Workshop Explainable AI
Part 3: Marine Application Cases

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DFKI – German Research Center for Artificial Intelligence

629 researcher

350 ongoing projects

130 Mio. € project volume

98 spin-offs

DFKI is one of the leading (applied) AI research centers
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
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).
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!
Plastic waste and emission detection

Intelligent sensors and situational awareness

Marine Perception
• 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

13/12/2022

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

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

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
How accurate are the results?
Plastic litter detection with machine learning using a two-step approach

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

⇒ Quantitative results and characterization of dominant pollution classes for plastic waste and other litter
PLD CNN architecture and training details

Adam($\text{lr}=0.001$, $\text{beta}_1=0.9$, $\text{beta}_2=0.999$, amsgrad=False)
Dense Layers with L2 regularization
Data augmentation enabled during training

Figure 3. Architecture of the plastic litter detection convolutional neural network algorithm.
1st CNN: Plastic Litter Detection - dataset

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

Example dataset from Cambodia project (enhanced dataset is planned to make OpenSource soon)
CNN probability outputs for test samples

<table>
<thead>
<tr>
<th>True label</th>
<th>Litter - high</th>
<th>Litter - low</th>
<th>Organic debris</th>
<th>Other</th>
<th>Sand</th>
<th>Stones</th>
<th>Vegetation</th>
<th>Water</th>
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<td>3</td>
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<td>762</td>
<td>0</td>
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Predicted label

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CNN probability outputs for test samples
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Investigation of result samples

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

- What features occur (or do not occur), if the CNN is making mistakes?

<table>
<thead>
<tr>
<th>Category</th>
<th>Worst results</th>
<th>10% steps</th>
<th>Best results</th>
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<td>58.32</td>
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<td>99.99</td>
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13/12/2022
38,417 Training samples from multiple Southeast Asian and European countries. Split: 70 / 15 / 15 (Training, Validation, Test)
Recall probabilities for waste type classifications.
Waste type classifications: worst to best

Which waste types can the CNN detect?

How certain are classifications?

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

13/12/2022
Next steps

• Use of well known explanation 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
• 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
Overall vision: From perception to action

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

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)
• 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
Assistance System for Nautical Officers

- 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
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
- No crew onboard

Autonomy level 4
- Fully autonomous vessel
- No crew onboard
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

• 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

APLASTIC-Q

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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