of Electronic and Electrical Engineering, University of Strathclyde Glasgow, UK
Sea, Zierikzee, Netherlands
Department of Engineering and Technology School of Computing and Engineering, Huddersfield, UK

Wall Crack Detection Using Transfer Learning-based CNN Models

Sayyed Bashar Ali, Reshma Wate, Sameer Kujur, Anurag Singh, Santosh Kumar
IIT, Naya Raipur, India
(basher18100; reshma18101, sameer18100, anurag, santosh)@iitnr.edu.in

Dong, Yao Zhao, Senior Member, IEEE
Member, IEEE

sing performance in single-label image classification is an open problem, mainly due to the complex underlying problem. To propose a flexible deep CNN infrastructure, called HCP, different hypotheses are taken as the inputs, then the results from different hypotheses are aggregated with the characteristics of this flexible deep-CNN infrastructure. (1) the whole HCP infrastructure is robust to possibly different types of images; (2) the whole HCP infrastructure is robust to possibly different types of images; (3) the shared CNN may be well pre-trained with a

Image Pre-processing and Segmentation for Real-Time Subsea Corrosion Inspection

Craig Pirie and Carlos Francisco Moreno-Garcia^(✉)

Robert Gordon University, Garthdee Road, Aberdeen AB10 7GJ, UK
(c.pirie1, c.moreno-garcia)@rgu.ac.uk

Learning Techniques for Underwater Image Classification

Sparsh Mittal¹, Srishiti Srivastava², and J. Phani Jayanti³

In recent years, there has been an enormous interest in learning to classify underwater images to identify objects such as fishes, plankton, coral reefs, seagrass, and gestures of sea divers. This classification is thus guiding preservation campaigns. Image processing complement other techniques, such as physicochemical analysis of water and sonar-based detection.

Characterization of External Corrosion in Pipelines



eth N^a, S. Kumar Ranjith^b, C.V. Jiji^a

^aCommunication Engineering, College of Engineering Trivandrum, Kerala, India
^bElectrical Engineering, College of Engineering Trivandrum, Kerala, India

ABSTRACT

In this paper, we proposed a computer vision based approach to detect corrosion in water, oil and gas pipelines. For this, we created a dataset containing more than 140,000 optical images of pipelines with different levels of corrosion. This in-house fabricated CNN was applied to classify the images of pipelines into two classes: corroded and non-corroded. This proposed network has very few parameters to be learned. NN classifiers. However, it produced significantly higher classification accuracy between images of corroded pipelines and images without corrosion. The proposed network surpassed most of the state-of-the-art methods. In addition, we proposed a localisation algorithm based on a recursive neural network to detect the location of the corrosion.

Estimating Wall Loss Risk Distributions using Machine Learning and Geospatial Analytics

Joseph Mazzella¹
Engineering Director, Inc.
807 Davis Street, Unit 314
Evanston, IL 60201

Thomas Hayden²
Northwestern University
2211 Campus Drive

A Visual Inspection Proposal to Identify Corrosion Levels in Marine Vessels Using a Deep Neural Network

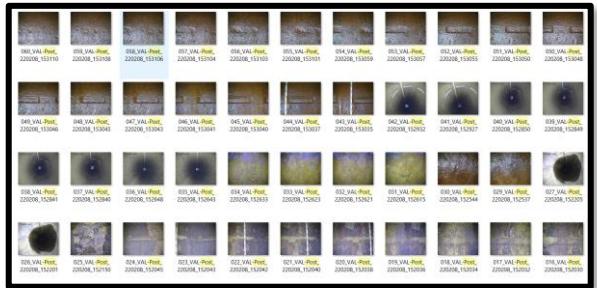
Luciane Soares¹, Silvia Botelho¹, Ricardo Nagel¹, Paulo Lilles Drews Jr¹

Abstract—The increase in oil production in Brazil, consequently, resulted in the concern with the integrity of the

General corrosion, which appears as noticeable rust, which can occur evenly on unc

Pitting, a localized process that is normally

Stage 1 – Data Preparation



Dataset



Inpaint

Original

Grayscale

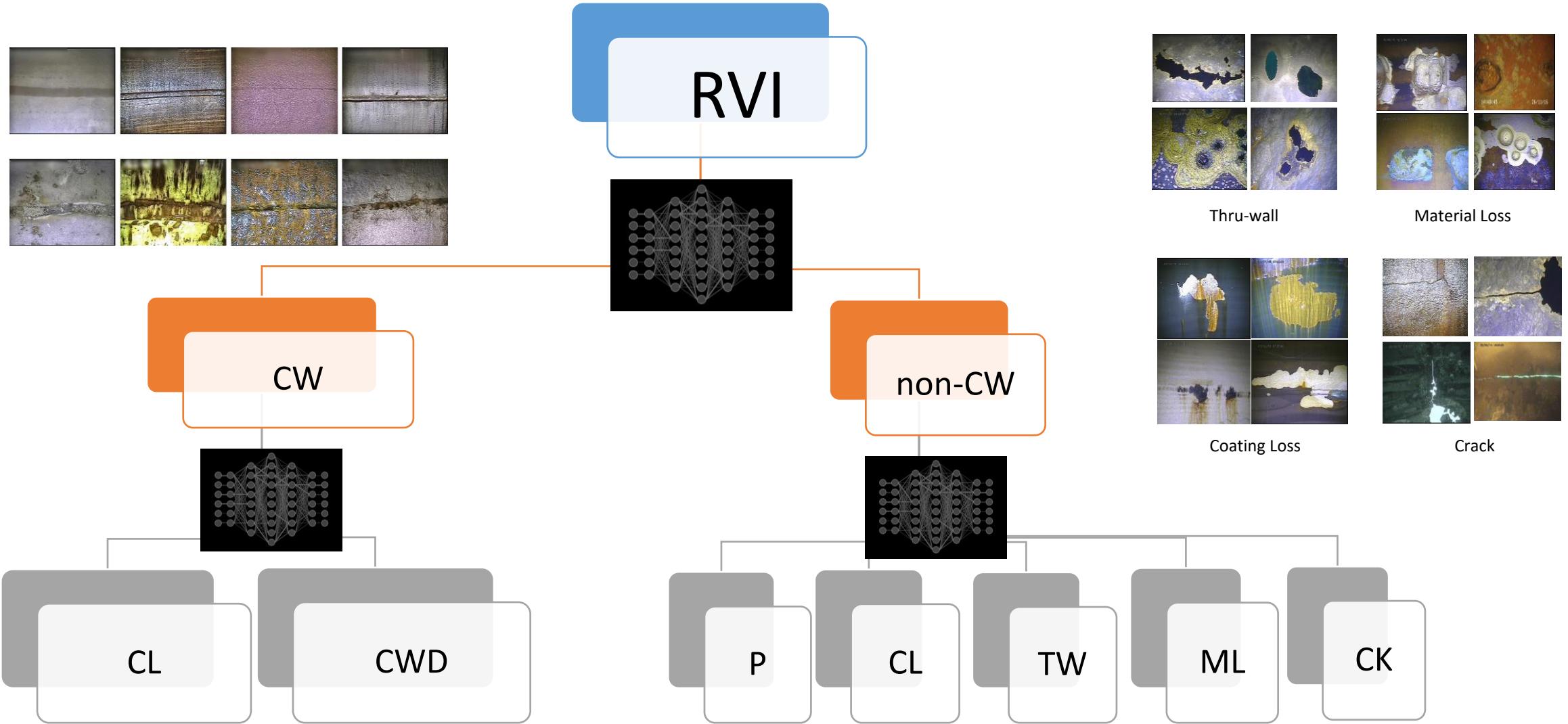


CLAHE

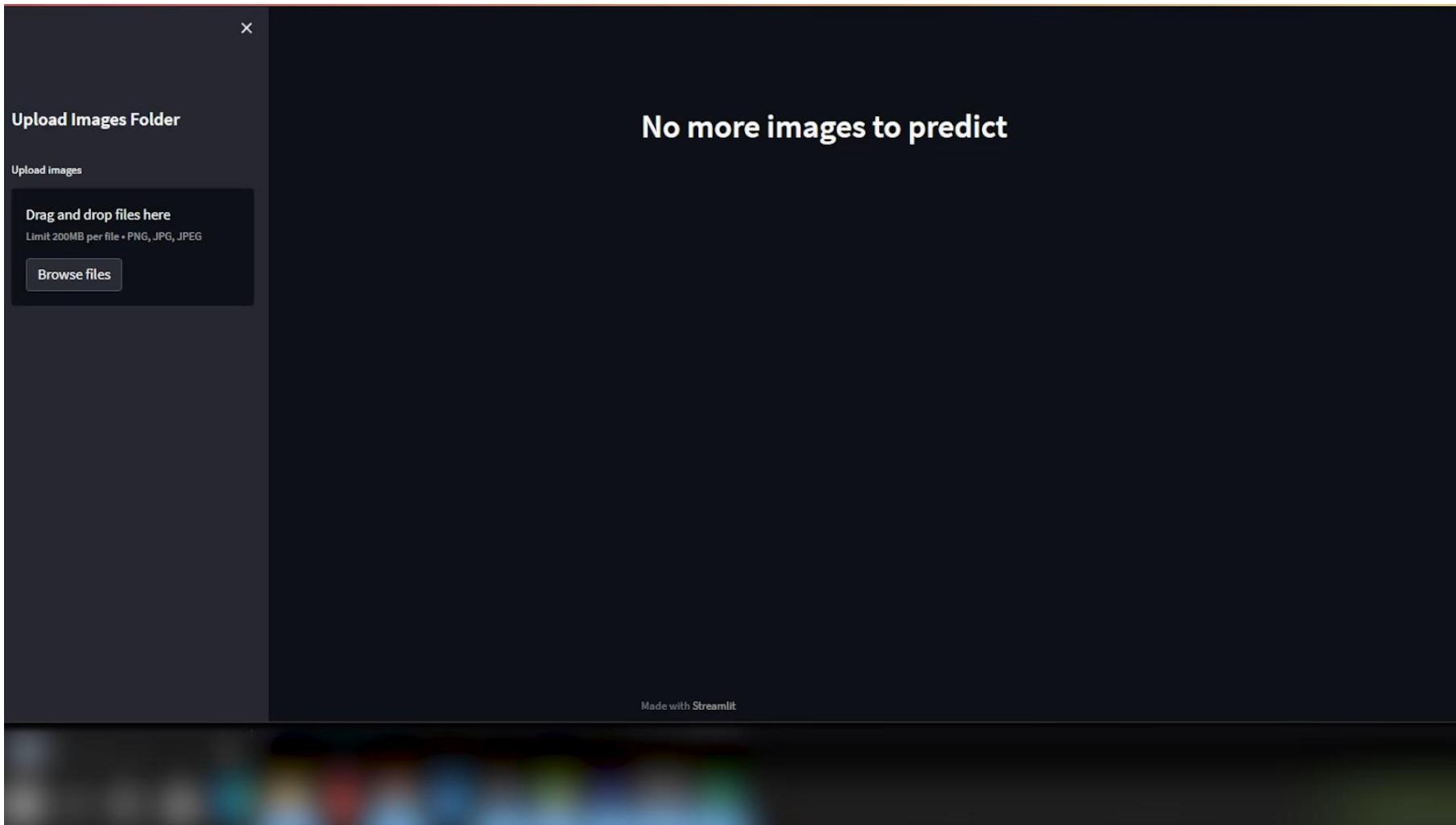
Custom Filter

HSV

Stage 3 – Deep Learning Framework

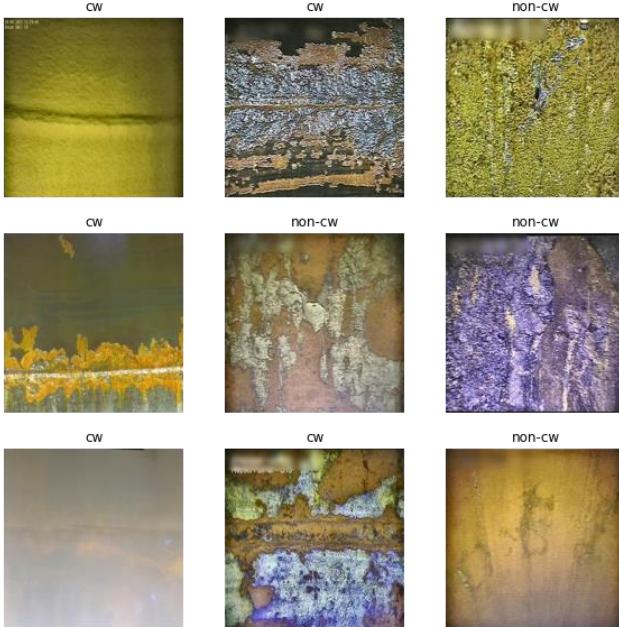


Stage 4 – Human in the loop

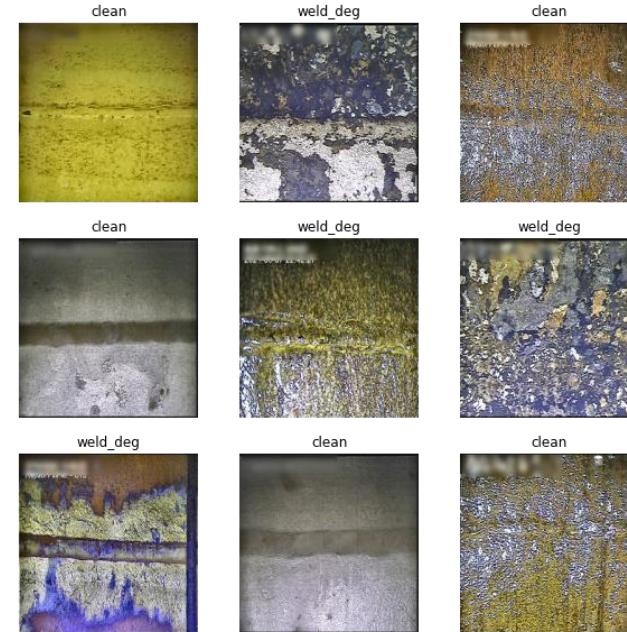


Stage 5 – Evaluation Results

GC



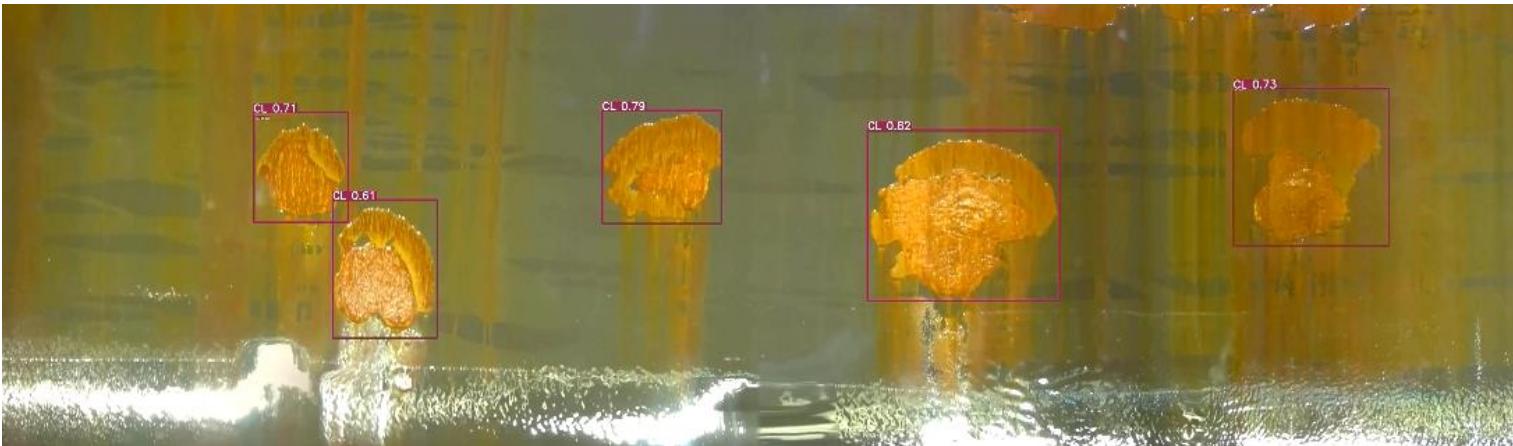
WC



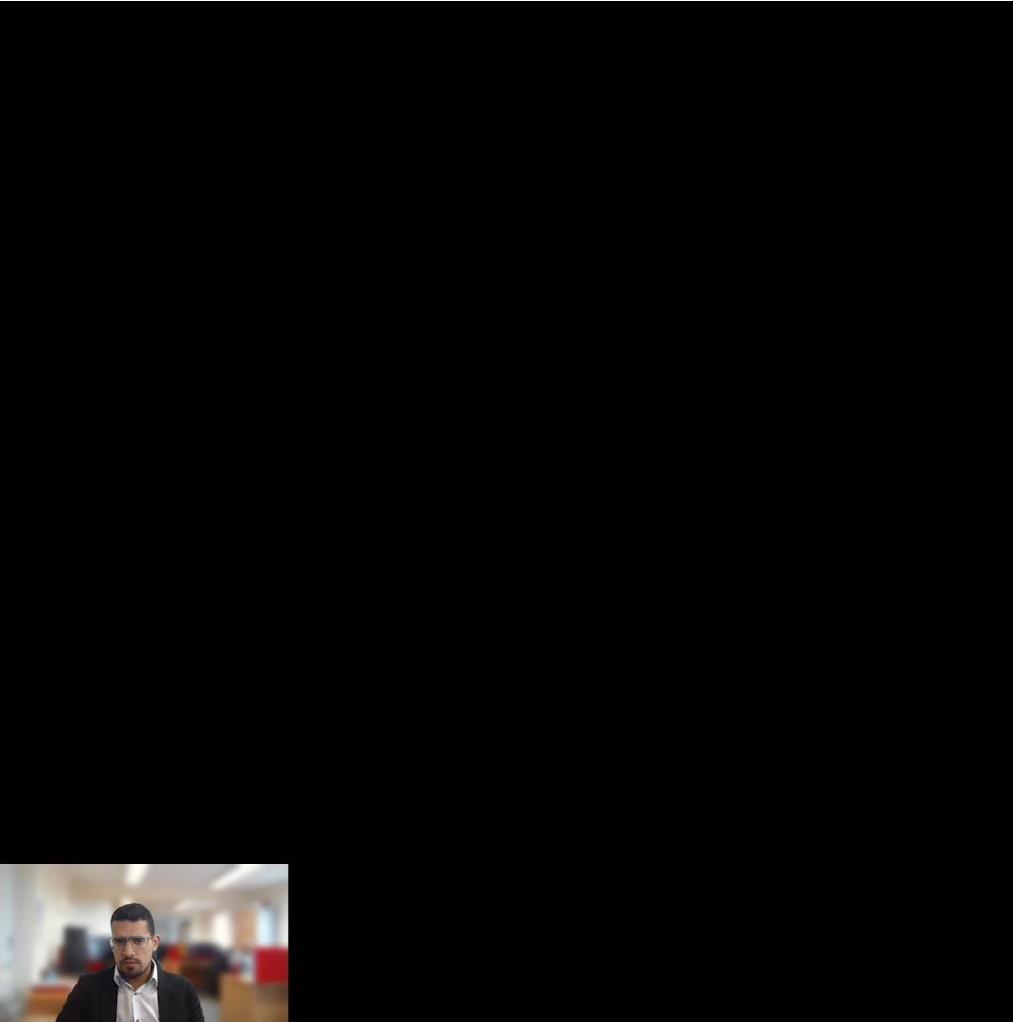
Precision	Recall	F1-Score
90% --> 96%	90% --> 94%	90% --> 96%

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

Stage 5 – Evaluation Results



Stage 5 – Evaluation Results



06

Other Applications

Photogrammetry

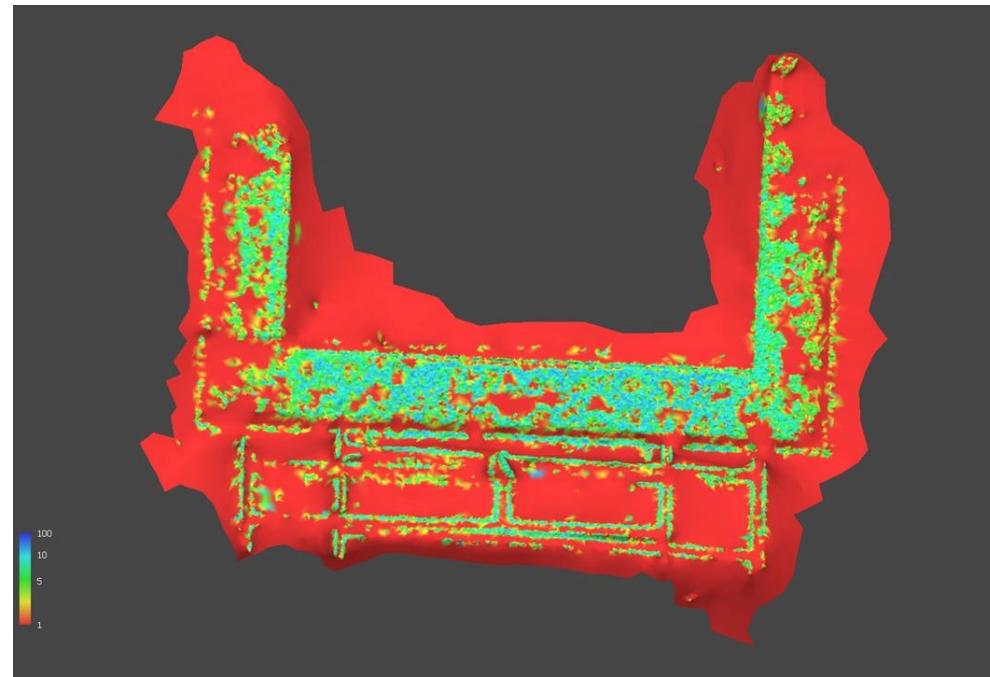
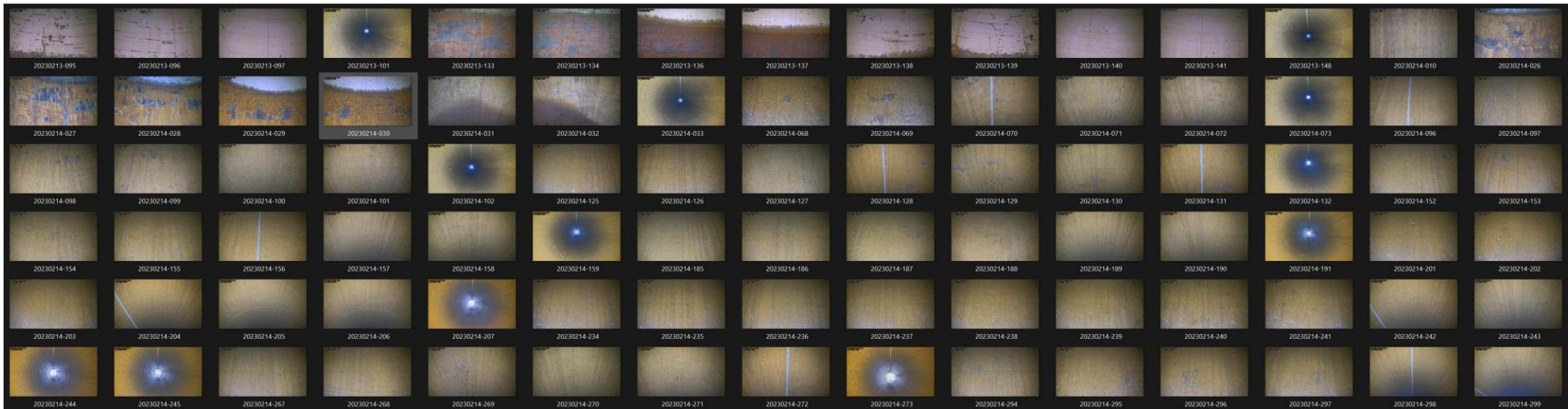


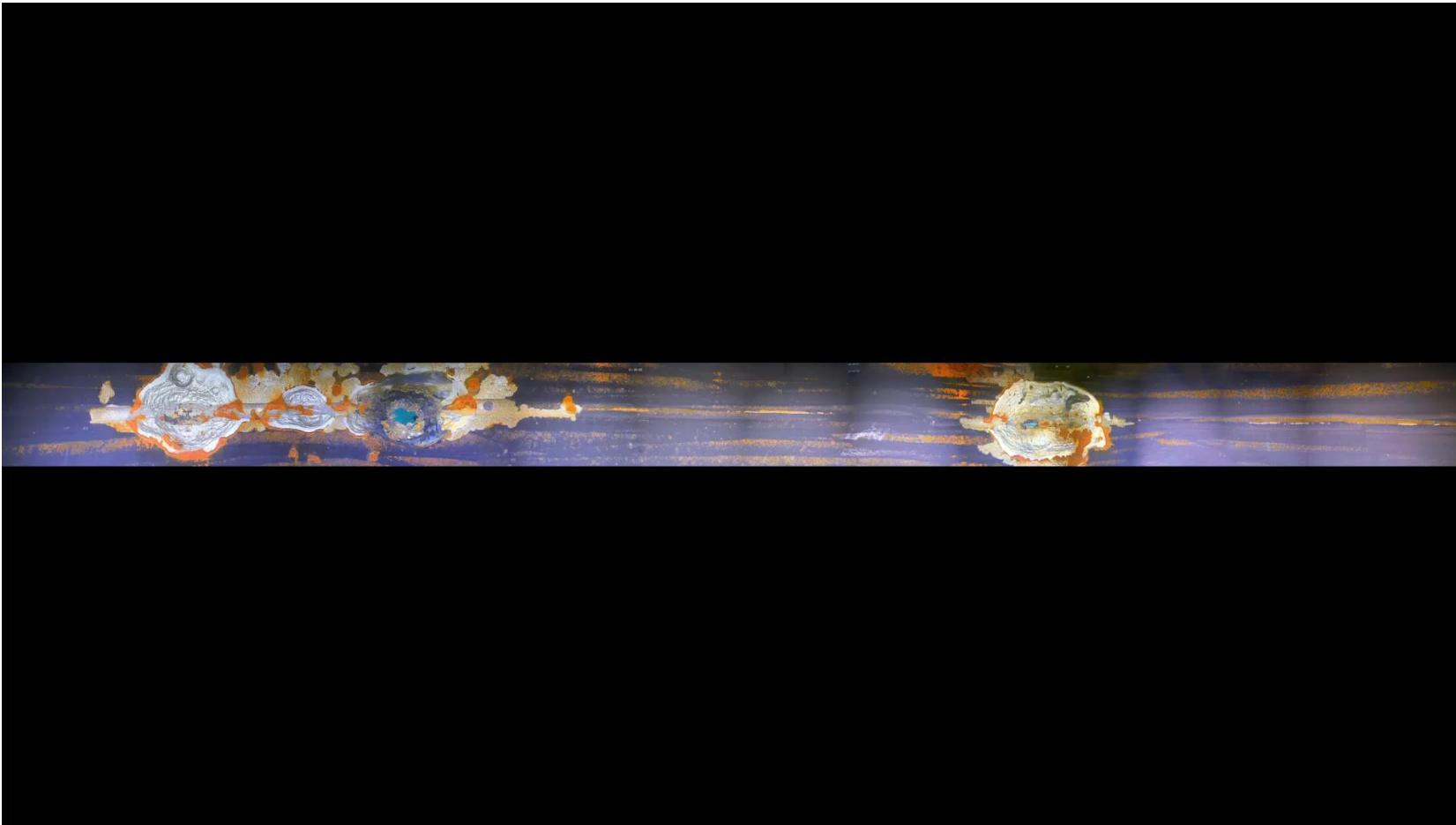
Image / Video Enhancement



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.



