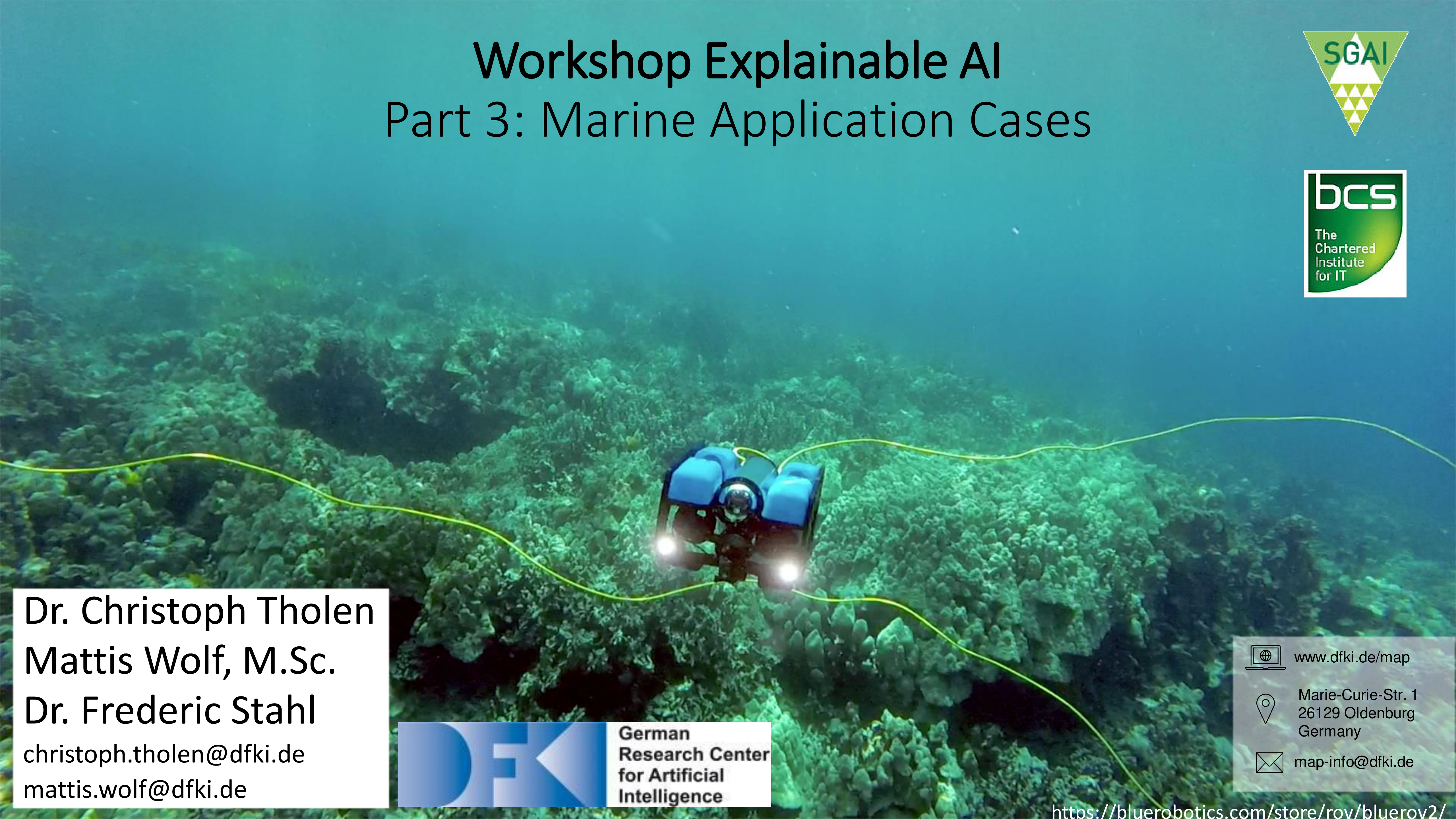
Workshop Explainable AI

Part 3: Marine Application Cases



https://bluerobotics.com/store/rov/bluerov2/

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DFKI – German Research Center for Artifi Intelligence

629 researcher

1.2

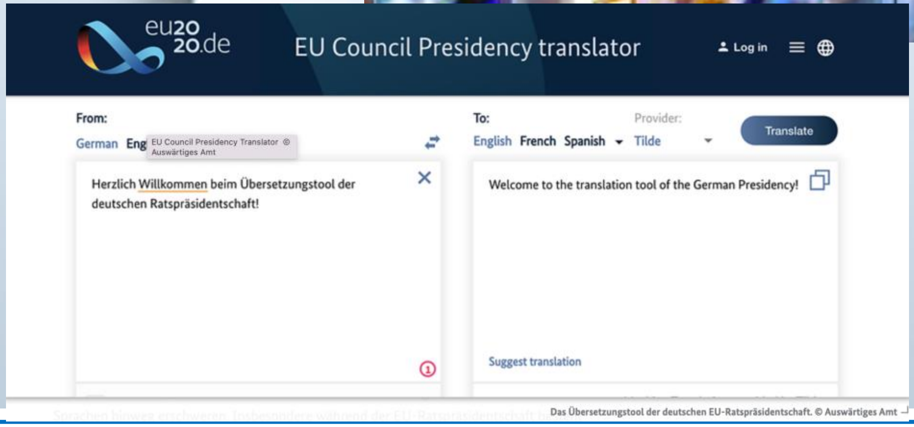
Bremen

Trier

350 ongoing projects

130 Mio. € project volume

98 spin-offs



DFKI is one of the leading (applied) AI research centers

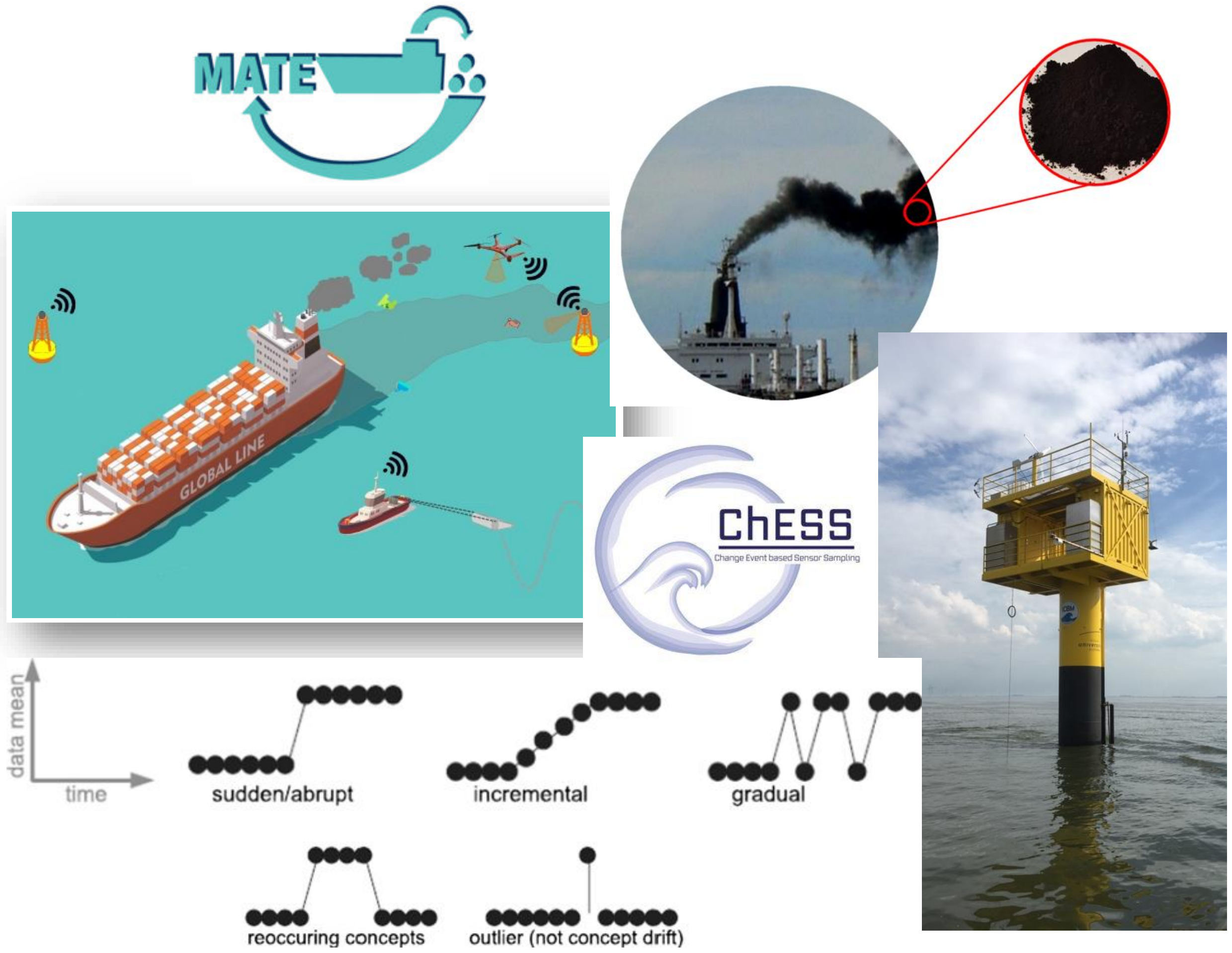
DFKI Marine Perception (MAP)

German Research Center for Artificial Intelligence

Sensing is believing…

- Intelligent sensors and distributed systems for automatic perception and classification in the aquatic environment
- Autonomous analysis of multisensory data using artificial intelligence methods, techniques and tools
- Real-time data stream analysis and integration into a high-dimensional situation picture

➔ **We combine sensor technology and artificial intelligence to evaluate environmental situations and identify options for action**



Why marine sciences?

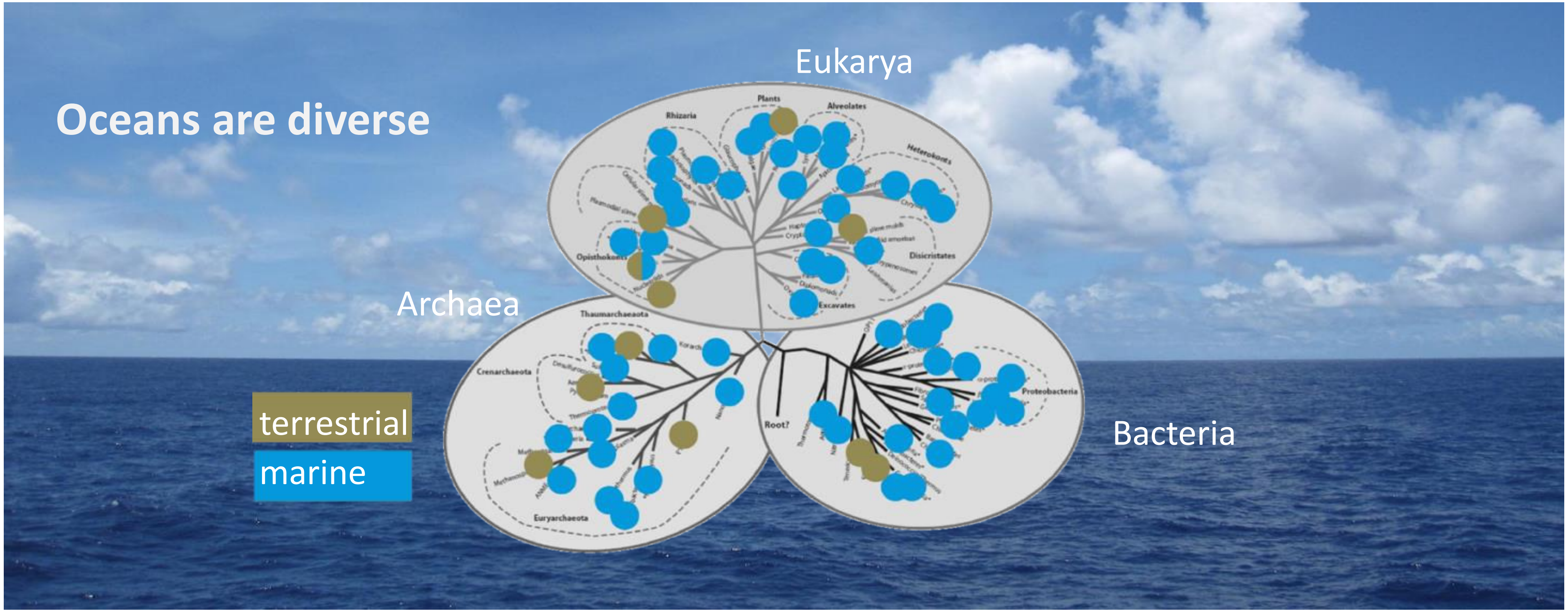
Blue planet: oceans are the lungs of the planet.

50% of the global oxygen production is produced by photosynthesis of marine algae.

Why marine sciences?

Oceans are home to the world’s largest diversity of species and habitats.

Annually 100 Mio tons of marine organisms are exploited as food source.



Why marine sciences?

50% of the human population lives in coastal areas (< 100km).

Including 12 out of 16 mega cities (> 10 Mio. inhabitants).

Why marine sciences?

Global warming is causing sea levels to rise. Pesticides and nutrients end up in coastal waters. Sewage discharge and litter runoff into the oceans. And many more…

Oceans are at risk!

ZuSiNe

ChESS
Change Event based Sensor Sampling

DFKI

Marine Perception

PLASTIC OBS+

iMagine

Plastic waste and emission detection

COPDA

MATE

NAUTILOS

Intelligent sensors and situational awareness

DFKI MAP Projects

German Research Center for Artificial Intelligence

- Common in all past projects is a strong connection to different stakeholders from various different fields like
  - Local Governments
  - NGOs
  - UN
  - Etc.
- Often stakeholders questioned the outcome of the AI algorithms, especially if the results did not help their own agenda
- Here XAI methods can help to increase the trust of stakeholders

→ XAI next natural step

Agenda

Plastic waste detection

Assistance System for Nautical Officers

Floating Litter Detection: Machine learning on drone image data

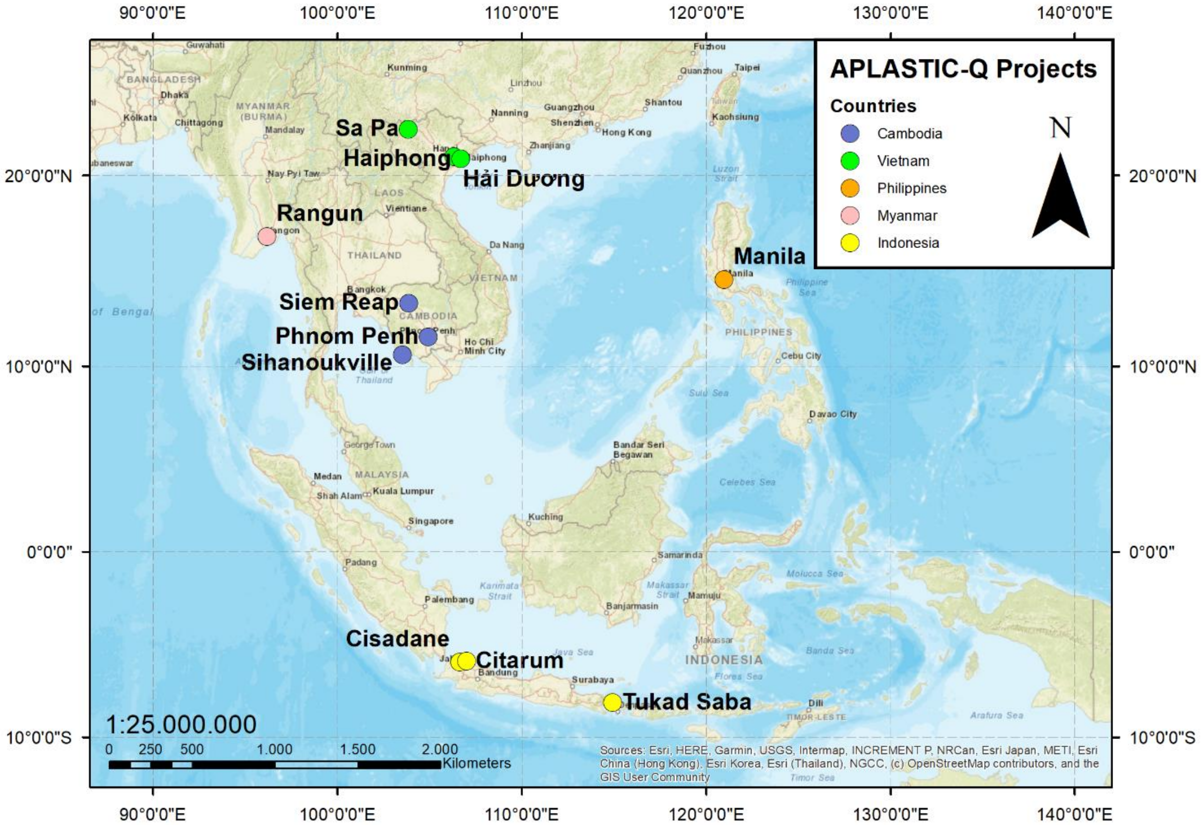
Plastic Waste
A global problem that affects many aspects of human and natural life

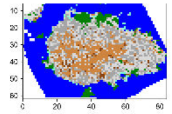
Plastic waste detection in ASEAN

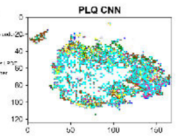
German Research Center for Artificial Intelligence

Conducted monitoring projects in five ASEAN countries

- Collaborated with local universities / companies
- Projects involved plastic waste assessment using:
    - **Drone / action cam surveys with AI-based waste analysis**
    - Field surveys (net surveys)
    - Remote sensing via satellites
- Impact & Capacity Building: local, regional and national scope
- Focus on **easy-to-use methodologies** that enable assessment and monitoring







AI-based waste monitoring example: Cisadane river mouth

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PT.LAPI ITB To Serve for Your Betterment and the Nation

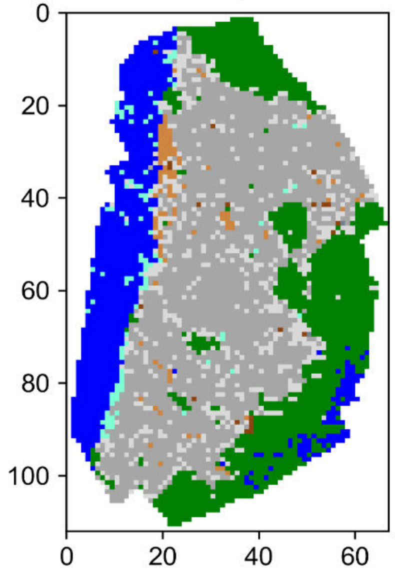
Level A:
High resolution imagery of river section
→ Identify waste hotspots

Level B:
Very high resolution imagery for waste accumulations
→ Assess waste quantities & waste types

Cisadane river mouth

Input image

PLD CNN



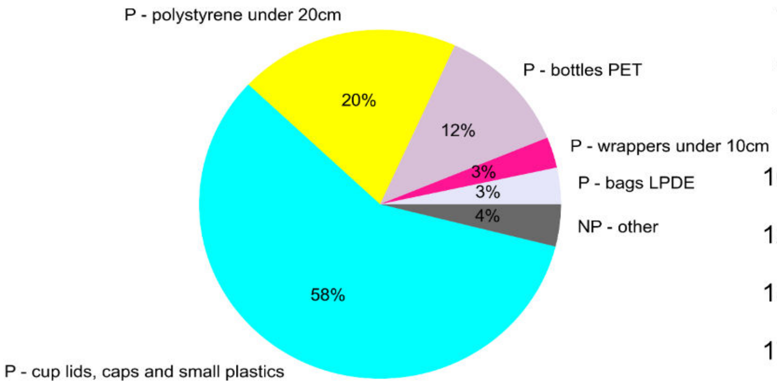
Assessed classifications, abundances, areas and volumes

Litter - high	2257
Litter - low	601
Organic debris	22
Other	104
Sand	102
Stones	2
Vegetation	1266
Water	868
Litter abundance	12487
Litter m²	167
Litter m³	47
Org. Debris m²	1
Org. Debris m³	0

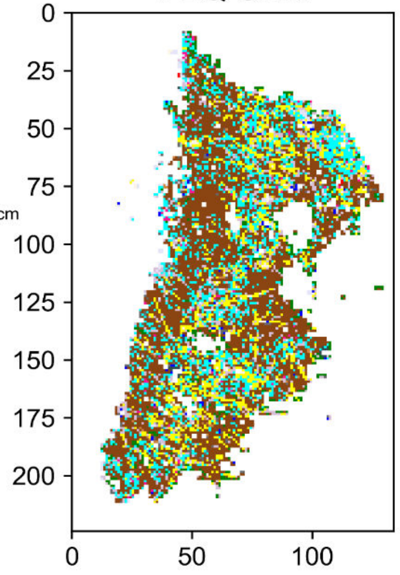
- no data
- Water
- Vegetation
- Stones
- Sand
- Other
- Organic debris
- Litter - low
- Litter - high

Waste quantities

Share of waste types



PLQ CNN



Altitude corrected assessed areas and pollution type abundances

	Classifications	Assessed abundances
P - bags LPDE thick	2	1
P - bags LPDE	256	256
P - bags robust PET	0	0
P - wrappers under 10cm	108	216
P - wrappers over 10cm	8	8
P - bottles PET	908	908
P - polystyrene under 20cm	1497	1497
P - polystyrene over 20cm	97	29
P - PPCP bottle	0	0
P - PPCP medical waste	0	0
P - PPCP other	0	0
P - fishing gear	0	0
P - cup lids, caps and small plasti	2202	4404
P - other plastics over 20cm	29	20
NP - rubber	0	0
NP - metal	0	0
NP - glass	0	0
NP - other	296	296
NW - sand	75	0
NW - vegetation	442	0
NW - wood	5415	0
NW - water	76	0
NW - other	21	0

- No pollution
- NW - other
- NW - water
- NW - wood
- NW - vegetation
- NW - sand
- NP - other
- P - other plastics over 20cm
- P - cup lids, caps and small plastics
- P - polystyrene over 20cm
- P - polystyrene under 20cm
- P - bottles PET
- P - wrappers over 10cm
- P - wrappers under 10cm
- P - bags LPDE
- P - bags LPDE thick

Waste types

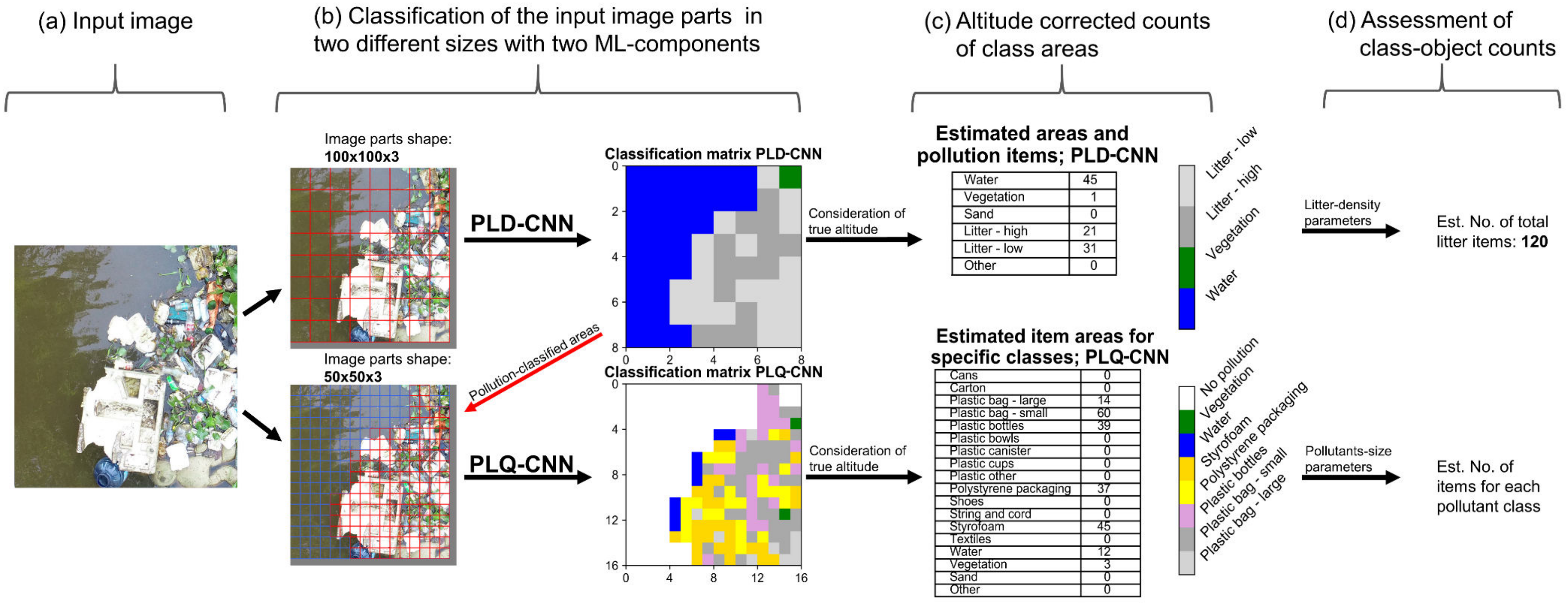
How accurate are the results?

Image / video analysis with an AI based approach

German Research Center for Artificial Intelligence

Plastic litter detection with machine learning using a two-step approach

- Assessment of plastic wast images (JPG, PNG, TIFF)
- Assessment of:
  - area covered
  - waste volume
  - types of waste
  - top 10 items



OpenSource

➔ **Quantitative results and characterization of dominant pollution classes for plastic waste and other litter**


ENVIRONMENTAL RESEARCH LETTERS

LETTER • OPEN ACCESS

Machine learning for aquatic plastic litter detection, classification and quantification (APLASTIC-Q)

Mattis Wolf[1,2], Katelijn van den Berg[3], Shungudzemwoyo P Garaba[1,2], Nina Gnann[1], Klaus Sattler[3], Frederic Stahl[1,4] and Oliver Zielinski[1,2]

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Environmental Research Letters, Volume 15, Number 11

Citation Mattis Wolf *et al* 2020 *Environ. Res. Lett.* **15** 114042

DOI 10.1088/1748-9326/abbd01

10515 Total downloads

28 14

Turn on MathJax

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APLASTIC-Q GitHub Link to improved APLASTIC-Q algorithm and CNNs trained on ~6x larger dataset compared to Wolf et al. 2020.

PLD CNN architecture and training details

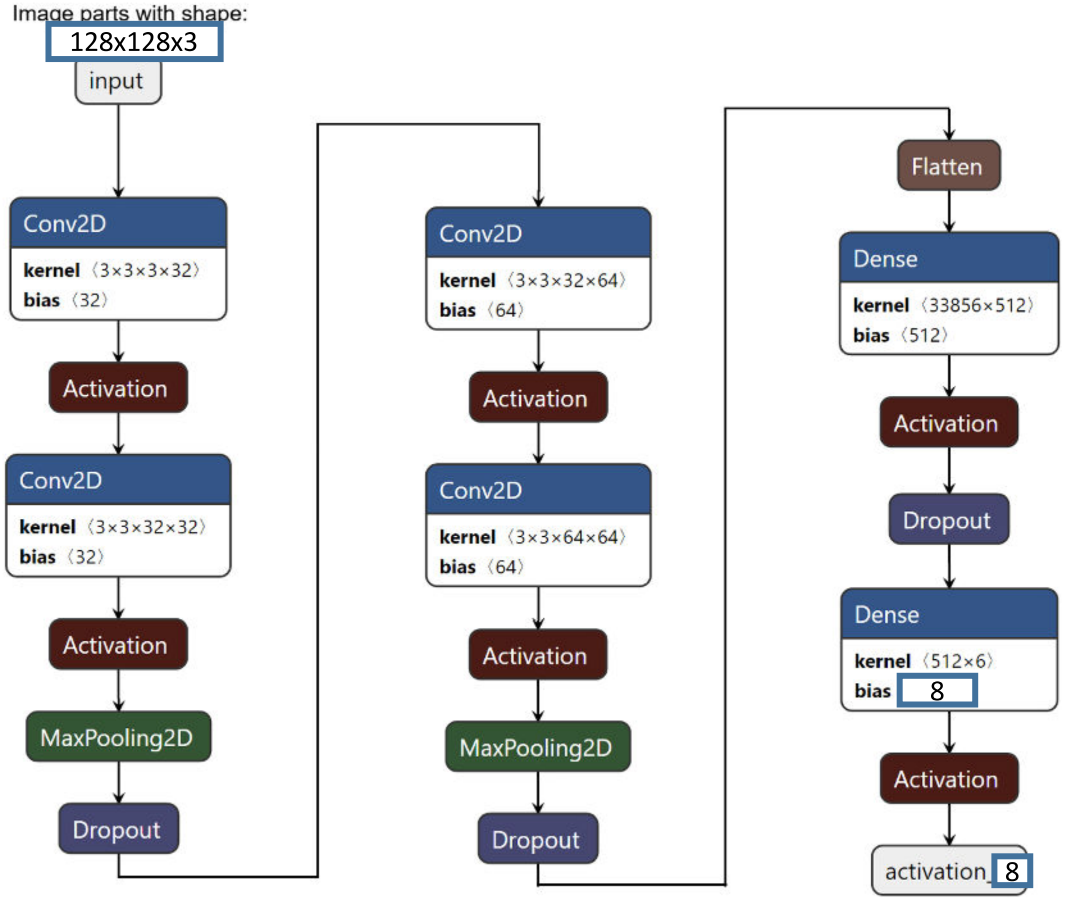
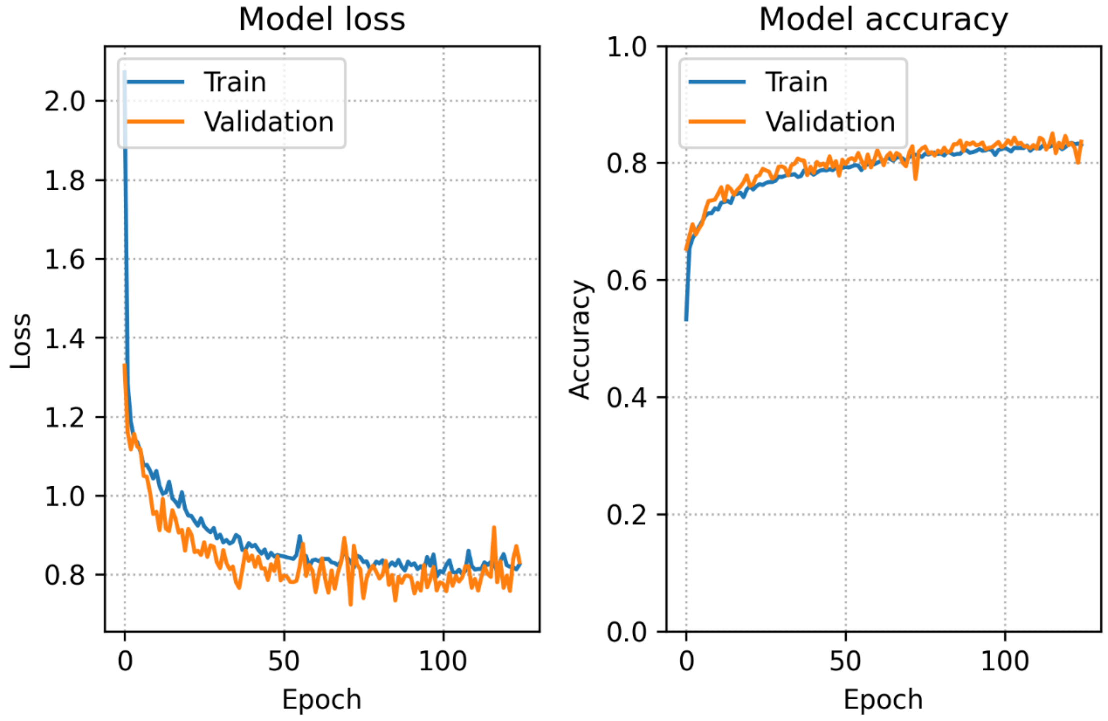


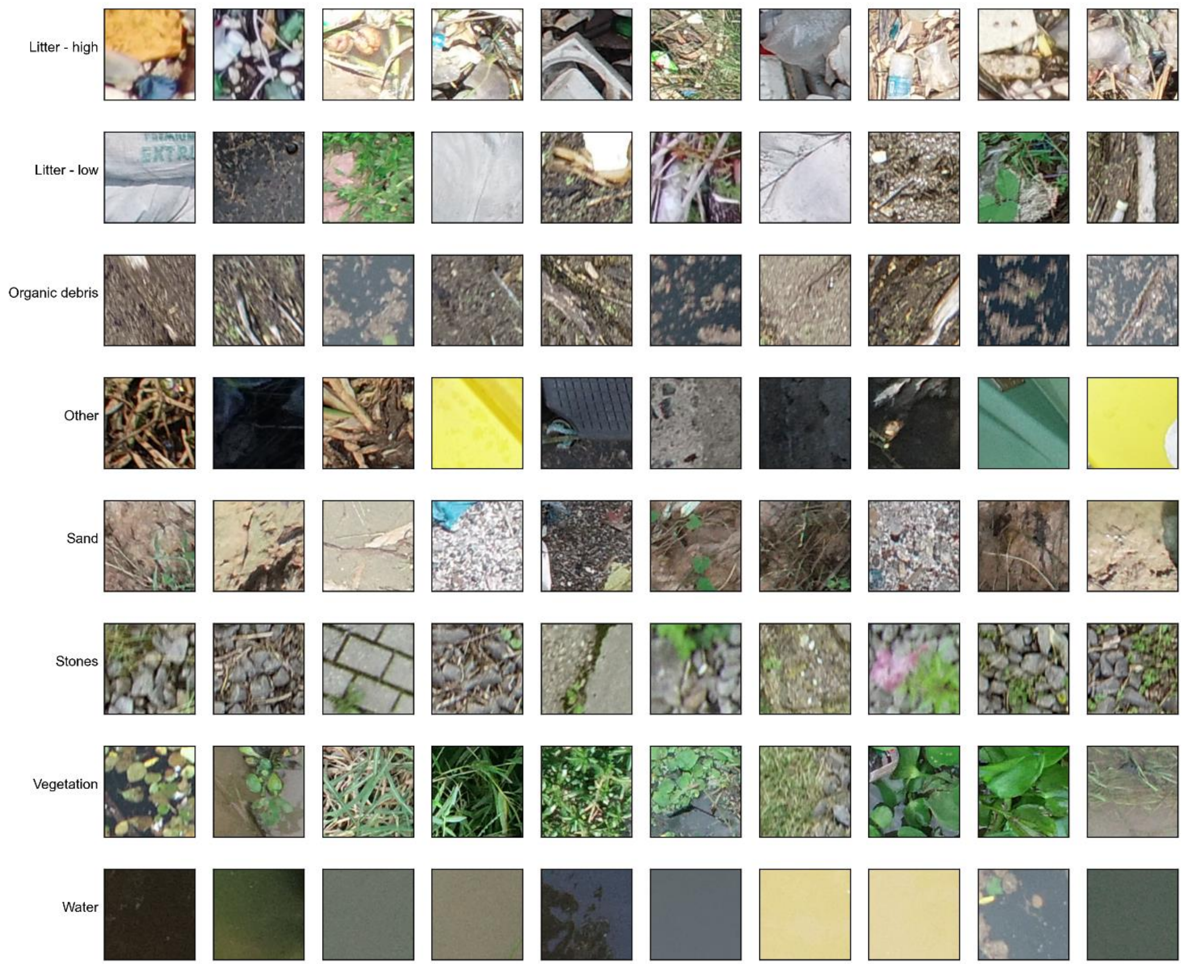
Figure 3. Architecture of the plastic litter detection convolutional neural network algorithm.

Adam(lr=0.001, beta_1=0.9, beta_2=0.999, amsgrad=False)
Dense Layers with L2 regularization
Data augmentation enabeld during training



1st CNN: Plastic Litter Detection - dataset

German Research Center for Artificial Intelligence

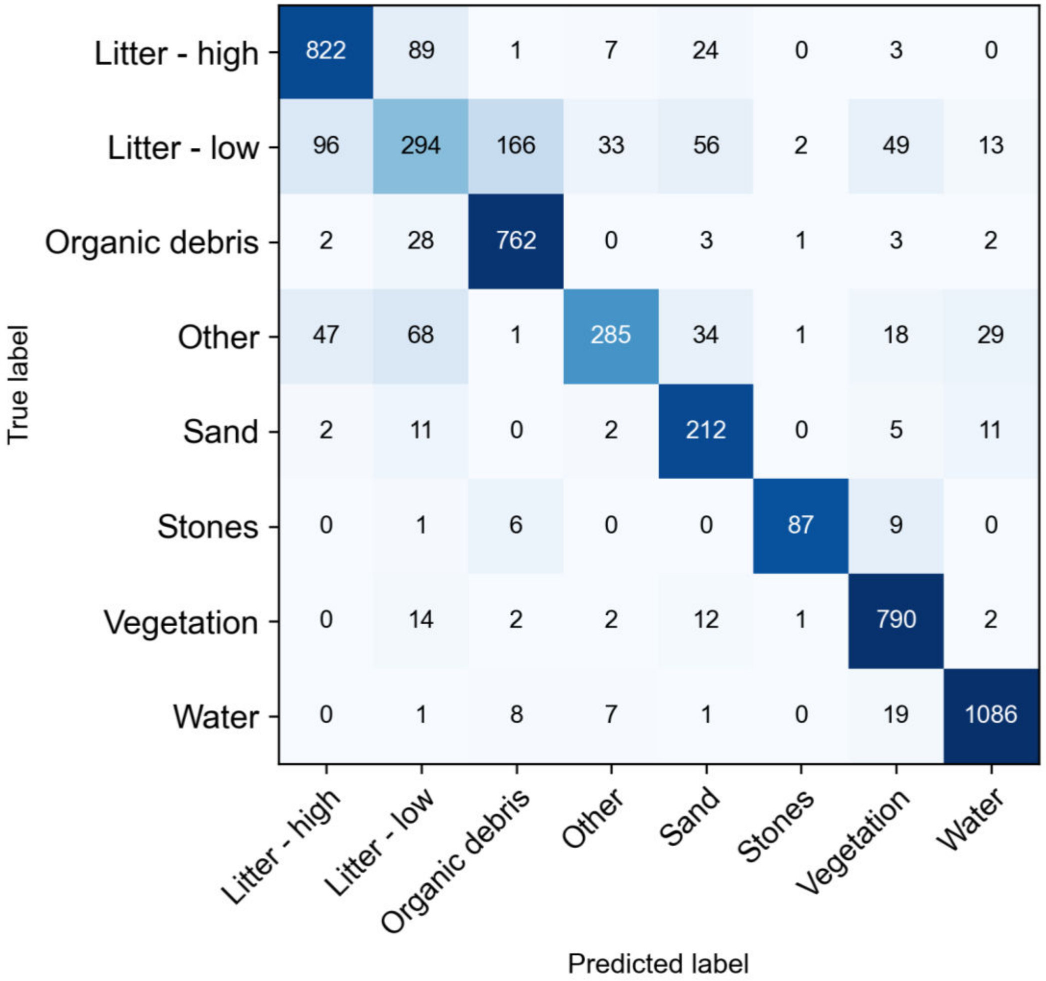


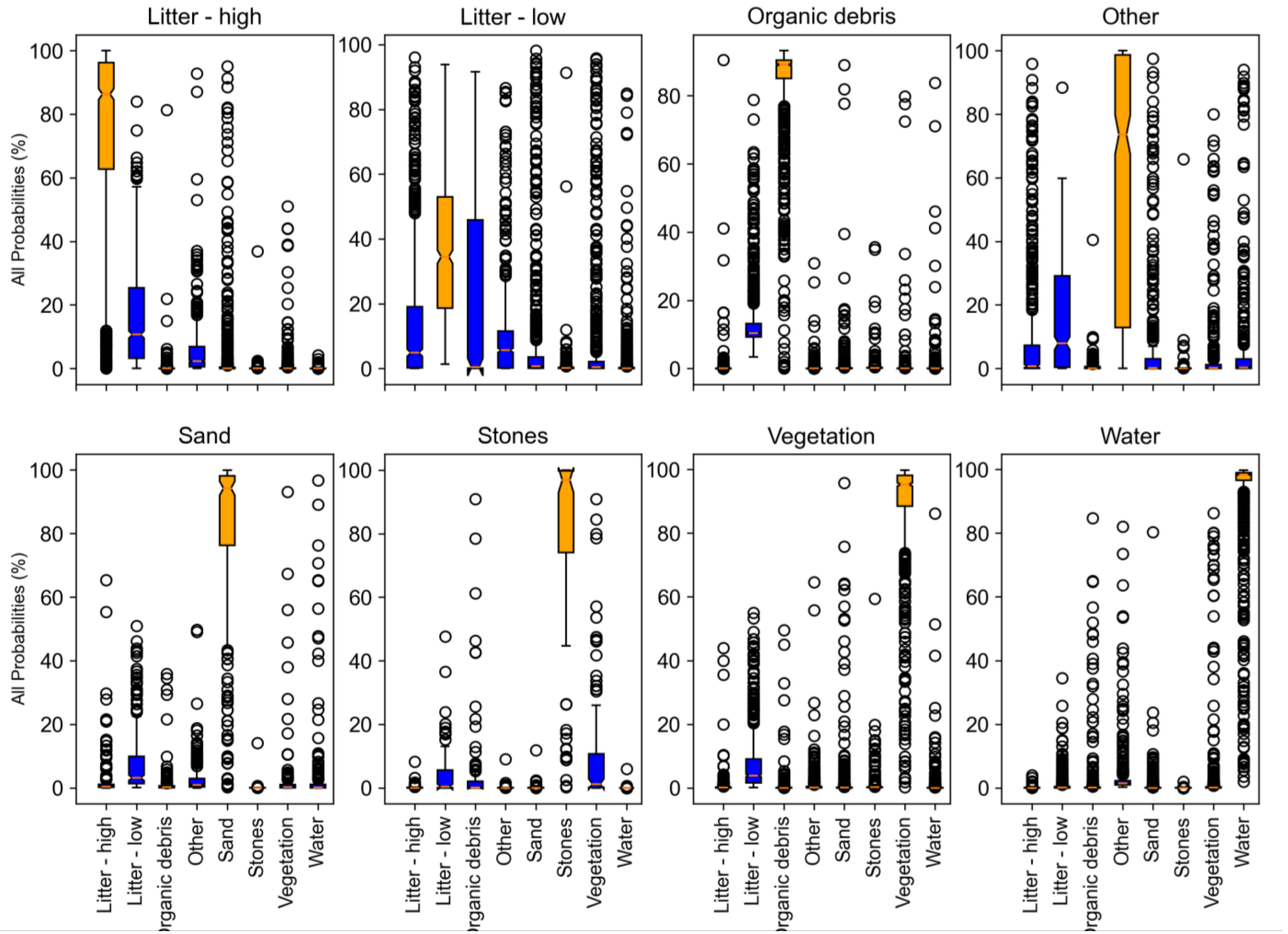
True label \ Predicted label	Litter - high	Litter - low	Organic debris	Other	Sand	Stones	Vegetation	Water
Litter - high	822	89	1	7	24	0	3	0
Litter - low	96	294	166	33	56	2	49	13
Organic debris	2	28	762	0	3	1	3	2
Other	47	68	1	285	34	1	18	29
Sand	2	11	0	2	212	0	5	11
Stones	0	1	6	0	0	87	9	0
Vegetation	0	14	2	2	12	1	790	2
Water	0	1	8	7	1	0	19	1086

Example dataset from Cambodia project (enhanced dataset is planned to make OpenSource soon)

26.147 Training samples from multiple Southeastasian and European countries.
Split: 70 / 15 / 15 (Training, Validation, Test)

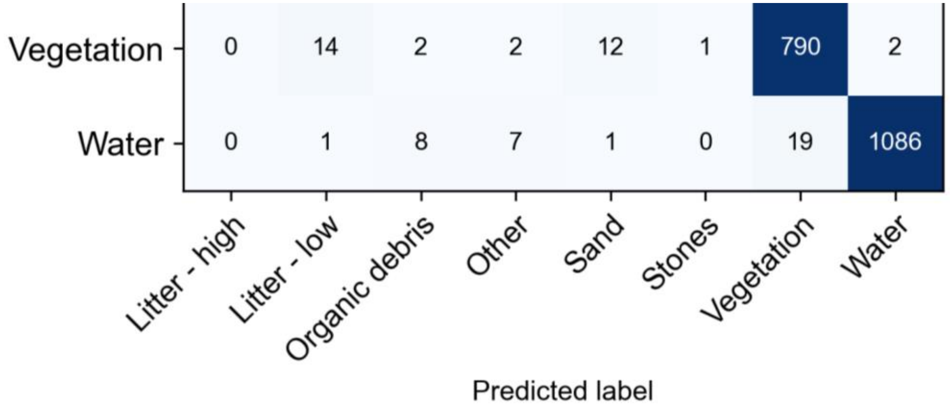
CNN probability outputs for test samples

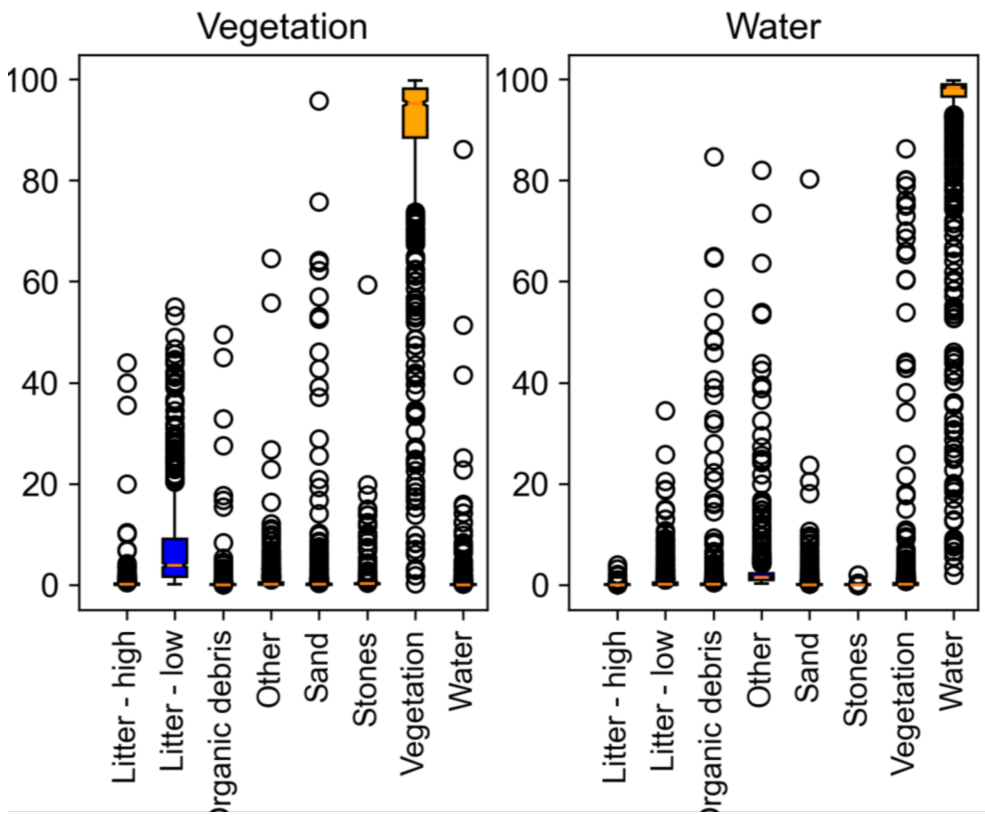




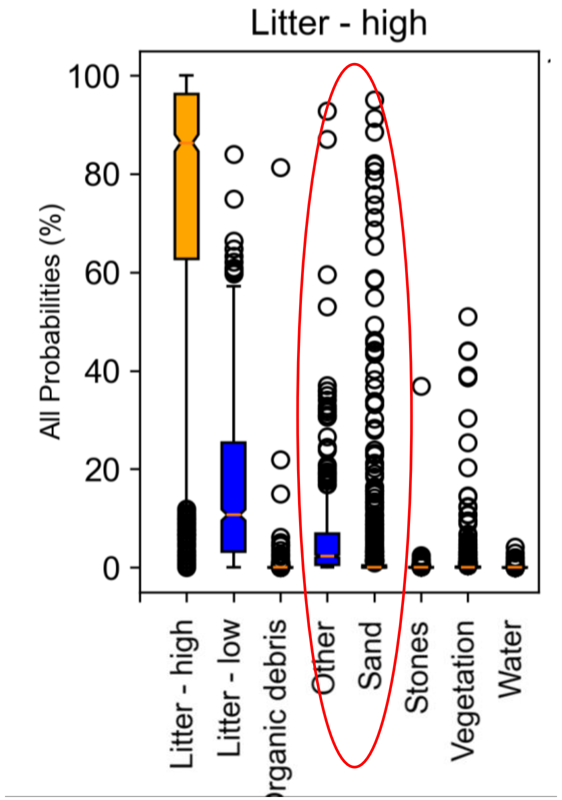
CNN probability outputs for test samples

German Research Center for Artificial Intelligence





CNN probability outputs for test samples



Investigation of result samples

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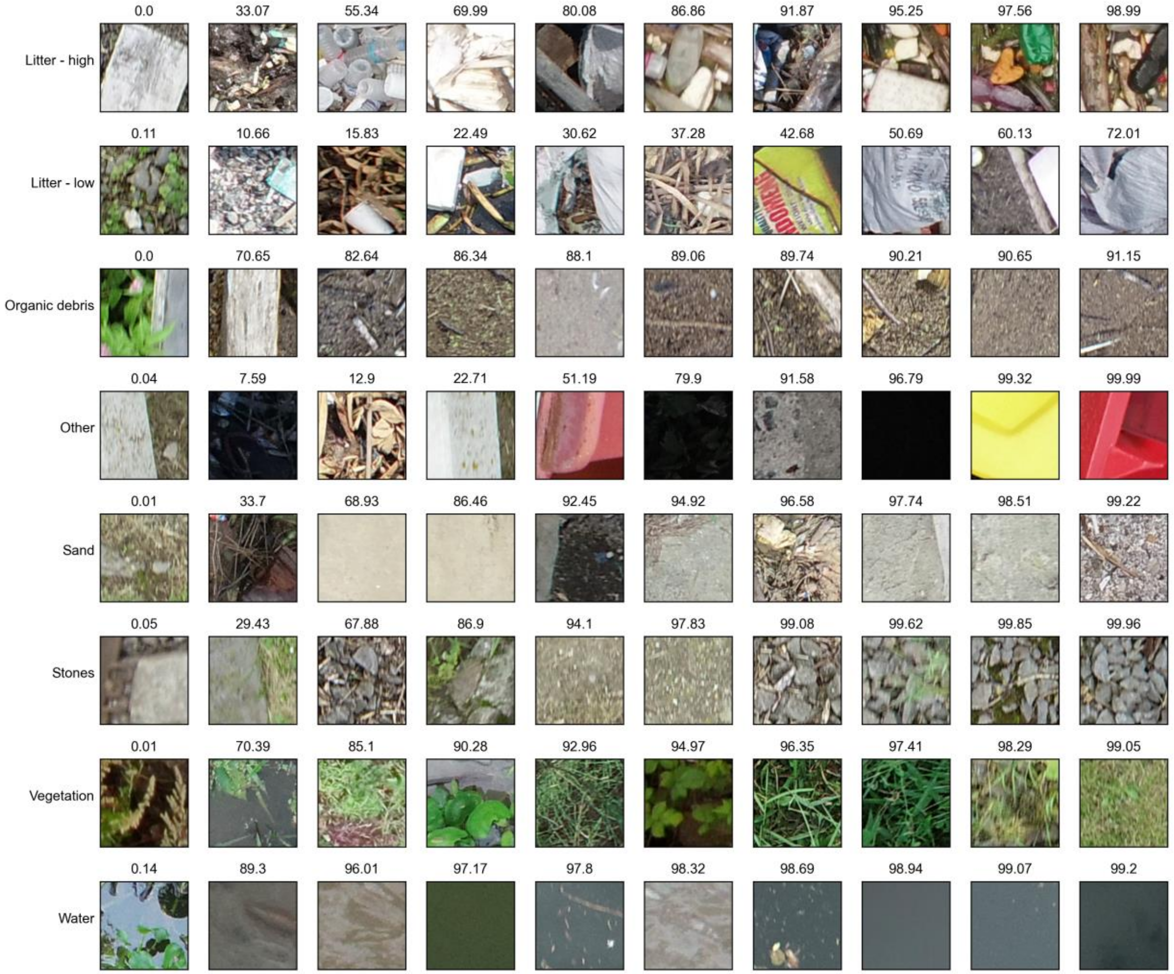
- What features occour (or do not occour), if the CNN is certain about classifications?
- What features occour (or do not occour), if the CNN is making mistakes?

Worst results ----- 10% steps ----- best results



2nd CNN: Plastic Litter Quantifier - dataset

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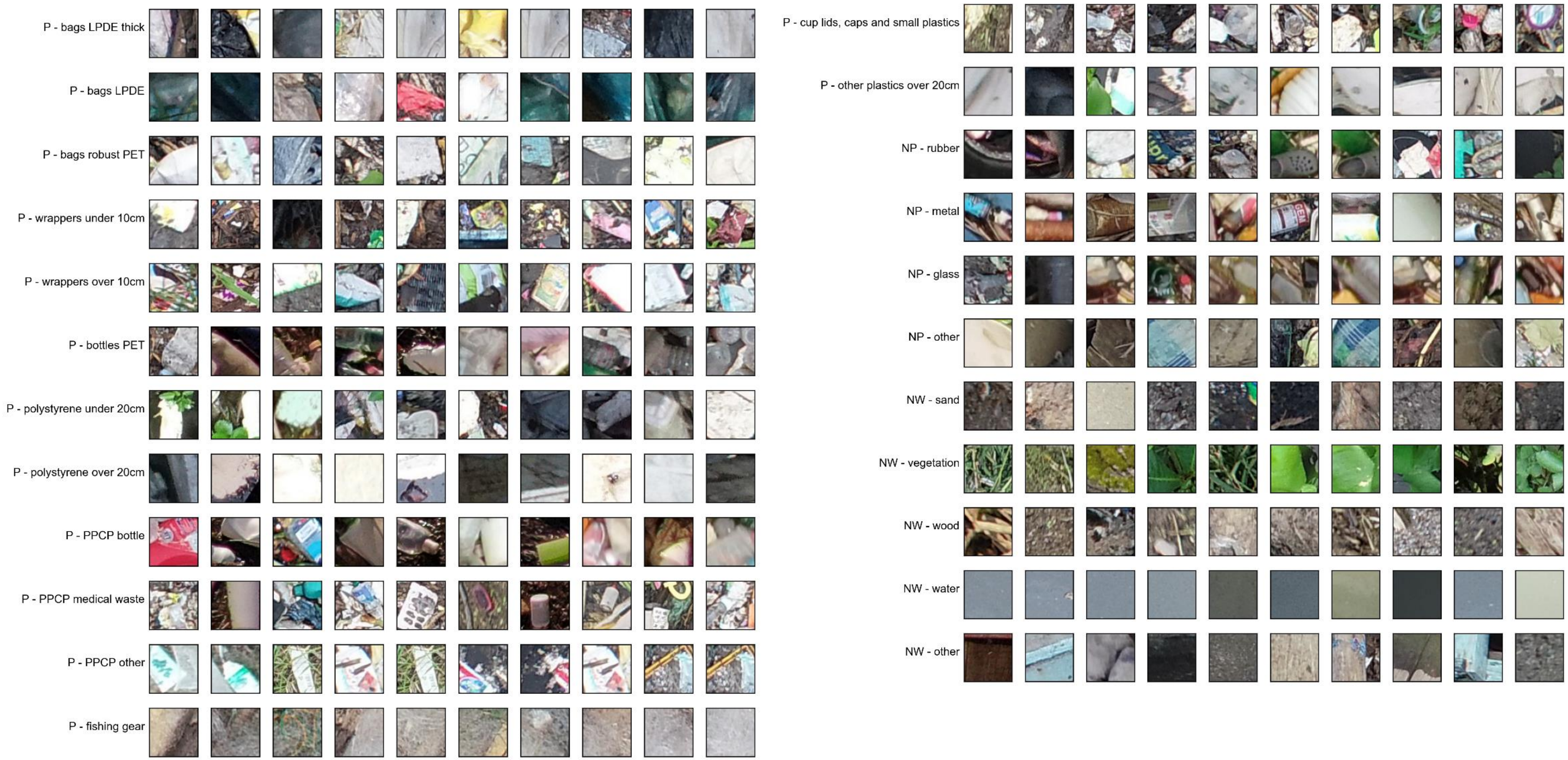

38.417 Training samples from multiple Southeastasian and European countries.
Split: 70 / 15 / 15 (Training, Validation, Test)

Recall probabilities for waste type classifications

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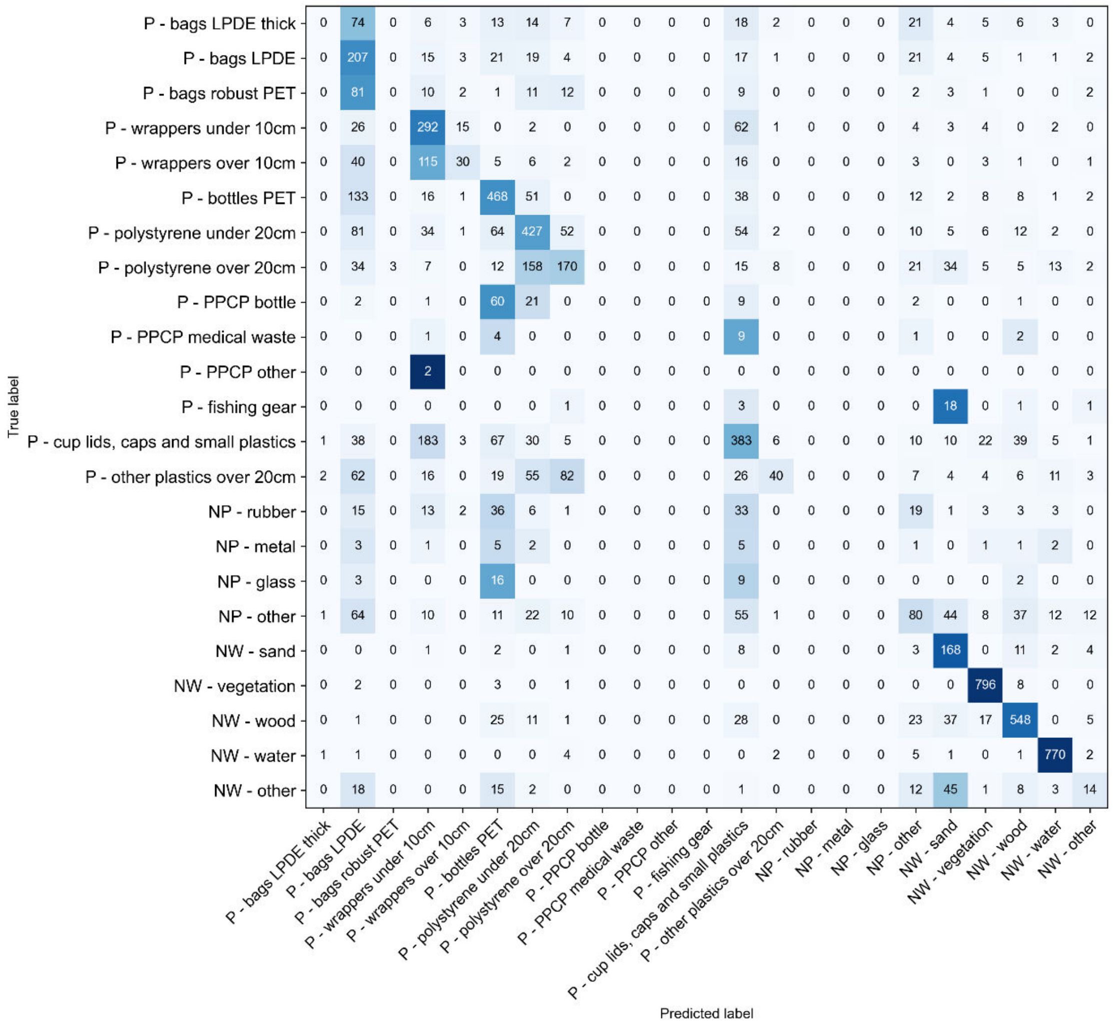

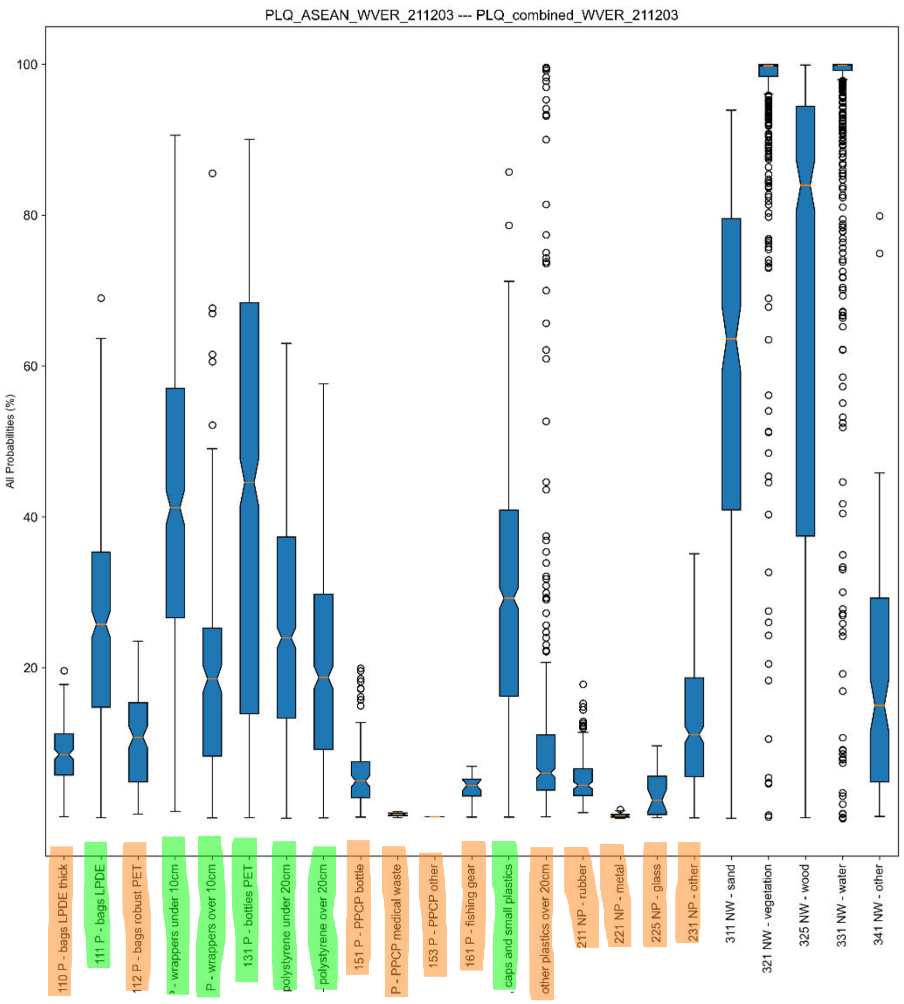

Waste type classifications: worst to best

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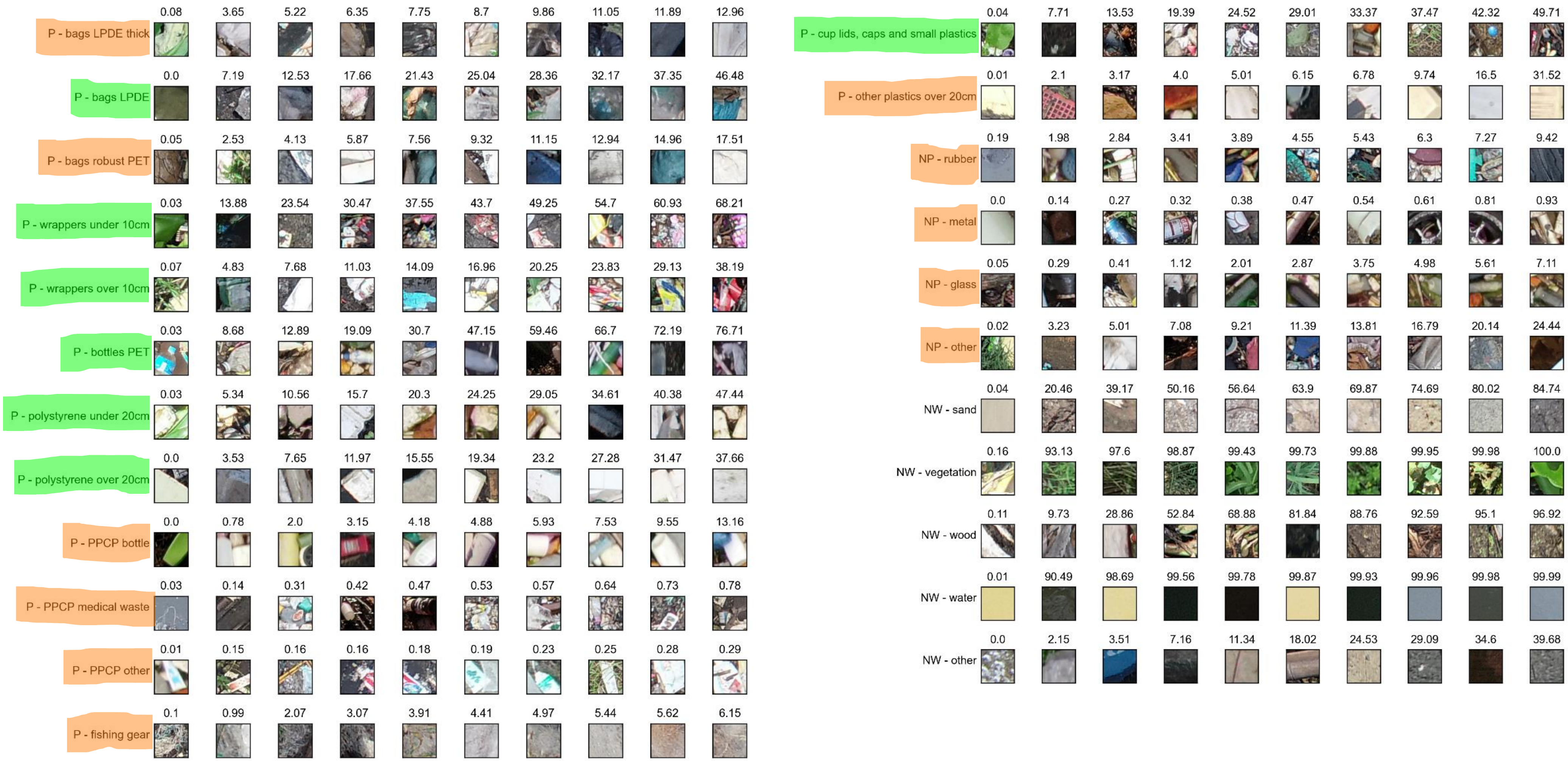


Which waste types can the CNN detect?

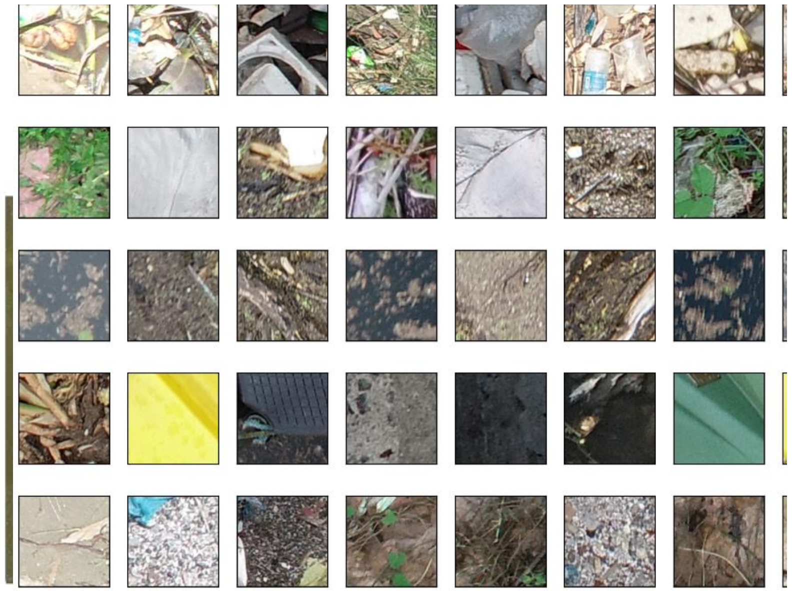
How certain are classifications?

-> info needs to be provided to give context for waste assessment

Next steps

German Research Center for Artificial Intelligence

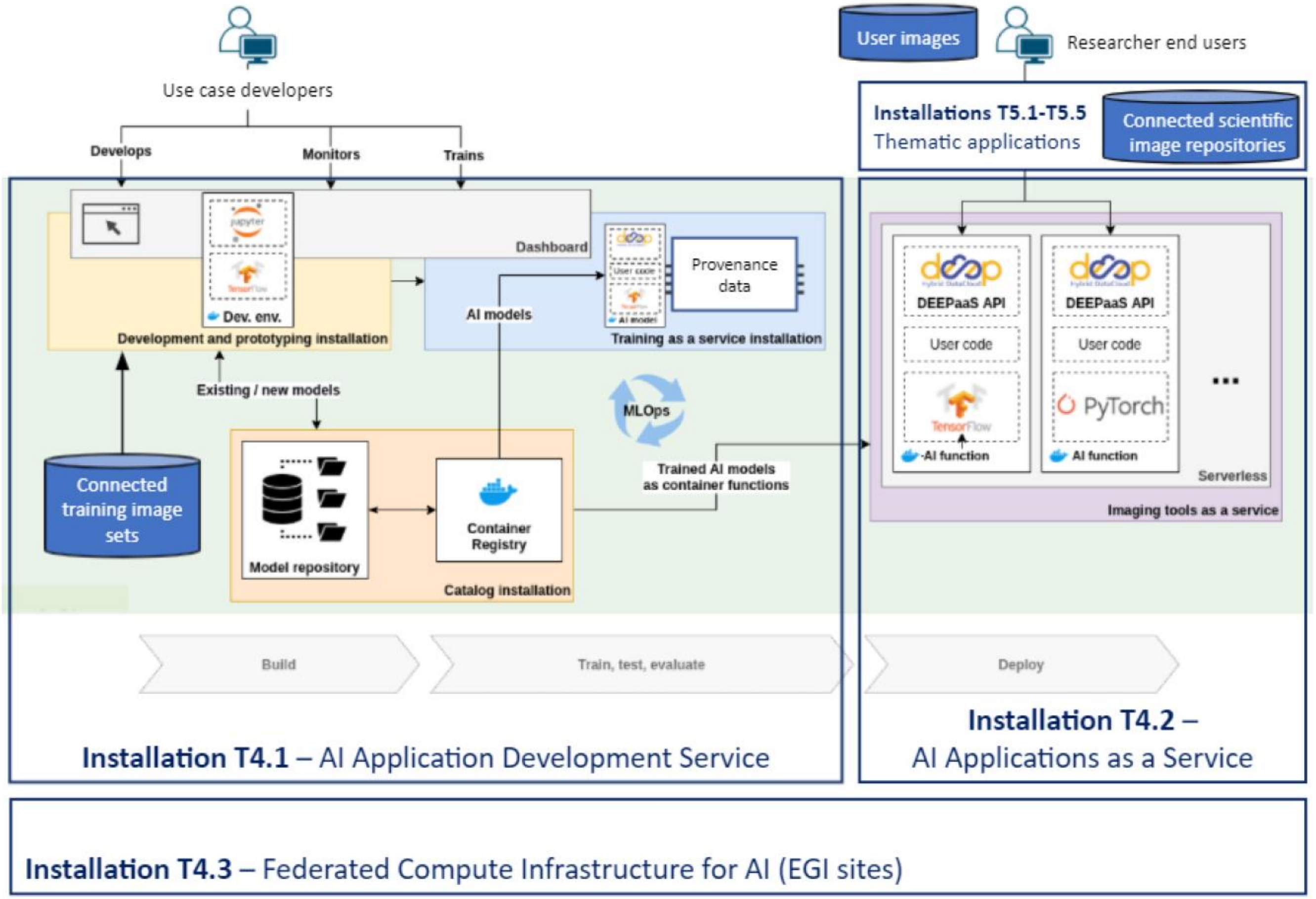
- Use of well known explaination methods like
  - Local Interpretable Model-agnostic Explanations (LIME)
  - SHapley Additive exPlanations (SHAP)
- Problems:
  - APLASTIC-Q works on small tiles of the image
  - Explanations also must work on tiles
  - Usefulness questioned for larger images
- Approach:
  - Use methods on the training samples
  - Show users what part of the image the algorithms used for decision



iMagine - AI as a web service: APLASTIC-Q as application

German Research Center for Artificial Intelligence

- Enable Natural Scientists to use AI Techniques
- Plastic Waste Analysis as Use Case
- Offering pre-trained AI-Modules
- Allow Training with User Images
- Free at point of use
  - image datasets
  - image analysis tools
- **Enable better and more efficient processing and analysis of imaging data**
- Accelerating scientific insights

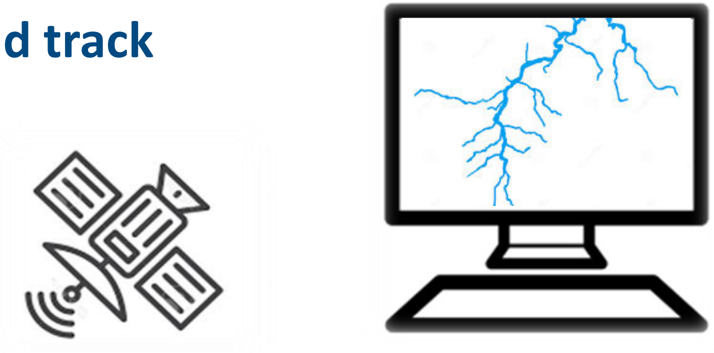


Horizon Europe
THE NEXT EU RESEARCH & INNOVATION PROGRAMME (2021 – 2027)
European Commission
iMagine
egi

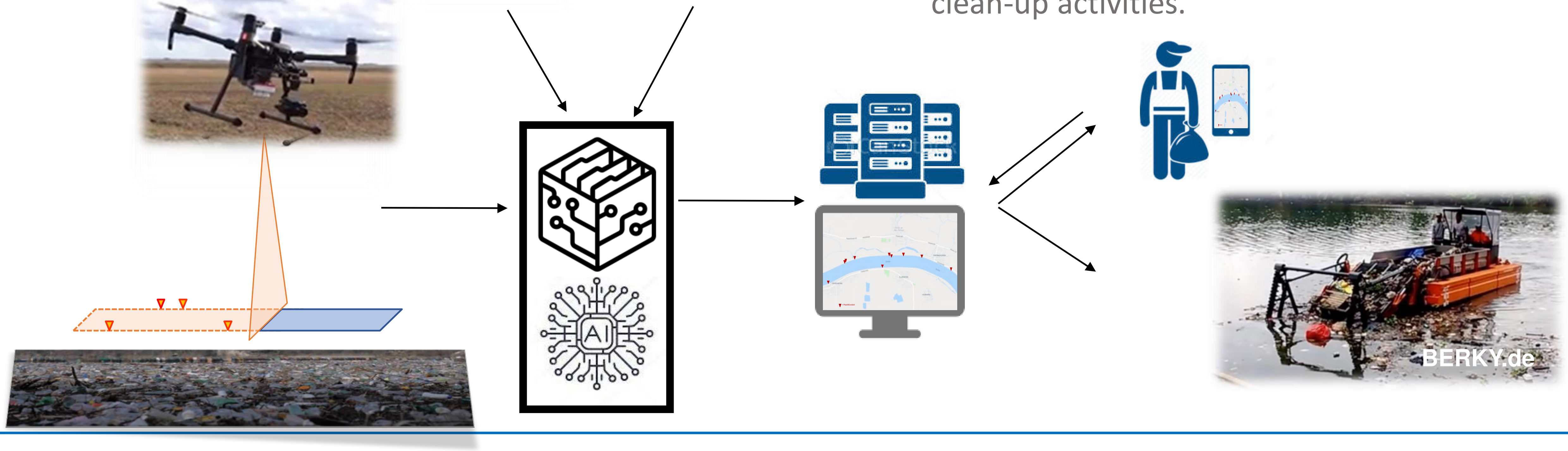
Overall vision: From perception to action

German Research Center for Artificial Intelligence

Detect, identify, quantify and track floating plastic litter



Combining local remote sensing (drones + bridges), **satellite-based information** and **models** in an **AI-enhanced digital twin** providing automated analysis for decision support and near real-time guidance for clean-up activities.



Assistance System for Nautical Officers

Assistance System for Nautical Officers

German Research Center for Artificial Intelligence

90 % of world trade carried over the oceans

reducing costs of operation is mandatory

- reduce staff onboard
- faster operations
- larger ships
- force automatisation of processes

increasing mental load of staff

- dangerous situations
- situational awareness errors account for almost every third accident (Grech et al. 2002)

Instagram/fallenhearts17

Assistance System for Nautical Officers

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Research Center
for Artificial
Intelligence

- Autonomous ships could be a solution
- Many different directions of research in this field
  - (small) prototypes unmanned surface vehicles
  - autonomous ferries (NTNU)
- Main reasons for automatisation
  - Reducing risks
  - Saving energy
  - Reducing emissions
  - Reducing costs
  - Protecting humans

IBM and ProMare

norwegianscitechnews.com


maritimerobotics.com

Assistance System for Nautical Officers

German Research Center for Artificial Intelligence

- Current rules and standards are not made for autonomous ships
  - International Regulations for Preventing Collisions at Sea (COLREGS) (Ventura 2005)
- Regularisation is done by international and national organisations (IMO, DNVGL, etc.)
- IMO defined four levels of autonomy for sea going vessels
- Autonomous systems must ensure to follow the COLREGS (DNVGL 2018)
  - Need of certification

Autonomy level 1
- Vessel with automated processes and decision support systems
- Crew on board

Autonomy level 2
- Remotely operated vessel
- Crew onboard

Autonomy level 3
- Remotely operated vessel
- No crew onboard

Autonomy level 4
- fully autonomous vessel
- No crew onboard

Assistance System for Nautical Officers

Autonomy level 1
- Vessel with automated processes and decision support systems
- Crew on board

Autonomy level 2
- Remotely operated vessel
- Crew onboard

Autonomy level 3
- Remotely operated vessel
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Autonomy level 4
- fully autonomous vessel
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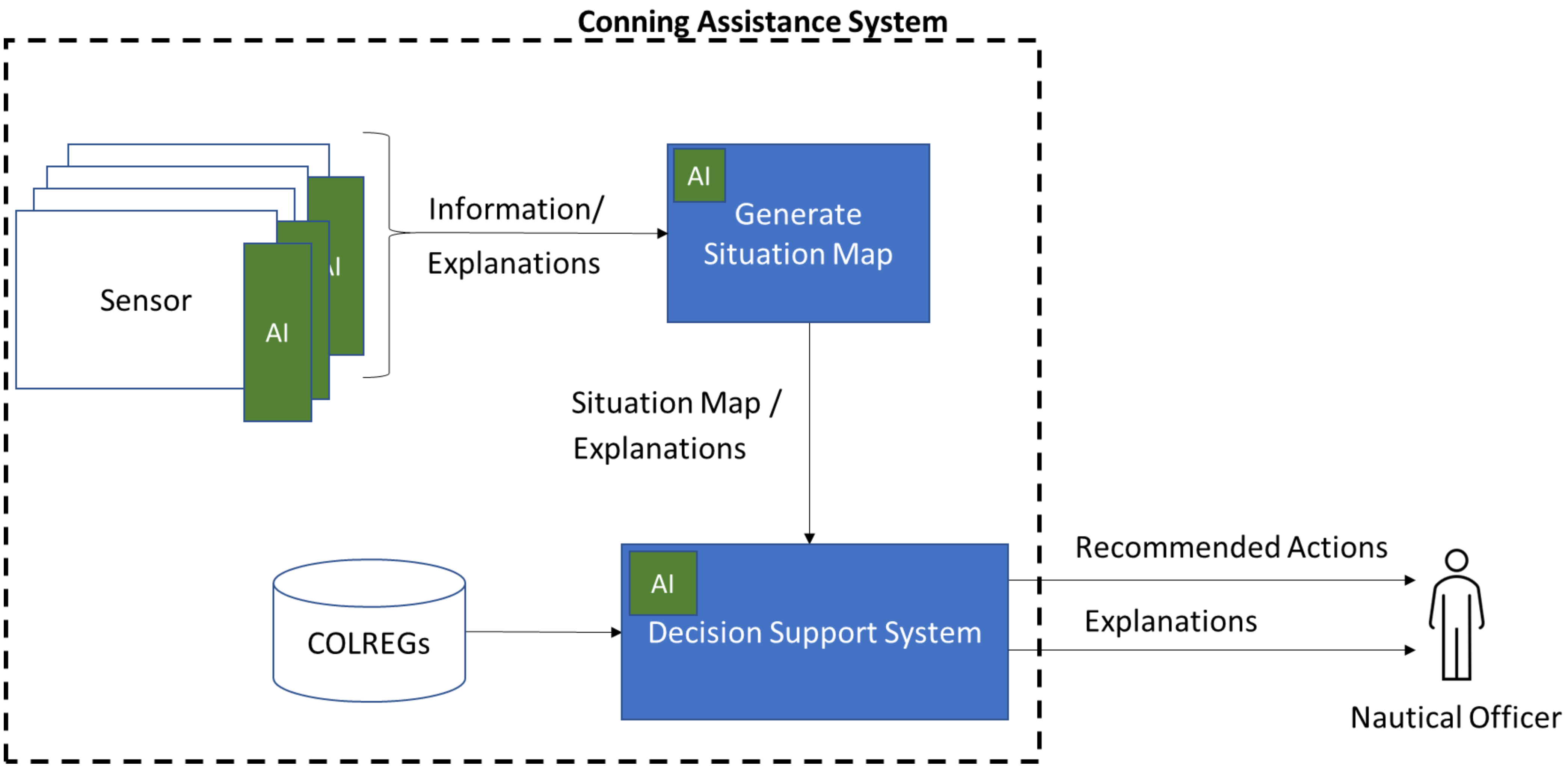
Assistance System for Nautical Officers



Assistance System for Nautical Officers

- Development of explainable assistance system for nautical officers
- Provide COLREG conform recommended actions
- Deliver explanations for decisions
- First step towards autonomous ships
- Planned start: Summer 2023

Conclusions

APLASTIC-Q

- Explanations helped stakeholders to gain confidence in AI solutions
- Explanations helped to identify worse working classes in plastic waste quantification
- Potentially further use of model agnostic methods to improve explainability

Assistance System for Nautical Officers

- Long way towards autonomous ships
- Research is needed in this area
- XAI could be a tool to enable certification of autonomous ships in the future

Thanks for your attention!

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