Cross-Domain Applications of Data Science in Autonomous Robotics: A Study of Methods and Insights

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HAW HAMBURG

Motivation

- In 3 separate autonomous robotics projects, progress with the current data was stagnating.
- Making significant contributions without domain knowledge is difficult.
- By doing a broad analysis between projects, I could potentially draw new insight.

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- Perform a ground-up analysis of each project in parallel.
- Highlight potential improvements and considerations before collecting more data.

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3 **data driven** autonomous robotics projects:

- SmartRecycling-UP
  - Autonomous sorting of coarse waste for recycling.
- RoLand
  - Semi-autonomous strawberry harvesting robot.
- AuTag BeoFisch
  - Autonomous deep-sea robot for fish monitoring and tracking.

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Labelled multi-spectral images of unsorted construction waste (UV, VIS, NIR, SWIR)

- Complex and unpredictable environment
- 15 dimensional data from images
- Labelled between 7 materials

- Goal: Material classification

Scene in a recycling facility (Lange, 2023).

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Multi-spectral images of strawberry plants (UV, VIS, NIR, SWIR)

- Challenging natural environments
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- Labelled between 4 classes
  - 4 subclasses for strawberry ripeness

- Goal: Detection of ripe and unripe/defective strawberries.

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Underwater video and sonar data from the Baltic Sea.

- Turbid and challenging underwater environments
- Unlabelled
- Needs to be temporally aligned

- Goal: Detection of fish and other aquatic animals

Video frame of a moon jelly (Zach, 2021)

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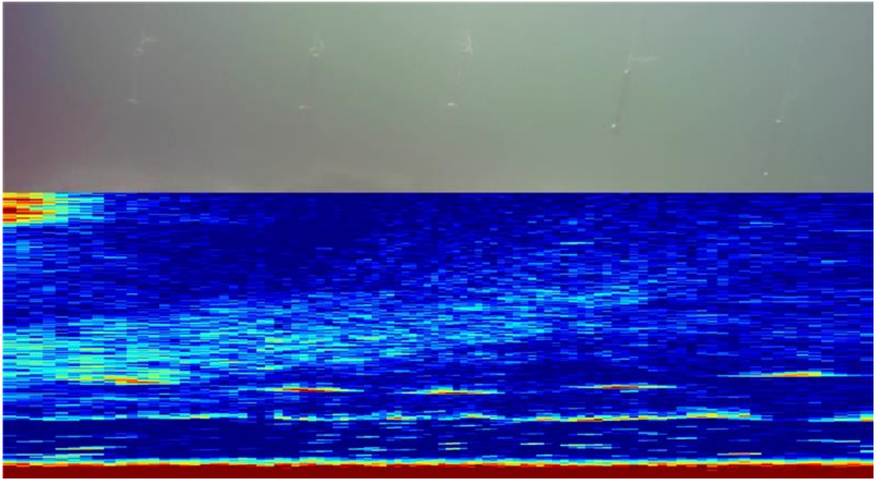

Data Summary

- Characteristically challenging environments.
- Two datasets of high dimension labelled images.
- A strongly dissimilar dataset of especially difficult data.

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Methodology

Ground-up data analysis

1. Pre-processing
2. Histograms and Correlation Maps
3. Outlier Detection and Box Plots

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4. Dimensionality reduction and visualization
5. Clustering

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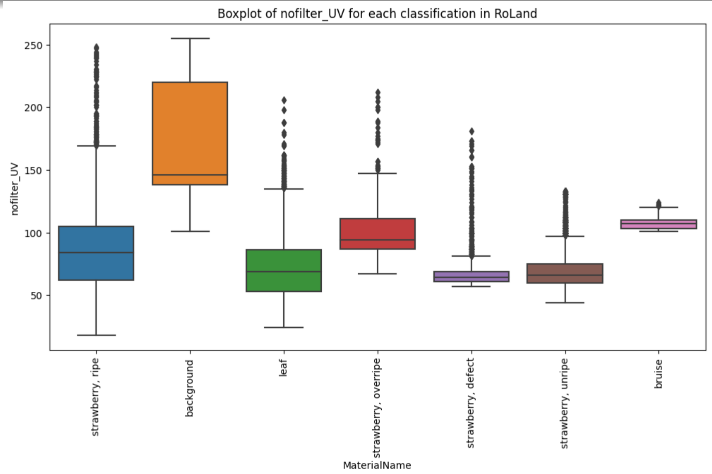
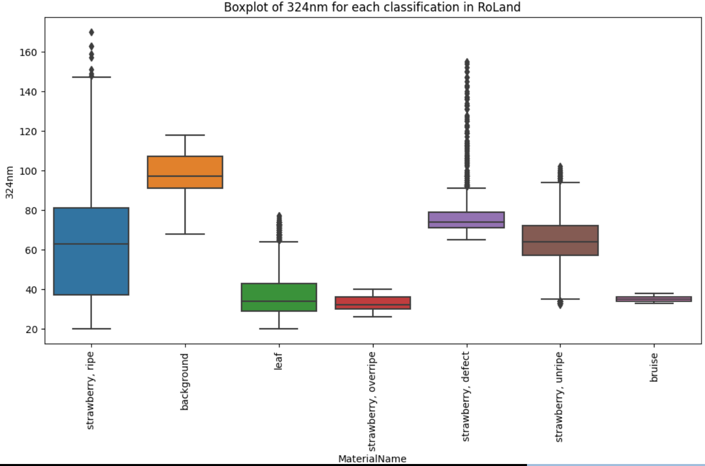
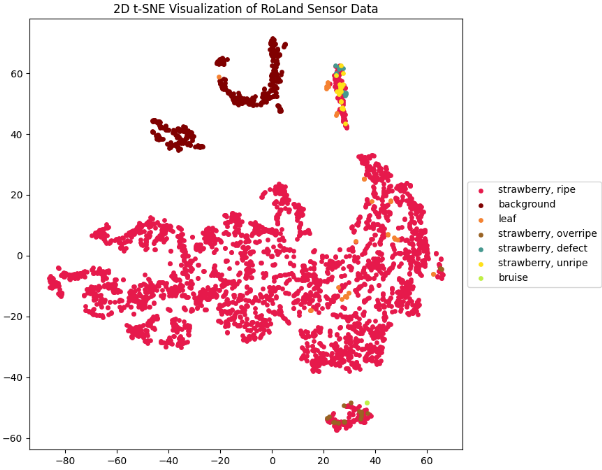
RoLand


Boxplot of nofilter_UV for each classification in RoLand
nofilter_UV
250
200
150
100
50
strawberry, ripe
background
leaf
strawberry, overripe
strawberry, defect
strawberry, unripe
bruise
MaterialName

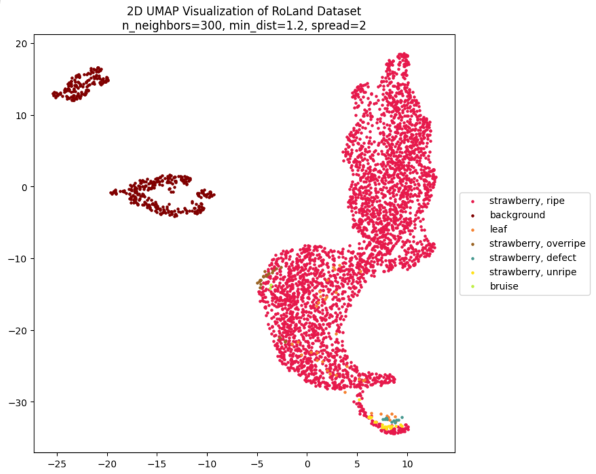
RoLand


Boxplot of 324nm for each classification in RoLand
324nm
160
140
120
100
80
60
40
20
strawberry, ripe
background
leaf
strawberry, overripe
strawberry, defect
strawberry, unripe
bruise
MaterialName

RoLand


2D t-SNE Visualization of RoLand Sensor Data
60
40
20
0
−20
−40
−60
−80
−60
−40
−20
0
20
40
60
strawberry, ripe
background
leaf
strawberry, overripe
strawberry, defect
strawberry, unripe
bruise

RoLand


2D UMAP Visualization of RoLand Dataset
n_neighbors=300, min_dist=1.2, spread=2
20
10
0
−10
−20
−30
−25
−20
−15
−10
−5
0
5
10
strawberry, ripe
background
leaf
strawberry, overripe
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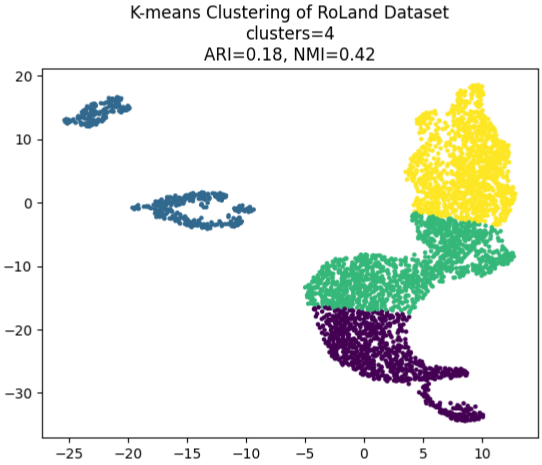
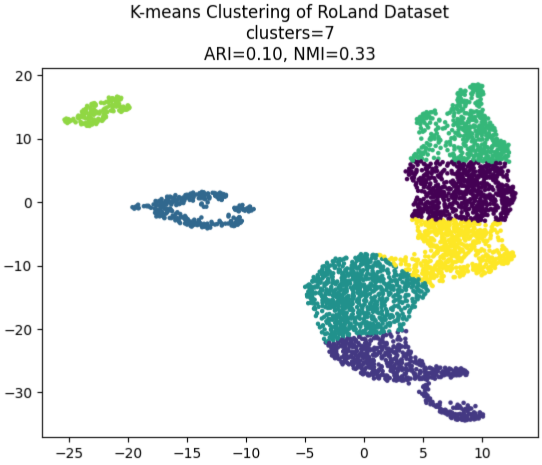
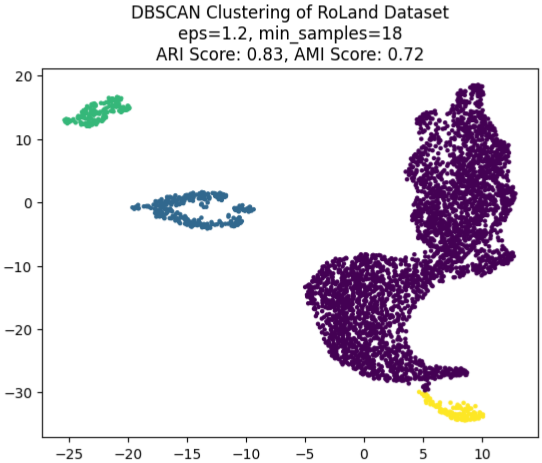

K-means Clustering of RoLand Dataset
clusters=4
ARI=0.18, NMI=0.42
20
10
0
−10
−20
−30
−25
−20
−15
−10
−5
0
5
10

RoLand


K-means Clustering of RoLand Dataset
clusters=7
ARI=0.10, NMI=0.33
20
10
0
−10
−20
−30
−25
−20
−15
−10
−5
0
5
10

RoLand


DBSCAN Clustering of RoLand Dataset
eps=1.2, min_samples=18
ARI Score: 0.83, AMI Score: 0.72
20
10
0
−10
−20
−30
−25
−20
−15
−10
−5
0
5
10

RoLand

- Strong under-representation of non-ripe strawberry data.
- Background and non-ripe clustering is relatively easy using DBSCAN.
  - Clustering by specific ripeness is more difficult and requires more representation.
- UV and 324nm wavelengths had greatest differences in ripeness subclasses.

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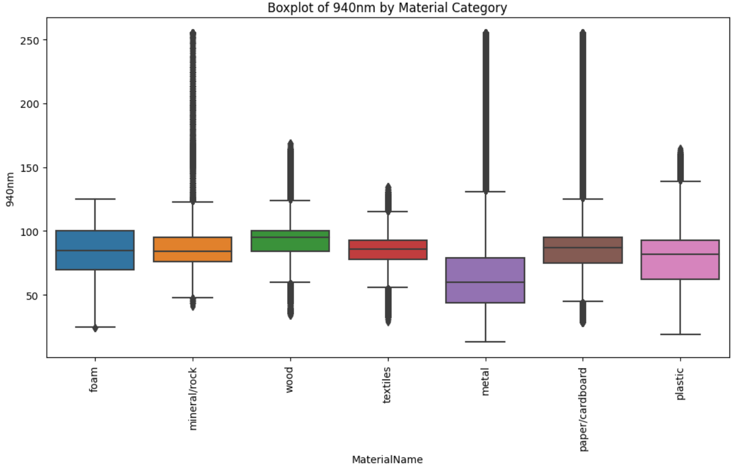

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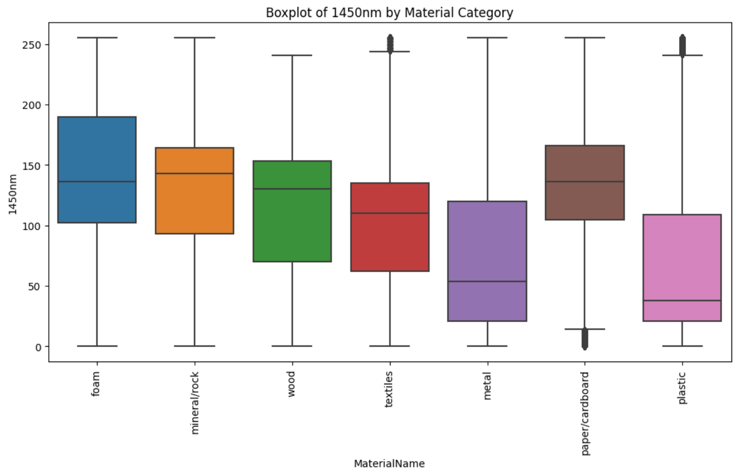

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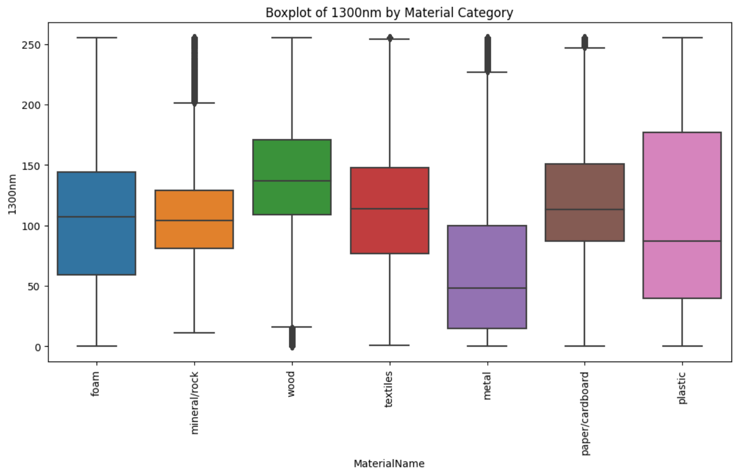

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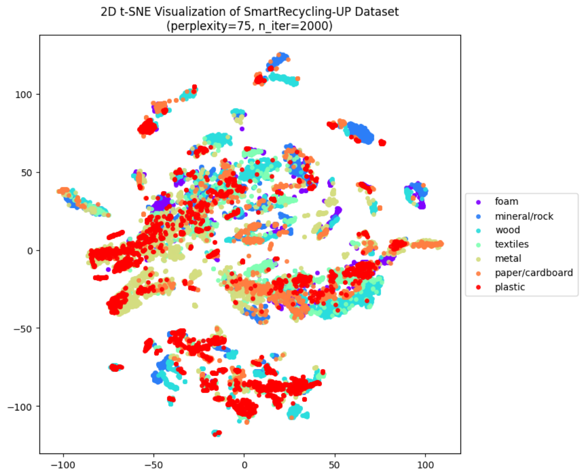

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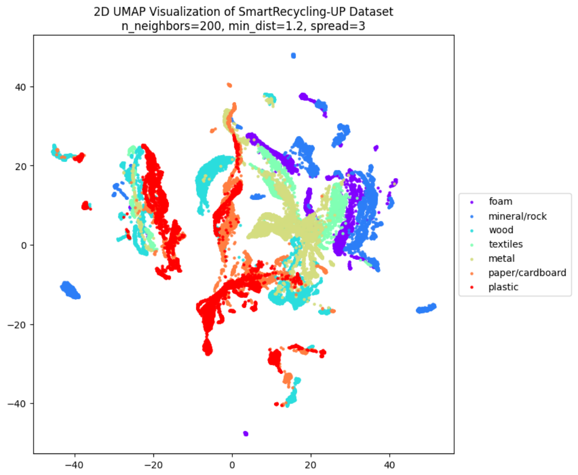

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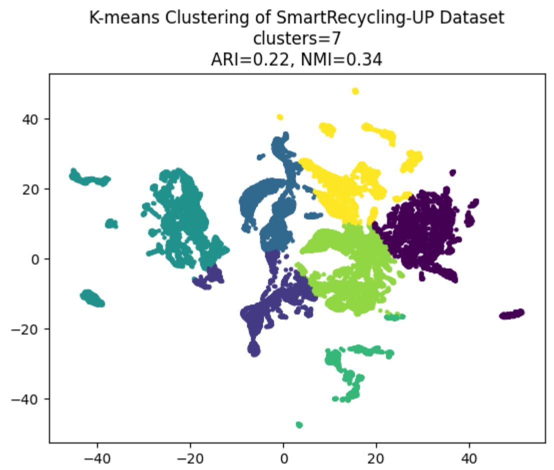

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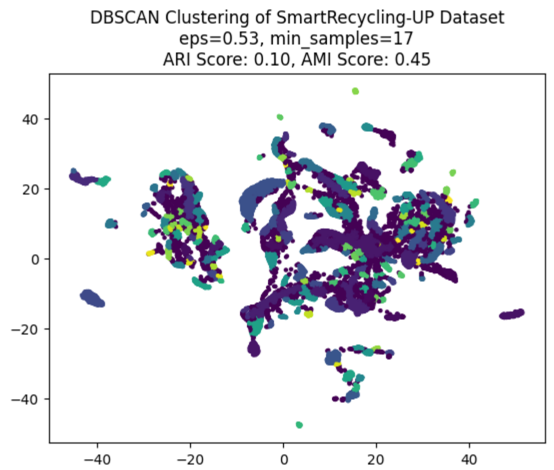

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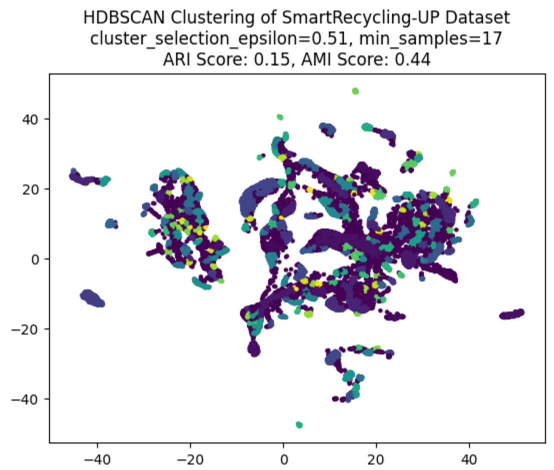

SmartRecycling-UP

- Clustering with the current data looks promising, but further distinction is needed for better results.
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What happened with the 3rd project?

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- Not much **valuable** data.
- Too dissimilar to draw any comparative insight.
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- Performing clustering from UMAP with k-Means and DBSCAN had different results
- Cross-domain hyper-parameter adjustments

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- Attempt a similar analysis approach with data more similar to AuTag BeoFischs'.
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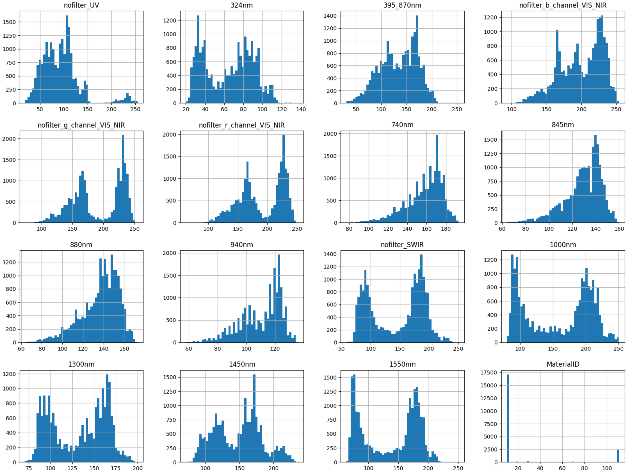
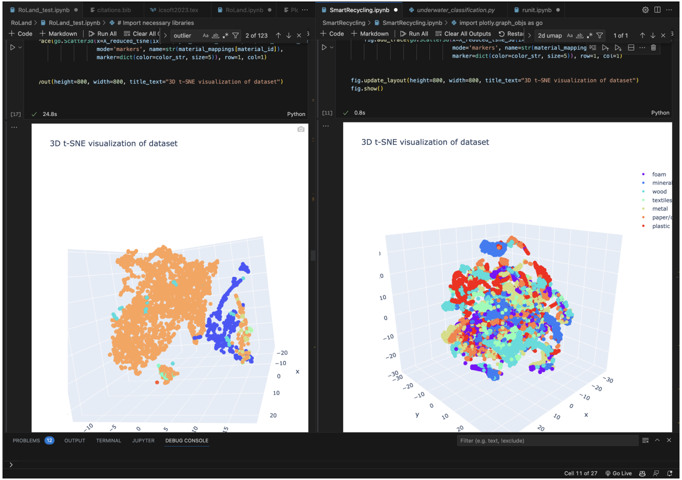
Thank you for your attention!

Questions?

Appendix


nofilter_UV
324nm
395_870nm
nofilter_b_channel_VIS_NIR
nofilter_g_channel_VIS_NIR
nofilter_r_channel_VIS_NIR
740nm
845nm
880nm
940nm
nofilter_SWIR
1000nm
1300nm
1450nm
1550nm
MaterialID

Appendix


3D t-SNE visualization of dataset
3D t-SNE visualization of dataset
foam
wood
metal
plastic

Appendix

Appendix

References I

Lange, T., Babu, A., Meyer, P., Keppner, M., Tiedemann, T., Wittmaier, M., Wolff, S., and Vögele, T.
First lessons learned of an artificial intelligence robotic system for autonomous coarse waste recycling using multispectral imaging-based methods.
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Towards non-invasive fish monitoring in hard-to-access habitats using autonomous underwater vehicles and machine learning.
In *OCEANS 2021: San Diego – Porto*, pages 1–8, San Diego, CA, USA, 2021.