

The background is a deep blue, textured surface representing water. It is filled with various pieces of plastic waste, including several clear plastic bottles (some whole, some broken into fragments), a clear plastic cup, and numerous small, translucent, irregular fragments that resemble microplastics. The lighting is dramatic, with a bright light source from the upper left creating a strong lens flare and illuminating the plastic pieces, which have a glossy, reflective appearance.

15-51 trillion

microplastic particles floating in surface waters

microplastics
already found its
way back to us





physical and chemical damage
to organ systems

marine life mistakenly feeding
on plastics



The background is a deep blue, textured surface representing water. Scattered throughout are several broken glass bottles and sharp fragments of glass. The bottles are in various orientations, some upright and some upside down. The lighting creates bright highlights and reflections on the glass surfaces, giving a sense of depth and movement. A central white rectangular box with rounded corners contains the text.

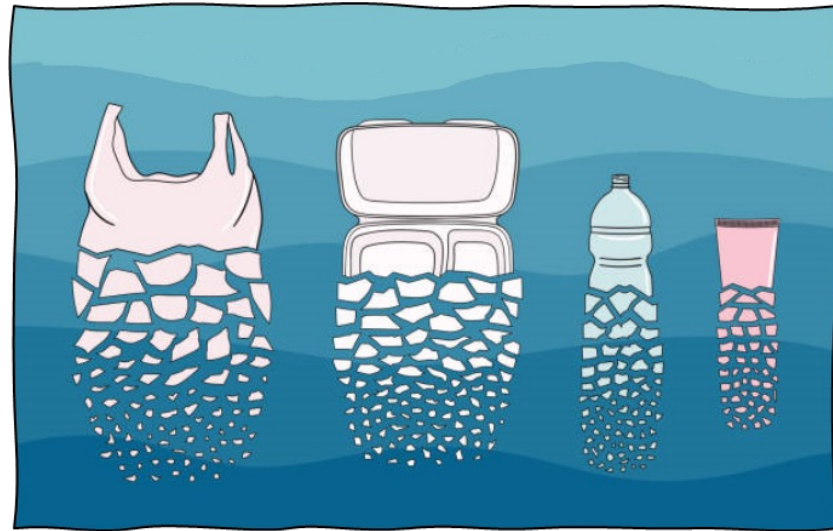
**what can we do to detect
microplastics in water?**

tiny plastic, big problem!

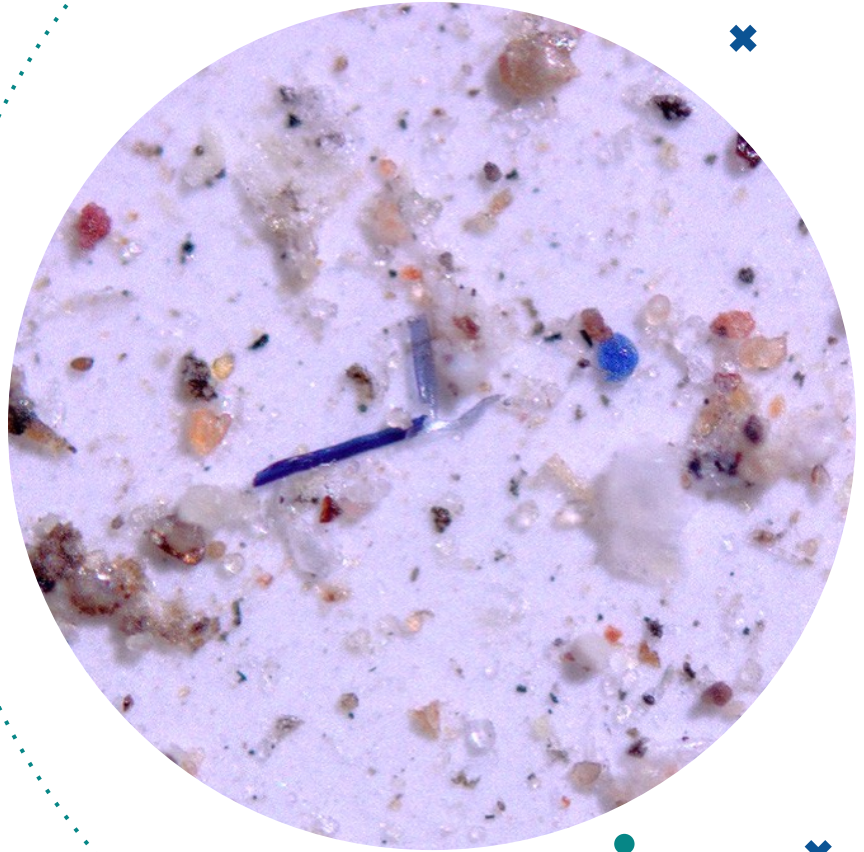
microplastics detection
with deep learning

gaspar | jayme | nepomuceno | paderes
cpt 5

ml3 public presentation, 18 mar 2022

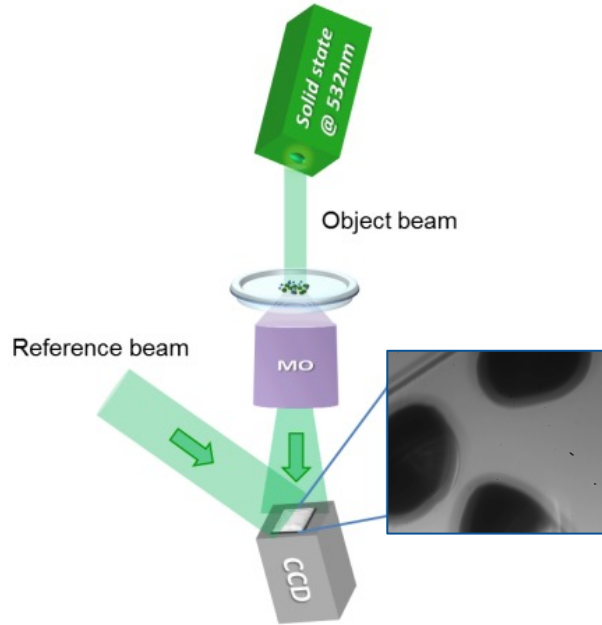


**microplastic count
indicate
pollution levels**





digital holographic microscopy

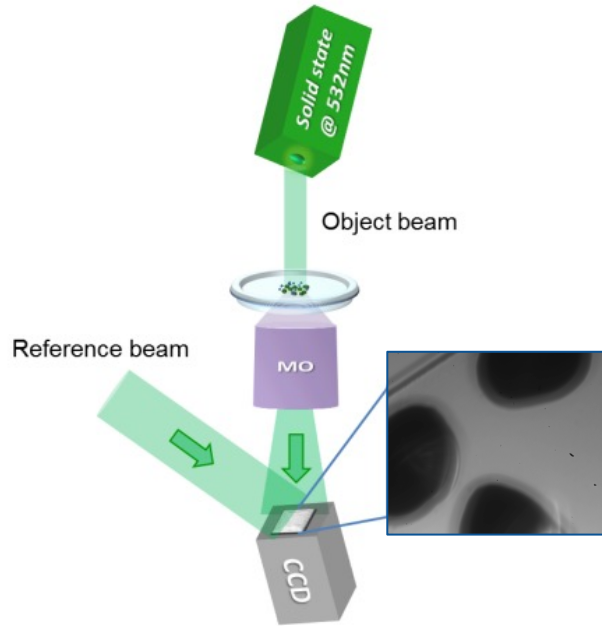


- ✓ non-invasive and non-contact
- ✓ suitable for underwater imaging where species are fragile
- ✓ offers more information on 3d shapes than 2d images
- ✓ compact and low-cost





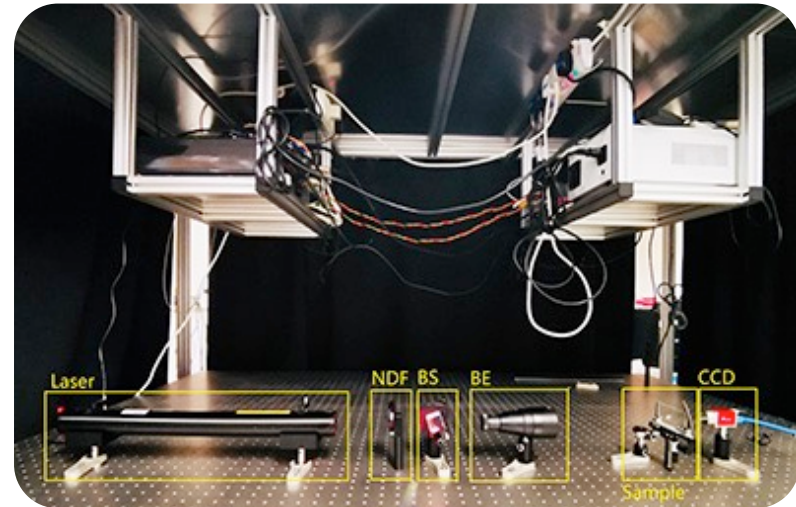
digital holographic microscopy



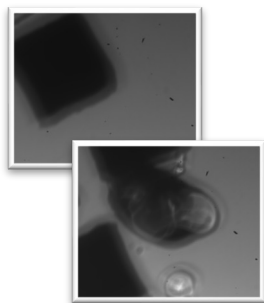
- × requires image pre-processing for feature extraction
- × classification and analysis dependent on SMEs



how can we use
deep learning to
enhance the
microplastics
detection process?



methodology



data
gathering

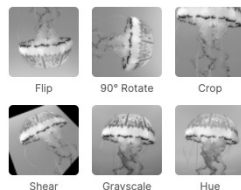
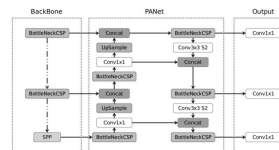
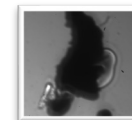
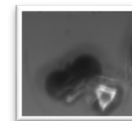


image annotation
& augmentation

YOLOv5



model
building



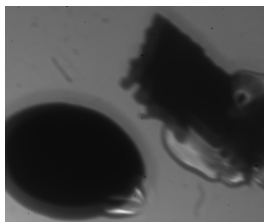
evaluation
of results



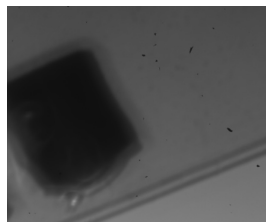
data



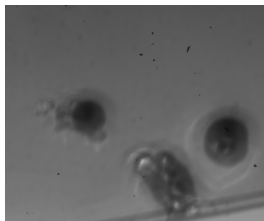
sample images



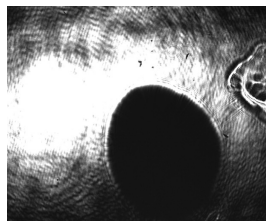
1 PE w/ dust



1 PHA



3 PS



1 LDPE

- 472 open-source hologram images
- includes various plastic types
- microplastic count varies from 0 to 5
- 40% of images include dust



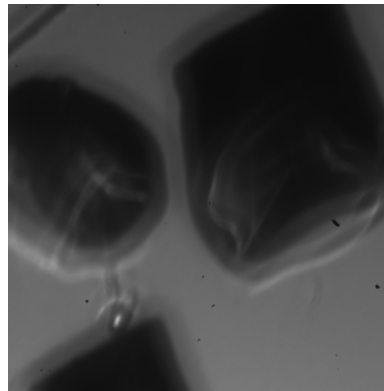
image annotation & augmentation



unannotated

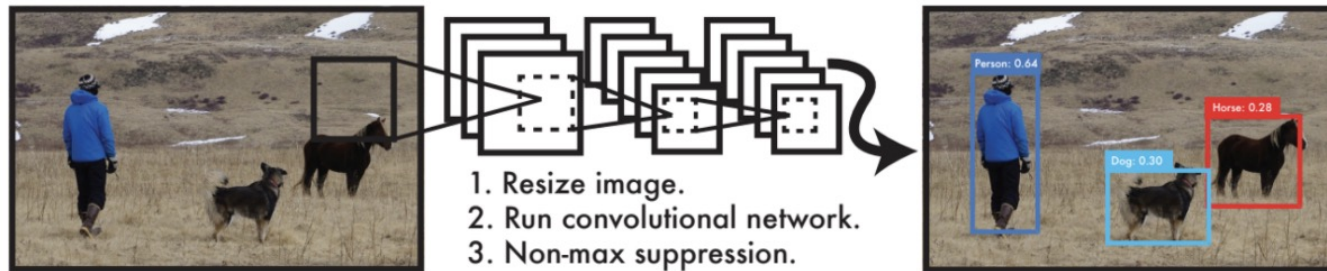
annotated

original image



augmented image

× microplastics detection with YOLOv5 ●



you only look once

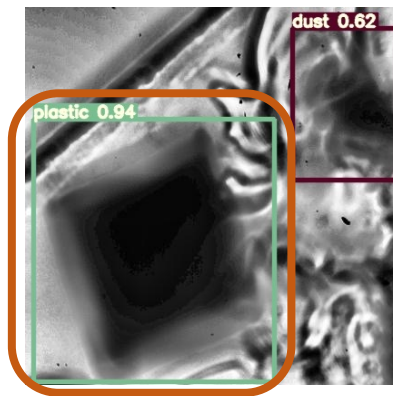
divides the image into regions and predicts bounding bo

1. resize image.
2. run convolutional network.
3. non-max suppression.

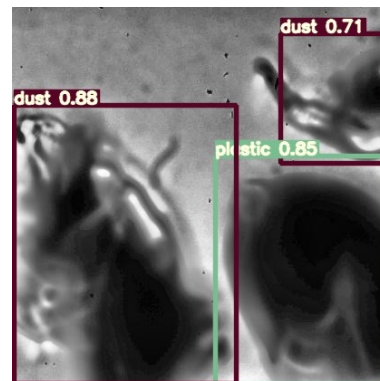
results

visual inspection

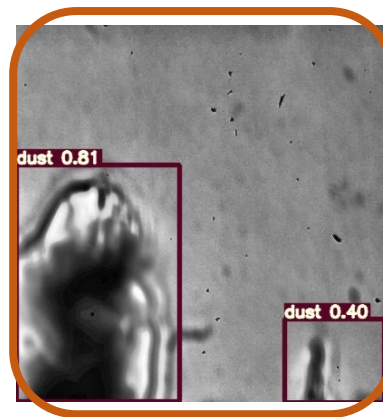
| | |
|------------------------------|---------|
| model | YOLOv5s |
| epochs | 500 |
| training time | 1h 25m |
| mean average precision (mAP) | 90.2% |
| inference time | 0.008s |



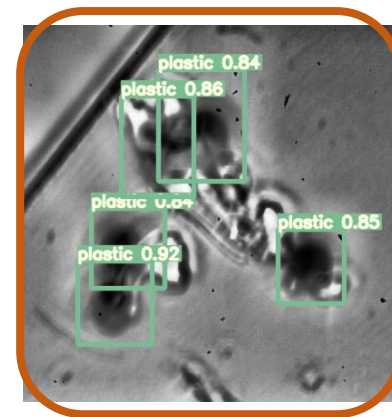
✓ 1 plastic, 1 dust



✓ 1 plastic, 2 dusts



✓ 0 plastic, 2 dusts



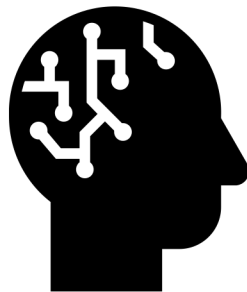
✓ 5 plastics



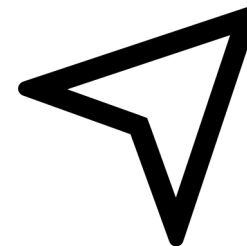
key takeaways



low-cost digital holographic microscopy is sufficient for microplastic classification tasks.



YOLOv5 performed well in automating feature extraction and classification of microplastics.



our implementation also **distinguished and located microplastics unlike previous studies.**



measuring
microplastic levels
will lead to
appropriate actions
and policies.



let's continue the conversation.



manu
gaspar



jazel
jayme



colleen
nepomuceno



mavel
paderes

join our meeting room after all the
presentations at

<https://bit.ly/microplastics-cpt5>

