PHD THESIS DEFENSE

# Risk-Informed Artificial Intelligence for Autonomous Inspection on Subsea Pipelines


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NTNU | Norwegian University of Science and Technology

**BRU21**
Better Resource Utilization in the 21st century

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# Presentation Outline



Image: BRU21

# Risk-Informed Artificial Intelligence

- *Risk* is the effect of uncertainty on objectives, which can be positive, negative, or both, and results in either *threats* or *opportunities*.
  - expressed in terms of three questions: What can go wrong, how likely is it, and what are the consequences?
  - A potential source of harm is termed **hazard.**

[Ref. ISO 31000. Risk management — Guidelines, International Organization for Standardization. Technical report International Organization for Standardization (2018).]

***Risk-informed approach:*** ensuring that the decisions between alternatives are taken *with an awareness of the risks* associated with options, and that the attributes of a decision are considered in an integrated manner.

[Ref. Risk-Informed Decision-Making Processes: An overview. Enrico Zio, Nicola Pedroni. Apports De La Recherche. Foundation for an Industrial Safety Culture. 2012]

**Artificial Intelligence (AI):** the study and development of computer systems that can copy intelligent human behavior.

- Often requires a lot of data to learn
  - Supervised learning
  - Unsupervised learning
  - Reinforcement learning
- e.g., Machine Learning, Computer Vision

[Ref. Oxford Learner's Dictionary]

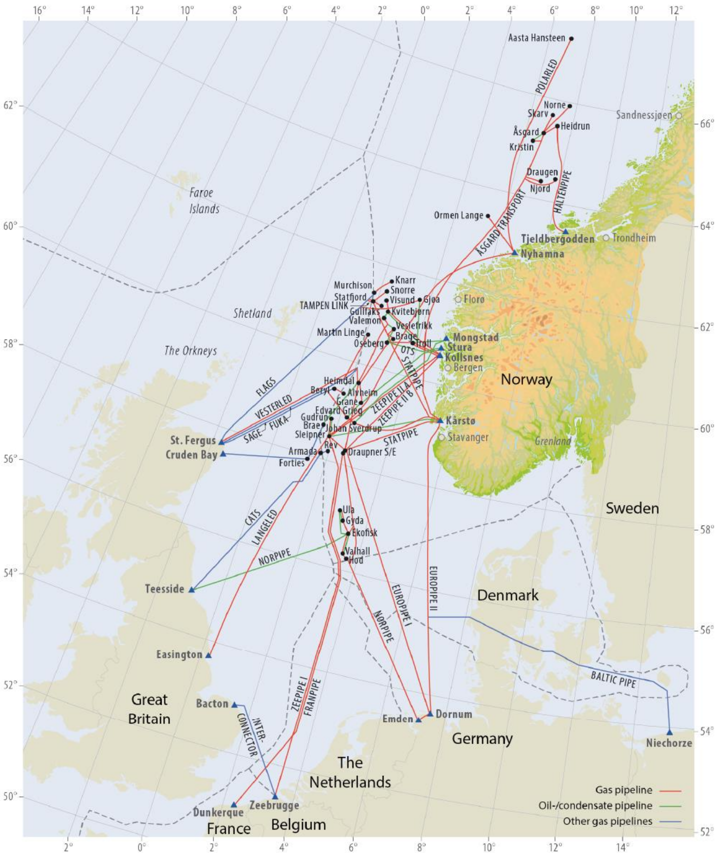
**Risk-based approach:** planning of an inspection on the basis of the information obtained from a risk analysis.

[Ref. Varde, P.V., Pecht, M.G. (2018). Risk-Based/Risk-Informed Applications. In: Risk-Based Engineering. Springer Series in Reliability Engineering. Springer, Singapore.]

Images source: Stock Image

# Energy demands and Subsea pipelines

- Oil and gas industry and global energy demands
- Since 1970s, 8,800km of pipelines on the Norwegian Continental Shelf




Pipelines on Norwegian Continental Shelf,
Image property of Norwegian Petroleum Directorate

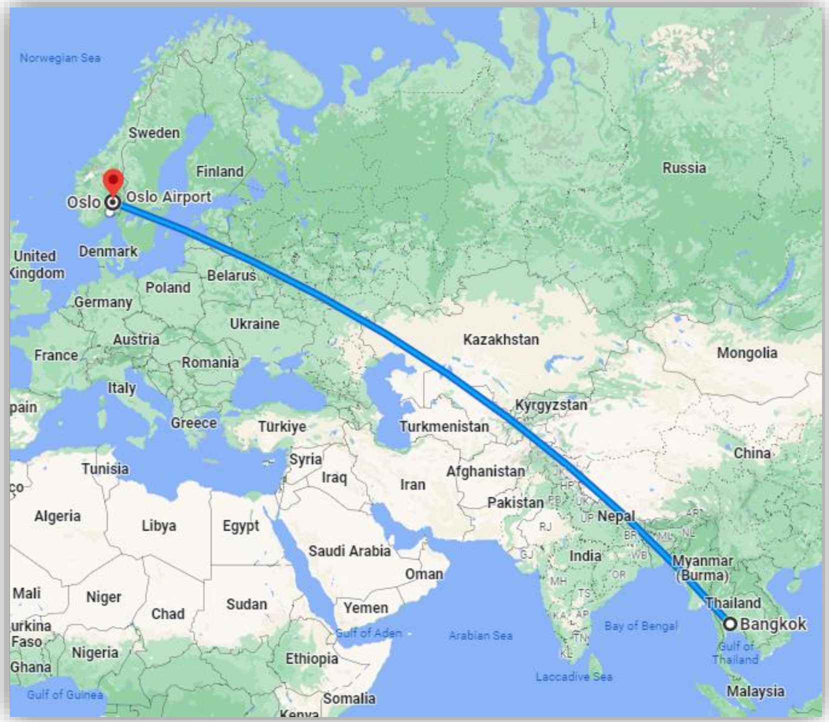
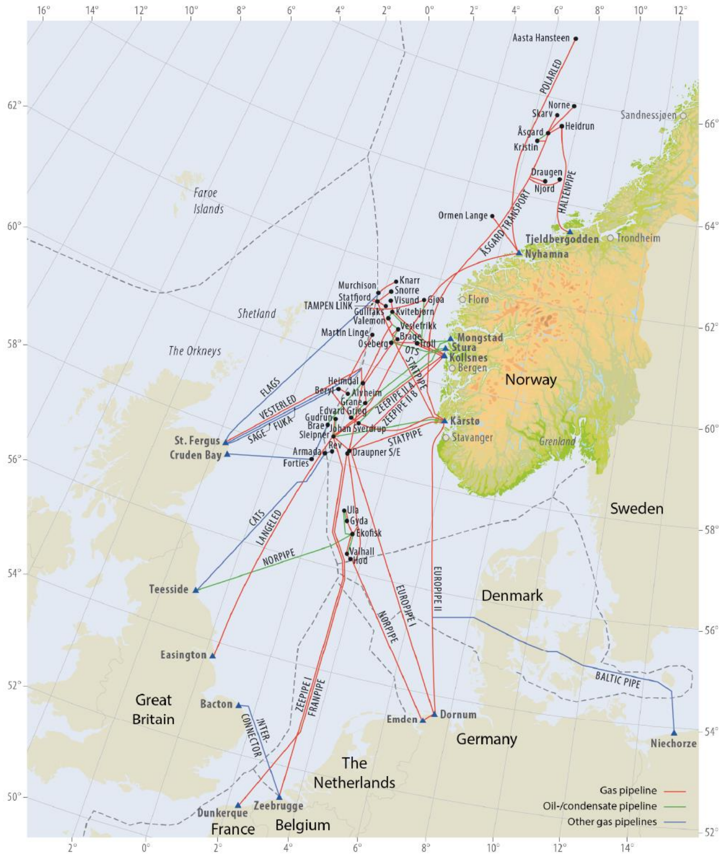



Image:
Google Maps



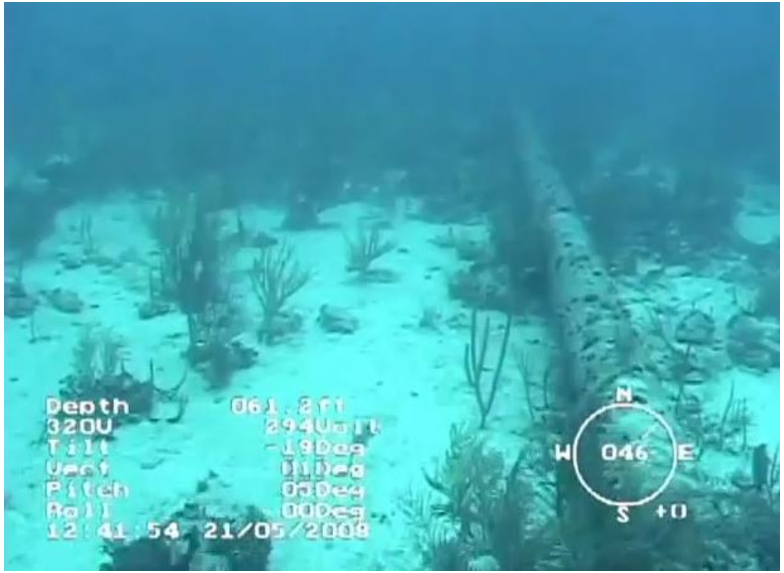

Pipelines on Norwegian Continental Shelf,
Image property of Norwegian Petroleum Directorate

# Energy demands and Subsea pipelines

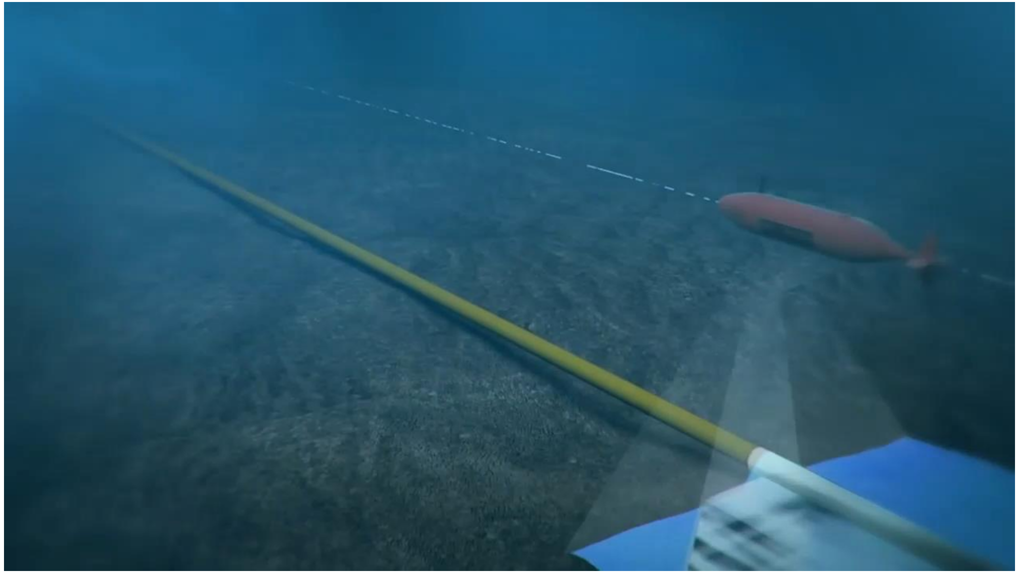
- Oil and gas industry and global energy demands
- Since 1970s, 8,800km of pipelines on the Norwegian Continental Shelf

- Environmental factors impact pipeline integrity, potentially resulting with catastrophic environmental, and financial consequences
- Need for a responsible, financially sustainable inspection system for pipeline inspection and monitoring

# Pipeline Inspection
# Remotely Operated Vehicle (ROV) and Underwater Autonomous System (UAS)




Pipeline inspection with a
Remotely operated vehicle (ROV)



Pipeline inspection with an
Underwater Autonomous Vehicle, a part of Underwater Autonomous System (UAS)

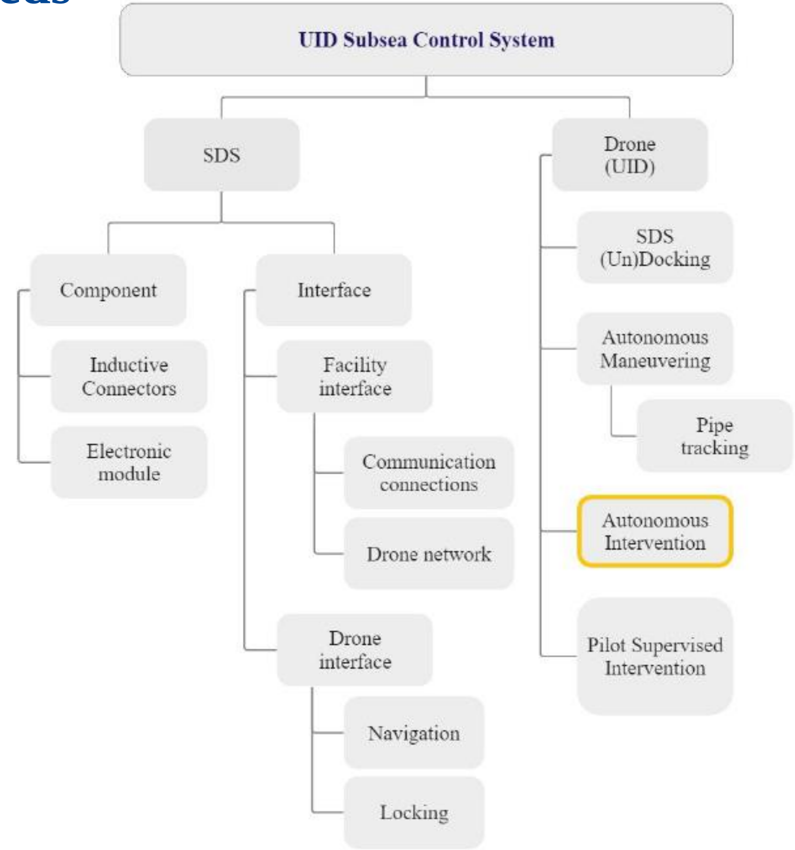
Ref.: Underwater pipeline inspection with ROV, Hibbard Inshore
https://www.youtube.com/watch?v=-09as6aooWk (Accessed on 08.08.2023)

Ref.: How to inspect subsea piplines six times faster, Kongsberg Gruppen
https://www.youtube.com/watch?v=7VMTsGYJ7JY (Accessed on 08.08.2023)

# Industry Needs

Underwater Intervention Drone (UID) System:
Subsea Docking Station (SDS) + Intervention Drone

Ref.: Eelume Underwater Robot UID and SDS, Equinor
https://www.youtube.com/watch?v=oFNeQln1f2c (Accessed on 08.08.2023)




Ref.: Daniel Abicht, Jan Christian Torvestad, Pål Atle Solheimsnes, and Karl Atle Stenevik. Underwater intervention drone subsea control system. Proceedings of the Annual Offshore Technology Conference 2020 (May), 4–7 ISSN 01603663. doi: 10.4043/30701-ms.

# Industry Needs and Expectations

Autonomous systems, which rely on AI, operate and make decisions independently of human operators and are intended almost entirely to replace human involvement in certain tasks.

[Ref.: Oxford University Press. Oxford Learner's Dictionaries (2021). https://www.oxfordlearnersdictionaries.com/.]

## Dimensions of Autonomy

### Machine automation

- Multi-system coordinated functions
- Mission-specific functions
- Combined functions

### Data deliberation

- Sensed data processing
- Local onsite data processing
- Reasoning on all data within mission context

### Risk management

- Warnings according to procedures and situation
- Suggesting feasible set of actions
- Autonomous risk management

[Ref.: Francesco Scibilia, Knut Sebastian Tungland, Anders Røyrøy, and Marianne Bryhni Asla. Energy industry perspective on the definition of autonomy for mobile robots. In Communications in Computer and Information Science volume 1056 CCIS pages 90–101. Springer International Publishing (2019). ISBN 9783030356637. doi: 10.1007/978-3-030-35664-4\9.]

## Literature Synthesis

## *Hazard Detection with Risk Assessment or with AI?*

**Traditional Risk-Based Approaches**

**Subsea Pipeline Hazard Detection**

**Artificial Intelligence**

Image property: Popular Mechanics

# Research Gaps

**1**

**Insights from risk and hazard analysis** are not sufficiently integrated in AI applications for subsea pipeline hazard detection with UAS.

**2**

The existing **data** for training AI applications for subsea pipeline hazard detection **is not adequate enough** to reliably represent the complex environment of subsea pipelines for inspection with UAS.

**3**

**Fusion of varied data sources** and integration of adaptive sensor technologies that lead to **new opportunities** of image-based UAS pipeline hazard detection is not sufficiently discussed.

Images: Equinor

# Research Questions


How can insights from **risk and hazard analysis supervise** the results of AI methods, such as anomaly detection and classification, and increase the reliability of UAS in detecting early warnings of subsea pipeline hazards?


How can the **adequacy of collected data** be ensured during autonomous data collection with UAS and how can **the training data** be enhanced to introduce evidence of hazards necessary for UAS training, while minimizing the manual labor and costs of data collection?


How can the image-based hazard detection with UAS be supplemented by utilizing varied data sources from sensor technologies for adaptive sensing, and how can anomaly classification be **reimagined for the future** of UAS subsea pipeline hazard detection?

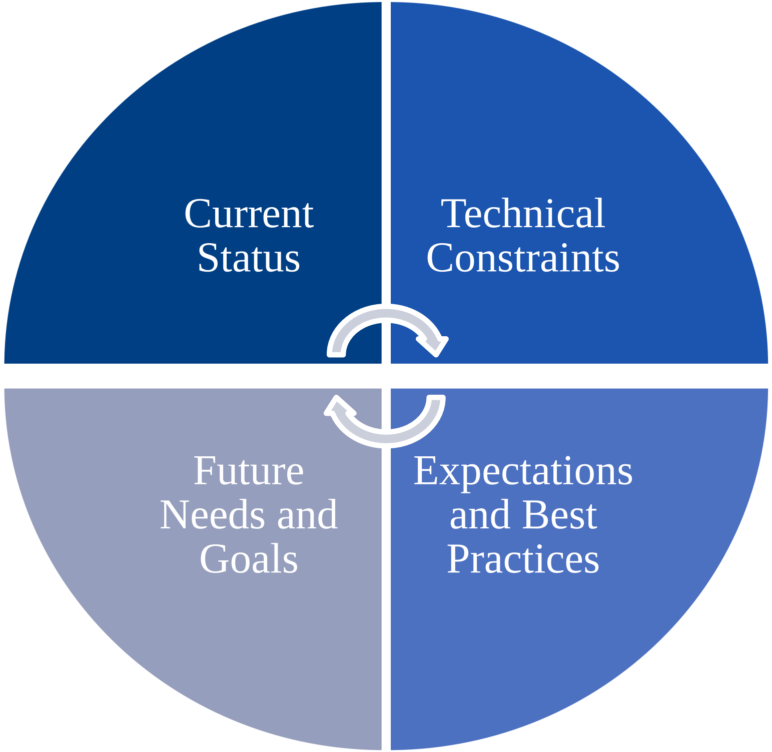
Images: Equinor

# Research Objective

Understanding the challenges and blindspots associated with using autonomous systems powered by AI for subsea pipeline inspection and propose novel approaches for combining traditional risk-based approaches with operation-specific AI methods for detecting hazards.

# Qualitative Approach

***Dialogues with Stakeholders***



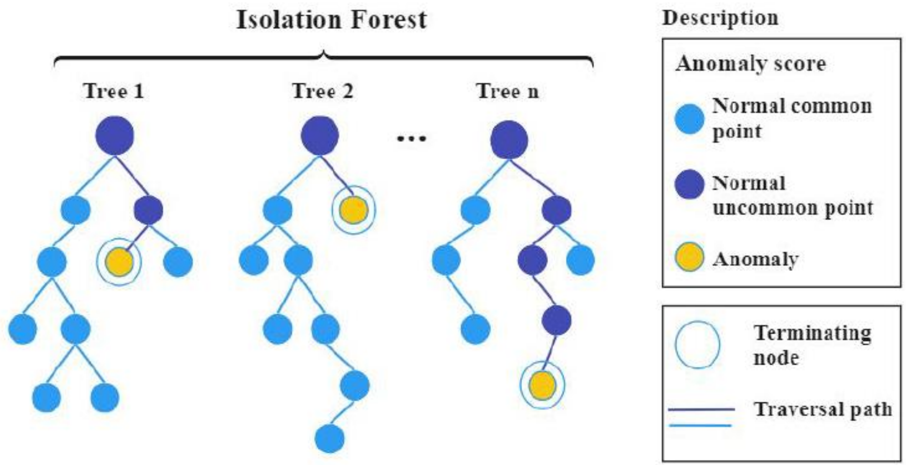
# Quantitative Approach

## Anomaly Detection and Classification

*Detecting deviations in data (anomalies, outliers)*

Anomalies:

- Noise data / false alarms
- Rare, significant data / hazard indicators
- Novelties




### *Isolation Forest*

Isolates anomalies with low computational requirements, working well in high-dimensional problems.

[Ref. Fei Tony Liu, Kai Ming Ting, and Zhi Hua Zhou. Isolation forest. In Proceedings IEEE International Conference on Data Mining, ICDM ]

# Quantitative Approach

## Image Analysis

*Discovering patterns and discriminant properties in images*

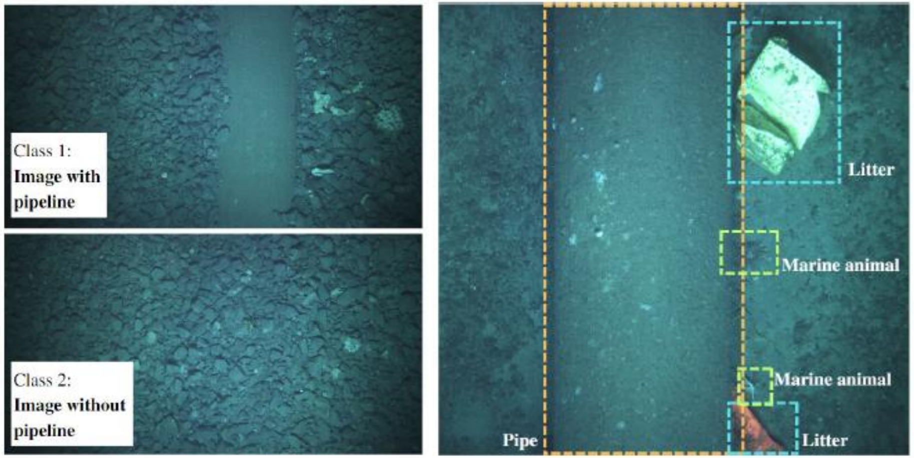



Image Classification and Object Detection

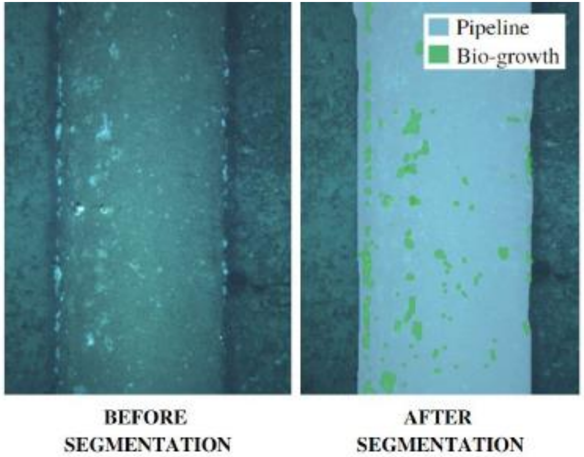



Image Segmentation

Images: Adapted from Equinor

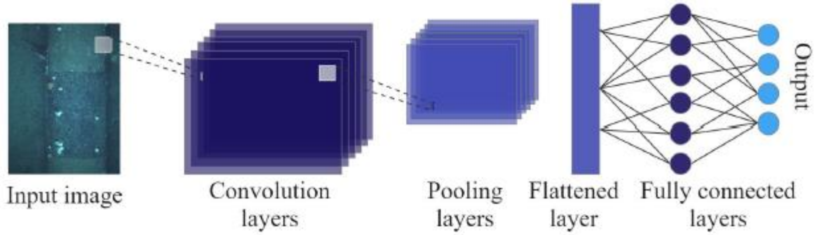
# Quantitative Approach

## Image Analysis

*Discovering patterns and discriminant properties in images*

### *Image Classification with Convolutional Neural Network (CNN)*

Deep learning technique that consists of convolutional layers whose primary function is to learn and extract the features required for efficient image comprehension with an objective to extract features such as edges, colors, texture, and gradient orientation.




[Ref. D. R. Sarvamangala and Raghavendra V. Kulkarni. Convolutional neural networks in medical image understanding: a survey. Evolutionary Intelligence 15 (1) (3 2022). ISSN 18645917. ]

# Quantitative Approach

## Data

### *Numerical and Categorical Data*

*Case Study 1:*

- Dataset with 20,187 samples of sensor measurements from remotely operated and autonomous underwater drone

  - Dataset adapted from: Alberto Castellini, Domenico Bloisi, Jason Blum, Francesco Masillo, and Alessandro Farinelli. Multivariate sensor signals collected by aquatic drones involved in-water monitoring: A complete dataset. Data in Brief 30 (2020)

*Case Study 2:*

- Dataset with 2,584 samples of sensor measurements of seismic events for tracking seismic tremors
- Dataset adapted from: Jozef Kabiesz, Beata Sikora, Marek Sikora, and Lukasz Wrobel. Application of rule-based models for seismic hazard prediction in coal mines. Acta Montanistica Slovaca 18 (4), 262 -277 (2013) and
M Sikora and P Mazik. Towards the better assessment of a seismic hazard—the Hestia and Hestia map systems. Mechanization and Automation of Mining 3 (457), 5-12 (2009)

### *Image Data*

*Case Study 3:*

- Dataset of 204,000 pipeline images recorded by an underwater autonomous drone
- Provided by Equinor

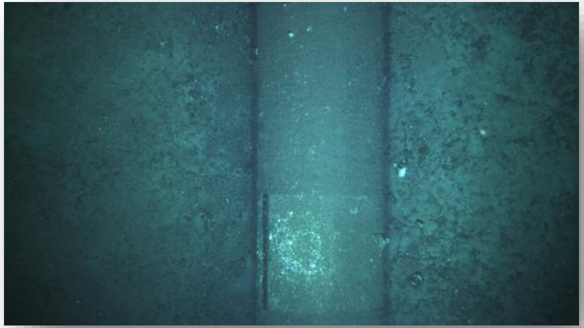


Image: Equinor

# Research Structure

**I**
**Exploration through theory**

1. Conceptual Warning Identification Framework (WIF)
2. Risk analysis and anomaly detection overlapping goals

**II**
**Applying theory through analysis of available numerical data**

3. Difference in data collected with UAS and ROV
4. Using WIF to test risk analysis supervising anomaly detection

**III**
**Analysis of industry-provided images**

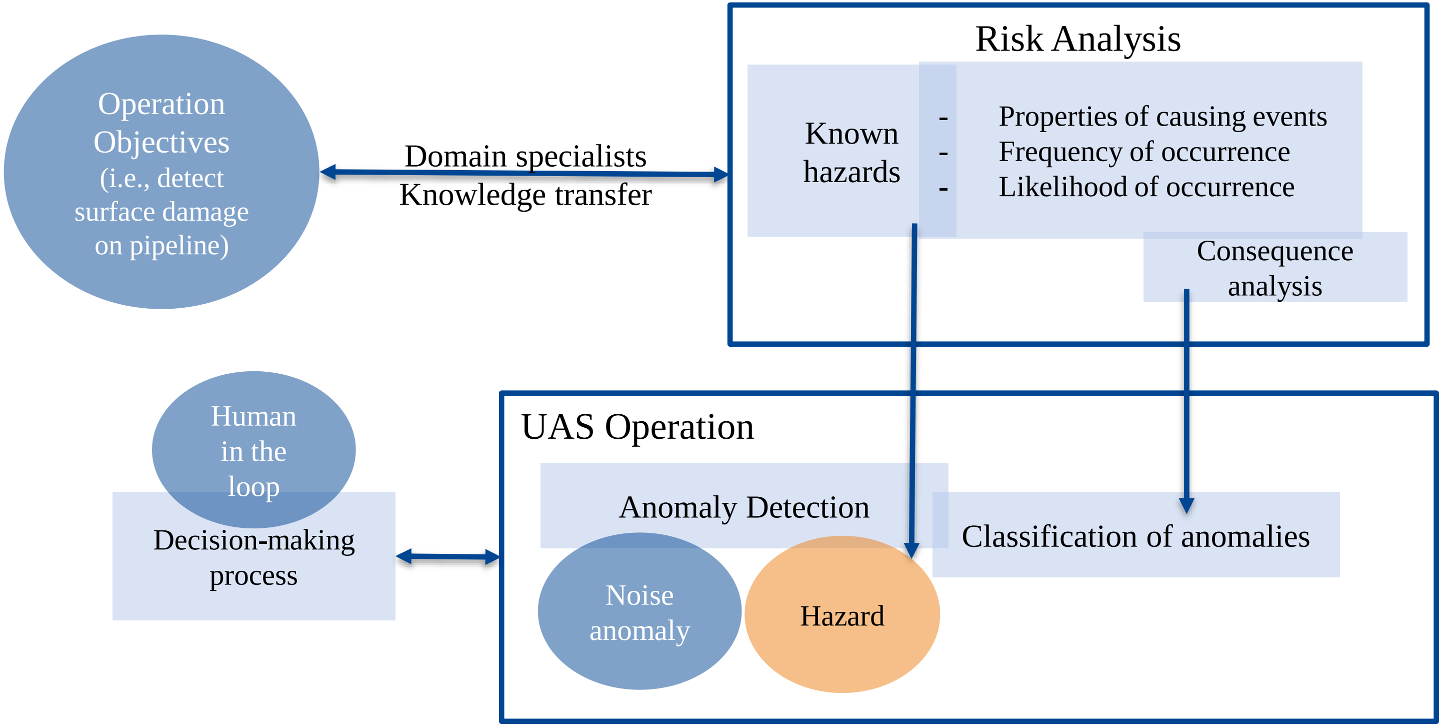
5. Generating synthetic training data with pipeline damage

**IV**
**Observations for future models**

6. Time-sensitive anomaly categories
7. Context-full AI models and data fusion

Image: Stock Images

# Result 1:
# Risk-Informed and Data-Driven UAS Operations




[Ref. Spahic, Rialda; Hepsø, Vidar; Lundteigen,Mary Ann. (2022) Using Risk Analysis for Anomaly Detection for Enhanced Reliability of Unmanned Autonomous Systems. Proceedings of the 32nd European Safety and Reliability Conference (ESREL 2022). DOI: 10.3850/978-981-18-5183-4-R08-03-390-cd]

**Research Question 1:** How can insights from risk and hazard analysis supervise the results of an AI method, such as anomaly detection and classification, and increase the reliability of UAS in detecting early warnings of subsea pipeline hazards?

# Result 2:
# Reliability of Sensor Data for Machine Learning

**Case Study 1:**
Under equal circumstances, use data collected by ROV and autonomous drones for classification of water flow with classification and anomaly detection methods

**Objective:** Testing the data collected by remotely operated and autonomous drones

**Findings:**
- No significant difference between data collected with remotely operated and autonomous drone
- Highly imbalanced dataset (representation of classes is imbalanced)
- High number of reported anomalies (10%) belonging to underrepresented class

[Ref. Spahic, Rialda; Lundteigen,Mary Ann, *Manually or Autonomously Operated Drones: Impact on Sensor Data towards Machine Learning* IEEE 9th International Conference on Computational Intelligence and Virtual Environments forMeasurement Systems and Applications (2022) DOI: 10.1109/CIVEMSA53371.2022.9853685]

**Research Question 2:** How can the adequacy of collected data be ensured during autonomous data collection with UAS and how can the training data be enhanced to introduce evidence of hazards necessary for UAS training, while minimizing the manual labor and costs of data collection?

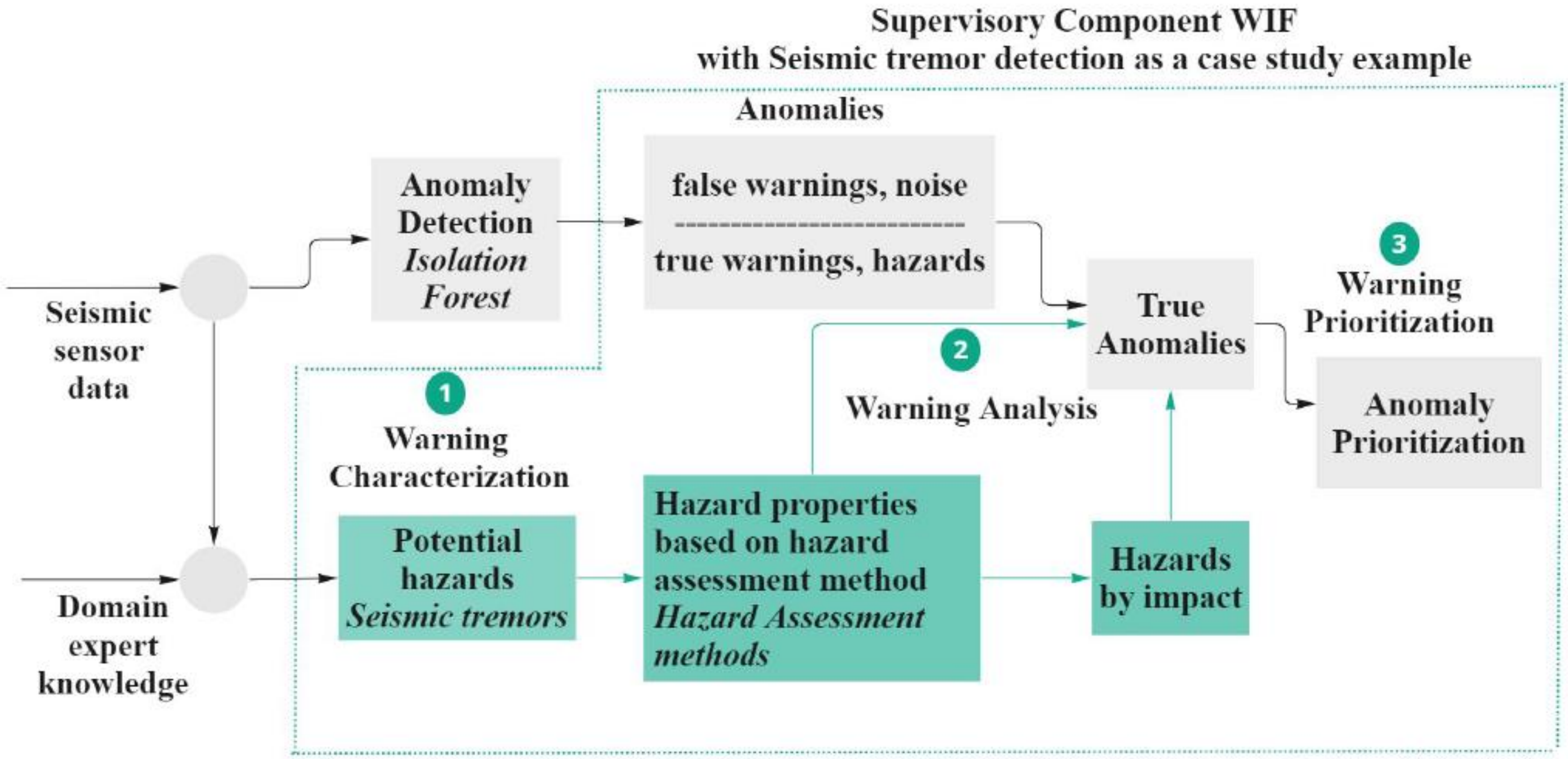
**Case Study 2:**
Analysis of dataset with sensor measurements for tracking and detecting seismic tremors with provided hazard analysis by domain specialists

- Three different methods of hazard analysis for recognizing seismic tremors:
  = Categories of hazards by their impact: no hazard, low-impact, medium-impact, high-impact

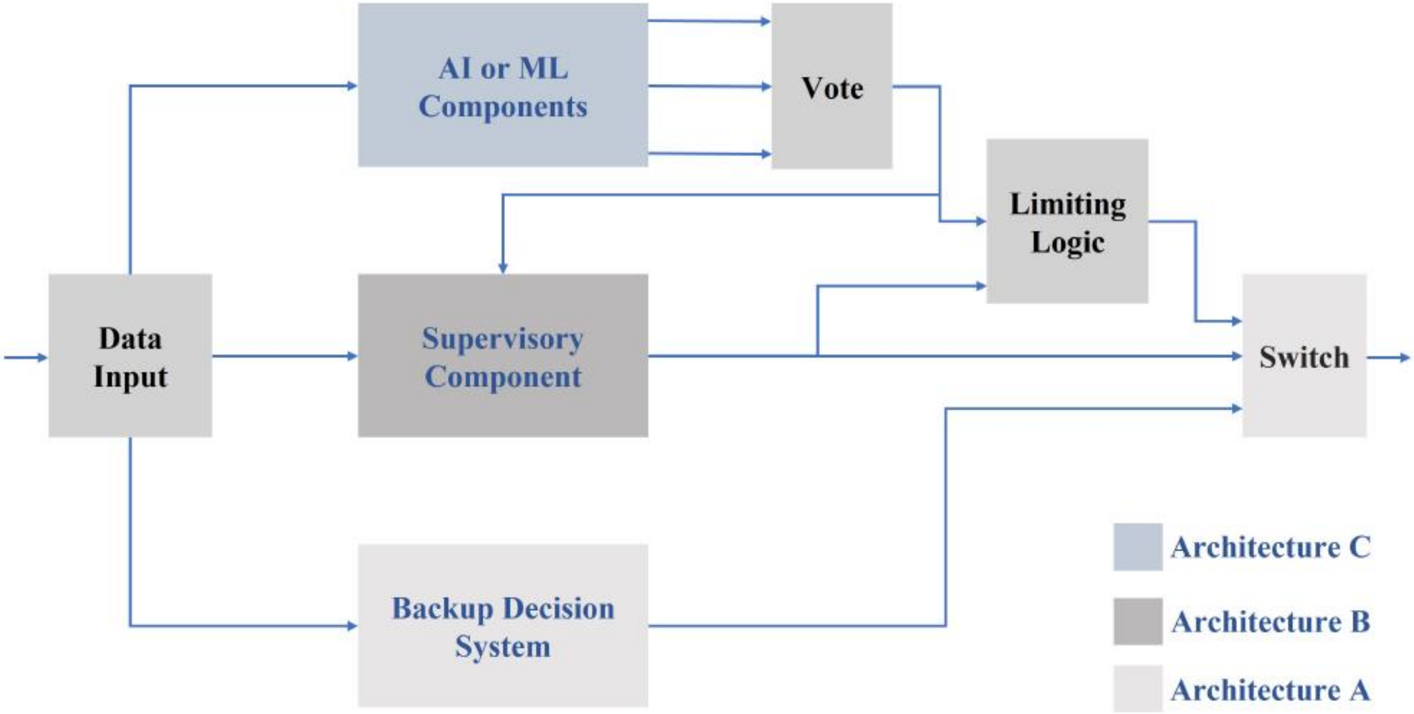
**Objective:** Use risk analysis to bring context to data and supervise detected anomalies to minimize noise anomalies, while not suffering the loss of hazard evidence in data

**Findings:**
- Distinction of hazards in detected anomalies and other anomalies
- Anomalies priorities according to hazard impacts
- A step to introduce context and reduce bias

[Ref. Spahic, Rialda; Hepsø, Vidar; Lundteigen, Mary Ann. A Novel Warning Identification Framework for Risk-Informed Anomaly Detection, Springer Nature Journal of Intelligent and Robotic Systems (June 2023) DOI: 10.1007/s10846-023-01887-2]




[Ref. Spahic, Rialda; Hepsø, Vidar; Lundteigen, Mary Ann. A Novel Warning Identification Framework for Risk-Informed Anomaly Detection, Springer Nature Journal of Intelligent and Robotic Systems (June 2023) DOI: 10.1007/s10846-023-01887-2]




**Architectural pattern for systems using AI, Adapted from ISO/IEC TR 5469 (draft)**

[Ref. Spahic, Rialda; Hepsø, Vidar; Lundteigen, Mary Ann. A Novel Warning Identification Framework for Risk-Informed Anomaly Detection, Springer Nature Journal of Intelligent and Robotic Systems (June 2023) DOI: 10.1007/s10846-023-01887-2]

# Result 3:
# Subsea Pipeline Visual Inspection of Anomalies

**Case Study 3:**

Creating synthetic data to increase the evidence of hazards in the data and train the image analysis model in recognizing pipeline damage.

**Objective:**

Propose a low-cost methodology to address lack of training data and increase the number of pipeline damage images, so that image anomaly detection method can learn the damage pattern.

**Findings:**

- Opportunity in creating training data with pipeline damage by only using the existing image data
- Enhanced explainability of algorithm by localizing anomaly on the image

[Ref. Image-based and risk-informed detection of Subsea Pipeline damage by Rialda Spahić, Kameshwar Poolla, Vidar Hepsø, and Mary Ann Lundteigen. Discover Artificial Intelligence, Springer Nature. June, 2023. DOI: 10.1007/s44163-023-00069-1]

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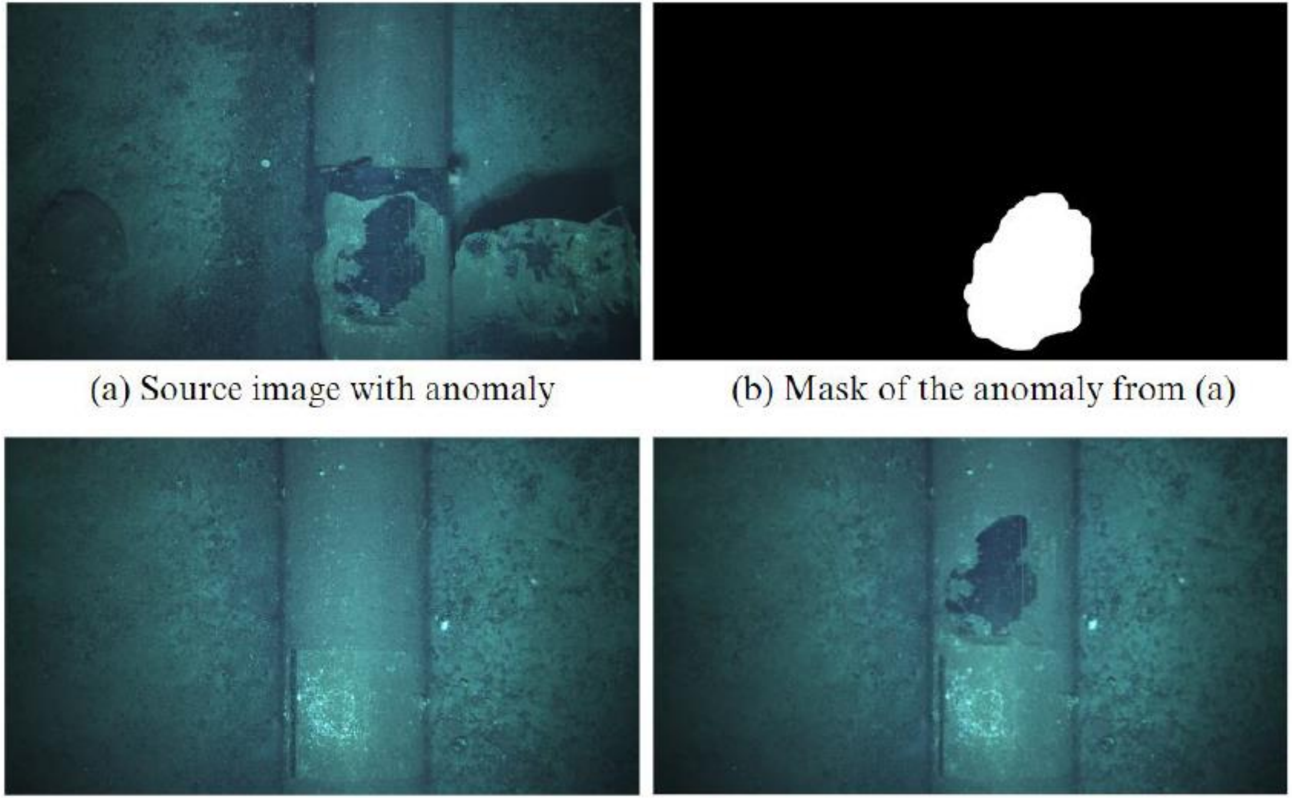


(a) Source image with anomaly

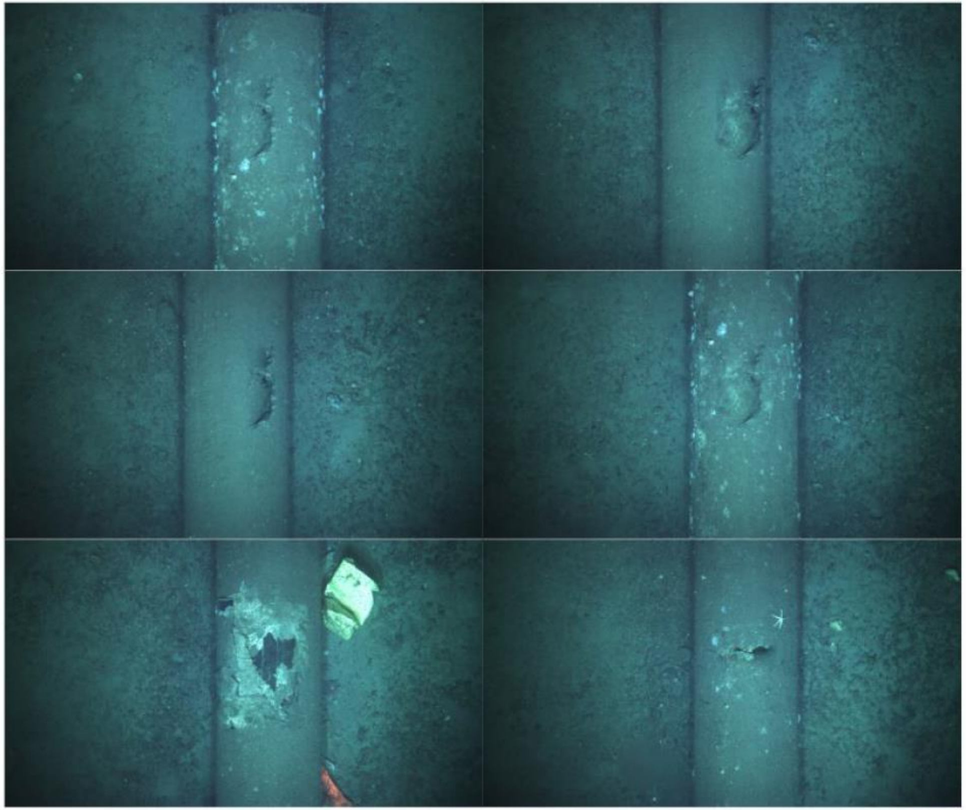
(b) Mask of the anomaly from (a)

(c) Destination image

(d) Result: Image after seamless blending

**Creating synthetic damage on real images**

[Ref. Image-based and risk-informed detection of Subsea Pipeline damage by Rialda Spahić, Kameshwar Poolla, Vidar Hepsø, and Mary Ann Lundteigen. Discover Artificial Intelligence, Springer Nature. June, 2023. DOI: 10.1007/s44163-023-00069-1]



**Synthetic damage on real images**

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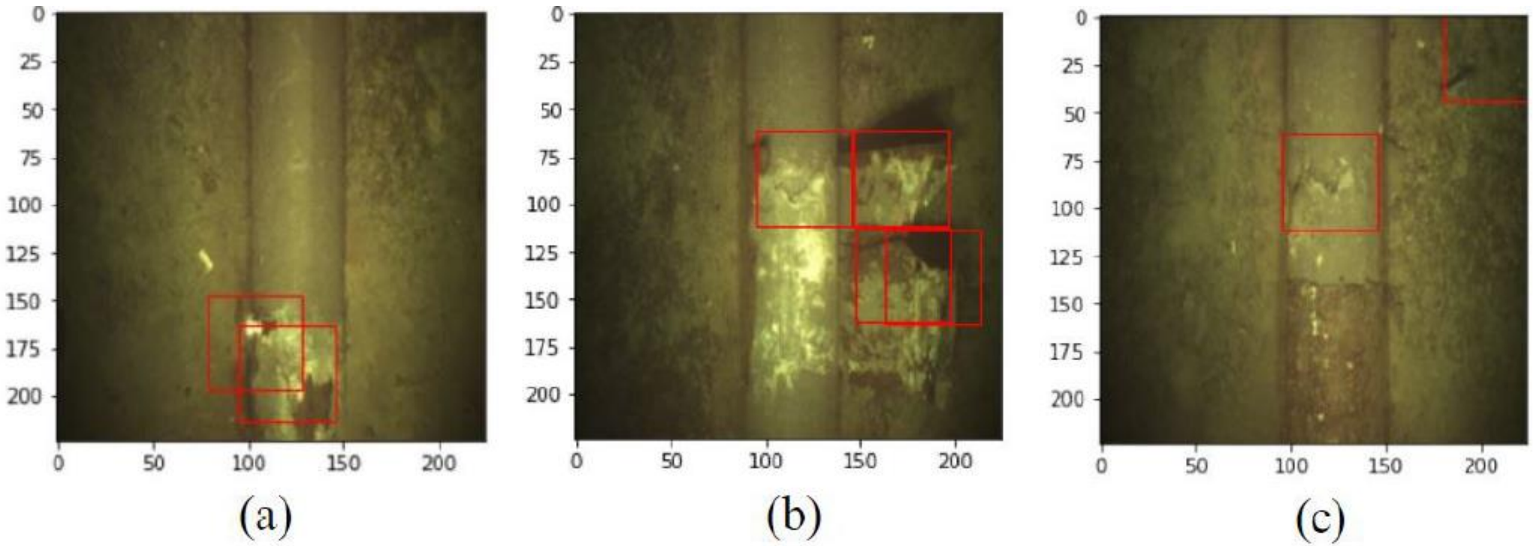



Localized mechanical damage

(a) Damage on pipeline

(b) Damage on pipeline + dislocated anode cover on the side of the pipeline

(c) Damage on pipeline + background noise

[Ref. Image-based and risk-informed detection of Subsea Pipeline damage by Rialda Spahić, Kameshwar Poolla, Vidar Hepsø, and Mary Ann Lundteigen. Discover Artificial Intelligence, Springer Nature. June, 2023. DOI: 10.1007/s44163-023-00069-1]

# New Models for Subsea Pipeline Inspection with UAS

## Conceptual categorization of Anomalies by Temporal Change

### 1 Frequent Anomalies

- Anomalies are deviations in data and are not frequent occurrences
- For subsea pipeline detection, anomalies can be recurring (i.e., biological growth covering early signs of material degradation)

### 2 Reappearing Anomalies

- Anomalies that disappear and reappear (i.e., seasonal changes in subsea environment) and may not necessitate additional resource allocation

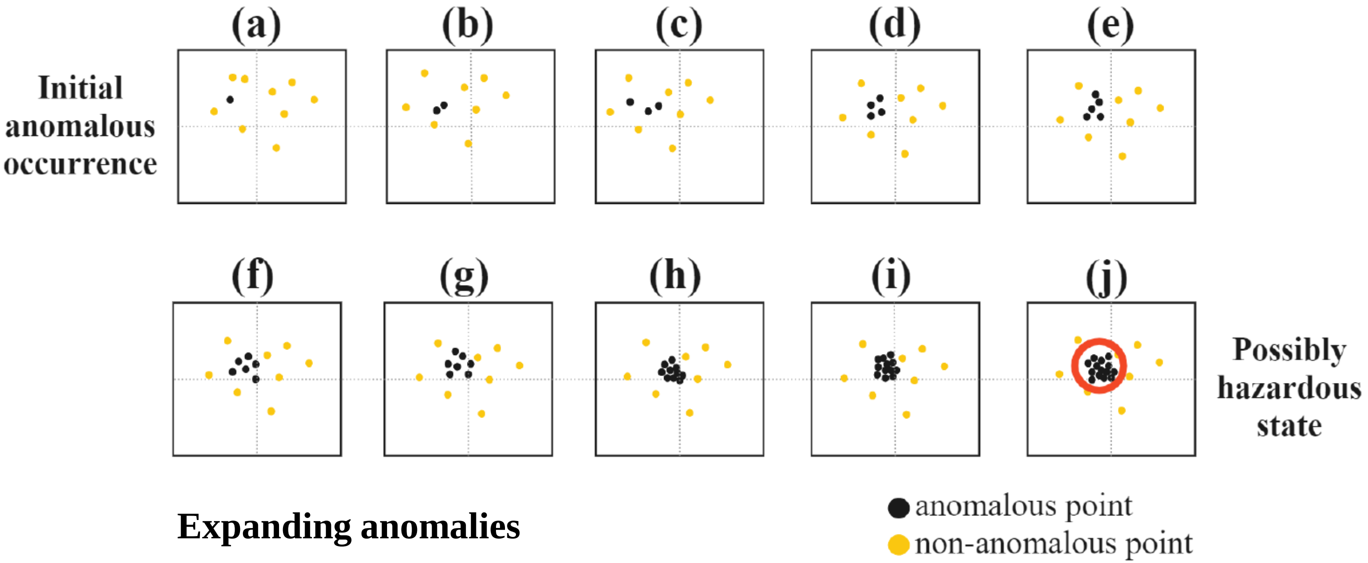
### 3 Expanding Anomalies

- Anomalies that evolve over time (i.e., expanding material degradation)
- Identify when the anomaly is reaching a possibly hazardous state

[Ref. Spahic, Rialda; Hepsø, Vidar; Lundteigen, Mary Ann, Enhancing Autonomous Systems' Awareness: Conceptual Categorization of Anomalies by Temporal Change During Real-Time Operations, The Eighteenth International Conference on Autonomic and Autonomous Systems (2022). ISSN: 2308-3913; ISBN: 978-1-61208-966-9]

**Research Question 3:** How can the image-based hazard detection with UAS be supplemented by utilizing varied data sources from sensor technologies for adaptive sensing, and how can anomaly classification be reimagined for the future of UAS subsea pipeline hazard detection?

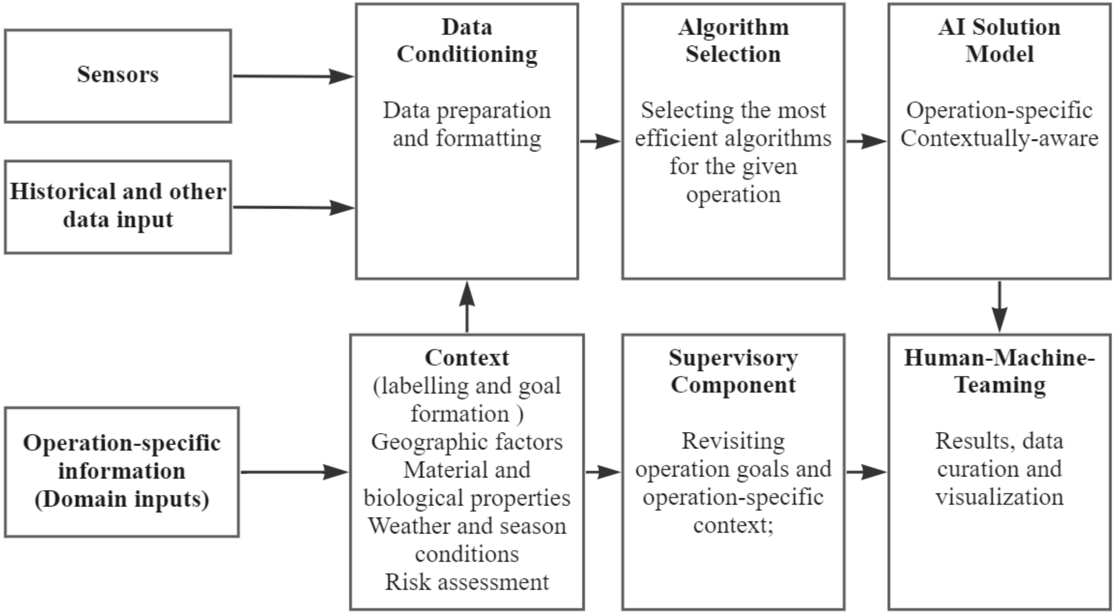
# Result 4:
# New Models for Subsea Pipeline Inspection with UAS




[Ref. Spahic, Rialda; Hepsø, Vidar; Lundteigen, Mary Ann, Enhancing Autonomous Systems' Awareness: Conceptual Categorization of Anomalies by Temporal Change During Real-Time Operations, The Eighteenth International Conference on Autonomic and Autonomous Systems (2022). ISSN: 2308-3913; ISBN: 978-1-61208-966-9]

**Research Question 3:** How can the image-based hazard detection with UAS be supplemented by utilizing varied data sources from sensor technologies for adaptive sensing, and how can anomaly classification be reimagined for the future of UAS subsea pipeline hazard detection?

# The need to supplement image-based inspection with adaptive sensor scheduling and context-based AI model




AI Model Architecture

[Ref. Spahic, R., Lundteigen, M.A., Hepsø, V. Context-based and image-based subsea pipeline degradation monitoring. Springer Nature Discover Artificial Intelligence 3, 17 (2023). DOI: 10.1007/s44163-023-00063-7]

C1 Spahic R., Hepsø V., Lundteigen M.A., **Reliable Unmanned Autonomous Systems: Conceptual Framework for Warning Identification during Remote Operations**, *IEEE International Symposium on Systems Engineering (ISSE), September 2021*, DOI: 10.1109/ISSE51541.2021.9582534

C2 Spahic R., Hepsø V., Lundteigen M.A., **Using Risk Analysis for Anomaly Detection for Enhanced Reliability of Unmanned Autonomous Systems**, *Proceedings of the 32nd European Safety and Reliability Conference (ESREL) - Dublin, 2022*, ISBN: 978-981-18-5183-4

C3 Spahic R., Lundteigen M.A., **Manually or Autonomously Operated Drones: Impact on Sensor Data towards Machine Learning**, *IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), 2022*, ISBN: 978-1-6654-3445-4

C4 Spahic R., Hepsø V., Lundteigen M.A., **A Novel Warning Identification Framework for Risk-Informed Anomaly Detection**, *Springer Nature Journal of Intelligent and Robotic Systems, 108, 17*. June, 2023. DOI: 10.1007/s10846-023-01887-2

C5 Spahic R., Poolla K., Hepsø V., Lundteigen M.A., **Image-based and risk-informed detection of Subsea Pipeline damage**, *Springer Nature, Discover Artificial Intelligence*. June, 2023. DOI: 10.1007/s44163-023-00069-1

C6 Spahic R., Hepsø V., Lundteigen M.A., **Enhancing Autonomous Systems' Awareness: Conceptual Categorization of Anomalies by Temporal Change During Real-Time Operations**, *The Eighteenth International Conference on Autonomic and Autonomous Systems, 2022*, ISBN: 978-1-61208-966-9

C7 Spahic, R., Lundteigen, M.A., Hepsø, V. **Context-based and image-based subsea pipeline degradation monitoring.** *Springer Nature, Discover Artificial Intelligence 3, 17*. May, 2023. DOI: 10.1007/s44163-023-00063-7

# Overview of Contributions

## *Journal articles:*

1. Springer Nature Discover Artificial Intelligence (2023)
2. Springer Nature Journal of Intelligent and Robotic Systems (2023)
3. Springer Nature Discover Artificial Intelligence (2023)

## *Conference articles:*

1. IEEE International Symposium on Systems Engineering (2021)
2. 32nd European Safety and Reliability Conference (2022)
3. IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications (2022)
4. 18th Conference on Autonomic and Autonomous Systems (2022)

# How far have we come?

## *Reflecting on Research limitations*

1. It is necessary to test the proposed methods with more case studies.
2. More extensive datasets with pipeline images, videos, and sensor measurements should be used for testing the proposed methods (i.e., seismic tremor case study).
3. Subsea pipeline images are analyzed with low computational power and suffer from a loss of information.

# Conclusion and the Way Forward

- Adopting domain knowledge-exchange and having a multidisciplinary approach shows opportunity in mitigating AI shortcomings

- It is critical to gain experience through extensive testing and development of the novel technologies, and revision of standards and legal acts on responsible AI

Tackle research limitations and expand theoretical proposals:

- Expand and test proposed approaches
- Simulation of real-time anomaly detection
- Detect multiple anomalies
- Increase focus on explainability of the applied AI methods

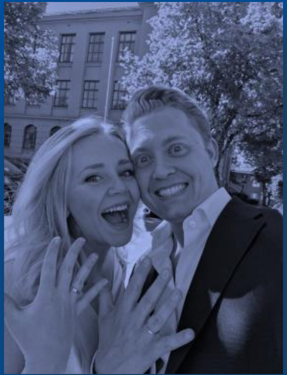





# Thank you for the journey





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# Thank you for your attention

## Risk-Informed
## Artificial Intelligence for
## Autonomous Inspection on Subsea Pipelines


| | |
|---|---|
| PhD Candidate | Rialda Spahić |
| Supervisor | Mary Ann Lundteigen |
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