Optically derived 3D models for munitions location and identification

MR23-3821

Art Gleason
University of Miami

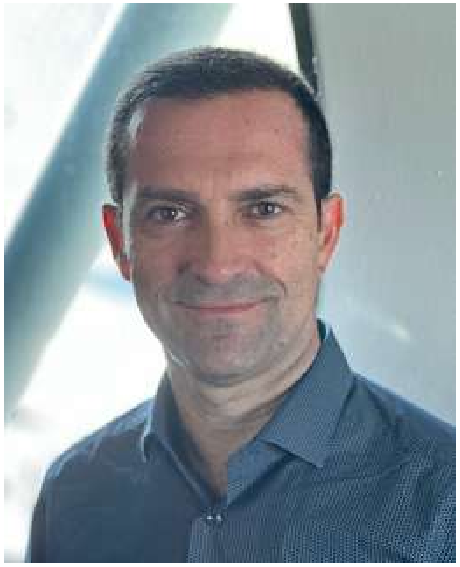
In-Progress Review Meeting

20 May 2025

Project Team

Art Gleason
University of Miami

Nuno Gracias



Rafael Garcia
University of Girona

Greg Schultz
White River Technologies

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Bottom Line Up Front

What technology or methodology is being evaluated during this demonstration?

- **Optical imagery, specifically 3-D point clouds derived from optical imagery, are being evaluated for A) geometrical accuracy as a function of environment and B) classification performance as a function of geometrical accuracy.**

What's been going well?

- **Data collection going well.**
- **Ahead of schedule on synthetic image generation component of project**

What's not working?

- **Delays due to subcontracting and labor needed for image labeling. Both of these will be fixed by June. Plan to catch up by September.**

What support do you need?

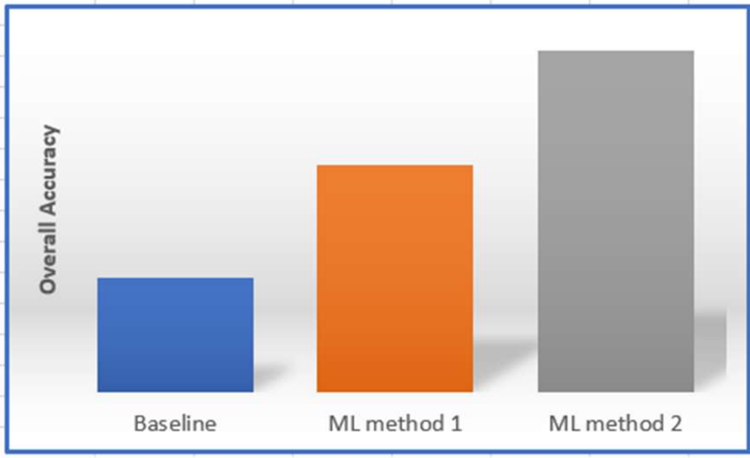
- **Patience as we assemble enough data to show results.**

Technical Objective

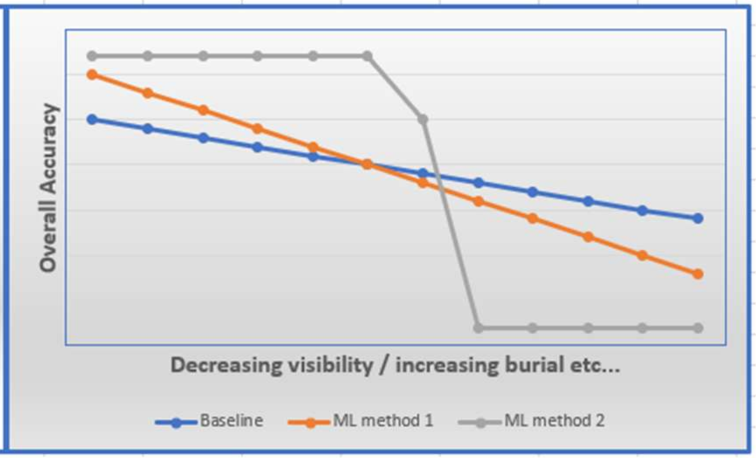
Three related objectives:

1. Build a large dataset of annotated images and concurrent environmental measurements.
2. Quantify how environmental parameters affect quality of the images in (1) and 3D models derived from those images.
3. Quantify how data quality (2) affects UWMM classification

These objectives should allow us to answer two critical questions:

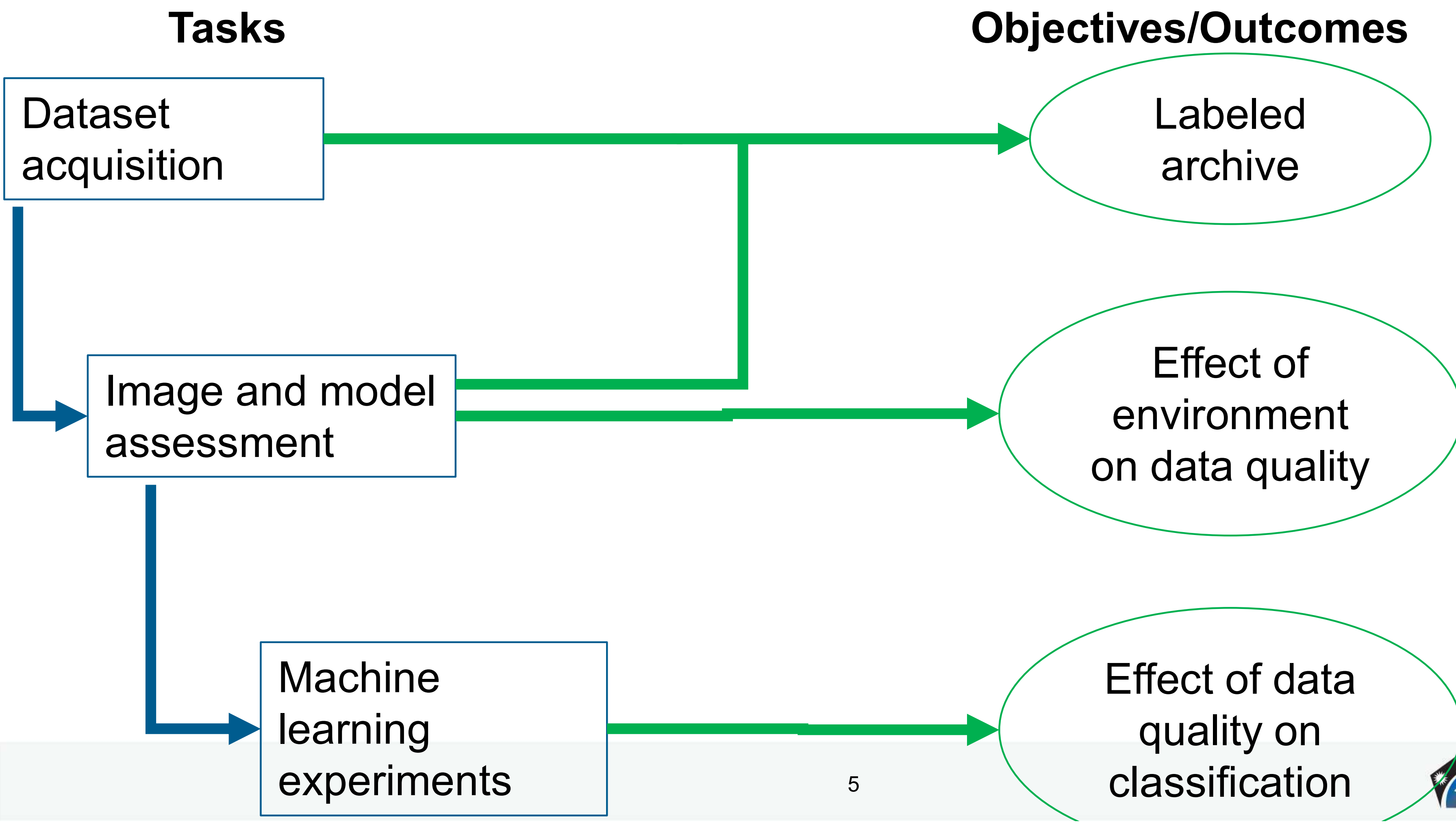


Which classification method has the best performance in optimal conditions?



How do the various methods perform as conditions degrade?

Technical Approach



Results to Date

- Data collection
- Data labeling
- Baseline algorithm
- Synthetic image generation
- Archive creation

Data Collection and Model Generation

Image totals as of 6 May 2025:

DSLR with 18 mm lens: 19,255 images

DSLR with 24 mm lens: 11,822 images

GoPro: 19,546 images

Total: 50,623 images collected

All 50,623 processed to generate

- 3-D point clouds
- Orthomosaics
- Meshed models
- Depth maps from the perspective of each image

BEFORE

AFTER 3 mo

AFTER 1 yr

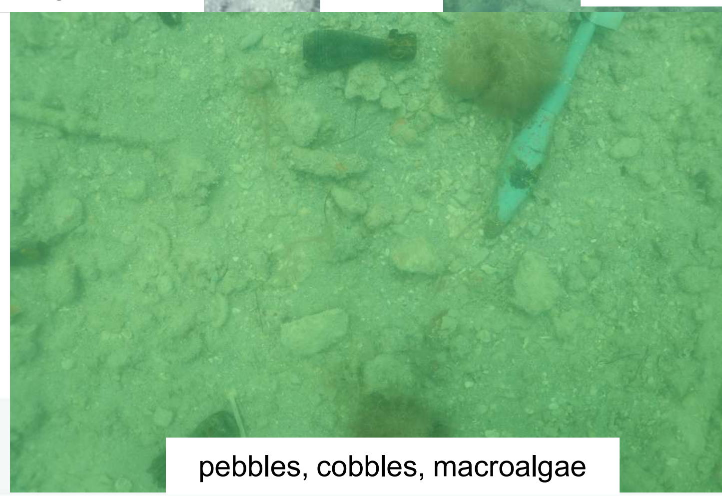
Data Collection and Model Generation

Variety of seabed types

hardbottom, turf algae, encrusting corals

sand, seagrass, macroalage

bare sand

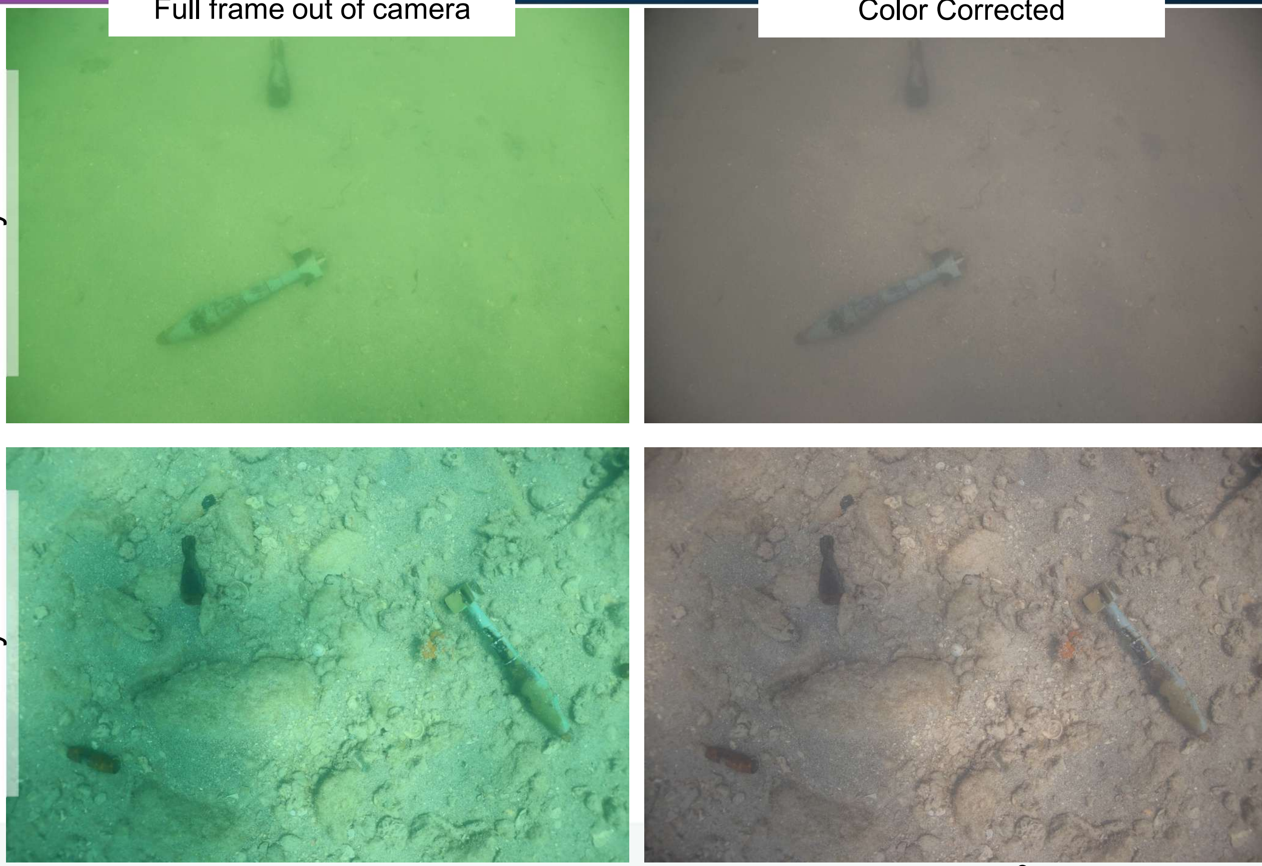


pebbles, cobbles, macroalgae

Sponges, pebbles, man-made “clutter”

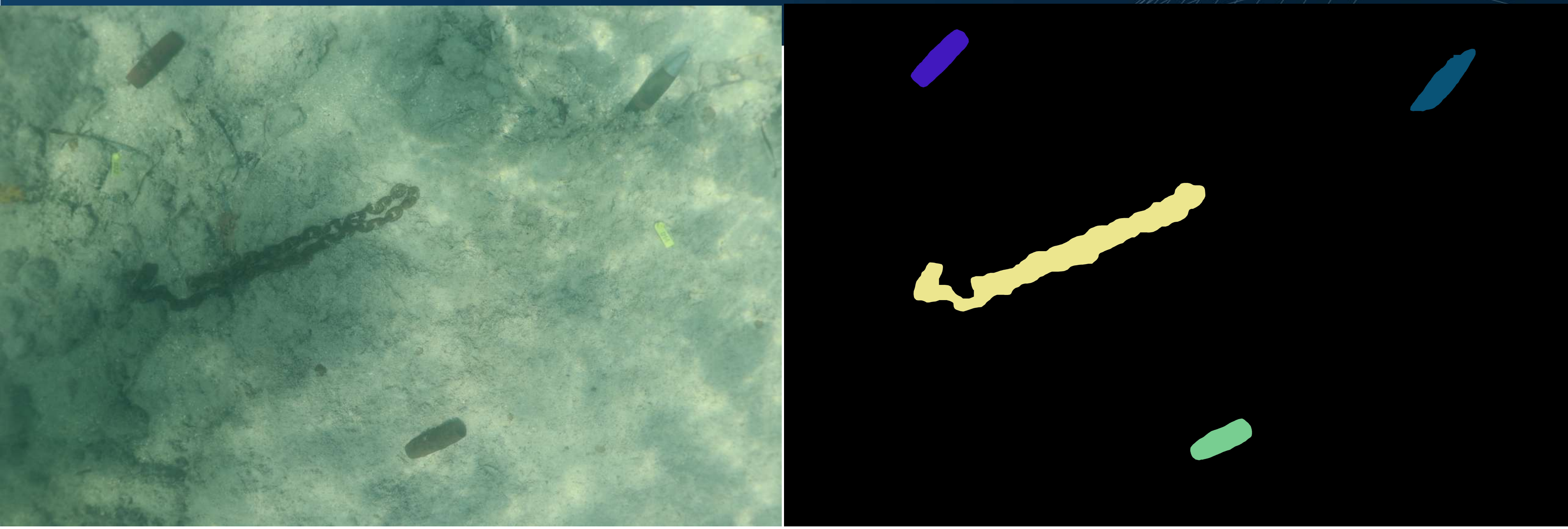
Data Collection and Model Generation

Variety of visibility conditions



Data Labeling (Annotation)

Image segmentation is essential for classification algorithm training and evaluation



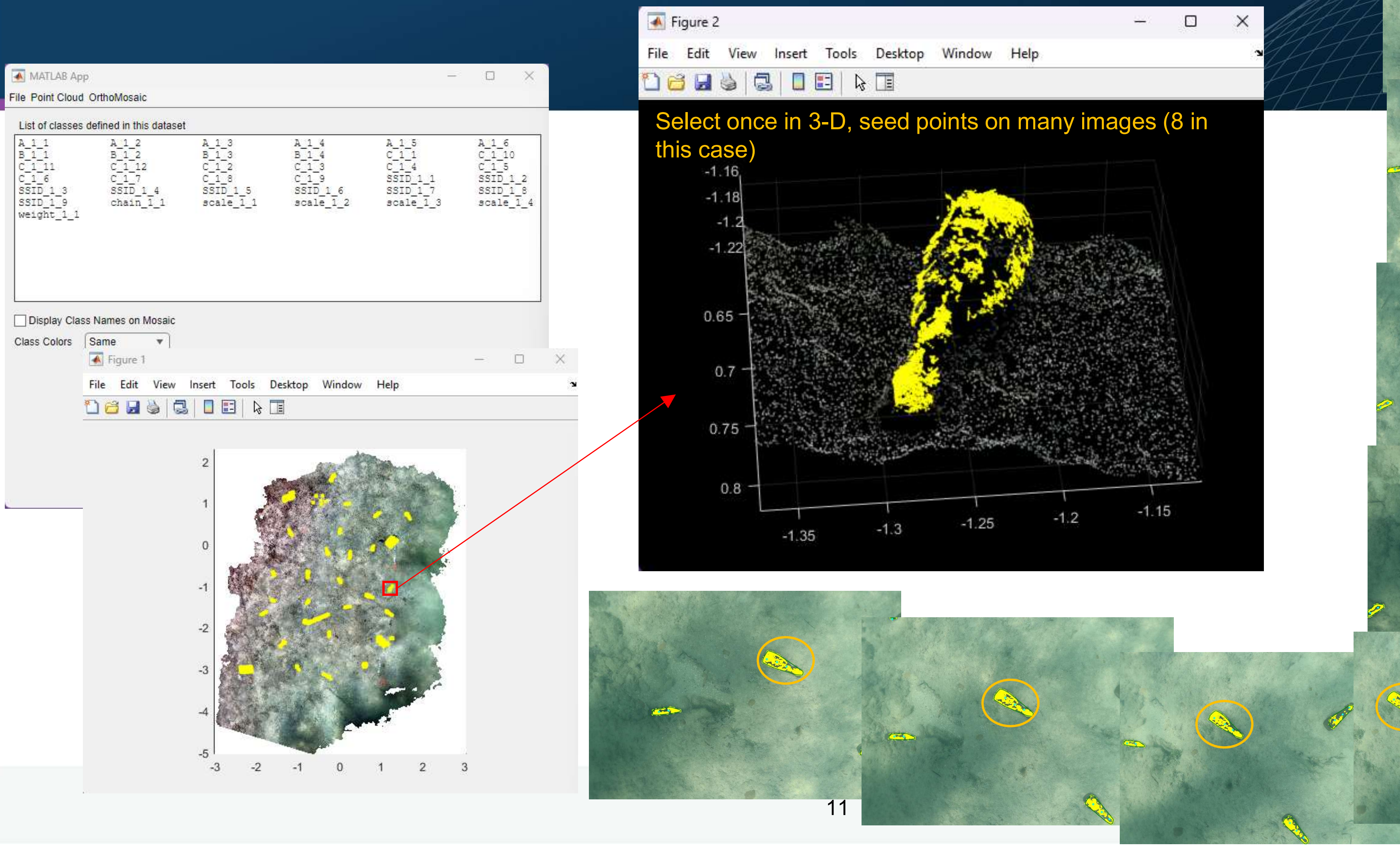
Manual (human) image segmentation

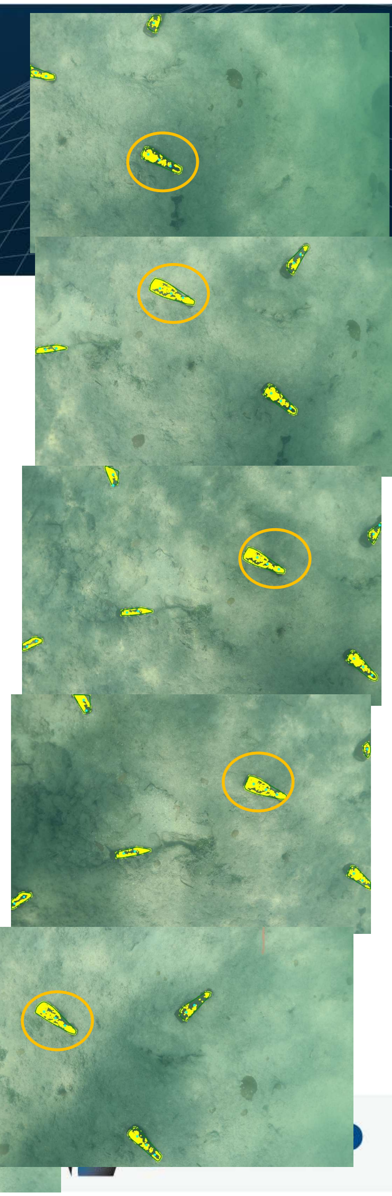
- Gold-standard quality
- Labor intensive
- Resulting datasets are valuable

Progress: 6289 labeled so far (~12%)

- Get more help
- Improve tools

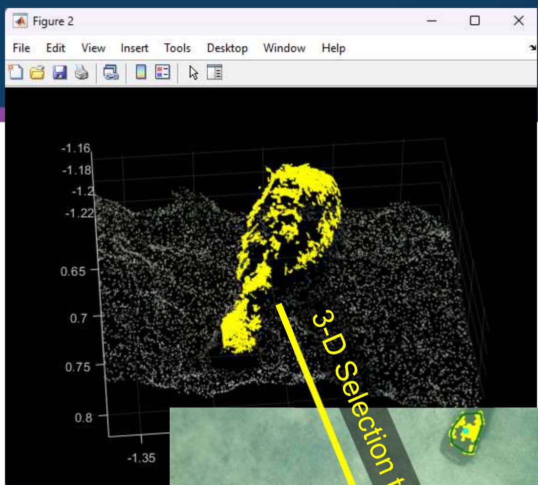
Data Labeling: Improved Tools

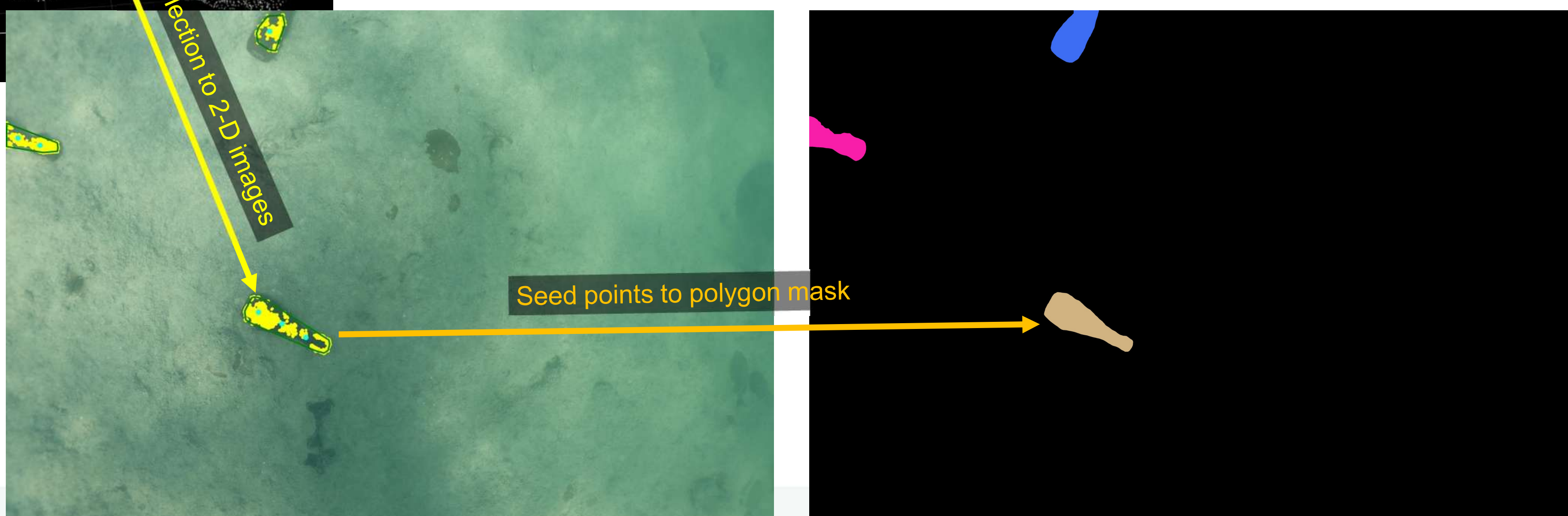




Data Labeling: Improved Tools

- Project labeled points to original images
- Use as seeds for segment anything algorithm (SAM)
- Result is high quality mask for each image (instance segmentation)





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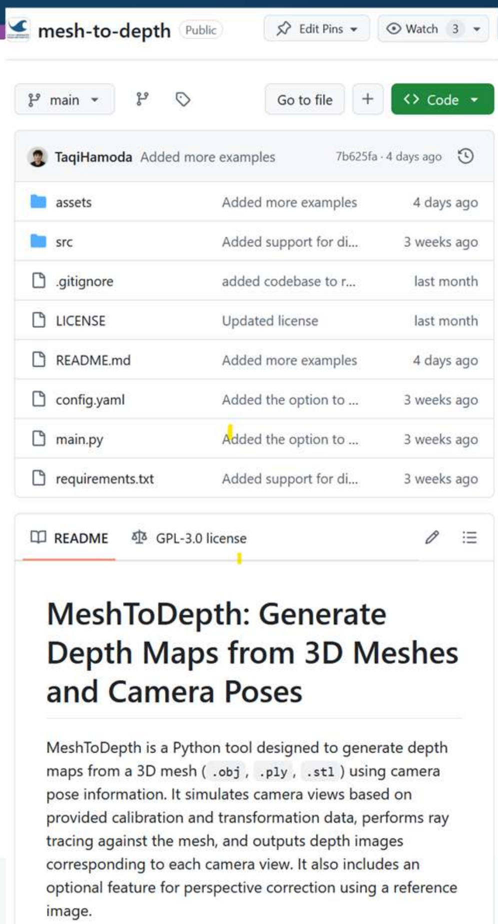
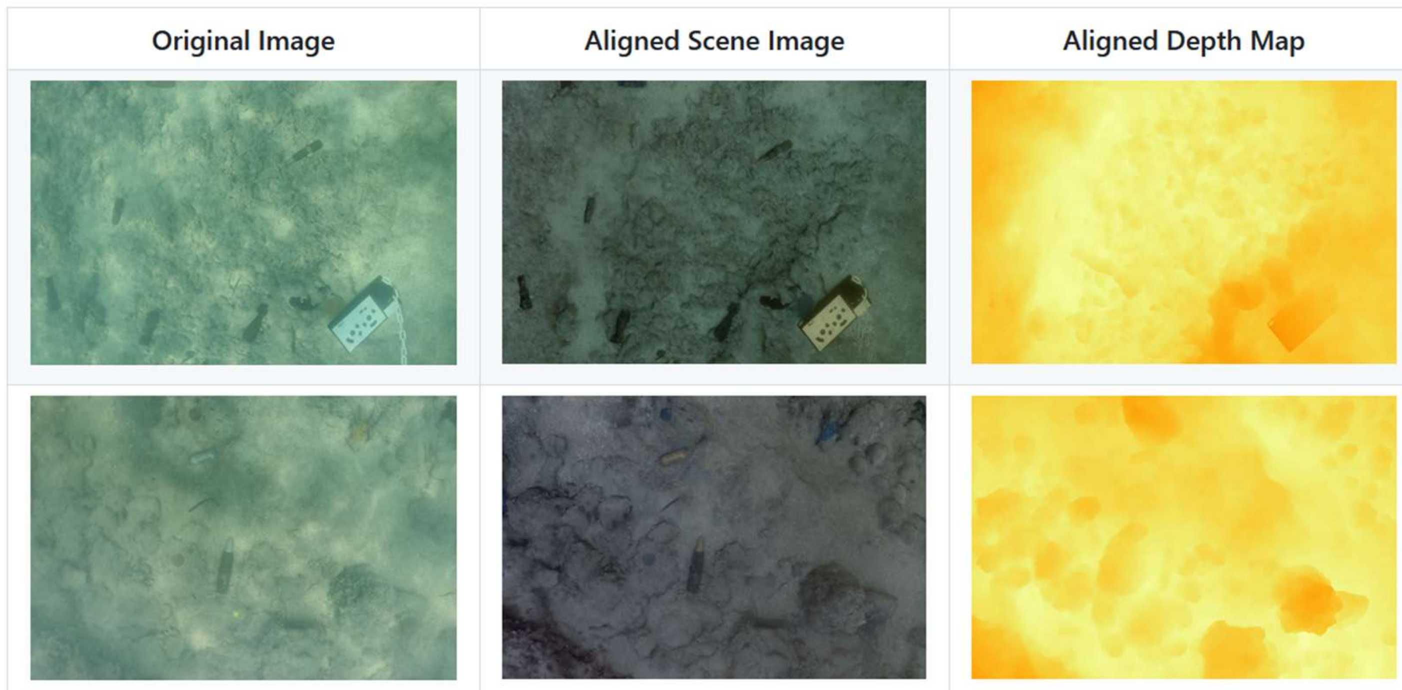
3D Data : Improved Tools



- Creation of accurate metric depth images well aligned with the original images, using the 3D reconstruction of the site



Baseline Algorithm Described

- Traditional Support Vector Machine algorithm from 2014 SEED project
- Updated code to use new python libraries and GPU compute

Initial experiment:

- 602 labeled images (one camera, one day, 3 plots)
- Samples are 256x256 pixel tiles ~220,000 total
- 90% tiles used for training, 10% for validation
- 3 munition types + background

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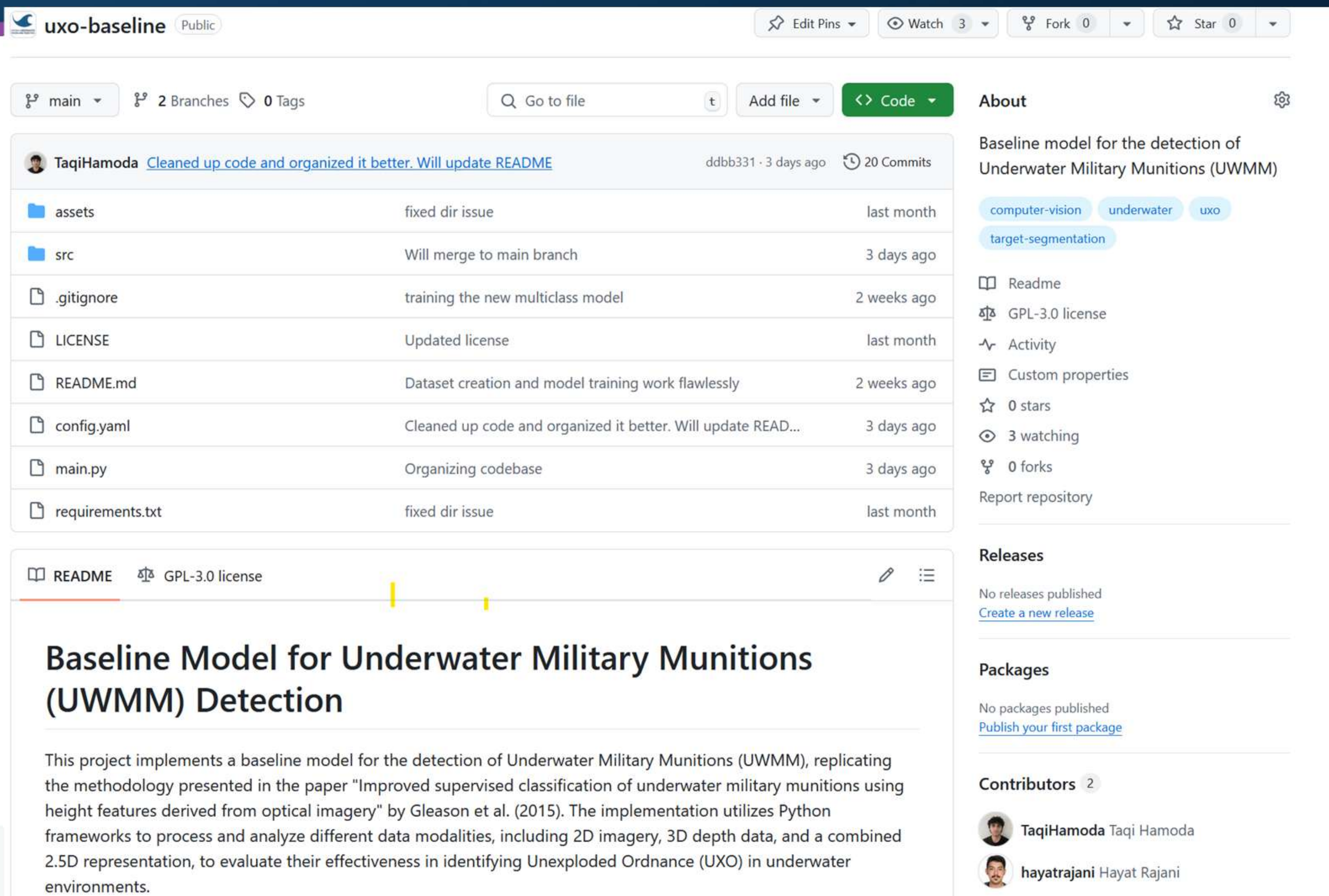
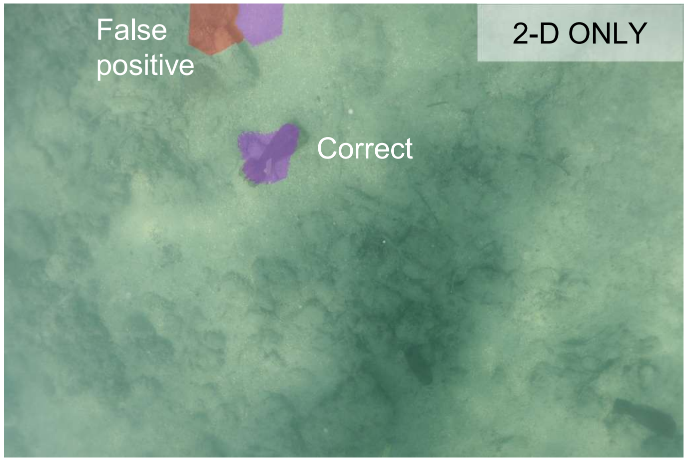
Baseline Algorithm Code

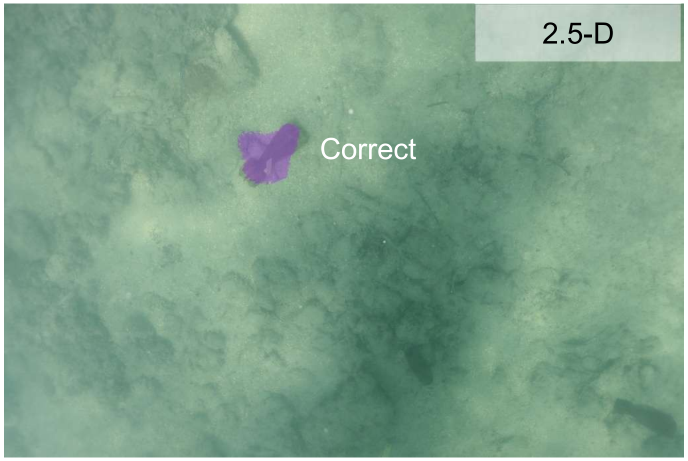


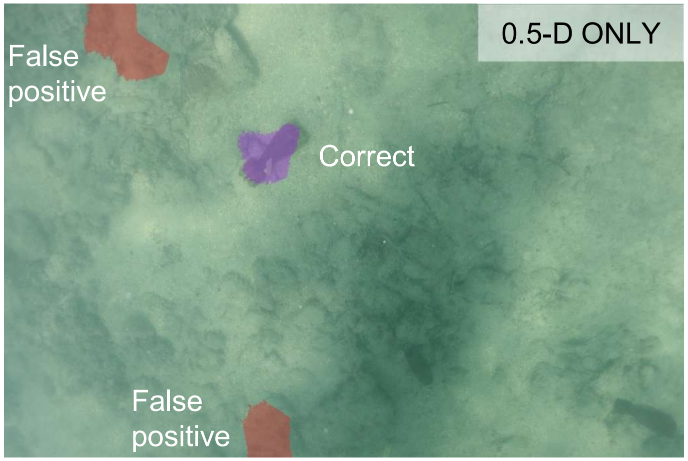
- Code has been modified and improved from scratch
- Posted on GitHub Can be easily used by other practitioners now.

Baseline Algorithm Results

	2-D (color, texture) ONLY			2.5-D (color, texture, AND depth)			0.5-D (depth features) ONLY			
	precision	recall	f1-score	precision	recall	f1-score	precision	recall	f1-score	N samples
Bofors no fuse	0.83	0.80	**0.82**	0.87	0.87	**0.87**	0.78	0.76	**0.77**	3693
60 mm mortar	0.83	0.88	**0.86**	0.91	0.94	**0.92**	0.81	0.84	**0.83**	3693
Bofors w/fuse	0.79	0.79	**0.79**	0.89	0.87	**0.88**	0.82	0.79	**0.81**	3694
Background	0.99	0.99	**0.99**	1	0.99	**0.99**	0.96	0.97	**0.97**	11080
Accuracy			**0.91**			**0.94**			**0.88**	22160







- 2-D vs 2.5-D consistent with earlier results (good)
- 2.5-D better than 2-D or 0.5-D alone (makes sense)
- *0.5-D alone is not too bad* (new and encouraging!)

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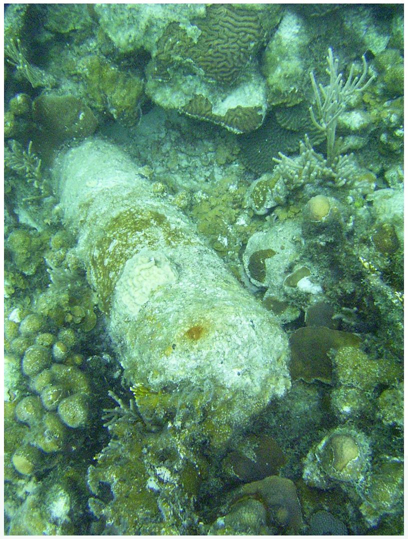
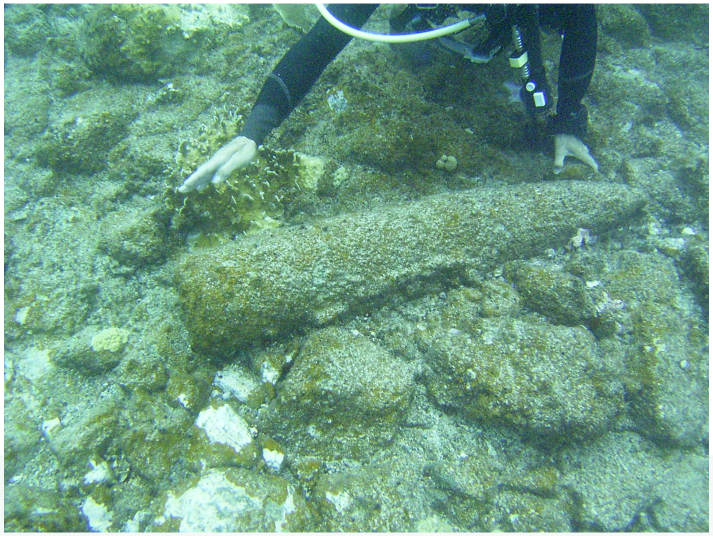
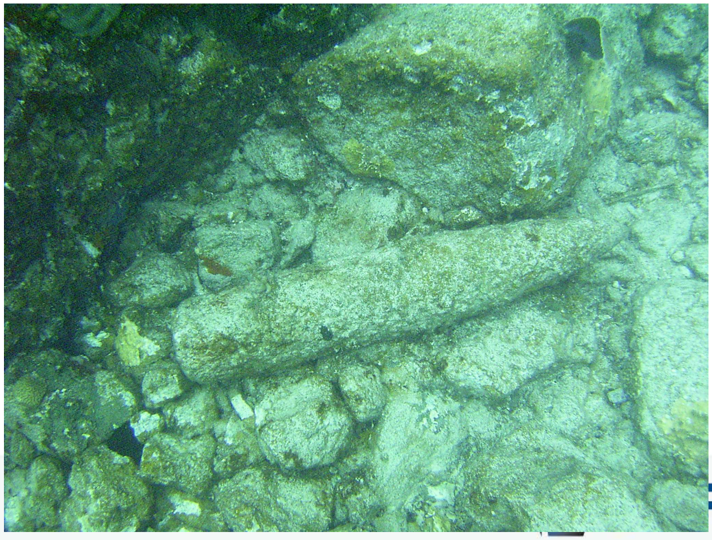
Relevant Action Item (from last IPR)

Action item: Coordinate with Technical Committee member Andy Schwartz to obtain UXO and MD photos from Culebra, Puerto Rico (circa 2005).

- Andy sent ~40 images; a few shown here.
- Biologic overgrowth was the point. 2-D color and texture features likely not helpful
- Baseline algorithm results suggest depth cues (0.5-D) features *alone* could still add value





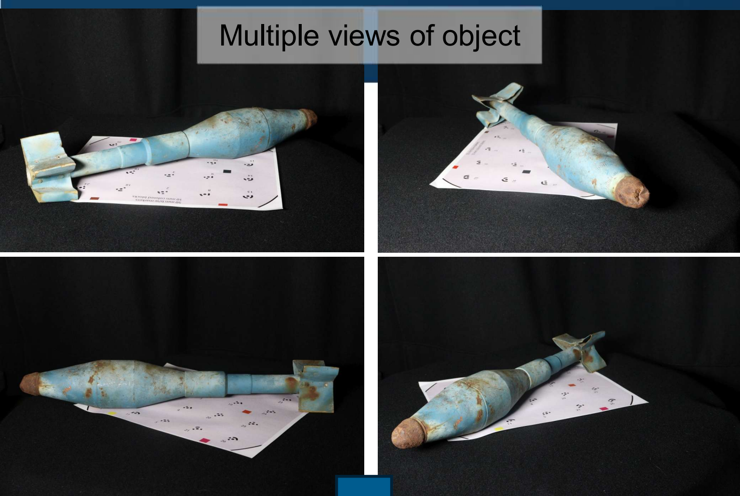


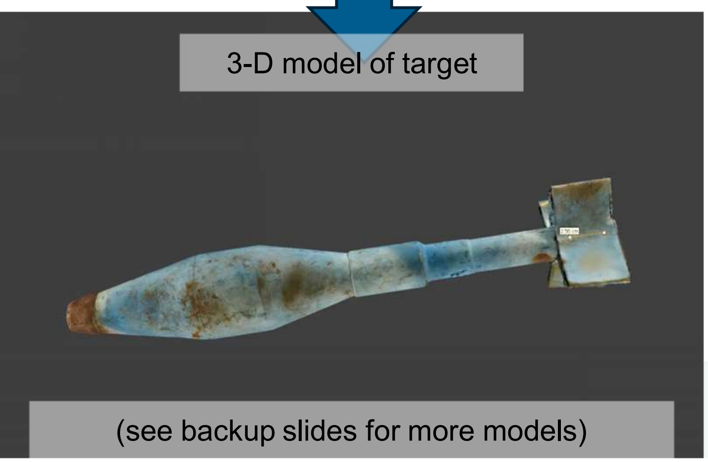
Relevant Action Item (from last IPR)

- Baseline algorithm results suggest depth cues (0.5-D) features *alone* could still add value
- How to test? A) 0.5-D experiments like we just showed
  B) Suggest using bottles at one of our sites

Synthetic Image Generation

Results from Alghfeli (2024)





Merge with other models to create virtual landscape
We created (a); (b)-(e) from open-source libraries

(a) UXOs models

(b) Rocks

(c) Coral models

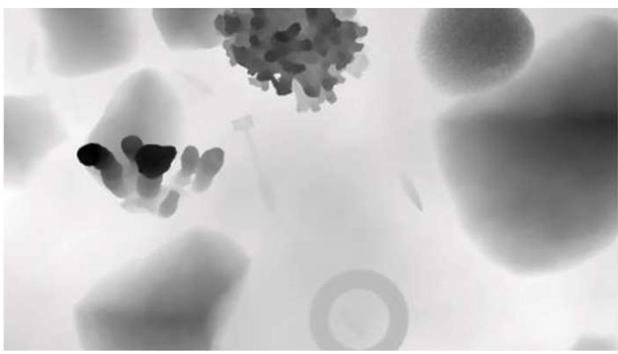
(d) Manmade objects

(e) Background sand

Synthetic Image Generation

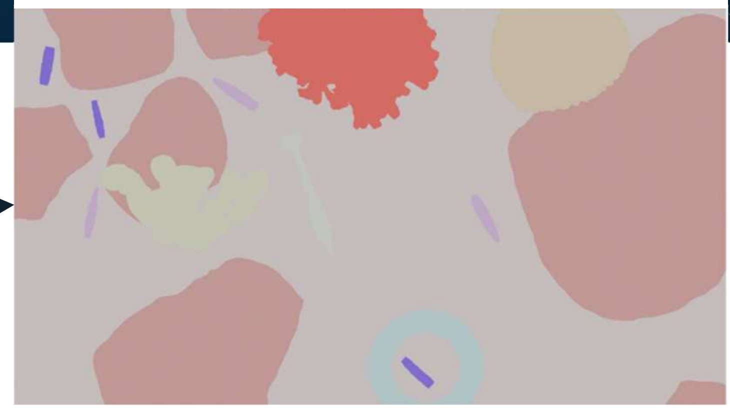
Virtual landscape created with 3-D models

Elevation / depth map of virtual landscape



Physically Guided Synthesis Module
Wen *et al (2023)*

Perfectly labeled training / validation data



Synthetic image with simulated water attenuation

Synthetic Image Classification

- Generated 4 synthetic scenes for training and 1 for validation
- Three "off the shelf" neural network algorithms tested with multiple configurations each
- Accuracy evaluated with intersection / union (IOU)

Synthetic image with water attenuation used for validation

IOU (%) for the best performing models.
Note all are > 90% overall (mean) accuracy.

Class	RT-Seg 4	RT-Seg 5	UNet 1	UNet 2
Background	96.9	96.8	97.0	95.5
Rocks	96.1	95.4	89.9	93.5
Corals	95.4	95.2	88.6	92.3
UXO	90.1	88.7	87.0	88.3
Other Manmade	92.2	94.0	89.3	91.9
Mean	94.2	94.0	90.4	92.3

Synthetic Image Classification

(a) Original water (b) Water type 1 (c) Water type 2 (d) Water type 3 (e) Water type 4

	Original	Water (1)	Water (2)	Water (3)	Water (4)
Class \ Model	RT-Seg 4	RT-Seg 5	RT-Seg 5	RT-Seg 5	RT-Seg 5
Background	96.9	95.9	87.6	97.4	91.3
Rocks	96.1	94.6	80.1	96.9	67.6
Corals	95.4	93.0	53.4	96.9	75.4
UXO	90.1	74.4	71.4	95.4	20.8
Other Manmade	92.2	72.3	44.9	94.2	38.4
Mean	94.2	86.1	67.5	96.2	58.7

- Changing the water model for the validation data (but not training data) greatly affected results

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Synthetic Image Generation Improvements

- Applying the data trained only on virtual scenes to real data yielded poor results, likely due to
  a) sensitivity to modeled water parameters as just shown
  b) oversimplified background texture
- Currently we are working to address these by putting real images into the synthetic model for background and to refine the parameters used in the water type model.

A model made at one of our sites with no targets

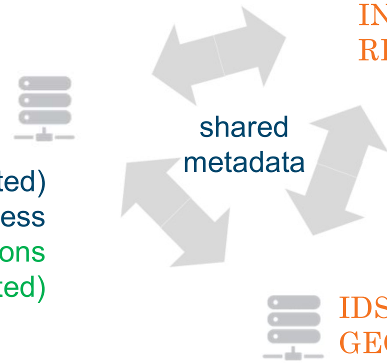
Real background used to create virtual scene by adding models of elements (no water effect applied yet)

Archive Creation

towards a FAIR data archive

Heirarchical Metadata:

- Project/Collection
  - Sites
    - Items
      - images
      - processed images
      - point clouds
      - match point lists
      - ortho images
      - surface models
      - meshes
      - annotations
      - segmentations
      - visualizations
      - code



PROJECT SERVERS

Filesystem storage (duplicated)
UM research network data access
WWW access to visualizations
WWW data download (duplicated)

UM LIBRARIES INSTITUTIONAL REPOSITORY

All sites in library catalog with DOIs
WWW metadata access and discovery (duplicated)

IDSC GEOSPATIAL DIGITAL SPECIAL COLLECTIONS

Filesystem storage (duplicated)
WWW metadata access and discovery (duplicated)
WWW data download (duplicated)

* WWW access/download - multiple modes of access to the collections of data

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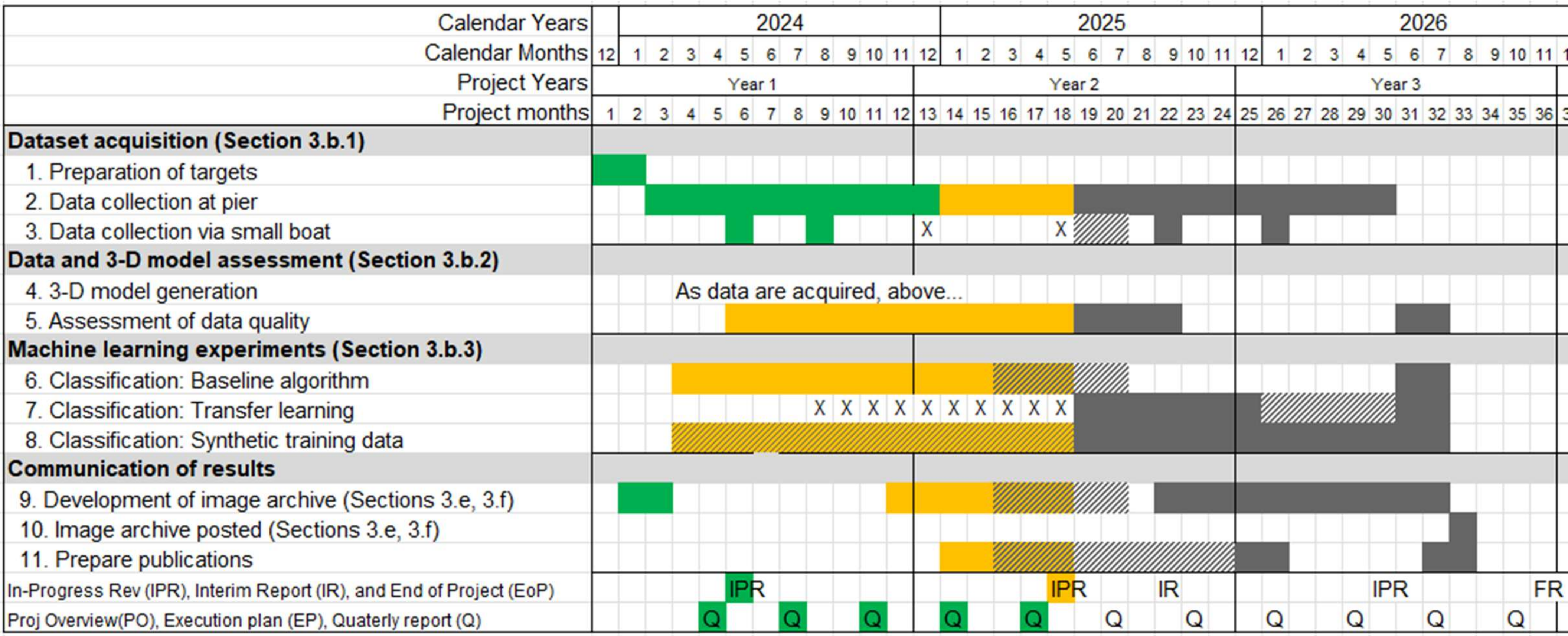
Next Steps

- Complete
- In progress
- Planned
- X Revised (original)
- Revised (adjusted)



Technology Transfer

- Online archive of images, labeled and with coincident environmental data
- Peer reviewed paper describing archive
- Peer reviewed paper describing data quality as function of survey parameters
- Peer reviewed paper describing image classification as function of survey parameters and classification method
- 2x M.P.S. students (in each project year) and 1 undergraduate student (Miami)
- 1x MS student already complete; 1x Post-doc and 1x Ph.D. student planned (Girona)
- Code posted to GitHub (mesh2depth, baseline algorithm)

Issues

- Behind anticipated spending due to contracting delay but this has finally been resolved.
- Image labeling is lagging behind image collection and 3-D model generation. Adding 3 new students this month and shifting effort of existing lab members to rectify this over summer 2025.

BACKUP MATERIAL

These charts are required, but will only be briefed if questions arise.

MR23-3821: Optically derived 3D models for munitions location and identification

Performers

- *Art Gleason (U Miami), Nuno Gracias, Rafael Garcia (U Girona), Greg Shultz (White River Technologies)*

Technology Focus

- *Optically-derived 3-D data sets for underwater military munitions mapping, classification, and monitoring*

Research Objectives

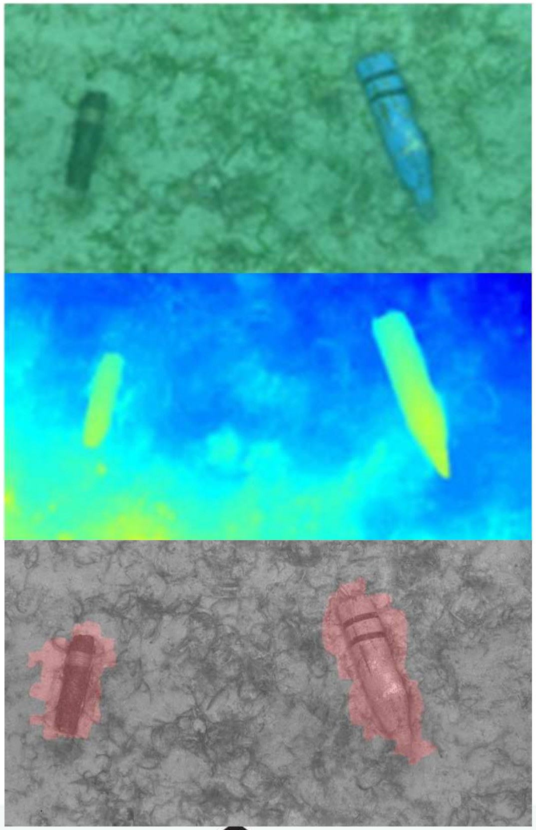
- *What is the effect of the environment on the quality of optically-derived underwater 3-D data sets?*
- *What is the effect of the quality of optically-derived underwater 3-D data on classification accuracy?*

Project Progress and Results

- *Over 50,000 images collected so far; this will be an amazing dataset for not just this project but for future development of AI image classifiers in general.*

Technology Transition

- *Next steps after this project would be to integrate optics with other geophysical techniques (EMI, acoustic, magnetic) to evaluate the benefits of this technology in a data fusion approach. Potential end-use scenarios include virtually any underwater survey except in the lowest visibility conditions.*



Plain Language Summary

What problem are you addressing?

- **The overarching problem is developing optimal strategies to locate, identify, and monitor underwater military munitions (UWMM).**
- **The specific problem is how to incorporate optical data sources into UWMM surveys, which have traditionally used other geophysical techniques (acoustic, magnetic, and electromagnetic induction).**

What are you trying to achieve and how are you doing it?

- **There are two goals: 1) quantify how the environment (*e.g.* visibility) affects the quality of optically-derived underwater 3-D data sets. 2) understand the effect of the quality of optically-derived underwater 3-D data on classification accuracy.**
- **Our approach is to generate the world's largest annotated image dataset of UWMM, to run our own tests on this data, then to release this dataset as a challenge to the computer vision community.**

What are the expected outcomes and how is it advancing existing knowledge?

- **Adding optics to the toolkit of UWMM survey techniques is expected to increase accuracy and efficiency.**
- **Quantifying effects of environment on underwater optical 3-D data has not been done systematically. This increased knowledge will help all sorts of underwater surveys within and beyond DoD needs.**

Impact to DoD Mission

What's the most impactful thing that's happened since the last time you presented your work to us?

- **The suggestion that shape alone (*i.e.* depth cues or 0.5-D data) could provide nearly as much classification power as color and texture alone (*i.e.* 2-D data) will be very impactful assuming it bears out with more tests across our full dataset.**

Why is this important?

- **Improved capability to locate and monitor UWMM is important because UWMM pose potential hazards and are particularly challenging and expensive to address relative to terrestrial locations.**

How is your project advancing DoD capabilities?

- **Optical surveys of the seabed are understudied and underutilized relative to other marine geophysical techniques, yet optics has much to offer in terms of spatial resolution and discriminatory power.**
- **Quantifying effects of environment on underwater optical 3-D data has not been done systematically. This increased knowledge will help all sorts of underwater surveys within and beyond DoD needs.**

Include high quality images.

- **We are working on this. The rotating 3-D animations shown earlier in this presentation are probably the most eye-catching outputs from this project so far. Again, just getting started and more to come!**

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Action Items

- Defend a go/no-go decision point with clear metrics for success in your interim report. See proposal on next slide
- Coordinate with Technical Committee member Andy Schwartz to obtain UXO and MD photos from Culebra, Puerto Rico (circa 2005). His email is andrew.b.schwartz@usace.army.mil. Complete; discussed in main body of presentation.
- The next In Progress Review for this project will be May 2025. Additional meeting information will be provided 2-3 months in advance of the meeting. Acknowledged
- The SERDP & ESTCP Symposium will be held this year during the week of December 3 – 6, 2024 in Washington, D.C. A call for poster abstracts will be released in Spring 2024 with abstracts due in late July/early August. Please submit an abstract for this project at that time. Complete
- We would like to get a high-quality, landscape photo for the banner on your project page: Complete

Action Items

- Defend a go/no-go decision point with clear metrics for success in your interim report.

We propose that assembling a complete dataset of 100,000 images by the time of the interim report (9/30/2025) would be a rigorous but achievable go/no-go point. By “complete” we mean a) number of images collected b) 3-D models generated from all images c) all munitions labeled (annotated) within the image set. This is a good go/no-go point because it is a single point of failure; all of the objectives of the project hinge upon generating this data. If we complete it, we can address all of the objectives and if we do not then we are quite limited in what else could be accomplished. Achieving this objective will require doubling the number of images we have collected and generated into 3-D models. Also, achieving this objective on this time frame would be evidence that the staffing adjustment made in May 2025 has addressed our concerns about being behind with image labeling.

Status of Funds for Federal Performers

- Report on the status of funds for each MIPR received by a directly funded Federal performer. Provide information on each fiscal year for which there has not been 100% expenditure of funds. If you or your co-performer do not understand how to fill this out, contact your Program Manger in advance of the IPR.

FY20XX Funds			
Directly Funded Federal Performer(s)	Funds Received	Funds Obligated*	Percent Funding Obligated
Federal Performer A - Direct Cite MIPR			
Federal Performer A - Reimbursable MIPR			
Federal Performer B - Direct Cite MIPR			
Federal Performer B - Reimbursable MIPR			

Not Applicable

* Funds put on contracts and/or purchase orders that have been issued, and funds associated with internal labor or travel expenses that have been incurred.

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Publications

- Alghfeli, A. (2024) Synthetic Data Generation and Semantic Segmentation for underwater Unexploded Ordnance (UXOs) MS Thesis, University of Girona, Spain. 23 pp.
- Gleason, Gracias, Garcia, Schultz, Cohen, Alketbi, Alghfeli, Chen (2024) Optically Derived 3D Models for Munitions Location and Identification, 2024 DoD Energy and Environment Innovation Symposium, (poster).
- Gleason, Gracias, Garcia, Schultz (2023) Optically Derived 3D Models for Munitions Location and Identification, 2023 DoD Energy and Environment Innovation Symposium, (poster).

Literature Cited

Baseline algorithm described in:

Gleason, A., N. Gracias, ASM. Shiavuddin, G. Schultz, B. Gintert (2015), Improved Supervised Classification of Underwater Military Munitions Using Height Features Derived from Optical Imagery. MTS/IEEE OCEANS conference, Washington DC, USA, October 2015.

Shihavuddin, A.S.M., N. Gracias, R. Garcia, R. Campos, A. Gleason, B. Gintert (2014), "Automated Detection of Underwater Military Munitions Using Fusion of 2D and 2.5D Features From Optical Imagery," Marine Technology Society Journal, 48(4).

Physically based image simulation:

J. Wen *et al (2023)*., "SyreaNet: A Physically Guided Underwater Image Enhancement Framework Integrating Synthetic and Real Images," *IEEE (ICRA*, 2023), doi: 10.1109/ICRA48891.2023.10161531

Additional Slide(s) for High-Quality Photos

Acronym List

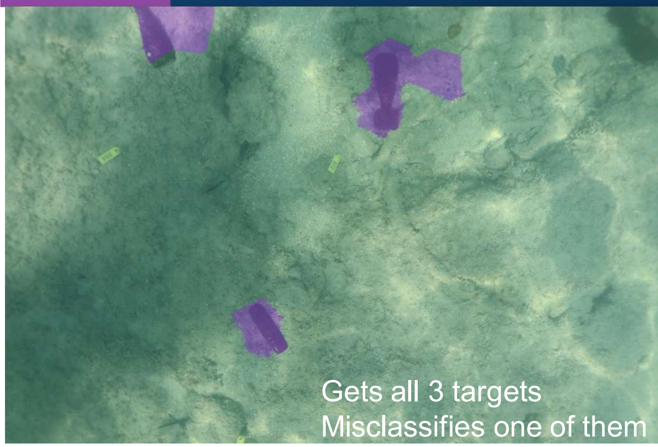
- 3-D = Three-dimensional
- AI = Artificial intelligence
- CNN = Convolutional neural network
- EMI = Electromagnetic Induction
- ML = machine learning
- UWMM = Underwater military munitions

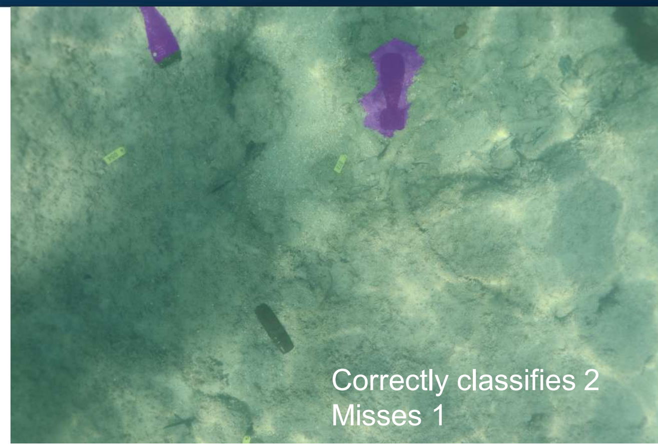
More Baseline Algorithm Results

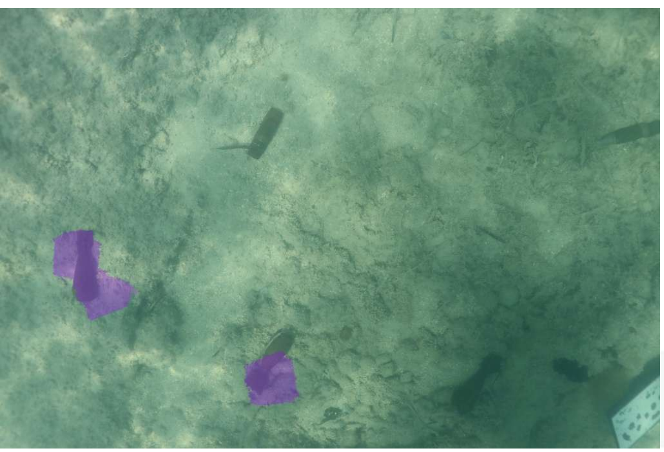
2-D ONLY

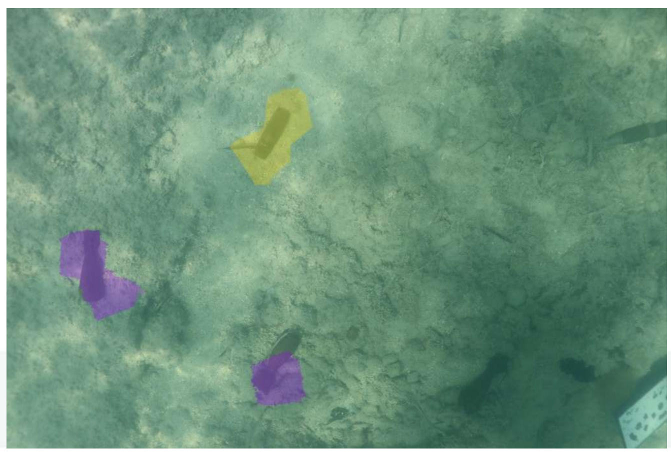
2.5-D

0.5-D ONLY

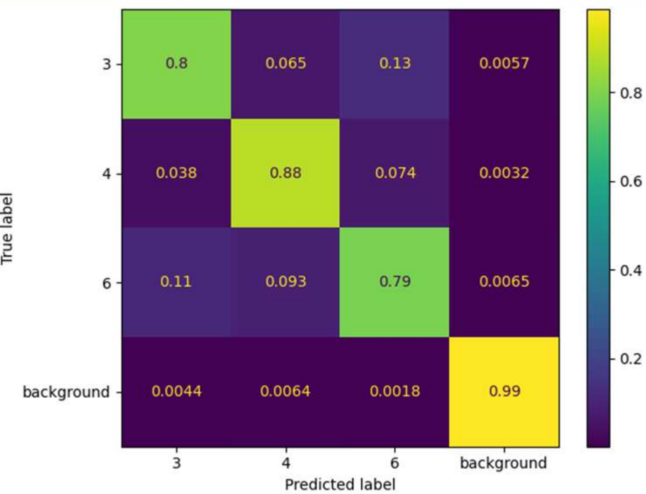


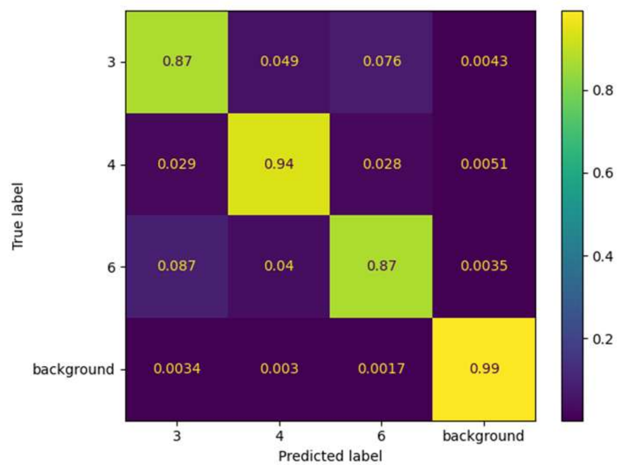


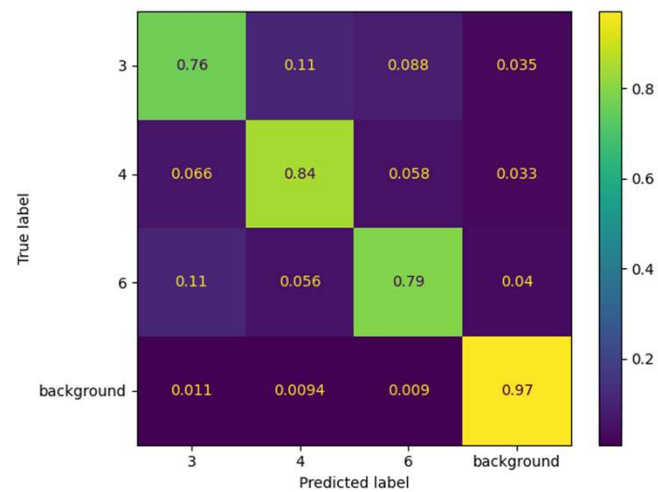




Baseline Algorithm Results







Same as presented above, except this is error matrix format rather than F-1 score

Synthetic Image Generation

- In past year we improved the creation of synthetic images by creating 4 additional 3D models of UWMM bringing total to 8 so far.