CMM560 Topic 2: Computer Vision-Related Problems in the Energy Sector

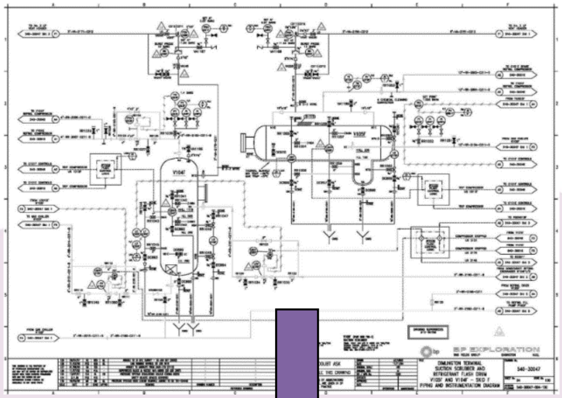
Digitising and Contextualising Complex Engineering Diagrams for Facility Inspection

Principal Supervisor: Prof Eyad Elyan

Collaborators: Laura Jamieson (PhD student), Ikenna Ekeke (PhD Student), Luis Toral Quijas (MRes student, graduated), Elena Rica (PhD student at URV, graduated)

The Problem

Complex Engineering Drawing (CED)



Standardised Parts Count

Event	Equip[illegible]ategory	Size	Number
JDY/CELLAR/RJAS/W	Piping	16	
JDY/CELLAR/RJAS/W	Act. Valve	16	0.5
JDY/CELLAR/JASIN/W	Piping	16	
JDY/CELLAR/JASIN/W	Act. Valve	16	0.5
JDY/PROC/JASIN/W	Piping	16	
JDY/PROC/JASIN/W	Act. Valve	16	2
JDY/PROC/JASIN/W	Flange	16	7
JDY/PROC/JASIN/W	Piping	6	
JDY/PROC/JASIN/W	Man Valve	16	3
JDY/PROC/JASIN/W	Piping	2	
JDY/PROC/JASIN/W	Flange	2	2
JDY/PROC/JASIN/W	Inst. Con.	2	2
JDY/PROC/JASIN/W	Man Valve	6	0.5

DNV

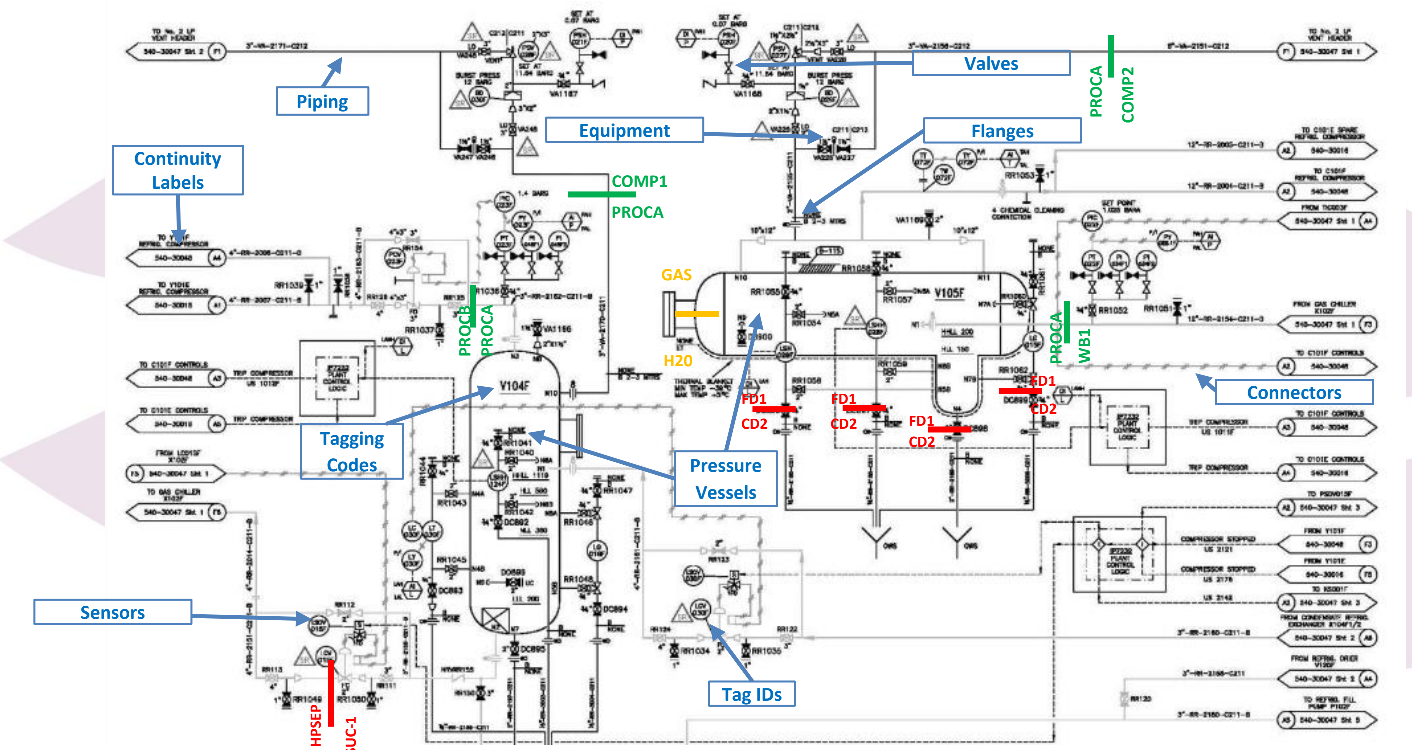
THE DATA LAB value from data

Oil & Gas Innovation Centre

-RGU and DNV GL join forces to create cost-saving image processing software. Available at https://cfmgcomputing.blogspot.com/2018/06/rgu-and-dnv-gl-join-forces-to-create.html

-OGIC backs digital Research projects to tune of £500k. Available at https://cfmgcomputing.blogspot.com/2018/09/ogic-backs-digital-research-projects-to.html

Information in a CED



Additional data

Change of Installation Area

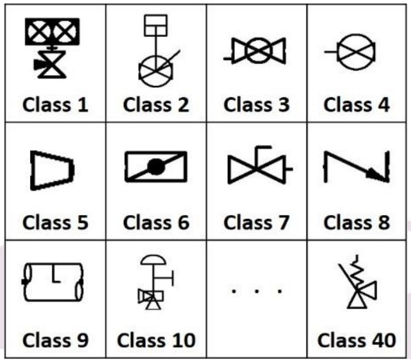
Change of Process Section

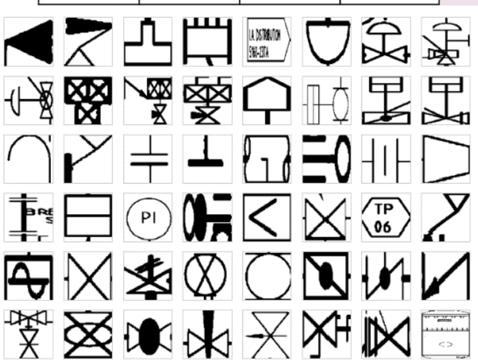
Change of Composition

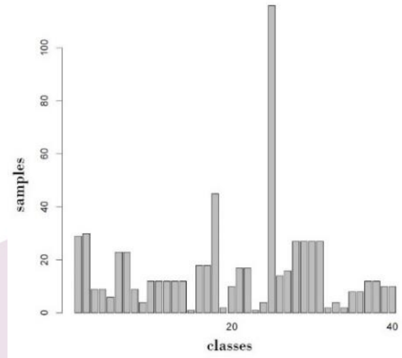
-Moreno-García, C. F., Elyan, E., & Jayne, C. (2018). New trends on digitisation of complex engineering drawings. Neural Computing and Applications, 1–18. https://doi.org/10.1007/s00521-018-3583-1

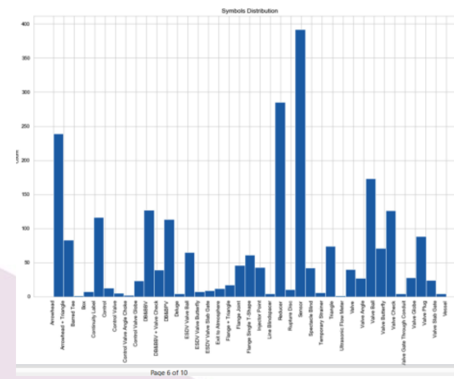
-Jamieson, L., Moreno-García, C. F., & Elyan, E. (2024). A review of deep learning methods for digitisation of complex documents and engineering diagrams. Artificial Intelligence Review, 1–37. https://doi.org/10.1007/s10462-024-10779-2

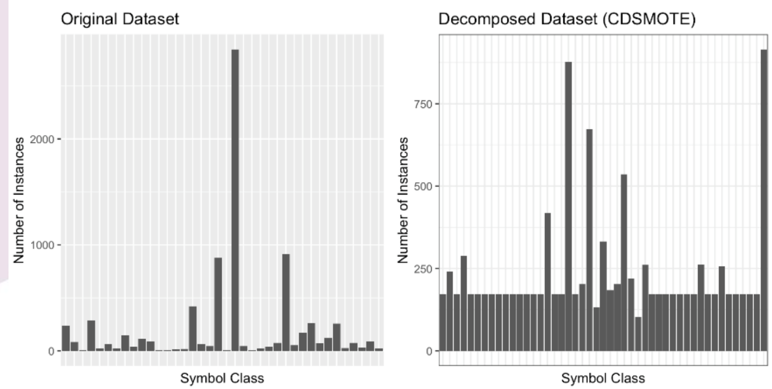
Symbols Detection & Classification











-Elyan, E., Moreno-García, C. F., & Jayne, C. (2018). Symbols Classification in Engineering Drawings. In International Joint Conference in Neural Networks (IJCNN). Available at https://www.researchgate.net/publication/327791936_Symbols_Classification_in_Engineering_Drawings.

-Elyan, E., Moreno-García, C. F. & Johnston P. (2020). Symbols in Engineering Drawings (SiED): An Imbalanced Dataset Benchmarked by Convolutional Neural Networks. In: *Engineering Applications of Neural Networks (EANN)*. ; 2020:215-224. https://doi.org/10.1007/978-3-030-48791-1.

-Jamieson, J., Moreno-García, C. F. & Elyan, E. (2024). A multiclass imbalanced dataset classification of symbols from piping and instrumentation diagrams", In: Barney Smith, E.H., Liwicki, M., Peng, L. (eds). International Conference on Document Analysis and Recognition (ICDAR 2024). Lecture Notes in Computer Science, vol 14804, pp. 3-16. Springer, Cham. https://doi.org/10.1007/978-3-031-70533-5_1.

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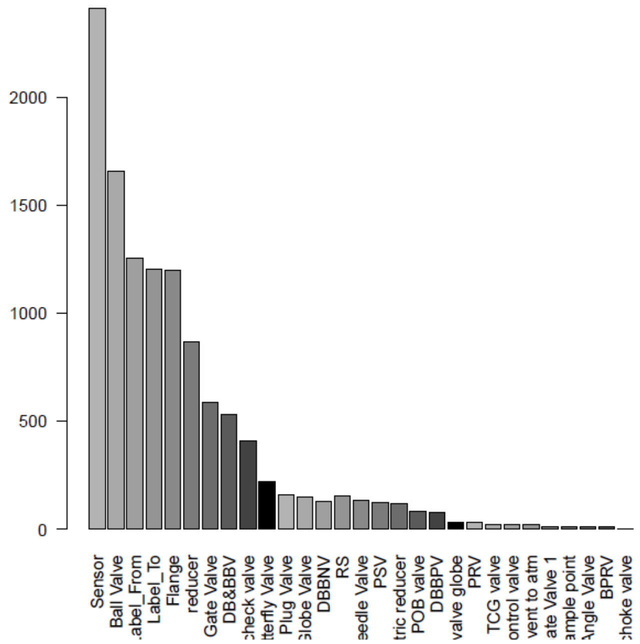
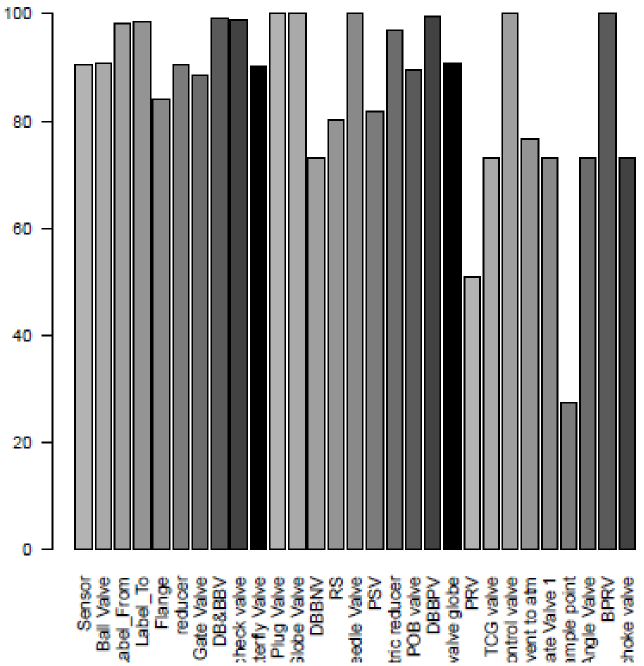
Distribution vs Precision

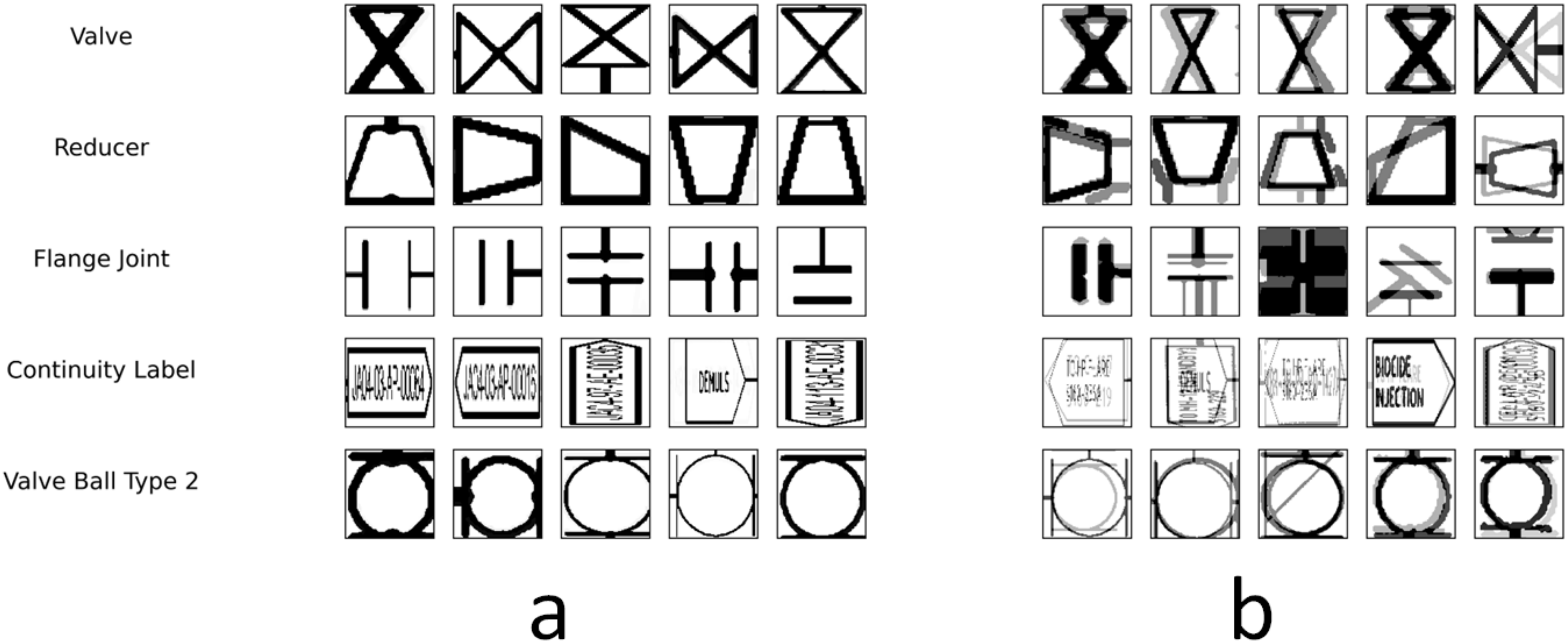
Class Distribution



Class Precision



Artificially Generated Symbols



Data Extraction Tool (DET)

-Moreno-García, C. F., Elyan, E., & Jayne, C. (2017). Heuristics-Based Detection to Improve Text/Graphics Segmentation in Complex Engineering Drawings. In Engineering Applications of Neural Networks (Vol. CCIS 744, pp. 87–98). https://doi.org/10.1007/978-3-319-65172-9_8

Data Contextualisation

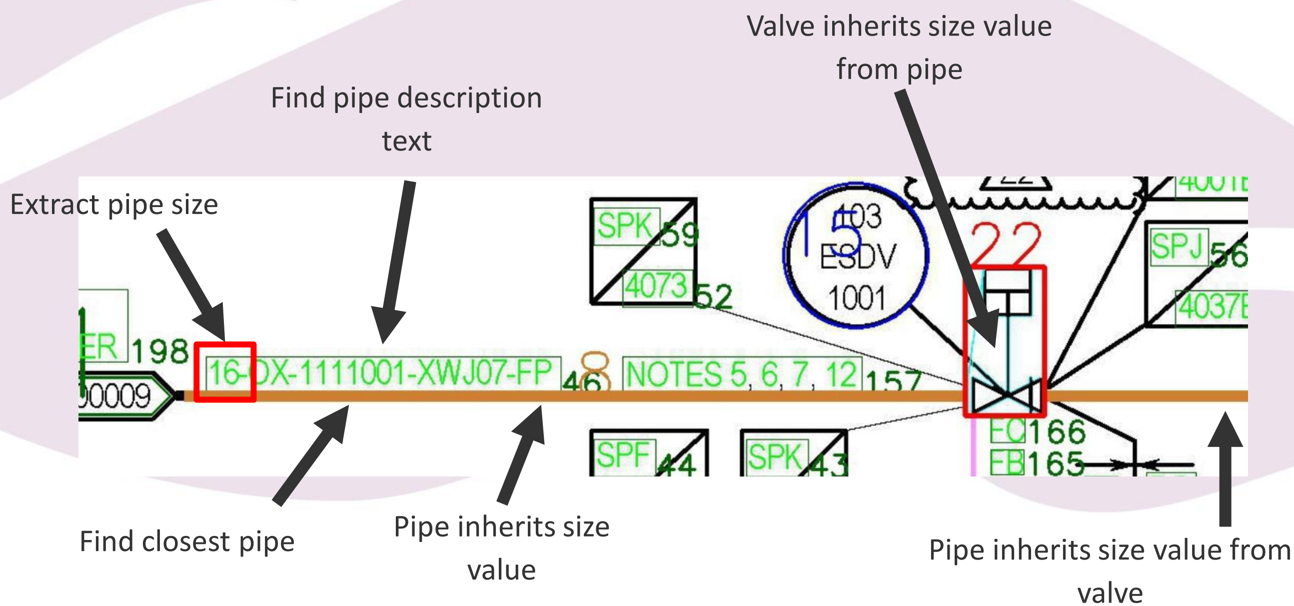
- Converting the netlist into the proper standard.

Number	Tag	x	y	w	h	Pointing	Location
1	JA03-03-AP-00009	182	3872	284	61	right	A5
2	JA04-03-AP-00131	182	2448	284	61	right	A3
Sensors							
Number	Tag	x	y	r	Location		
1	103-TT-1182	2564	2748	70	C4		
2	103-PT-1013	4224	1548	66	E2		
Equipment symbols							
Number	Class	x	y	w	h	Location	
1	Flange Joint 2 (Horizontal)	3089	4125	49	25	D5	
2	Barred Tee	2697	3863	94	52	C5	
Pipelines							
Number	Orientation	x1	y1	x2	y2	Thickness	Location
1	horizontal	1990	2479	2317	2479	4	C3
2	horizontal	467	2479	1885	2479	4	B3
Text Strings							
Number	Reading	x	y	w	h	Location	
1	41 058	2670	4316	74	36	C5	
2	40418	2516	4312	84	36	C5	
3	40058	2360	4312	84	36	C5	

Event	Equipment Category	Size	Number
JDY/CELLAR/RJAS/W	Piping	16	
JDY/CELLAR/RJAS/W	Act. Valve	16	0.5
JDY/CELLAR/JASIN/W	Piping	16	
JDY/CELLAR/JASIN/W	Act. Valve	16	0.5
JDY/PROC/JASIN/W	Piping	16	
JDY/PROC/JASIN/W	Act. Valve	16	2
JDY/PROC/JASIN/W	Flange	16	7
JDY/PROC/JASIN/W	Piping	6	
JDY/PROC/JASIN/W	Man Valve	16	3
JDY/PROC/JASIN/W	Piping	2	
JDY/PROC/JASIN/W	Flange	2	2
JDY/PROC/JASIN/W	Inst. Con.	2	2
JDY/PROC/JASIN/W	Man Valve	6	0.5

Data Contextualisation

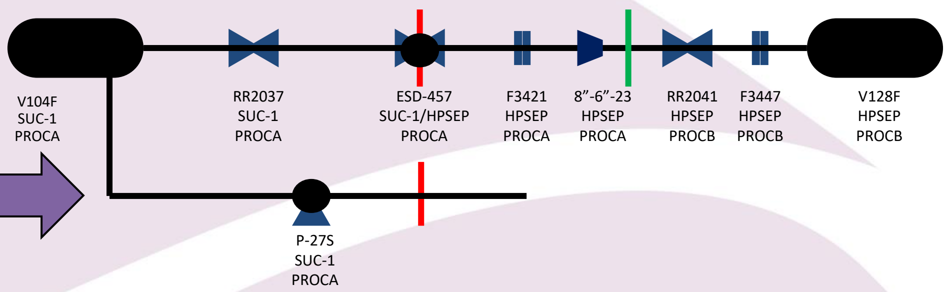
- Data Inheritance.



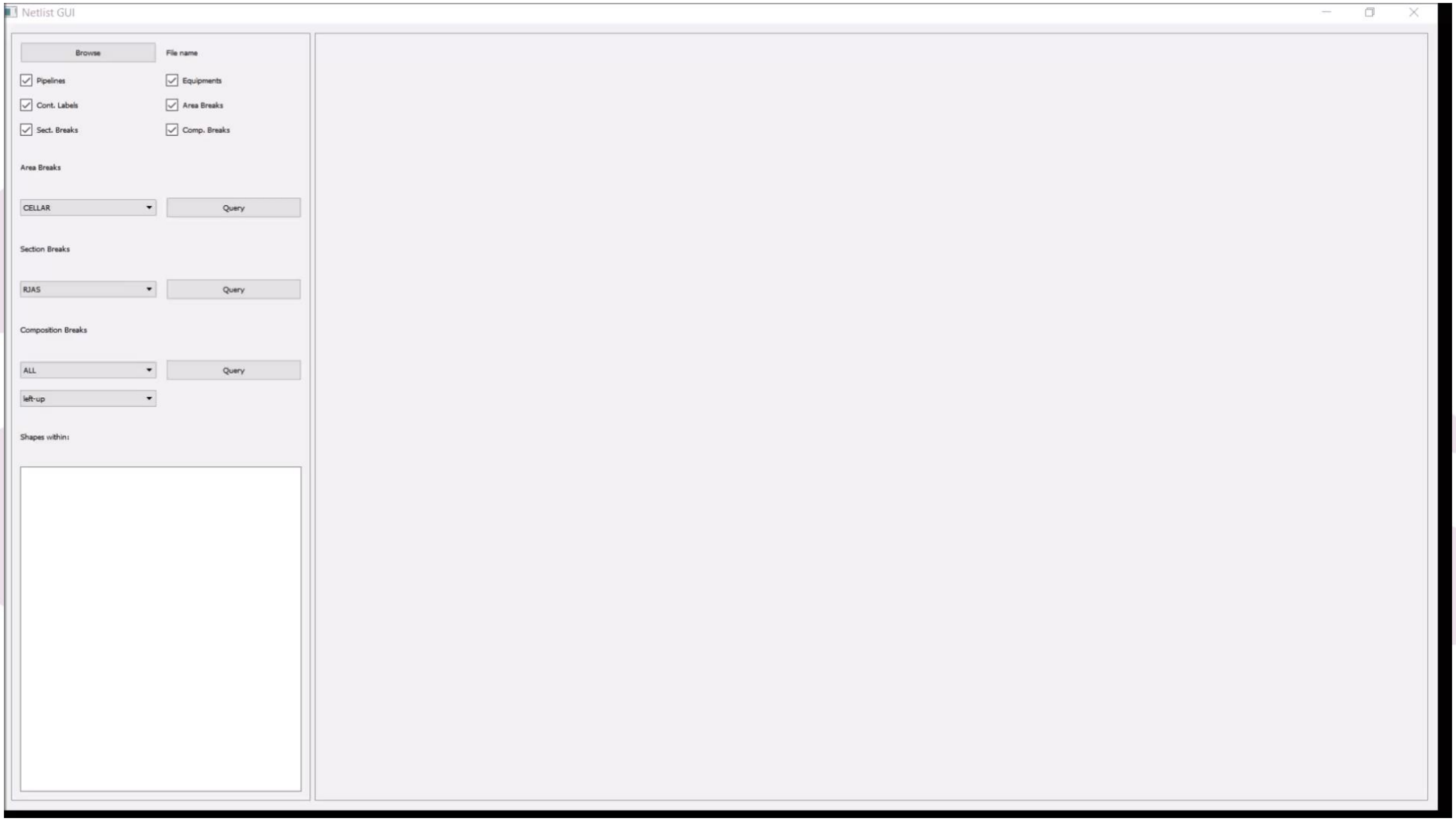
Data Visualisation

- Analysis of sub-sections.

Event	Area	Section	Stream	Type	SIZE	No./Len	TAG
PROCA/SUC-1/G	PROCA	SUC-1	S-23	H-VESS	8	0.6	V104F
PROCA/SUC-1/G	PROCA	SUC-1	S-23	M-VAL	8	1	RR2037
PROCA/SUC-1/G	PROCA	SUC-1	S-23	ESD-VAL	8	0.5	ESD-457
PROCA/SUC-1/G	PROCA	SUC-1	S-23	PIPE	8	4	-
PROCA/SUC-1/C	PROCA	SUC-1	S-27	H-VESS	4	0.4	V104F
PROCA/SUC-1/C	PROCA	SUC-1	S-27	PUMP	4	1	P-27S
PROCA/SUC-1/C	PROCA	SUC-1	S-27	PIPE	4	6	-
PROCA/HPSEP/G	PROCA	HPSEP	S-23	ESD-VAL	8	0.5	ESD-457
PROCA/HPSEP/G	PROCA	HPSEP	S-23	FLANGE	8	1	8"-6
PROCA/HPSEP/G	PROCA	HPSEP	S-23	PIPE	8	3.5	-
PROCA/HPSEP/G	PROCA	HPSEP	S-23	PIPE	6	2	-
PROCB/HPSEP/G	PROCB	HPSEP	S-23	REDUCER	8-6	1	RR2041
PROCB/HPSEP/G	PROCB	HPSEP	S-23	FLANGE	6	1	F3447
PROCB/HPSEP/G	PROCB	HPSEP	S-23	V-VESS	6	1	V128F
PROCB/HPSEP/G	PROCB	HPSEP	S-23	PIPE	6	3	-

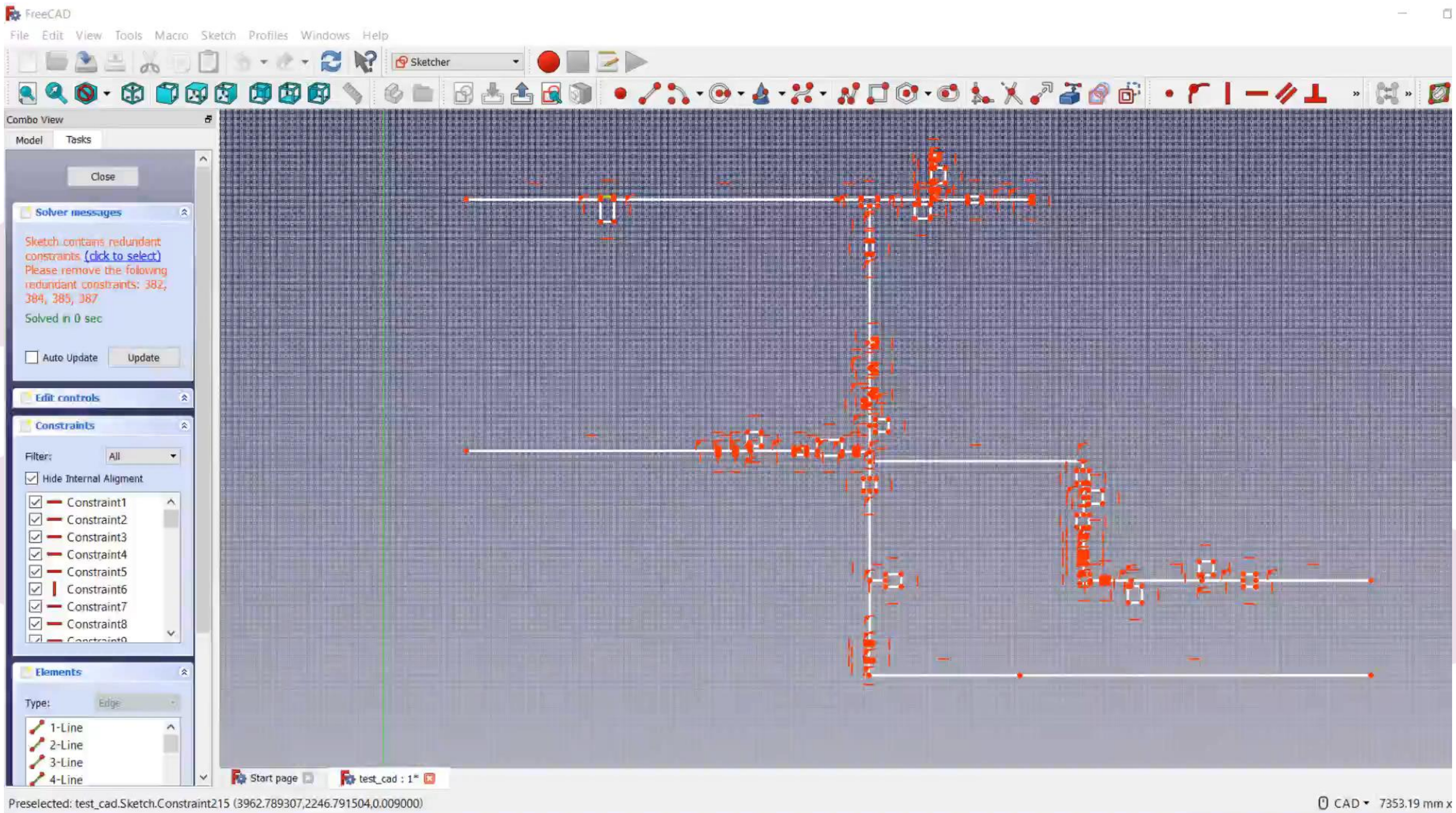


Netlist Visualizer



-Njoku, I. (2018). Visualising Subsections of Digital Assets from the Oil & Gas Industry using Graph Representations. Ms. C. Thesis. Supervisor: Moreno-García, C. F.

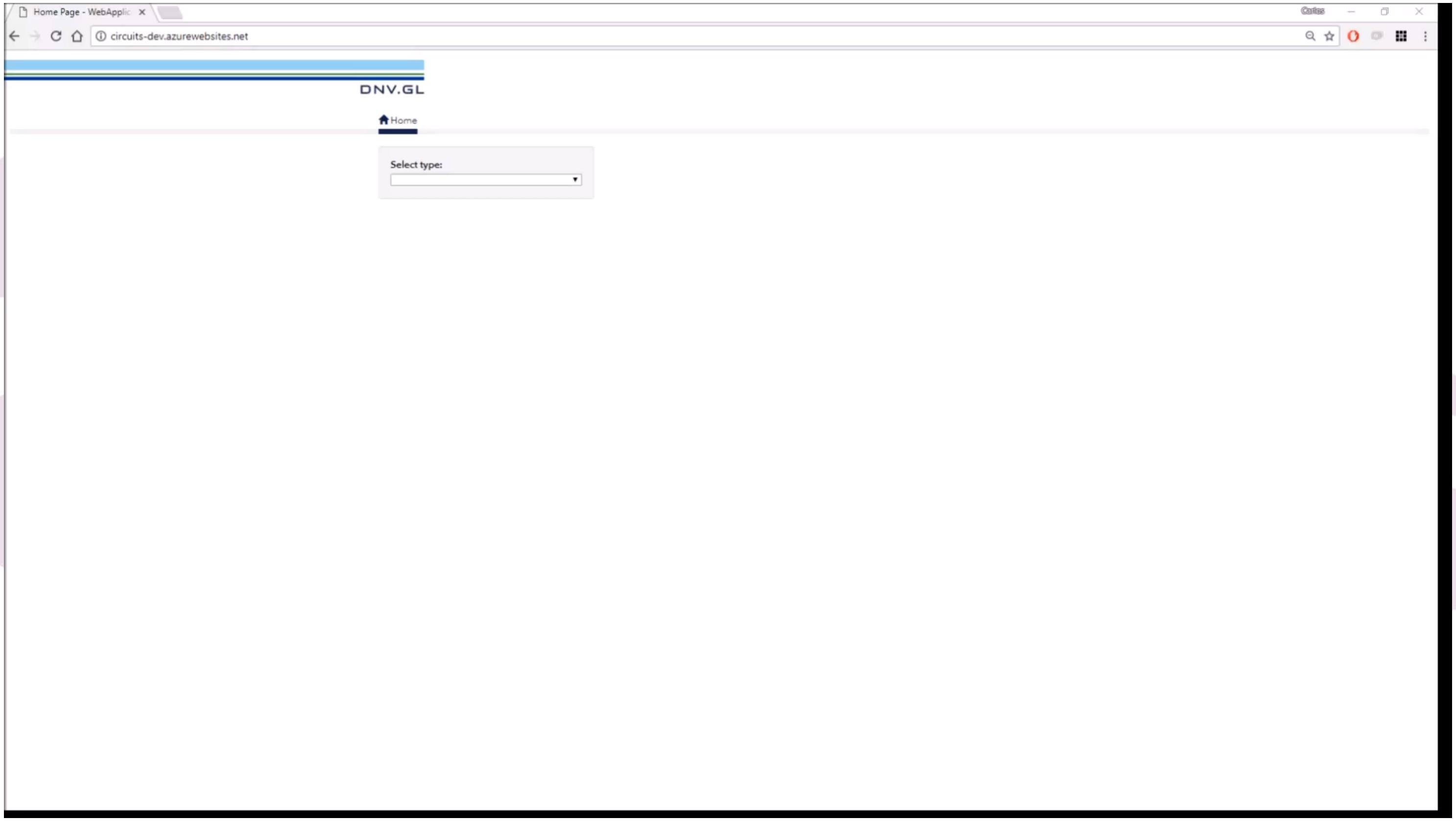
Netlist2CAD



-Chybowski, B.. (2018). Netlist2CAD. Standalone project. Supervisor: Moreno-García, C. F.

Sensor-Equipment Diagram Digitisation

DEMO AVAILABLE AT: http://cfmgcomputing.blogspot.com/p/circuits-dev-digitisation-tool.html



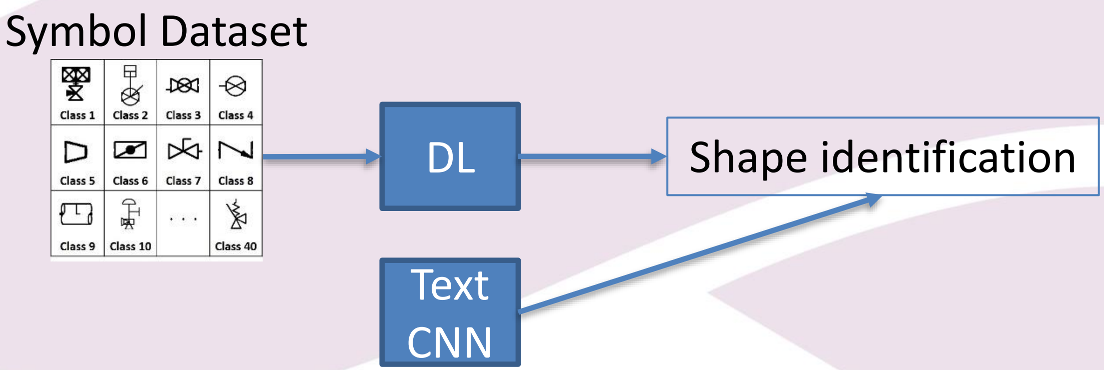
-Moreno-García, C. F., Digital interpretation of sensor-equipment diagrams, Proceedings of the SICSA Workshop on Reasoning, Learning and Explainability (ReaLX 2018), Aberdeen, Scotland, CEUR Workshop Proceedings, vol. 2151, http://ceur-ws.org/Vol-2151/Paper_s2.pdf

Corrosion Mark-up

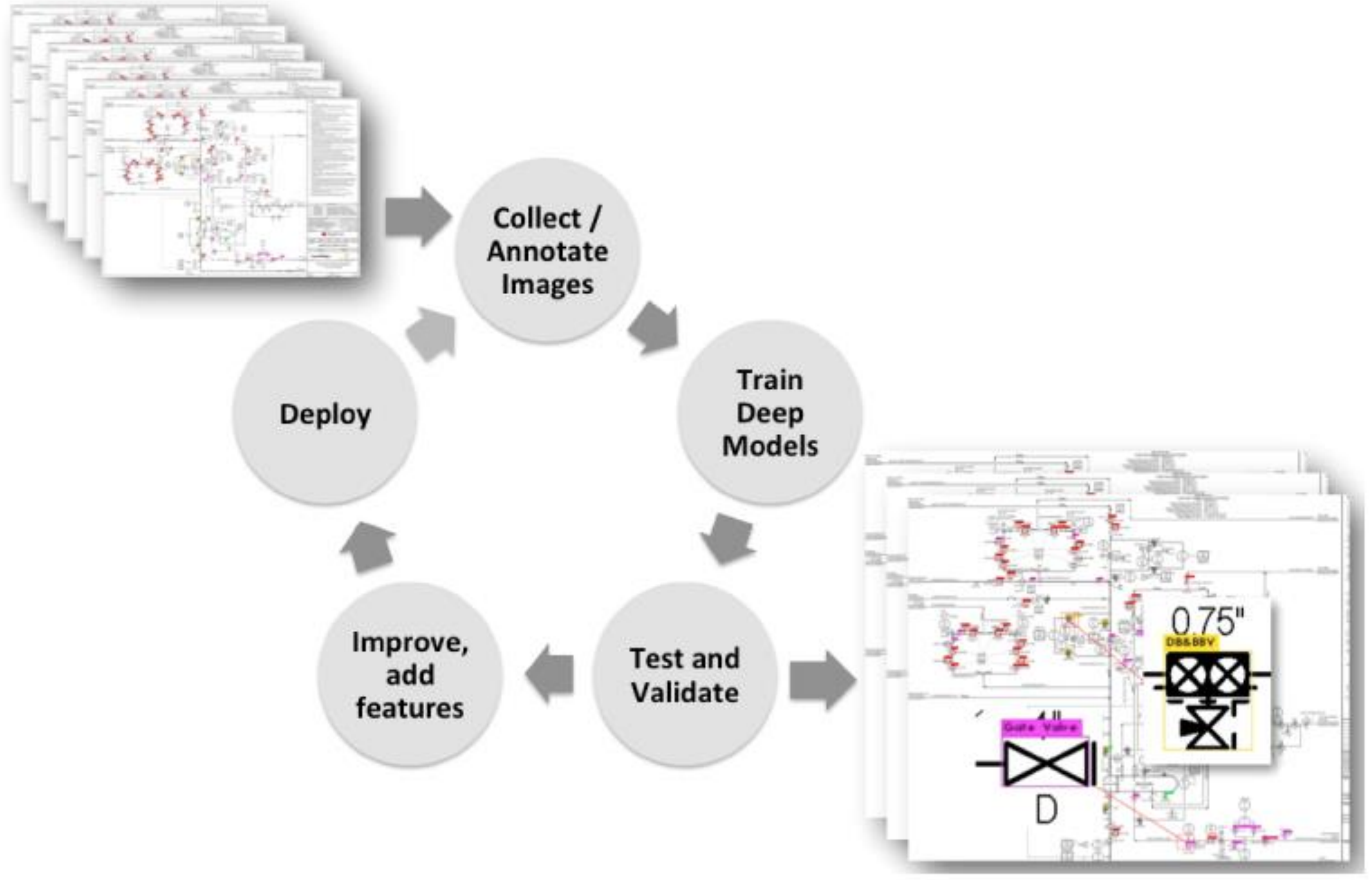
INNOVATION VOUCHERS

-Toral, L., Moreno-García, C. F., Elyan, E., & Memon, S. (2021). A Deep Learning Digitisation Framework to Mark up Corrosion Circuits in Piping and Instrumentation Diagrams. *WIADAR*, *LNCS 12917*, 268–276. https://doi.org/10.1007/978-3-030-86159-9

DL for shape detection and classification



Framework



Collect / Annotate Images
Train Deep Models
Test and Validate
Improve, add features
Deploy
0.75"
D

Text Detection

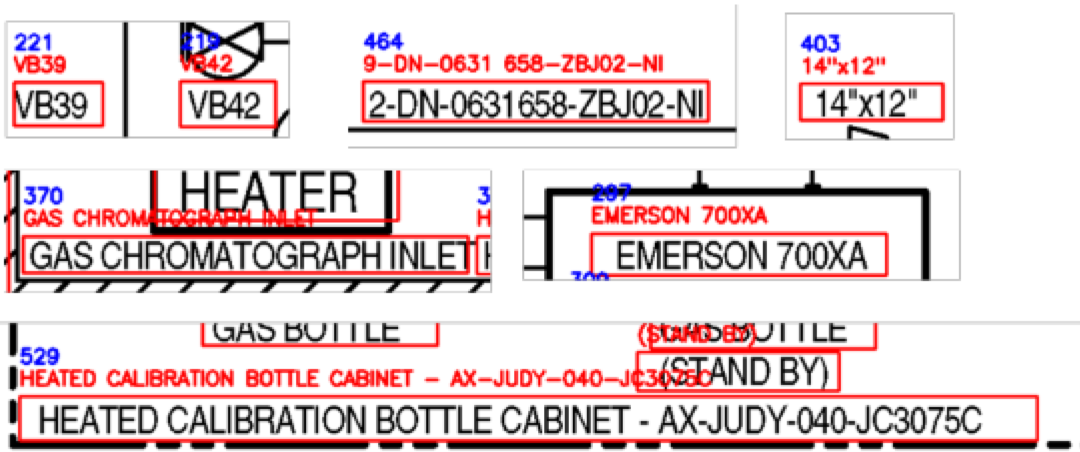
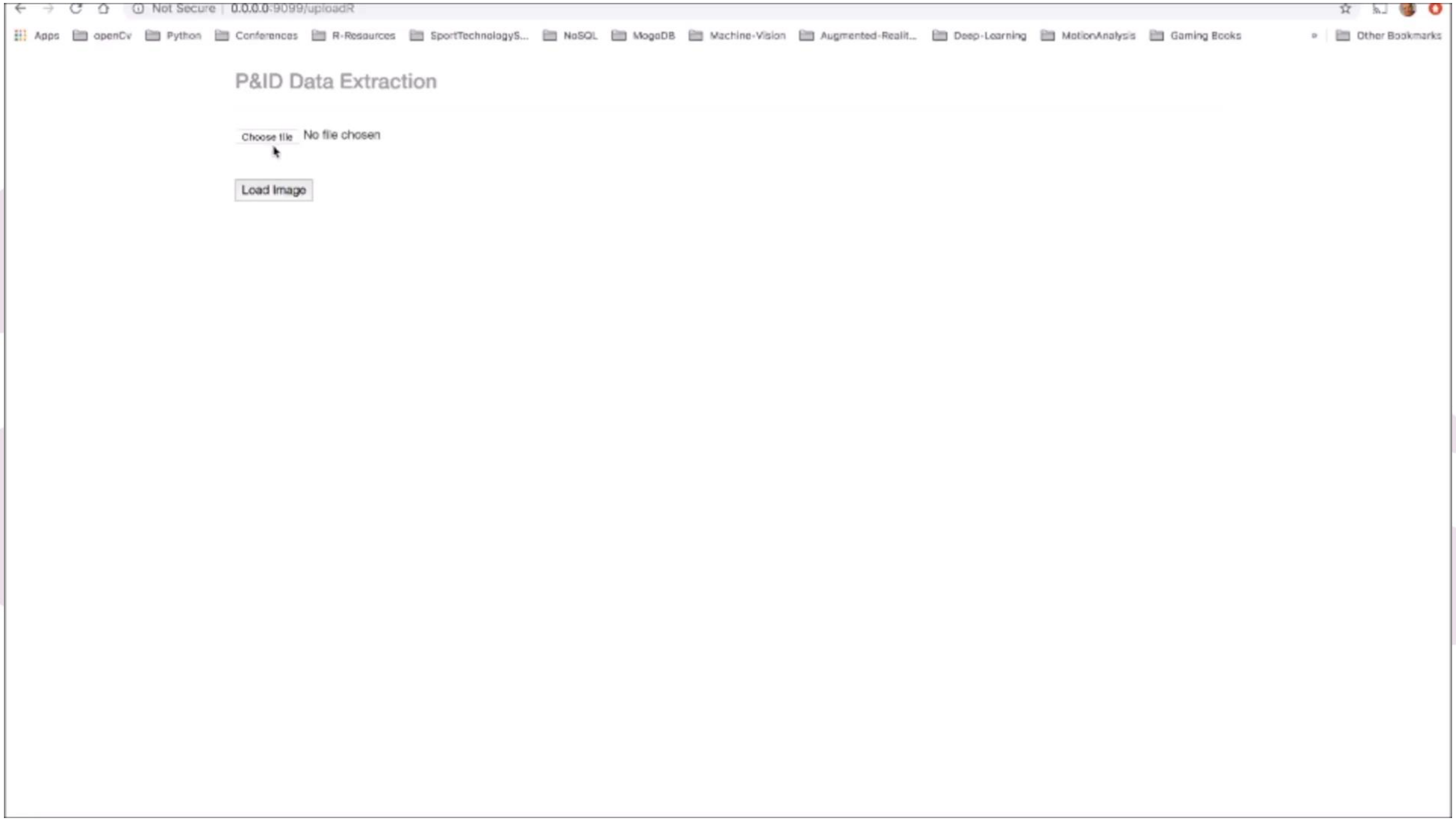


Diagram No.	Text Instances	Detected	FN	FP	Recognised
1	426	388	54	16	337
2	492	463	42	13	384
3	545	506	61	22	439
4	407	385	37	15	333
5	201	194	16	9	167

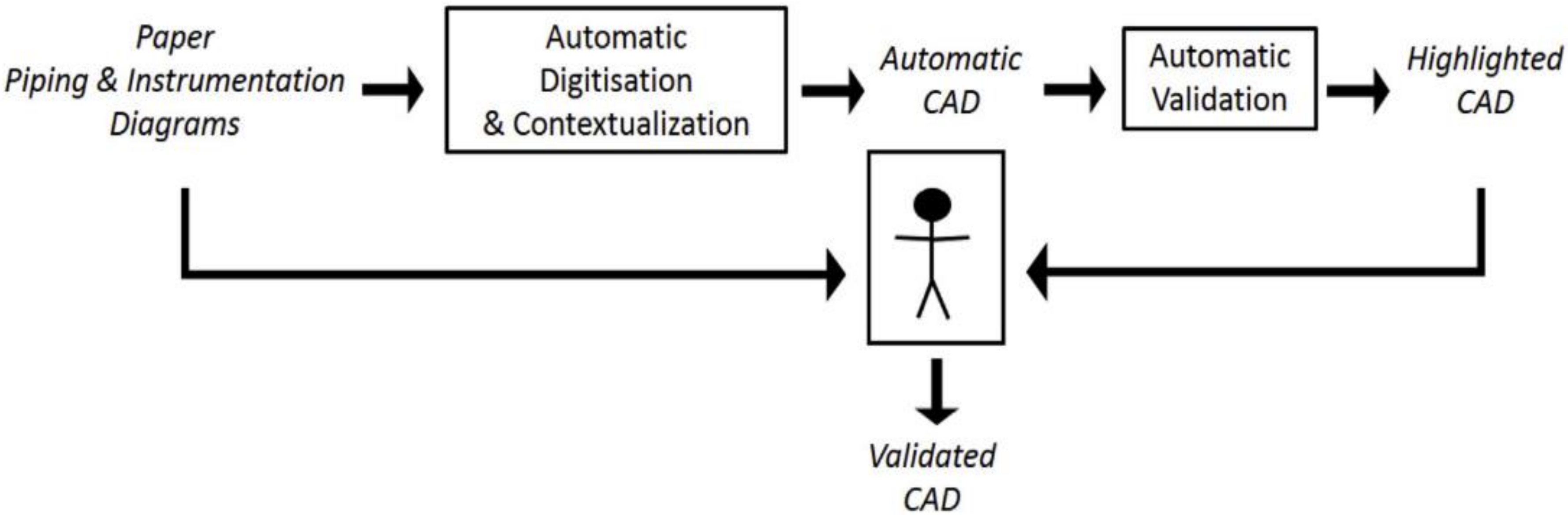
-Jamieson, L., Moreno-García, C. F., & Elyan, E. (2020). Deep learning for text detection and recognition in complex engineering diagrams. International Joint Conference on Neural Networks (IJCNN). https://doi.org/https://doi.org/10.1109/IJCNN48605.2020.9207127

Results



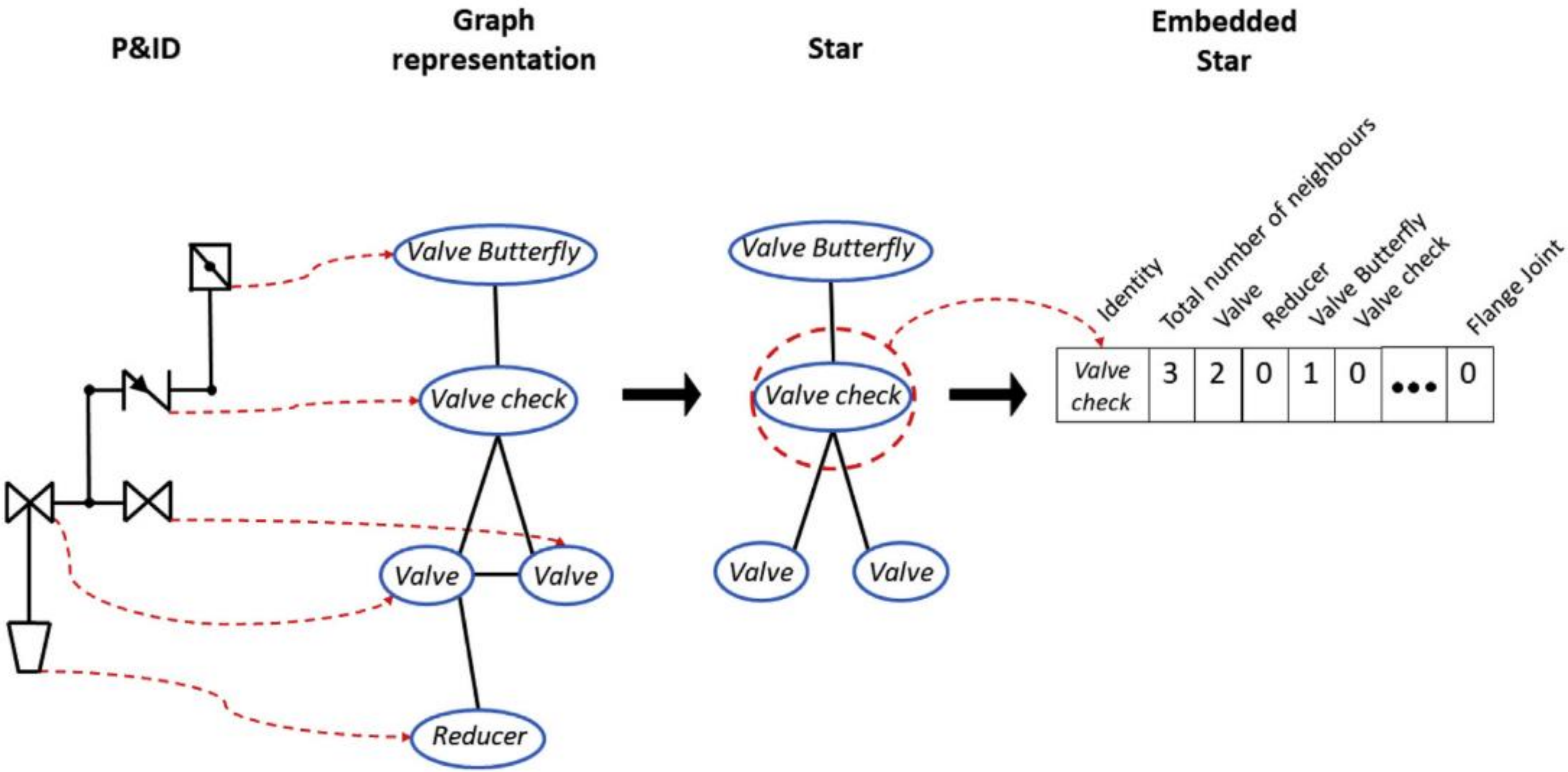
-Elyan E, Jamieson L, Ali-Gombe A. Deep learning for symbols detection and classification in engineering drawings. *Neural Networks*. 2020;129:91-102. http://doi.org/10.1016/j.neunet.2020.05.025

GNNs for automated error correction



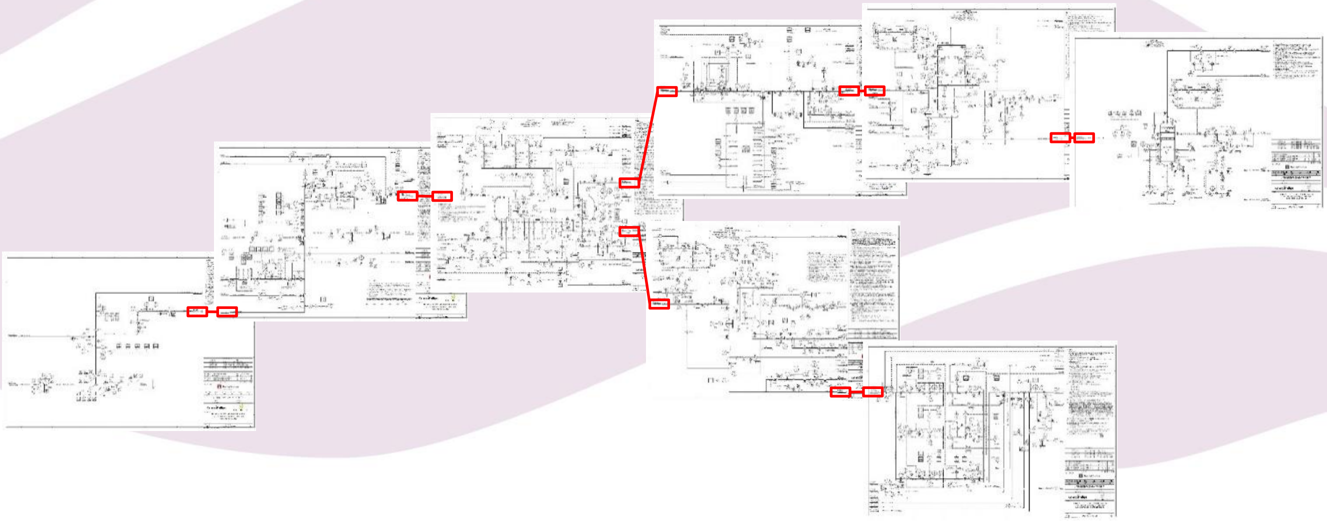
-Rica E, Moreno-García CF, Álvarez S, Serratosa F. Reducing human effort in engineering drawing validation. *Computers in Industry*. 2020;117.
http://doi.org/10.1016/j.compind.2020.103198

GNNs for automated error correction



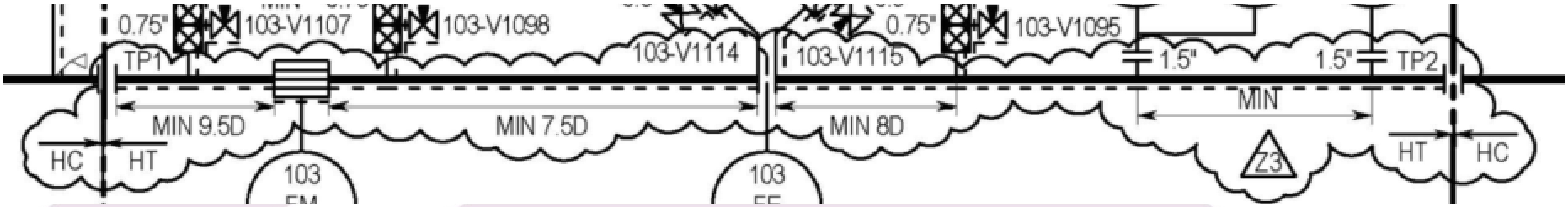
Linking Drawings

Proposed solution: Graph Representations.



-Moreno-García, C.F., Elyan, E., "Digitisation of Assets from the Oil & Gas Industry: Challenges and Opportunities," in International Conference on Document Analysis and Recognition (ICDAR), Workshop on Industrial Applications of Document Analysis and Recognition (WIADAR), pp. 16–19, 2019. https://doi.org/10.1109/ICDARW.2019.60122

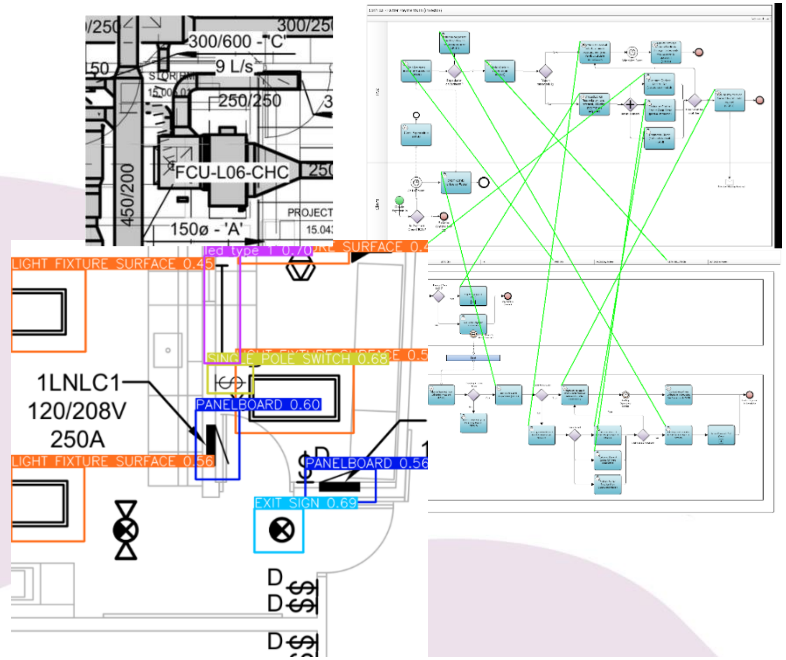
Revision Clouds

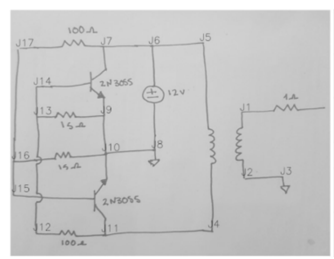


How to find (avoid) them, and how to find out if a drawing has been altered/revised?

More Projects

- Digitisation of financial process maps (firm in Edinburgh)
- Applying this work with a Canadian construction firm
  - Finding more complicated symbols
  - Understanding the connectivity of the electrical panels in a building
  - Provisional Patent in the US
- Creation of Digital Twins
- Visual Language Models to
  - Q&A for specific info
  - Make them more efficient





Question Type	Question	Answer
Simple Counting	What is the total resistor count within the circuit?	5
Spatial Counting	How many voltage-dc are connected directly to the left of inductor?	1
Value	What is the value associated with the voltmeter?	12V
Junction	Can we observe a transistor.bjt between junction 7 and junction 9?	Yes
Position	Can you tell me which circuit component is at the leftmost position?	Cross-over

Fig. 1. Sample circuit image from CircuitVQA, and question-answer pairs per question type

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https://github.com/rahcode7/Circuit-VQA

Crack Detection in Photovoltaic (PV) Panels and Wind Turbine Blades

Presented by DNV @ Image Processing Day

Project Aim

- Drones and ROVs collect high-resolution images, spectral, geolocation and other data about the health of a renewable asset
- Computer vision and algorithms process the data to identify faults or change in asset condition
- A report is automatically generated providing results
- Skilled engineers review results, make recommendations and complete client deliverables

Transition into Renewable Asset Inspection

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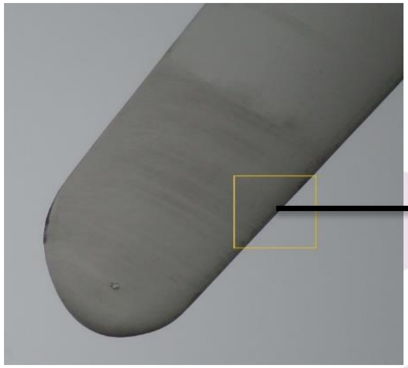
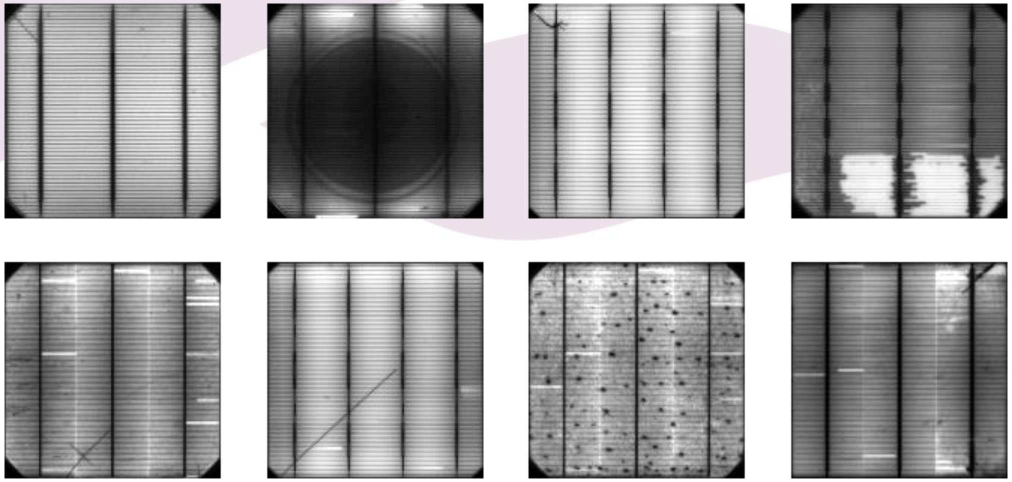
Main Challenges



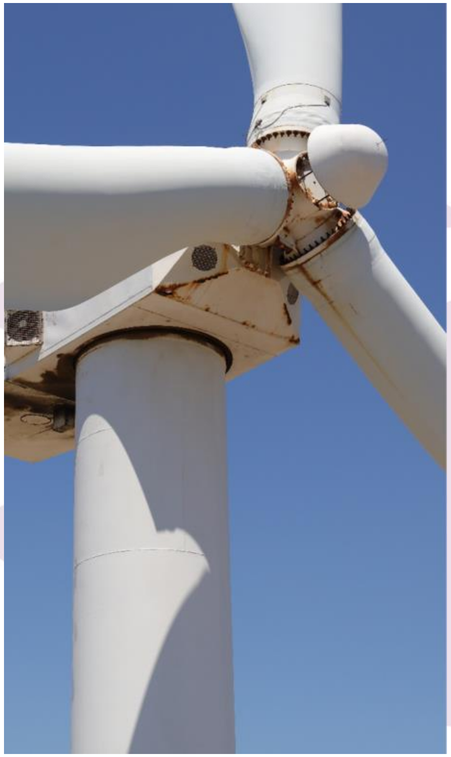
Wind turbine blade

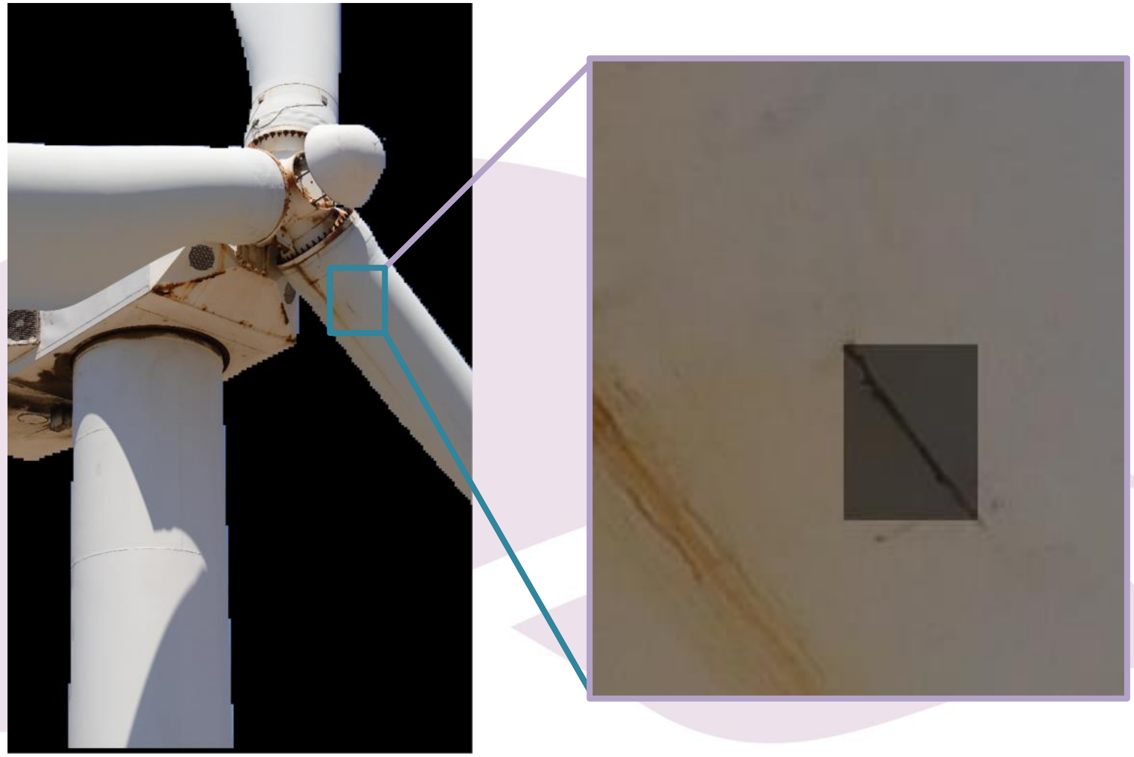
Damaged leading edge

Detection of faulty panels



Drone Turbine Data



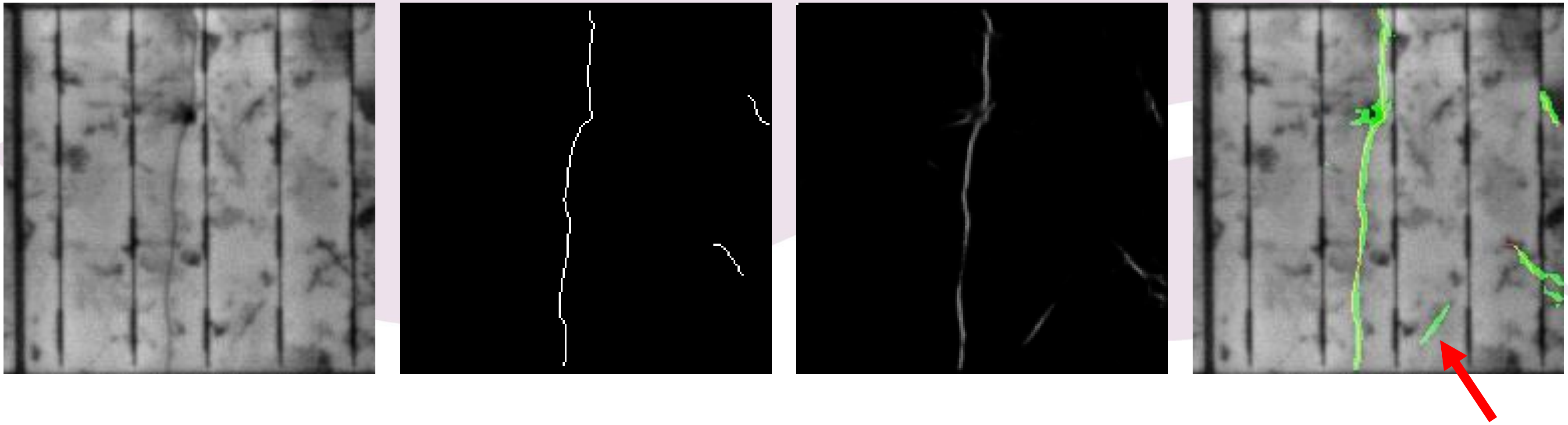


Part	Distance from hub	Side of Structure	Fault Type	Fault Size
Blade B	1.5m	LE	Crack	0.17m long

Crack Detection

DNV

Query image | Ground truth | Probability mask | Predictions



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Corrosion Detection in Underwater Images

Honours Project developed by Craig Pirie (PhD student) and supervised by Dr Carlos Moreno-Garcia

Project Aim

- Analyse and compare state-of-the-art computer vision techniques to provide a system that assists inspection engineers in the identification of corrosion.
- Main issues:
  - Few labelled data at hand
  - Computational requirements

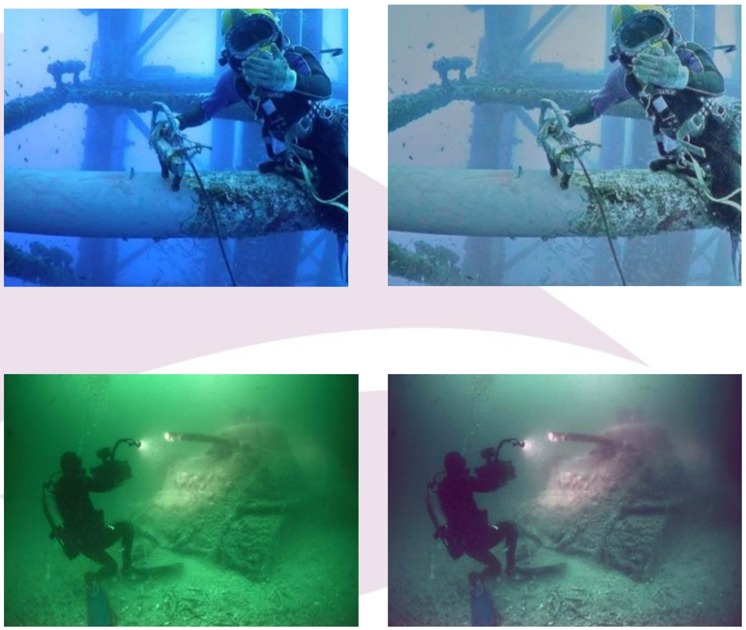
Image Pre-processing

Original

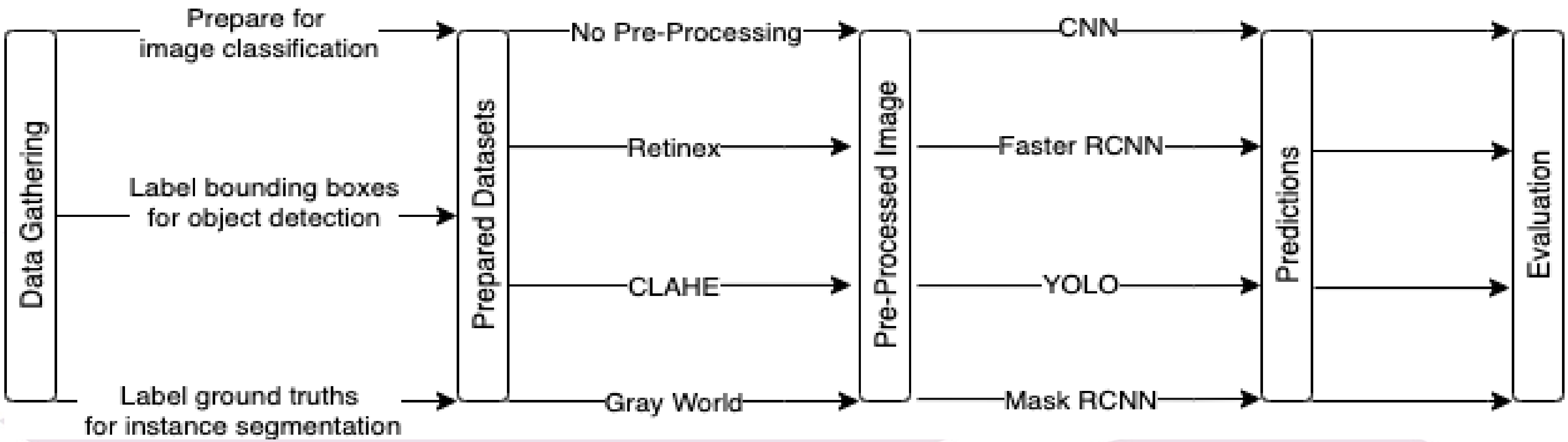
Gray World

Retinex

CLAHE



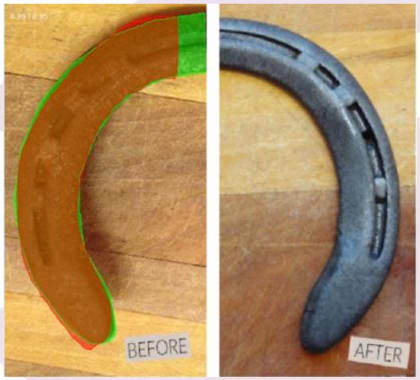
Classification and Recognition

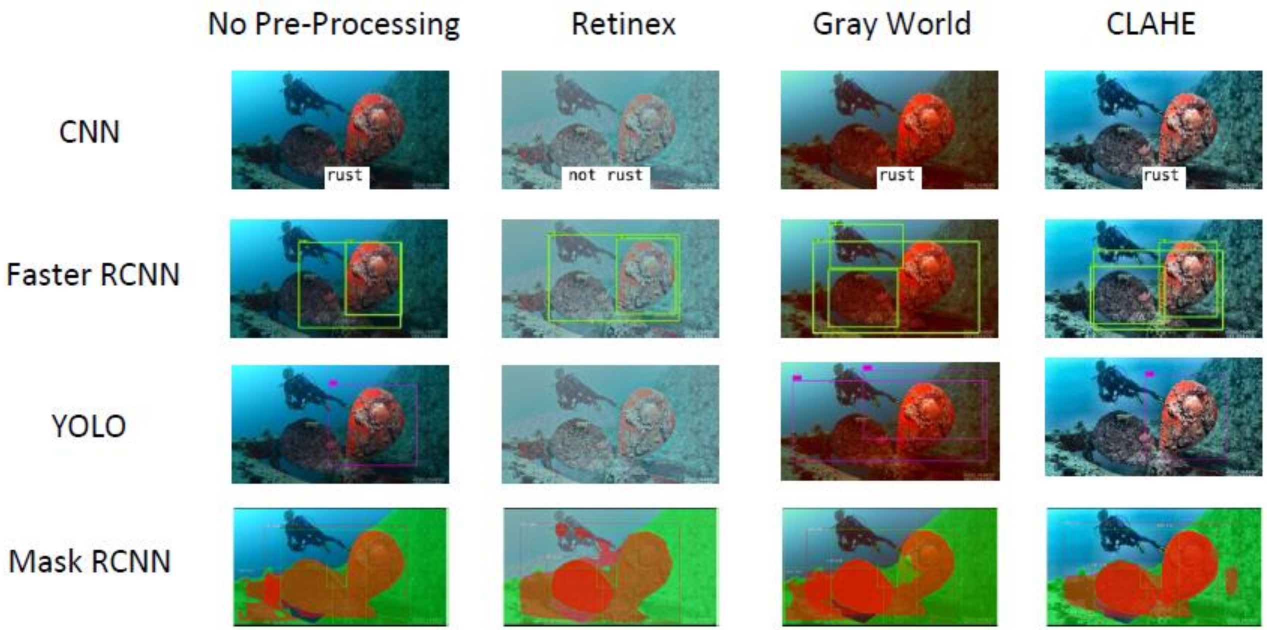


Dataset Acquired	Type	Rust	No Rust
	Surface	1105 (70% labelled)	128
	Underwater	24 (test only)	24

THIS IS YOUR COURSEWORK!

Results



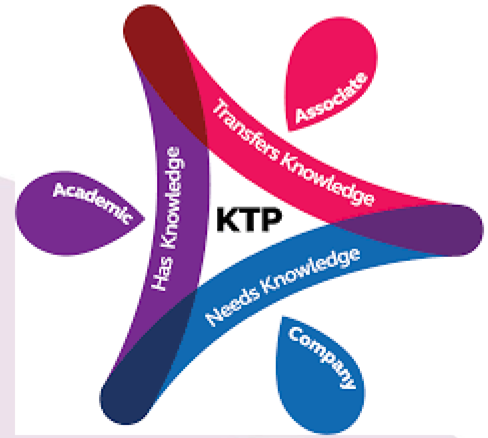


	Study of Network Performance (Precision [%])			
	CNN	Faster RCNN	YOLO	Mask RCNN
Surface	90.9	24.1	7.1	57.0
Underwater	75.0	37.8	9.0	77.1

More Anomaly Detection Problems!

We will learn more about these in Topic 6

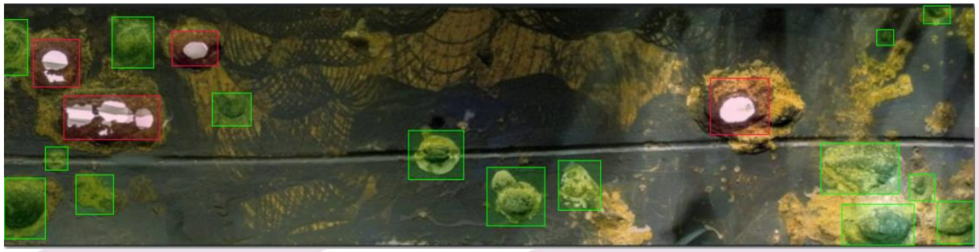
Underwater Image Enhancement

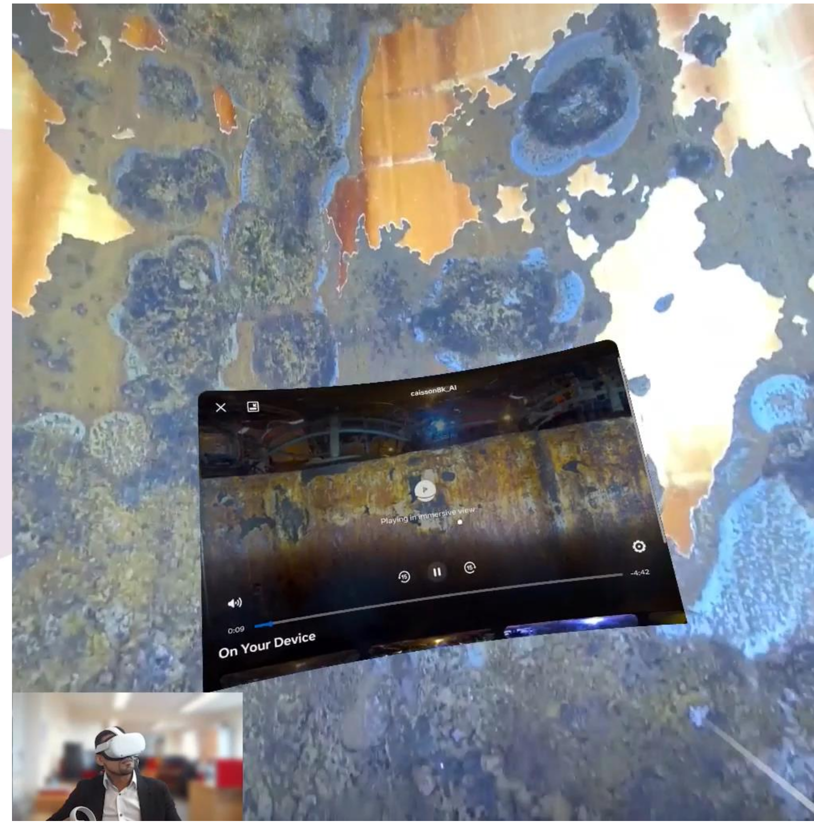


AISUS

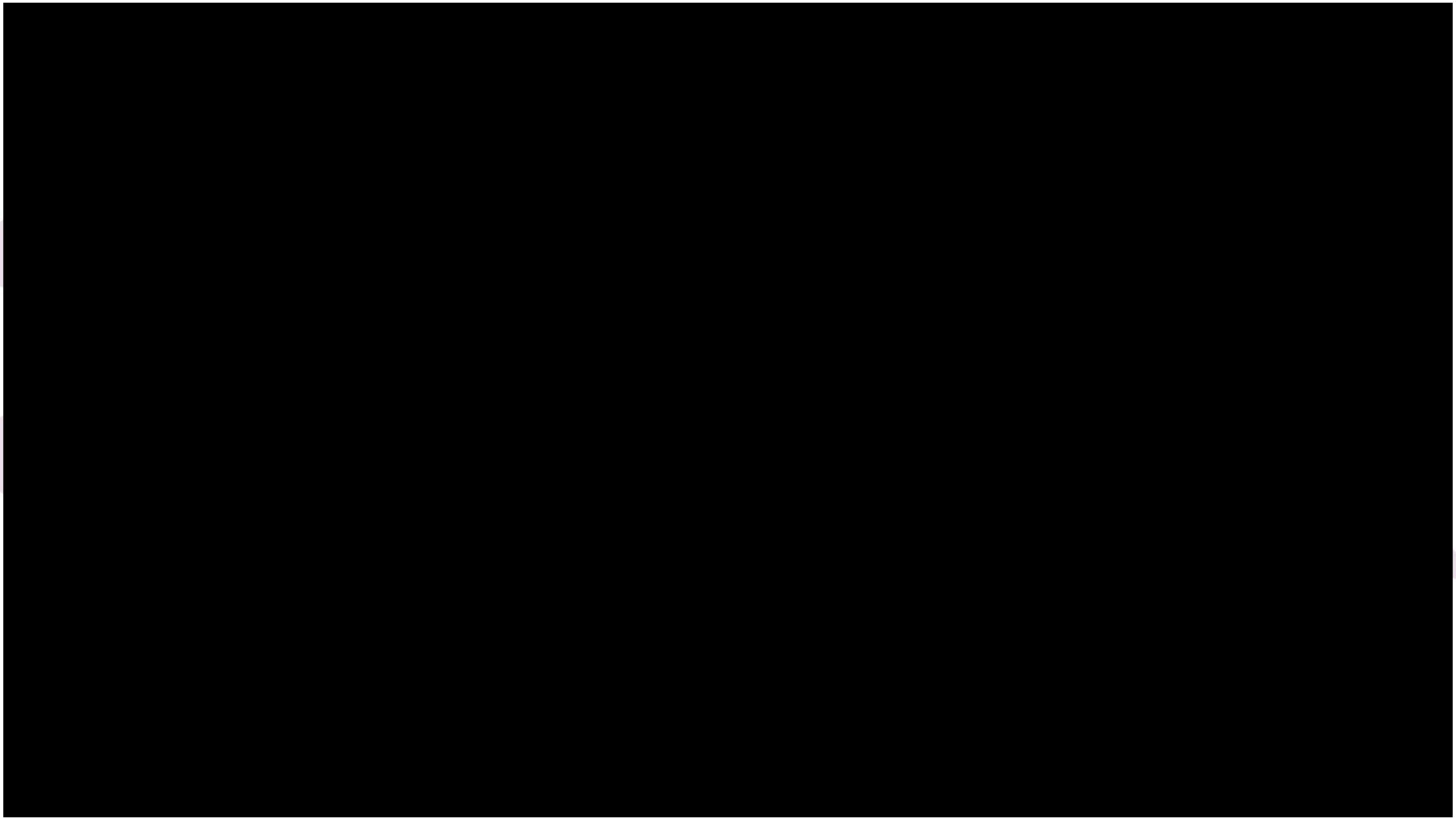
Anomaly Detection

AISUS

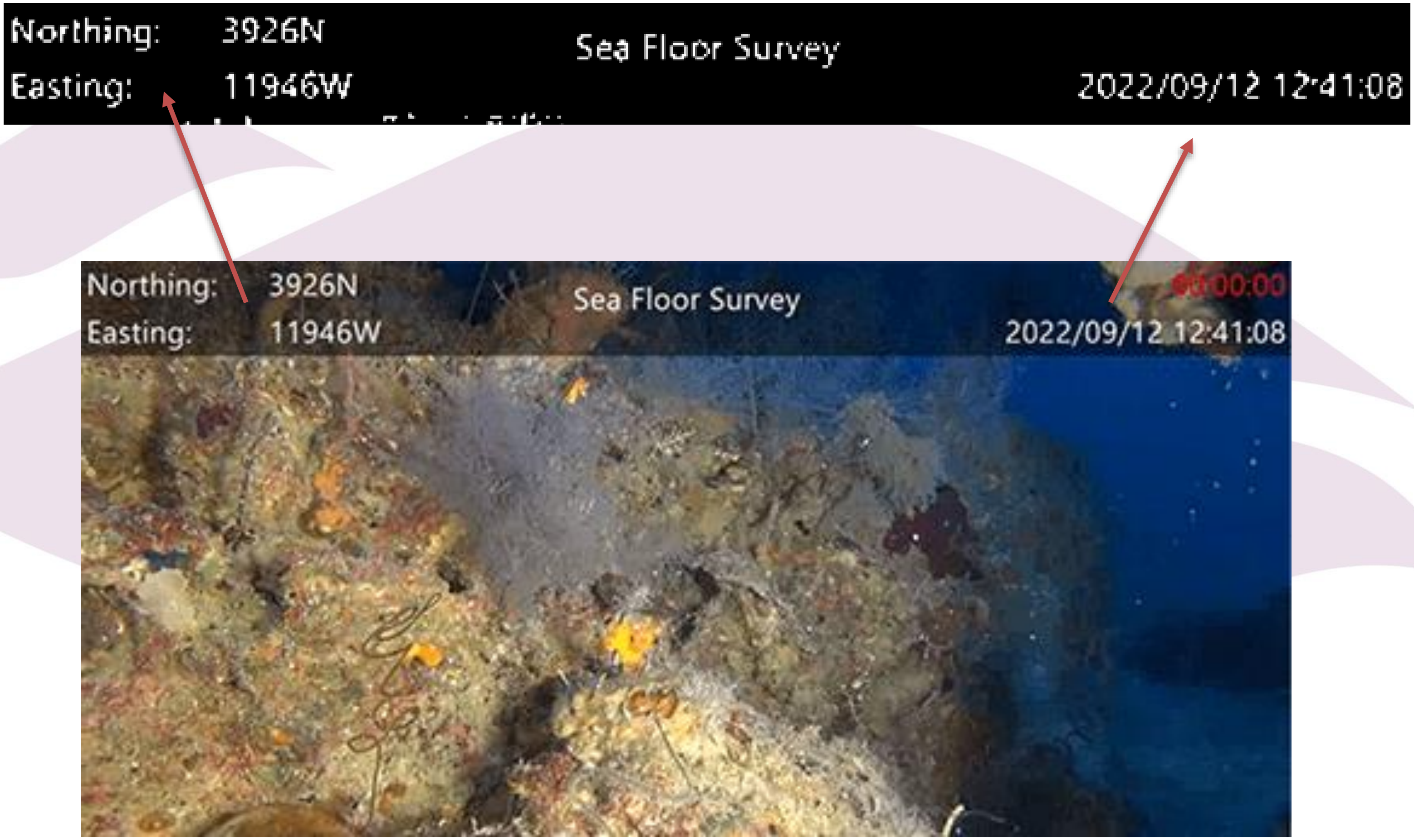




Weld Classification



InspectionTag Recognition (OCR)



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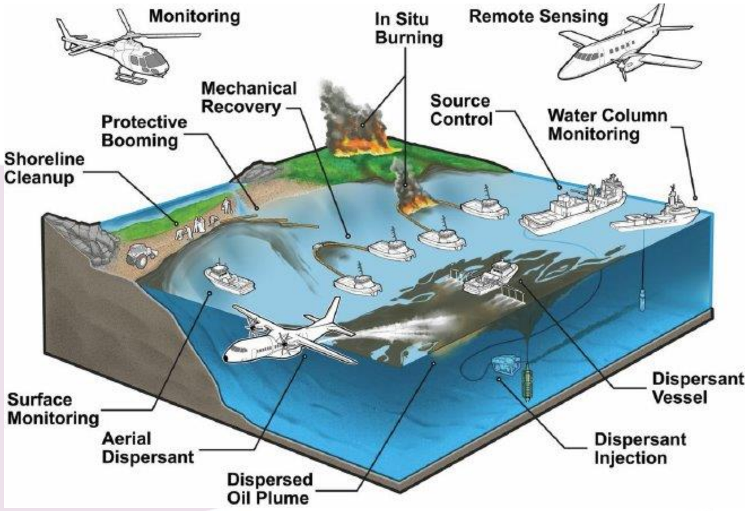
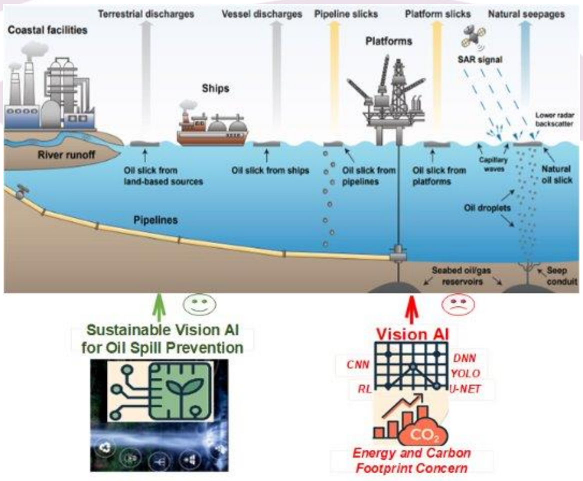
Oil Spill Prevention

PhD research currently in development by Mr Kuanyin Akech Malang, supervised by Dr Carlos Moreno-Garcia and Dr Pascal Ezenkwu

The Problem

- Oil spills cause long-term damage to marine ecosystems and coastal communities worldwide.
- Reactive approaches (response and cleanup) provide coverage, but often with delays and blind spots.
- Vision-based AI methods like CNNs, U-Net, YOLO, and RL agents could be used for preventive prevention.





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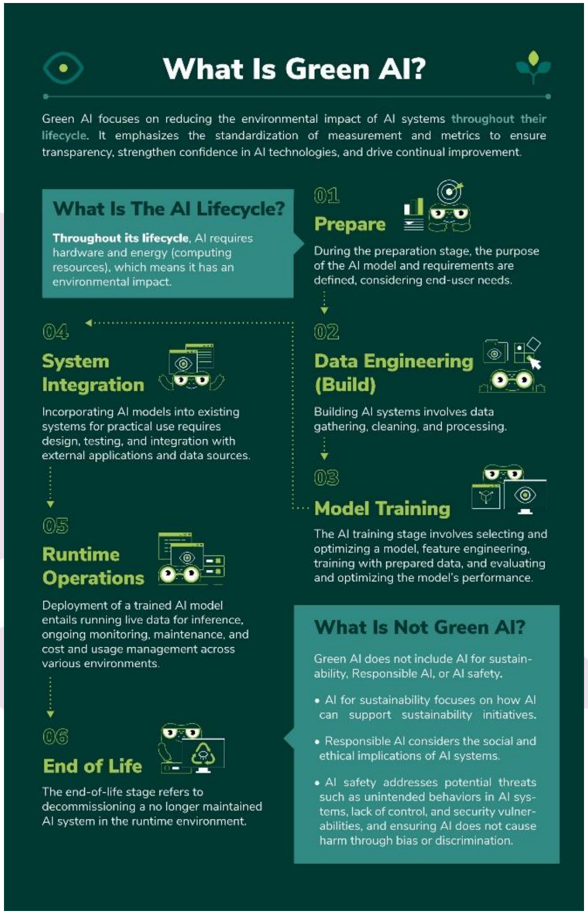
Methodology

- The study reviews nine research papers focusing on vision-based oil spill prevention systems.
- Examines data practices, model architectures, training, and deployment contexts in reviewed studies.
- Classifies methods into energy-intensive and energy-efficient based on accuracy and computational cost
- Evaluates energy consumption and carbon footprint to promote environmentally responsible AI development.



https://greensoftware.foundation/articles/green-ai-position-paper

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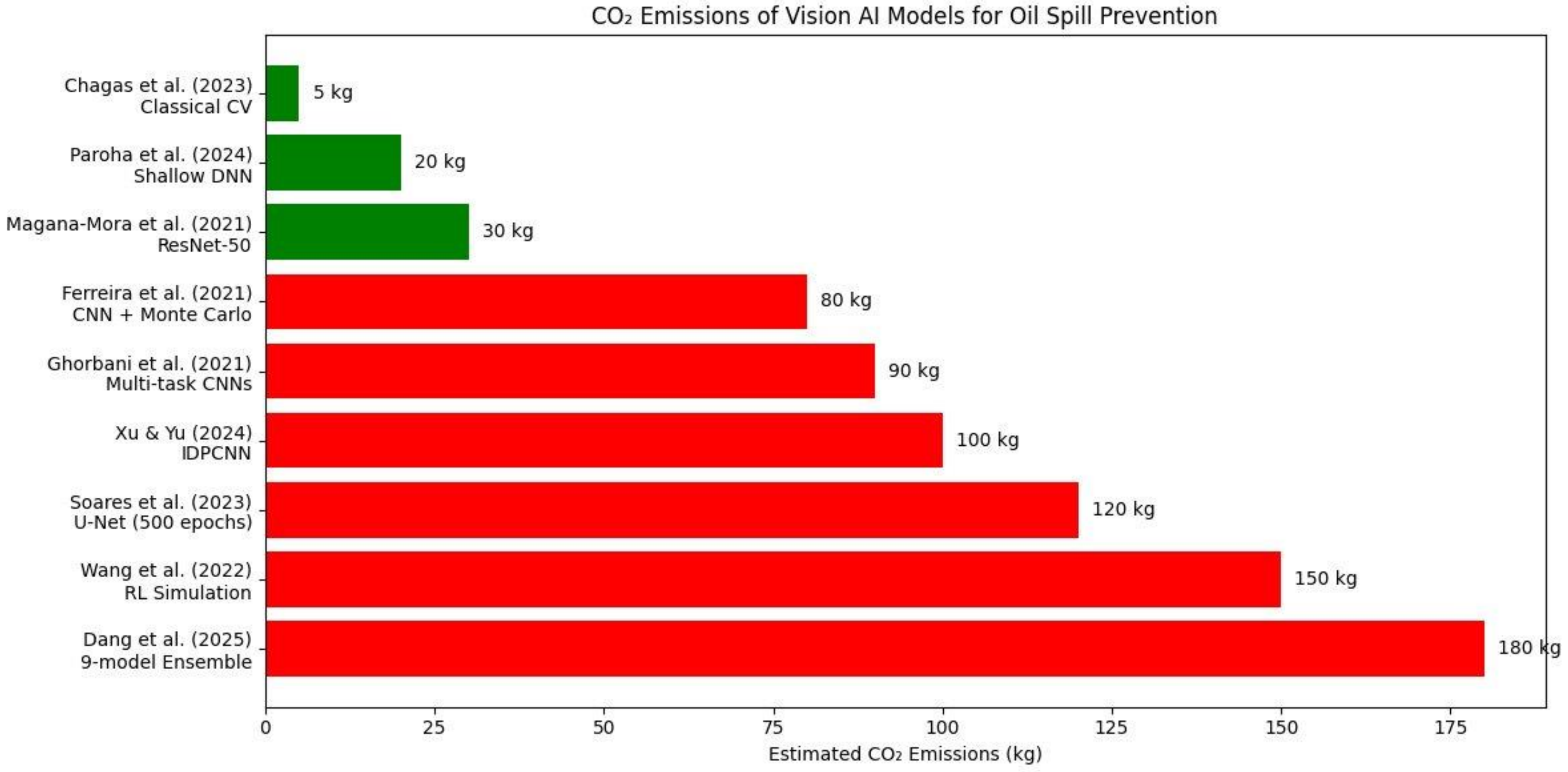
Table 1: Summary of nine vision-based OSP studies (2020–2025). Efficiency profiles are inferred from model design choices rather than direct energy measurements.

Study(Year)	Approach / Model	Reported Outcome	Profile
Soares et al. (2021)[20]	U-Net CNN with heavy augmentation	IoU ≈0.94 (peak); avg ∼87%	GPU intensive (672 images; 500 epochs; T4 GPU)
Ferreira et al. (2021)[18]	Multi-layer CNN regression on FEM + burst tests	$R^2 \approx 0.95$ for defect severity	High compute demand (100 Monte Carlo CV runs)
Xu et al. (2024)[24]	IDPCNN (immune CNN with 5 stages)	>99% accuracy; better than VGG/ResNet baselines	High complexity; more parameters; long training; not edge-suitable
Dang et al. (2025)[4]	Ensemble of 6 CNNs + 3 Transformers	Accuracy 78–99% across datasets	Very intensive (nine models per input; high inference cost)
Ghorbani et al. (2021)[6]	Multi-task CNNs (VGG16, Mask R-CNN, PSPNet, YOLOv3)	92% classification; IoU 49–68%; mAP ∼71%	High overhead (3 separate networks; cloud-only)
Wang et al. (2022) [23]	Deep Q-Network with transfer learning	98.97% accuracy (Bohai simulations)	Very intensive (days of RL simulation rollouts)
Chagas et al. (2020)[3]	Classical CV pipeline (blob detection)	20–87 FPS on CPU; accurate bubble leak flow estimates	Efficient (no training; real-time CPU execution)
Magana-Mora et al. (2021)[13]	ResNet-50 backbone for drilling safety	∼94–96% detection; +4.5% AP with aug.	Efficient (edge-ready; smaller backbone chosen for latency)
Paroha et al. (2024)[16]	Shallow DNN with LSTM for sensor data	92.5% accuracy; 0.28s detection latency	Moderate (lightweight; realtime on industrial PC)

Table 2: Dataset characteristics of nine vision-based OSP studies (2020–2025). Most datasets are small, synthetic, or imbalanced, limiting generalisability. Interpreting results requires attention to both dataset quality and unreported energy and carbon costs.

Study (Year)	Dataset	Characteristics
Soares et al. (2023) [20]	∼200 grayscale lab images (only 56 annotated)	U-Net segmentation; binary masks; heavy augmentation (lighting, blur, dust); small, homogeneous; risk of overfitting.
Ferreira et al. (2021)[18]	100 FEM-simulated cases	Synthetic corrosion defects; no augmentation; very small; validated with Monte Carlo CV only.
Xu & Yu (2024)	500 IR pipeline images	Thermal FLIR frames; binary expert labels; augmentation (flips, crops, rotations); balanced but limited scale.
Dang et al. (2024)[4]	ROV frames (A: 819, B: 5212, C: 1891)	Multi-class annotations; extensive augmentation; severe imbalance (e.g., 15 samples for concrete damage).
Ghorbani & Behzadan (2021)[6]	1292 aerial/ocean images	Mixed drone/satellite/ground sources; pixel masks (oil, vessel, rig); balanced spill labels; moderate size.
Wang et al. (2022)[23]	Bohai SAR + simulation	Fully synthetic (Envisat + ECOM model); single-event, scenario-specific.
Chagas et al. (2023)[3]	6 ROV videos (∼14k frames)	Bubble leaks; manual calibration; assumes no overlap; no augmentation; limited coverage.
Magana-Mora et al. (2021)[13]	1100 rig CCTV images	Drillstring tool joints; annotated; heavy augmentation (lighting, color shifts); domain-specific.
Paroha (2024)[16]	Proprietary sensor logs	Pressure, temperature, flow states; extensive preprocessing; no augmentation.



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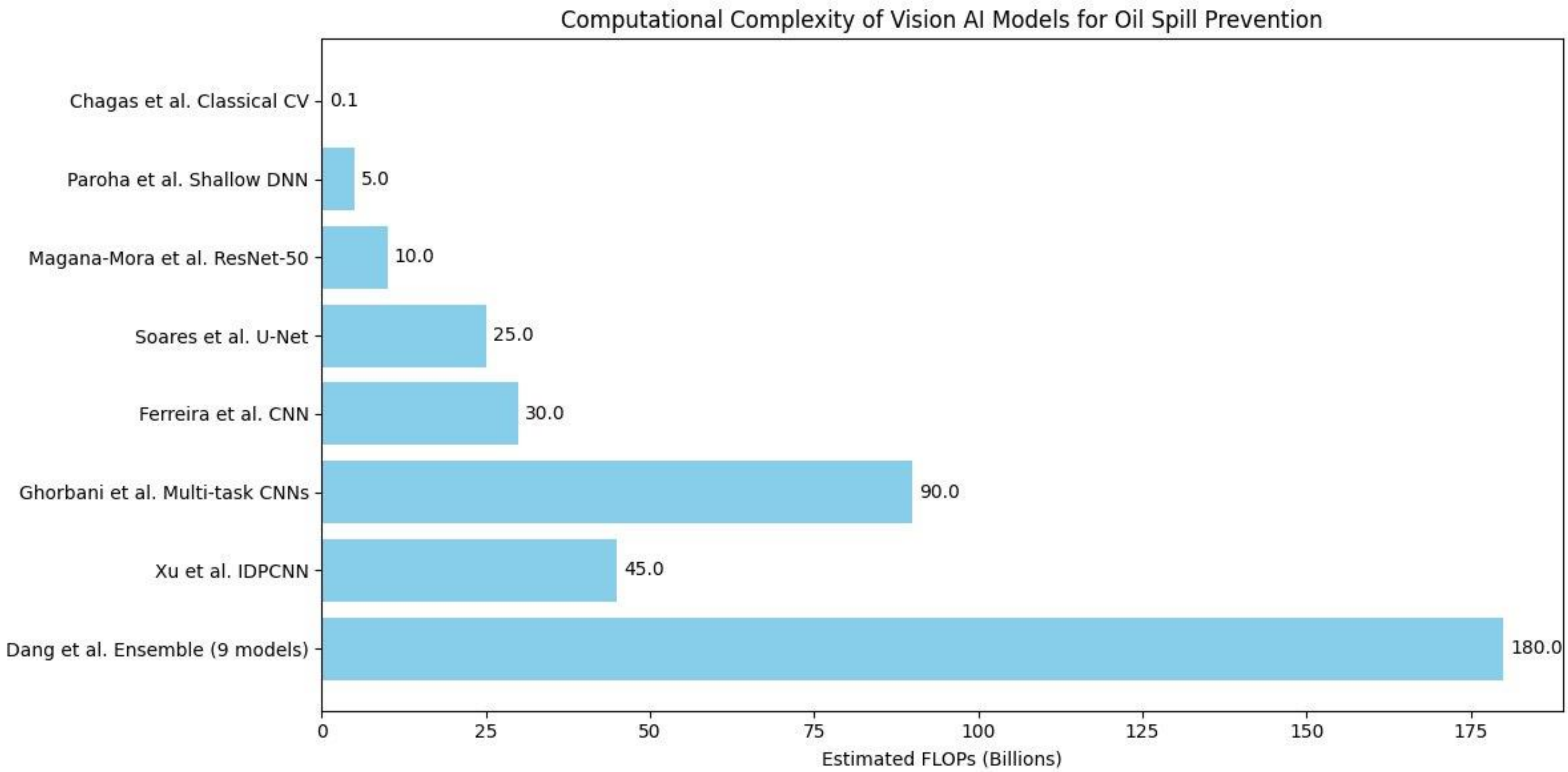

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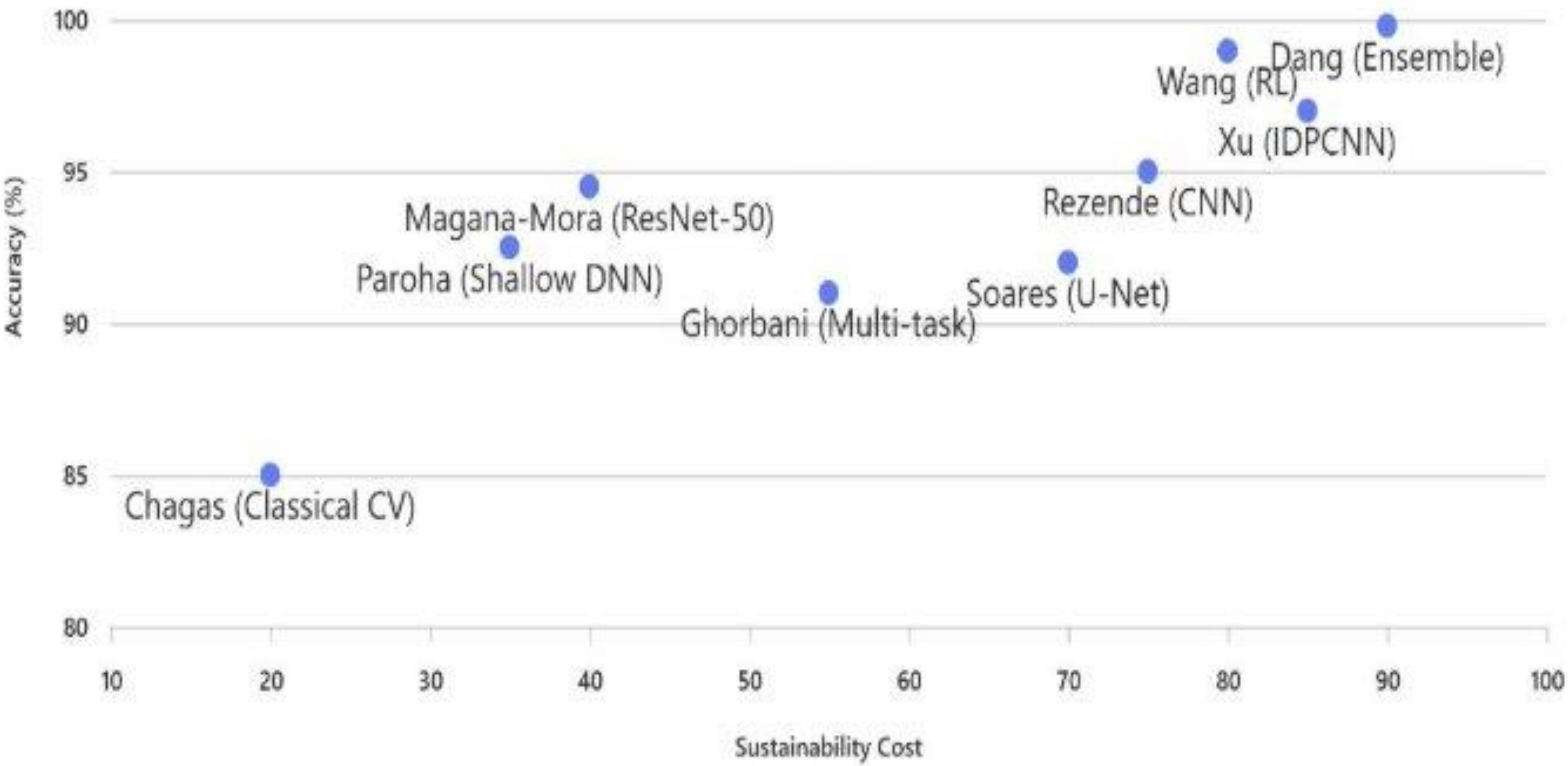

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Future Work

- Benchmark all methods (plus the newest ones) using **the same** conditions
- Implementing **optimisation/explainability** techniques to combine/improve the best
- Perform **AI Lifecycle Assessment** using appropriate metrics and tools
  - CodeCarbon
  - Eco2AI
  - CarbonTracker
  - Cumulator
  - others

Job Sustainability Cost (JSC)- Measures direct emissions from compute (CPU/GPU/memory) and infrastructure overhead (cooling, power loss) for a single job. **Analogy:** Fuel burned for one car trip.

Amortised Sustainability Cost (ASC): Adds the job's share of hardware manufacturing emissions, amortised over device lifetime and usage. **Analogy:** Fuel + your share of the car's manufacturing footprint.

Embodied Product Cost (EPC): Aggregates the **ASC** of all jobs involved in creating a model, dataset, or platform — including inherited emissions from reused components (like reused models or datasets). **Analogy:** Carbon cost of building a car, including reused components like recycled steel or a second-hand engine.

Expanded Amortised Sustainability Cost (ASCe): Cradle-to-grave footprint of running a job in context, combining direct, hardware, and inherited software emissions. **Analogy:** Full lifecycle of driving a car — fuel, manufacturing, and supply chain

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Egocentric Vision

In collaboration with Project Aria (Reality Labs - META)

PI: Dr Carlos Moreno-García

Co-PI: Dr Shahana Bano (Lecturer, RGU)

RAs/RFs: Salah Elshafey (Arab Academy for Science, Technology, and Maritime Transport, Egypt), Luis Toral Quijas (MRes, RGU, Ventex/HPR/Innosport), Joseph de Matia (MSci, RGU), Davidson Chisom (MRes, RGU)

ARIA

Meta

Home > Tech > Tech News

Meta Is Making AR Glasses But The First Version Won't Be For You

Meta's first-generation AR glasses will reportedly be a demonstration product for developers and won't be available to buy commercially.

BY KISHALAYA KUNDU PUBLISHED JUN 10, 2022

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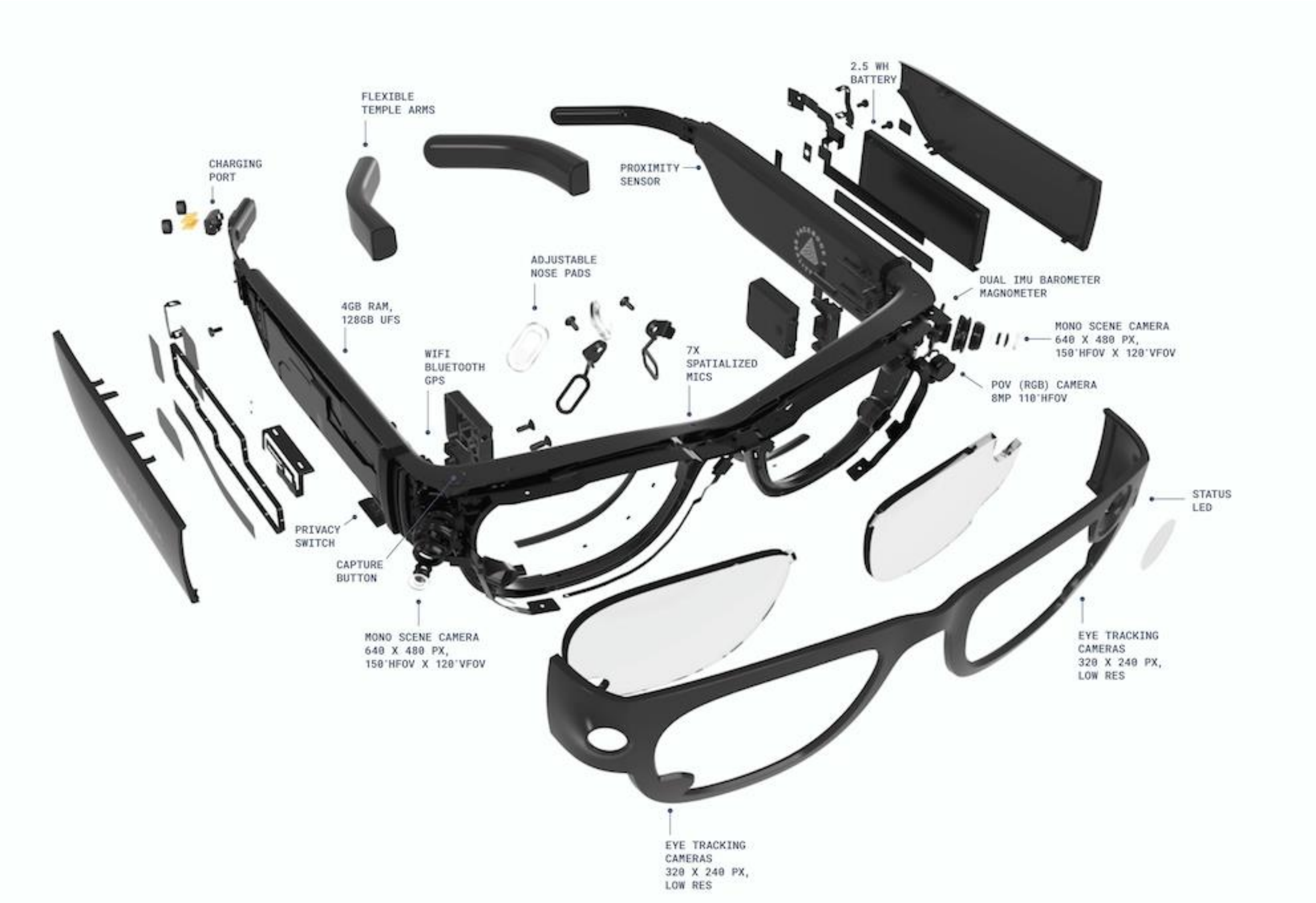
ARIA GEN 1


2.5 WH
BATTERY
FLEXIBLE
TEMPLE ARMS
CHARGING
PORT
PROXIMITY
SENSOR
ADJUSTABLE
NOSE PADS
DUAL IMU BAROMETER
MAGNETOMETER
4GB RAM,
128GB UFS
MONO SCENE CAMERA
640 X 480 PX,
150°HFOV X 120°VFOV
WIFI
BLUETOOTH
GPS
7X
SPATIALIZED
MICS
POV (RGB) CAMERA
8MP 110°HFOV
STATUS
LED
PRIVACY
SWITCH
CAPTURE
BUTTON
MONO SCENE CAMERA
640 X 480 PX,
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CAMERAS
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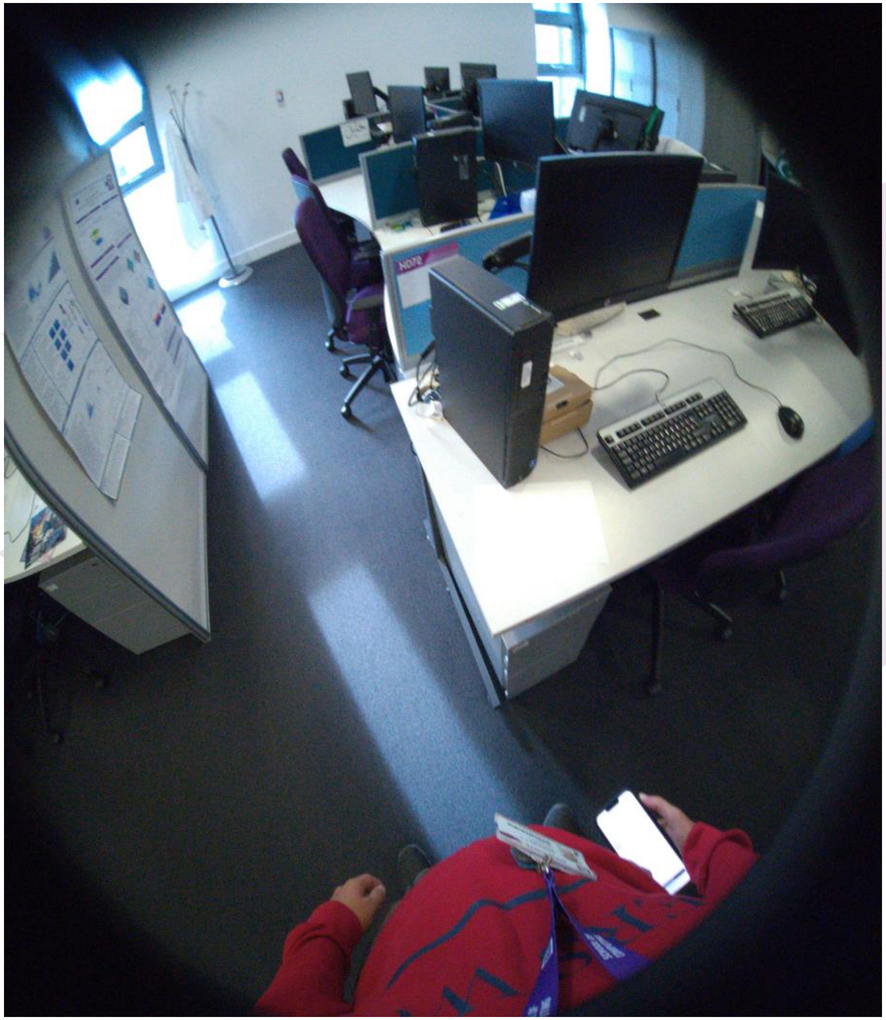
CAMERAS
320 X 240 PX,
LOW RES

Tests



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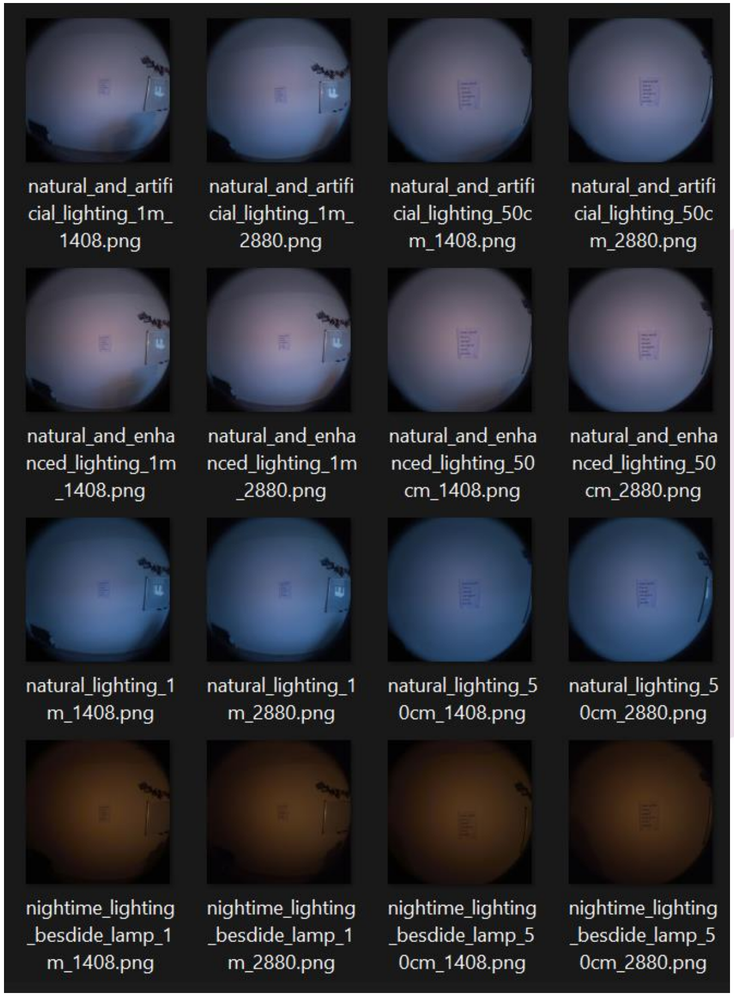
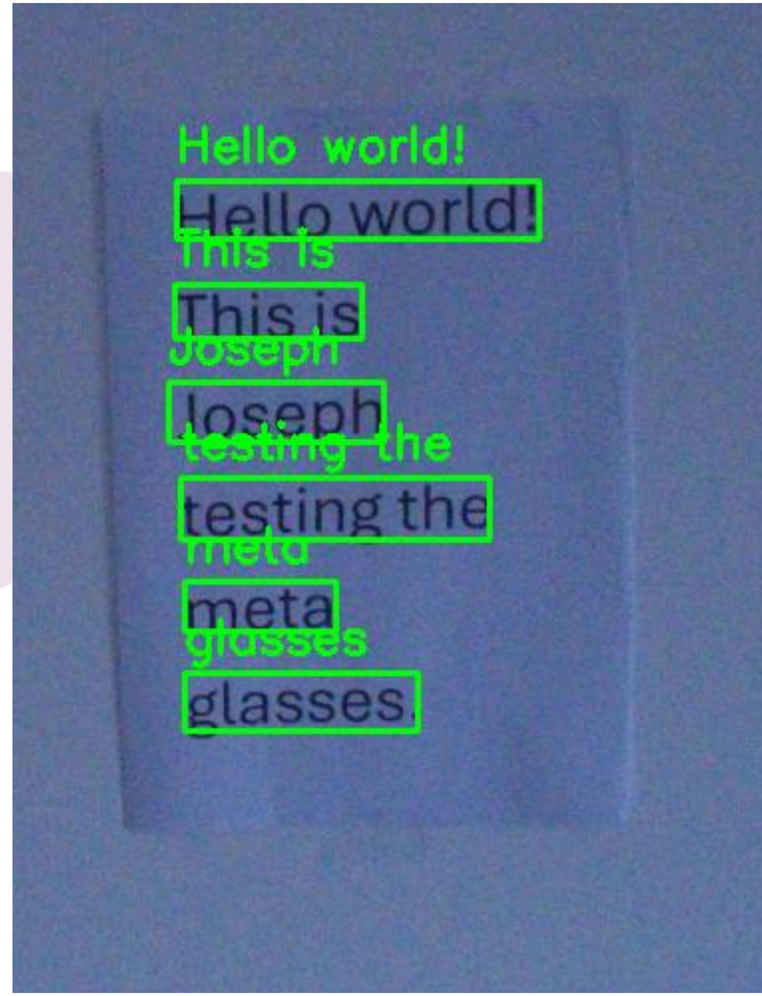
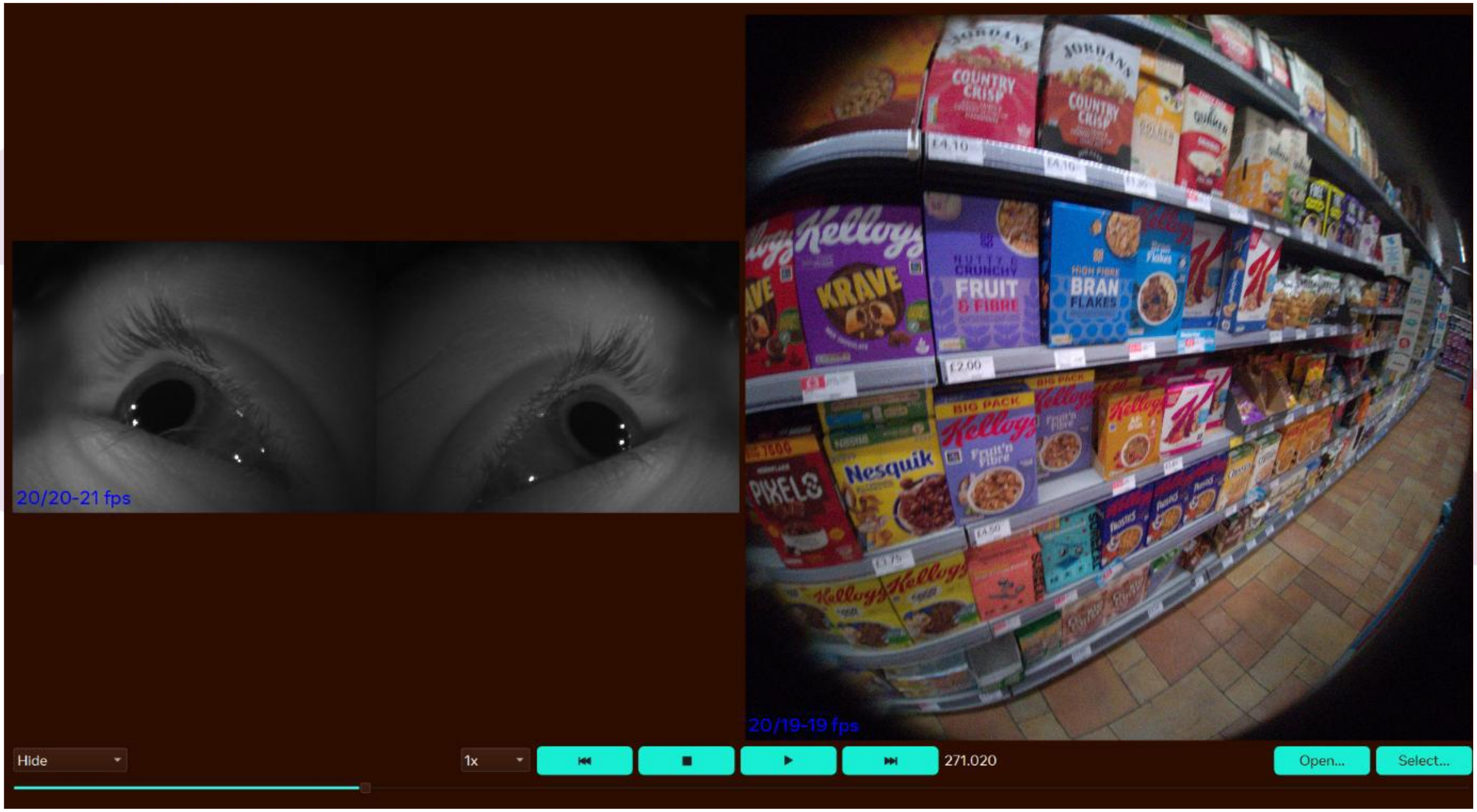
In the wild





De Mathia J, Moreno-García CF. Scene Text Detection and Recognition “in light of” Challenging Environmental Conditions using Aria Glasses Egocentric Vision Cameras. *arXiv preprints*. https://arxiv.org/pdf/2507.16330

In the wild



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Floodings

RGU leads international project to support Valencia after devastating floods.
https://www.rgu.ac.uk/news/news-2025/8541-rgu-leads-international-project-to-support-valencia-after-devastating-floods

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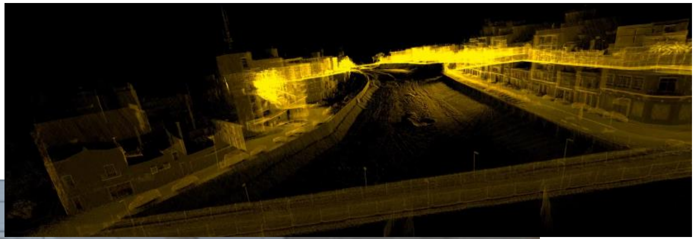
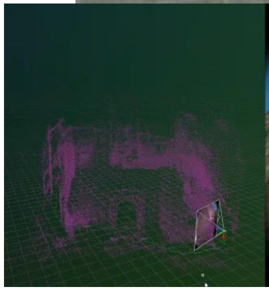
Floodings

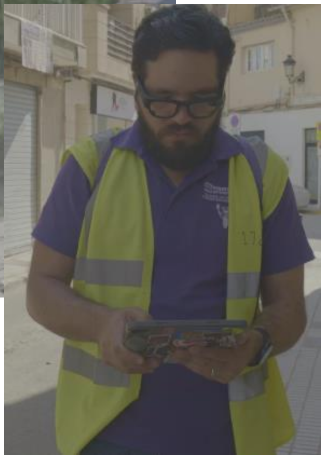
Meta

We identified the following use cases for the Aria glasses in this scenario:

1. Use them to scan areas which are difficult to access.
2. Map interior environments to the full model.
3. Create more realistic avatars that move around the simulated spaces.







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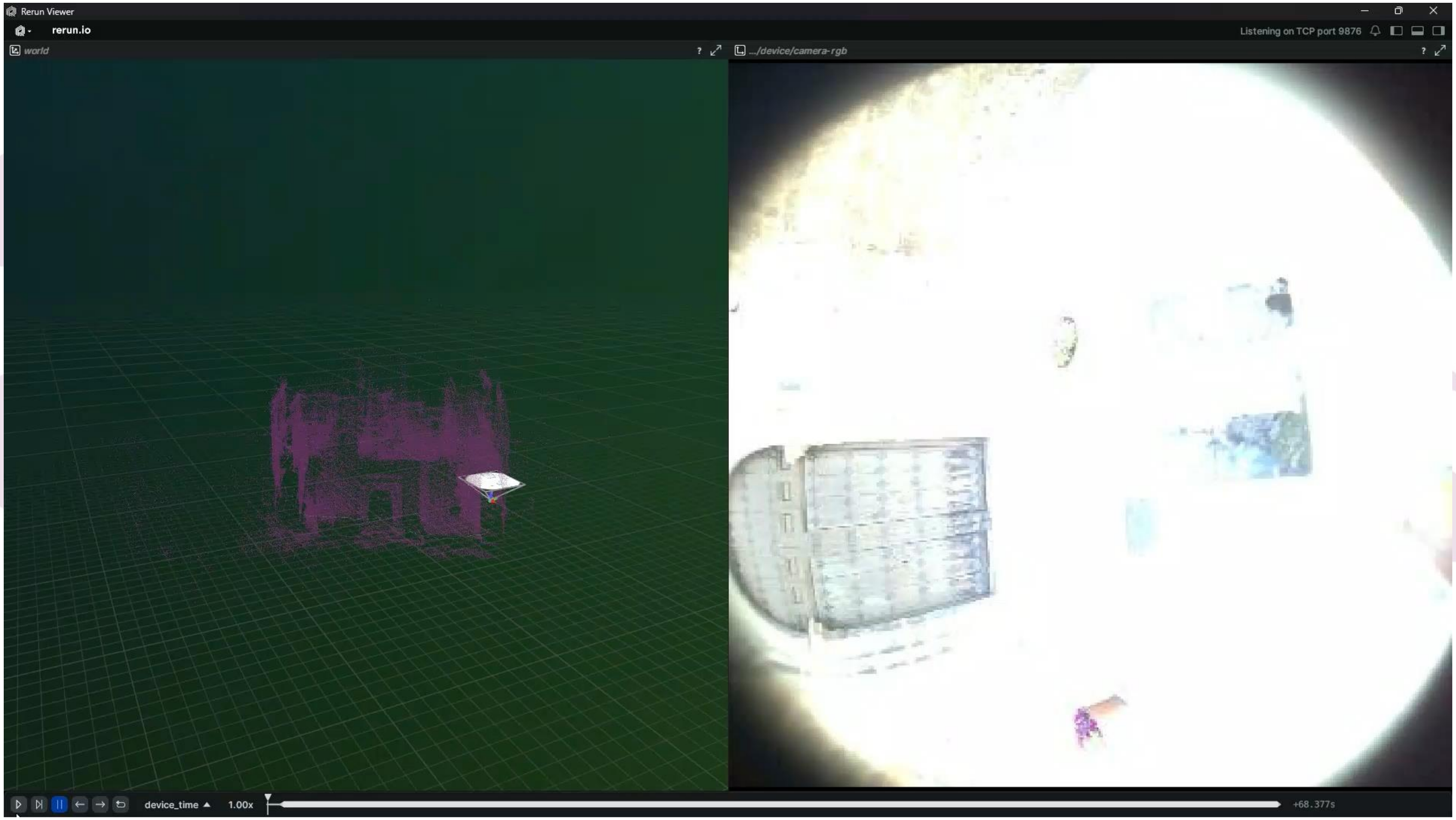

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Questions and Discussion