NOAA Workshop on Leveraging AI in Environmental Sciences

CoralNet: AI for Automatic Annotation of Benthic Imagery*

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Two Sigma

CoralNet 1.0 authors: Oscar Beijbom, Stephan Chan
Qimin Chen, Haoming Zhang, Jessica Bouwmeester

Collaborators: Greg Mitchell, Serge Belongie, Jules Jaffe
Davey Kline, Ben Neal, Paul Roberts, Tali Treibitz
Andreas Andersson, Travis Courtney

*This work was was funded by NSF and NOAA and was implemented at UCSD

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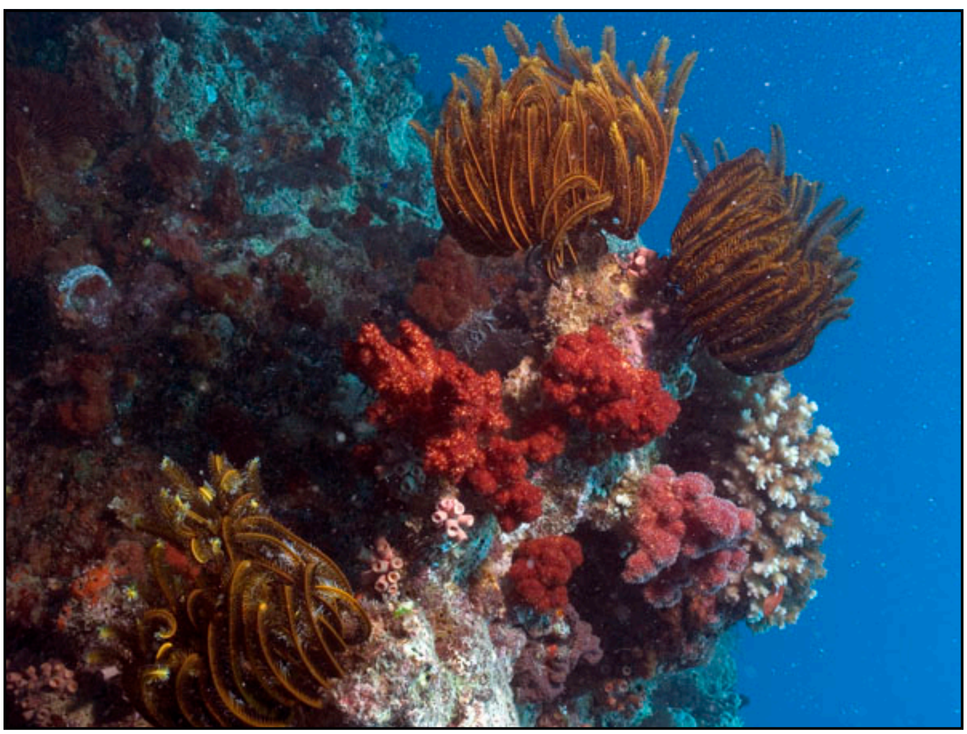

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Bocas del Toro, Panama

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Bocas del Toro, Panama

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Smithsonian Tropical Research Institute

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Bocas del Toro, Panama

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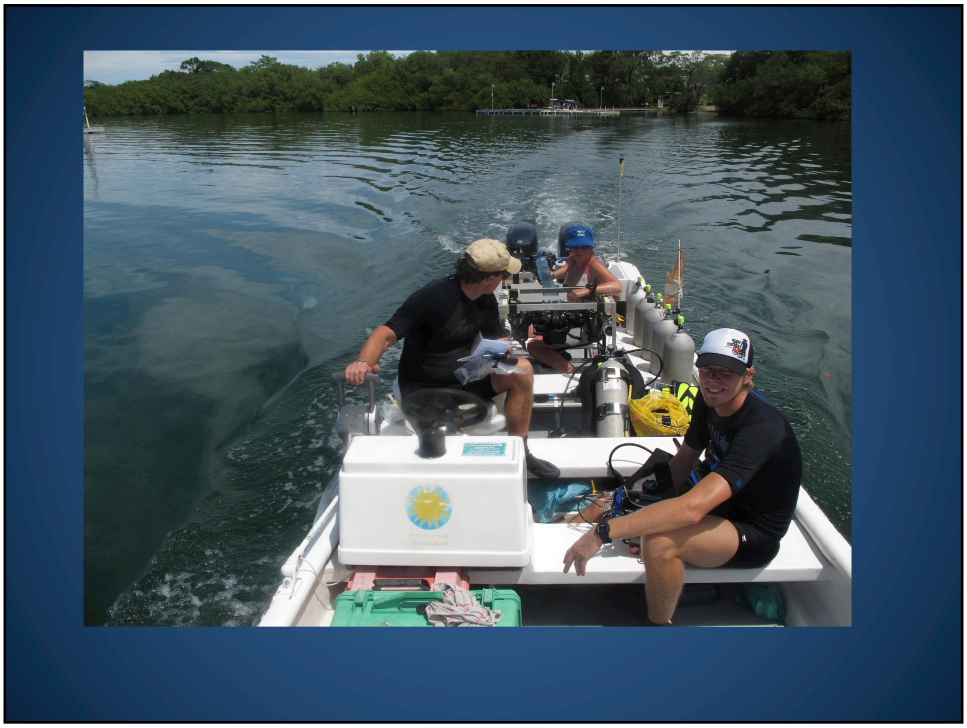

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In the last 30 yrs. coral coverage has declined by

- **80% in the Caribbean** [Gardner et al. 2003]
- **50% in the Indo-Pacific** [Bruno & Selig 2007]
- **50% on the Great Barrier Reef** [D'eath et al. 2012]

90% of global coral reefs will be severely degraded by 2050 [Kwiatkowski et al. 2015]

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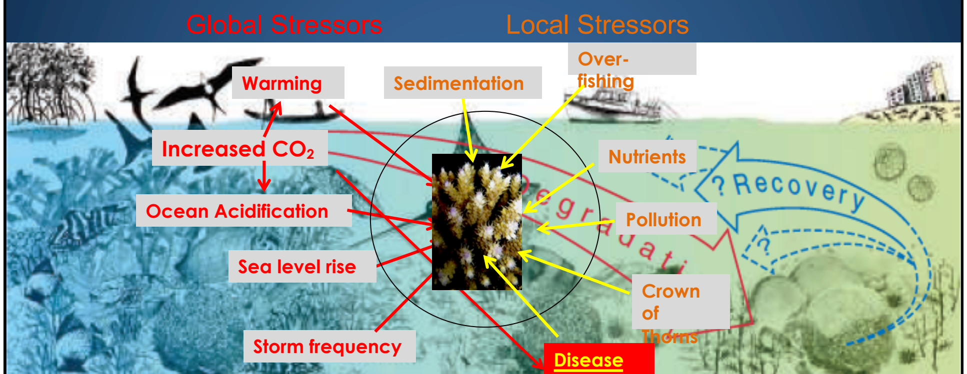
Multiple Stressors Impact Coral Reefs



Pandolfi et al. 2005

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Outline

1. Surveying Coral Reefs
2. Annotation using conventional vision techniques
3. CoralNet
4. Deep networks for automatic annotation

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Anatomy of a reef survey

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Anatomy of a reef survey

A researcher’s question: What is the coral cover at the outer reef at 10m depth Northeast of Piha’ena?

Moorea, French Polynesia

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Anatomy of a reef survey

Capture images along several line-transects

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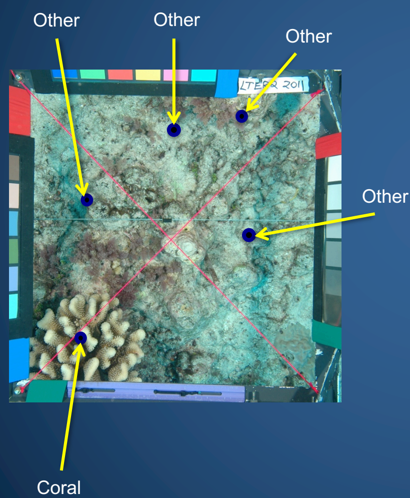
Anatomy of a reef survey



- Annotate image
  - Scatter random points (10–200)
  - Assign labels (10 – 100 labels)
- Calculate cover
  - 1 out of 5 points => 20% Coral
- Average over transects

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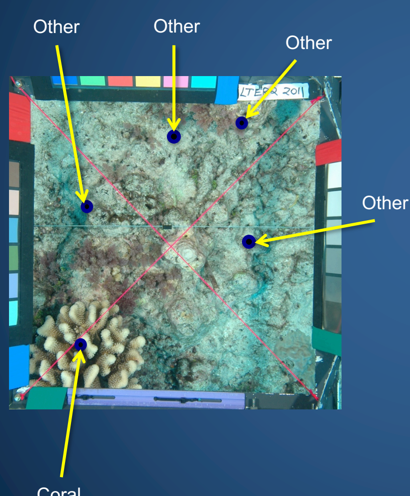
A Representative Survey



- Goal: Estimate cover of dominant functional groups
- 1,250 images acquired over two weeks
- Annotate images with Coral Point Count (CPCe)
- 200 annotations per image
- 250,000 annotations
- **6 months to annotate**

Pete Edmunds and Vincent Moriarty, Cal State Northridge

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CoralNet

- CoralNet Alpha: 2011
  - "Conventional Computer Vision" [CVPR 2012]
  - Deskside server
- CoralNet Beta: 2017
  - Deep learning
  - Hosted in cloud on Amazon Web Services
- CoralNet 1.0, January 2021
  - Large scale training of new network
  - API
  - Robust software engineering

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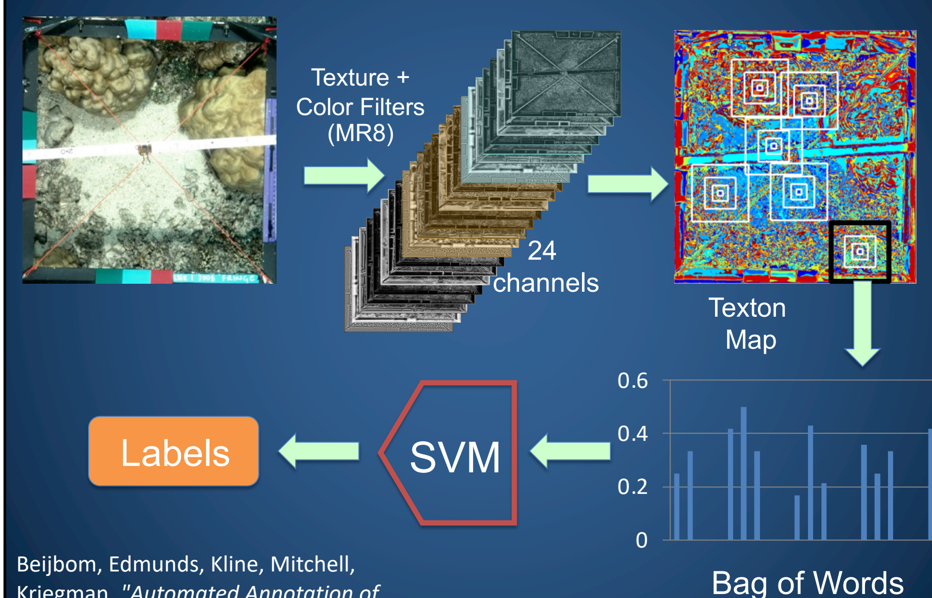
CoralNet Alpha: "Conventional Vision"



Beijbom, Edmunds, Kline, Mitchell, Kriegman, *"Automated Annotation of Coral Reef Survey Images"*, CVPR, 2012

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CoralNet Alpha: Accuracy

2008, 2009 ⇒ 2010 (83.1%)

Ground Truth / Estimated

		CCA	Turf	Macro	Sand	Acrop	Pavon	Monti	Pocill	Porit	
Other	CCA	.89	.04	.01	.04					.02	95701
	Turf	.40	.46	.01	.03		.03			.06	4759
	Macro	.69	.05	.19	.02		.01	.02		.02	3285
	Sand	.15	.01		.83					.01	11491
Hard Corals	Acrop	.13	.14	.01		.62				.10	182
	Pavon	.25	.06	.01	.03		.60	.01		.04	1586
	Monti	.41	.03	.01	.07			.42		.05	2118
	Pocill	.34	.03				.01		.60	.02	838
	Porit	.20	.02		.01					.76	9967

83% sounds good,
but how good are
the experts?
Is it good enough?

- Moorea NSF LTER survey

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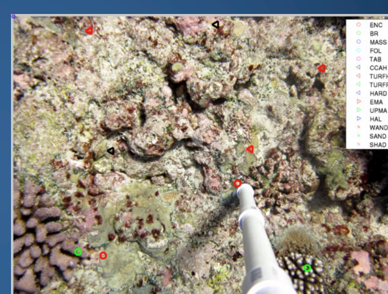
So, how good is this?
How accurate are human experts?



In a study by NOAA Coral Reef Ecosystem Division (CRED):
Humans displayed 80% accuracy

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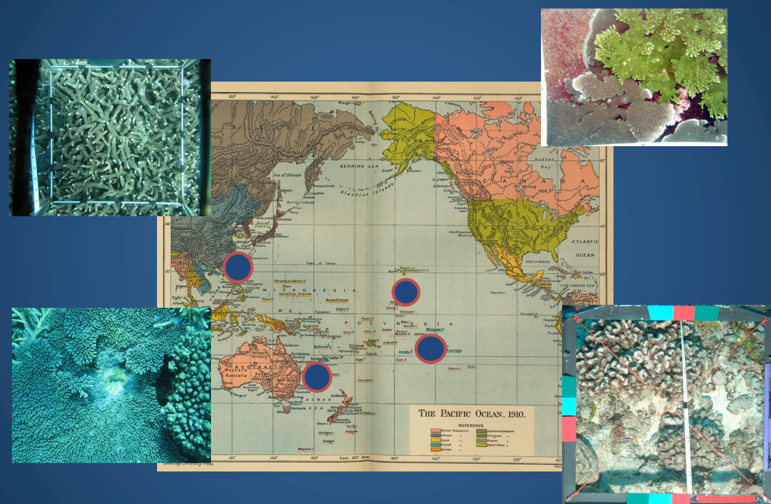
Multi Annotator Study



Beijbom, Edmunds, Roelfsema, Smith, Kline, Neal, Dunlap, Moriarty, Fan, Tan, Chan, Treibitz, Gamst, Mitchell, Kriegman, "Towards Automated Annotation of Benthic Survey Images: Variability of Human Experts and Operational Modes of Automation," PLOS ONE, 2015

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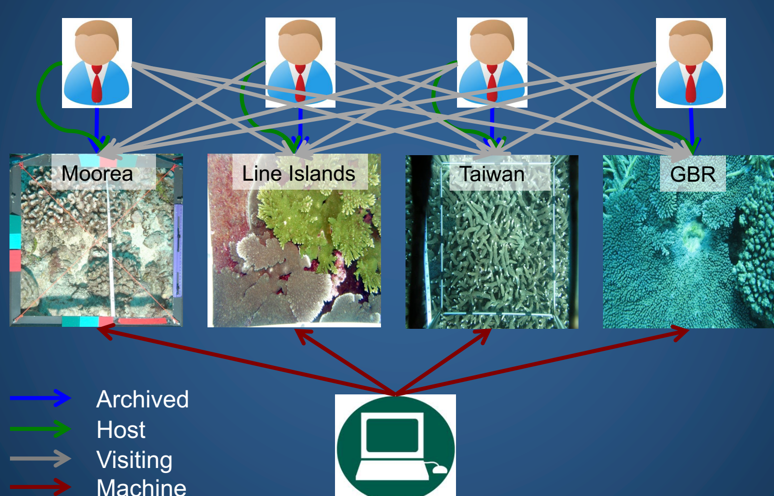
Multi Annotator Study



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Accuracy: Experts vs. CoralNet Alpha

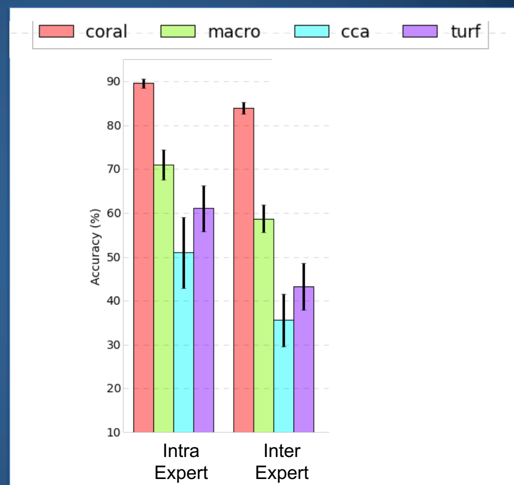
Kappa	Level of agreement
0-20 %	slight
21-40 %	fair
41-60%	moderate
61-80%	substantial
81-100%	almost perfect

Cohen's Kappa as measure of accuracy

$$K = \frac{P_o - P_e}{1 - P_e}$$

P_0 : Observed agreement amongst raters

P_e : Probability of chance agreement



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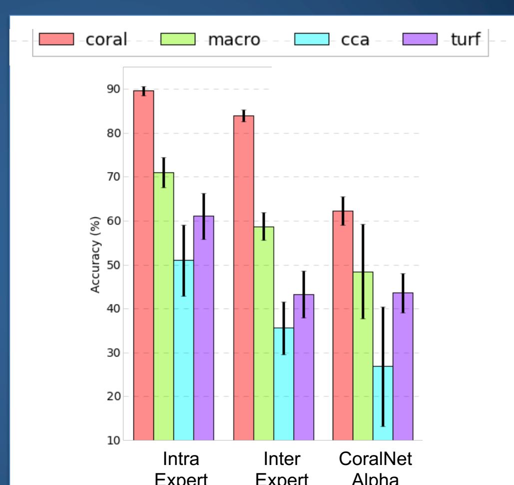

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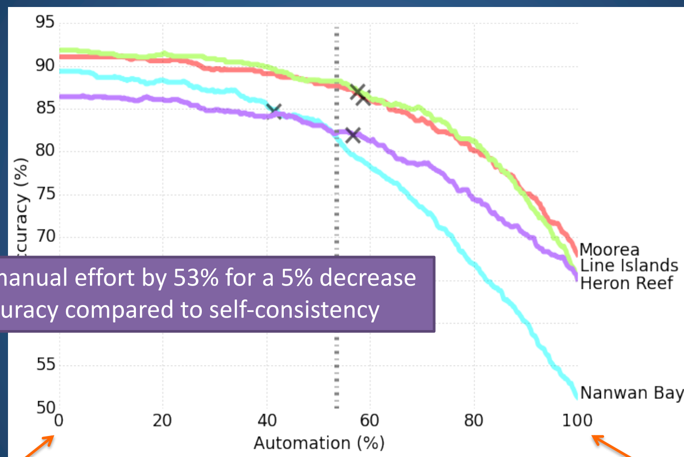
Semi-automated annotation



Reduce manual effort by 53% for a 5% decrease in accuracy compared to self-consistency

Fully Manual

Fully Automatic

Use confidence score to decide whether to accept classifier output or request manual label

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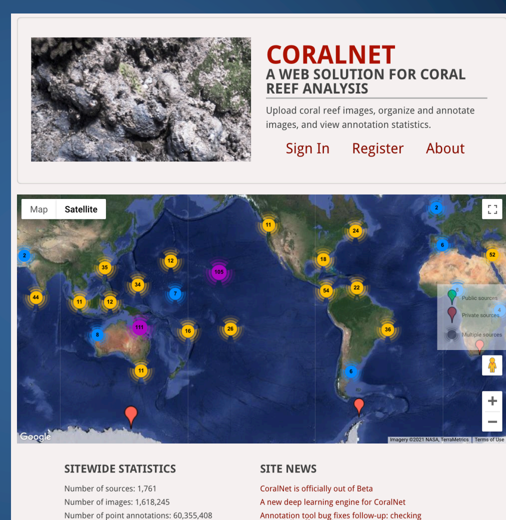
What is CoralNet?

- Web site and service for manual & automatic analysis of benthic images
- User Interface similar to CPCe
- Runs on AWS
- Open source, community resource
- Platform for aggregating and sharing coral reef images and data
- Real data to drive machine learning and computer vision



coralnet.ucsd.edu

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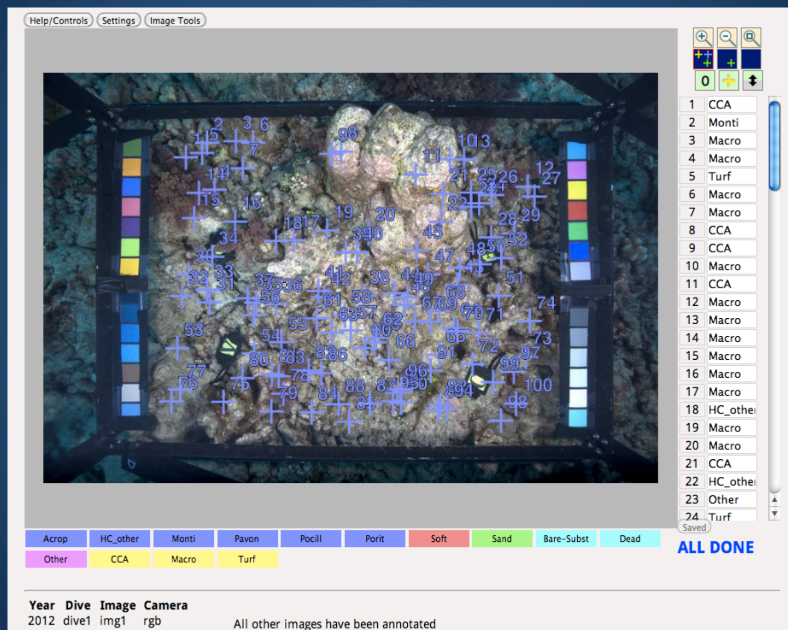
coralnet.ucsd.edu



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CoralNet Usage

- 1,617,421 images
- 2,000 new images /day
- 1760 image sets (sources)
- 60.3M annotations
- 2,400+ registered users

Australian Institute of Marine Science
Scripps Institution of Oceanography
National University of Singapore
Ahbu Dabi Environment Agency
University of New South Wales
Florida Institute of Technology
University of the Virgin Islands
Washington State University
University of North Carolina
University of Washington
Arkansas State University
Smithsonian Institution
University of Aberdeen
James Cook University
University of Victoria
University of Sydney
Cal State Northridge
University of Texas
University of Haifa
Tel-Aviv university
Qatar University
Colby College
Kaust
NYU

Power Users

- UQE/Catlin Seaview Survey - 100k+ images
- NOAA CREP 2016 surveys -150K images
  - Hawaiian Archipelago
  - American Samoa & Pacific Remote Island Areas
  - Marianas Archipelago (Guam, Northern Marianas Islands, Wake Atoll)

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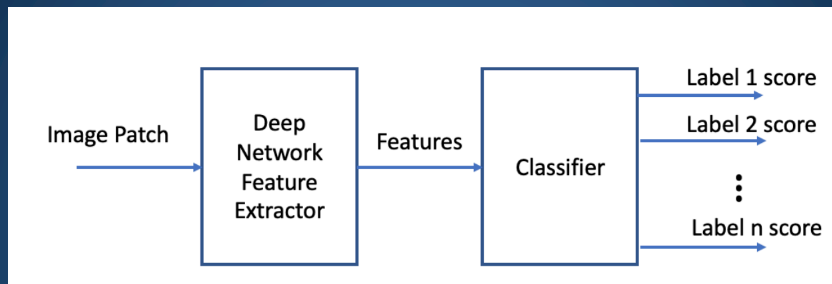
Transfer Learning



Training on a large labelled dataset :
- Train Deep Network Feature Extractor and Classifier

Transfer learning on smaller labelled dataset:
- Use trained deep network to compute features
- Train classifier on computed features

Inference
- Use trained network and classifier to classify unlabeled images

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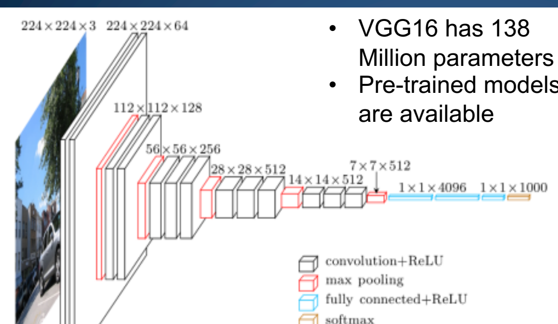
CoralNet Beta: Deep Learning



- VGG16 has 138 Million parameters
- Pre-trained models are available

"Very Deep Convolutional Networks for Large-Scale Visual Recognition," K. Simonyan, A. Zisserman, 2014

Train VGG on images and labels from **CoralNet Alpha**
- 62,000 images
- 956 classes
- 2.5 million point annotations

Transfer Learning: Calibrated Logistic Regression

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Accuracy: CoralNet Beta

Kappa	Level of agreement
0-20 %	slight
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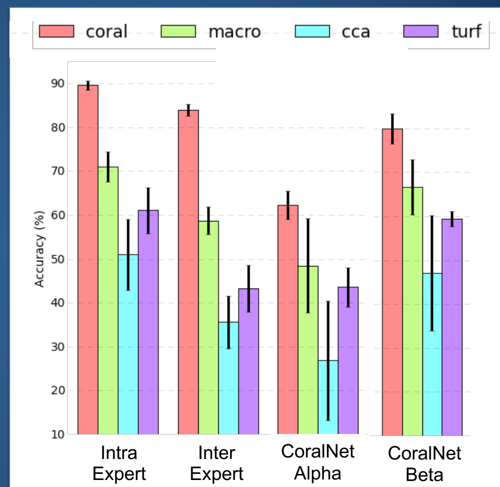

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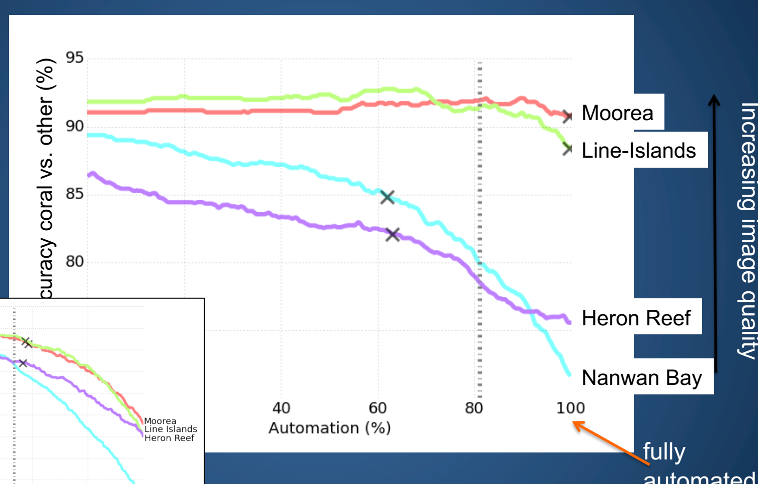
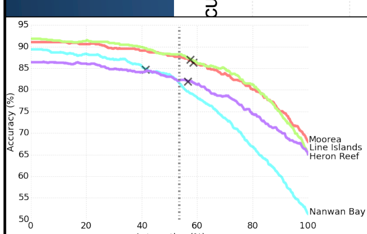
Semi-automation





"traditional" method

- Average automation level: 81%
- Full automation possible for Moorea & Line Islands
- Lower accuracy for Heron & Nanwan Bay

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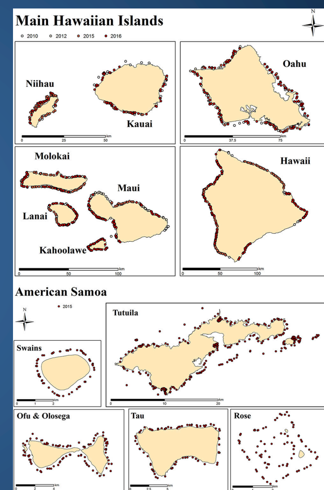
NOAA large scale evaluation of CoralNet Beta

- Data: 41,430 images from 1,381 sites
  - Main Hawaiian Islands: 2010-2016, 913 sites
  - American Samoa: 2015, 468 sites
  - 30 images per site,
- 414,300 annotation (10 per image)
- 31-85 benthic classes
- Ground truth using CPCe by pool of 19 trained analysts



Williams, Couch, Beijbom, Oliver, Vargas-Angel, Schumacher, Brainard, "Leveraging automated image analysis tools to transform our capacity to assess status and trends on coral reefs," Frontiers in Marine Science, April 2019.

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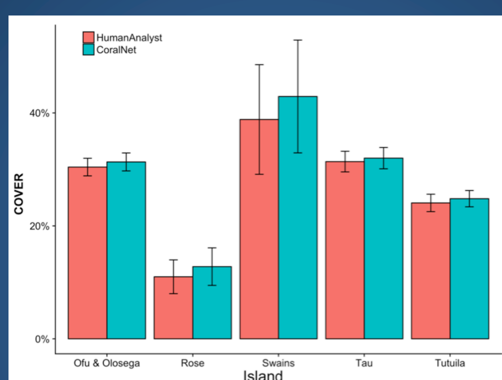
NOAA large scale evaluation of CoralNet Beta



- Site-level coral cover were highly comparable to those by human analysts (Pearson's r > 0.97 with bias < 1%)
- Effective at estimating cover of common coral genera (Pearson's r > 0.92 with bias < 2% in 6 of 7 cases)
- Mixed for other groups including algal categories

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CoralNet Beta vs CoralNet 1.0

	CoralNet Beta	CoralNet 1.0
Year launched	2017	2021
Network Architecture	VGG-16	EfficientNet B0
Classifier	Calibrated Logistic Regression	Calibrated Multilayer Perceptron
Number of Training Sources	33	304
Number of Images	~ 63,000	~590,000
Number Annotations	~ 2.57 Million	~ 16.5Million

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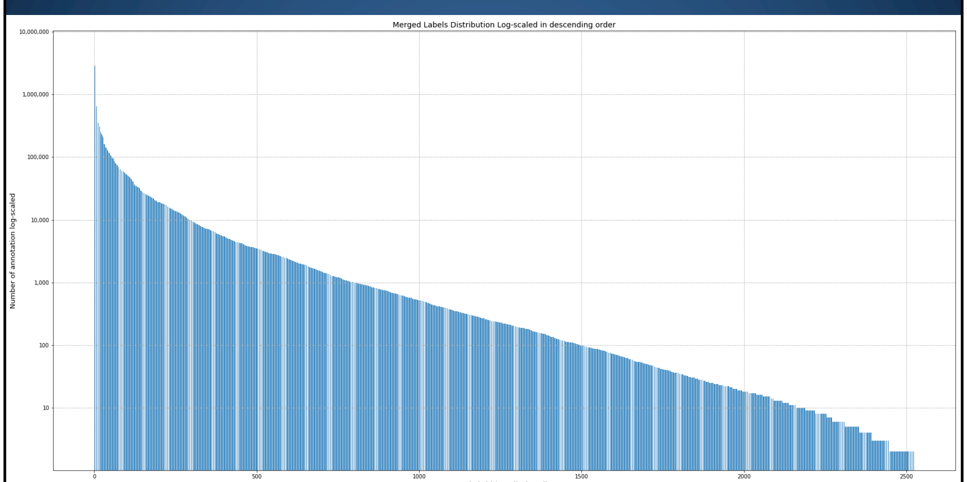
Frequency of labels in training images



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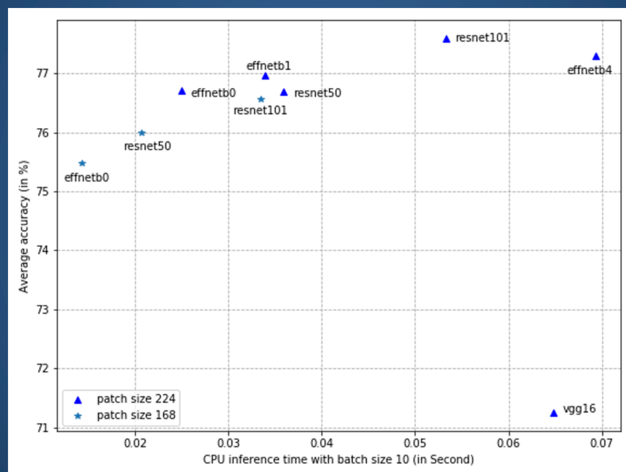
Accuracy vs. Inference time for different deep networks



Experiments and training CoralNet 1.0 used 9,751 GPU hours provided by UCSD Nautilus HyperCluster.

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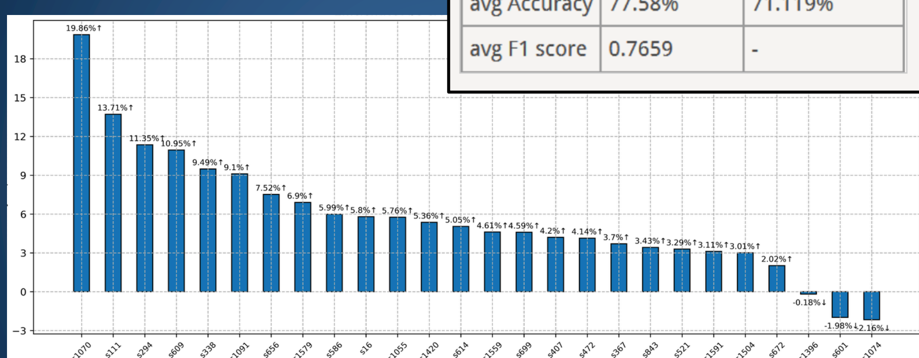
Accuracy of CoralNet V1.0 vs CoralNet Beta

-	CoralNet 1.0	CoralNet Beta
avg Accuracy	77.58%	71.119%
avg F1 score	0.7659	-



Across 26 varied sources

- Error rate reduced by 22.4%
- Absolute accuracy increased by as much as 19.8%
- Accuracy increased for 23 of 26 sources

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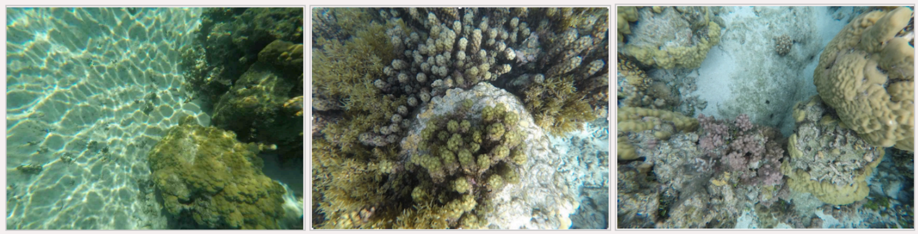
CoralNet API



1. Programmatic interface to apply trained classifier to additional images
2. REST API called with list of images (URL's) and point locations (up to 100 images, 200 pts per image)
3. **"Automatically annotating 175,000+ images using the CoralNet API,"** Scott Miller, University of Florida, Time-lapsed images from towed GoPro camera. See CoralNet Blog.

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Where to go from here?

- CoralNet
  - Estimation of calcification rates of reefs
  - Semantic segmentation
  - 3D reconstruction and annotation of reef topography
  - Anomaly detection – rare, but important species
  - Time series analysis – change and growth over time
- Complementary sensing – Fluorescence
  - Improved accuracy
  - Finding coral recruits
- CoralNet as a treasure trove of real data for ML
  - Generalization and low shot learning
  - Taxonomy, synonyms, embeddings
  - Domain transfer

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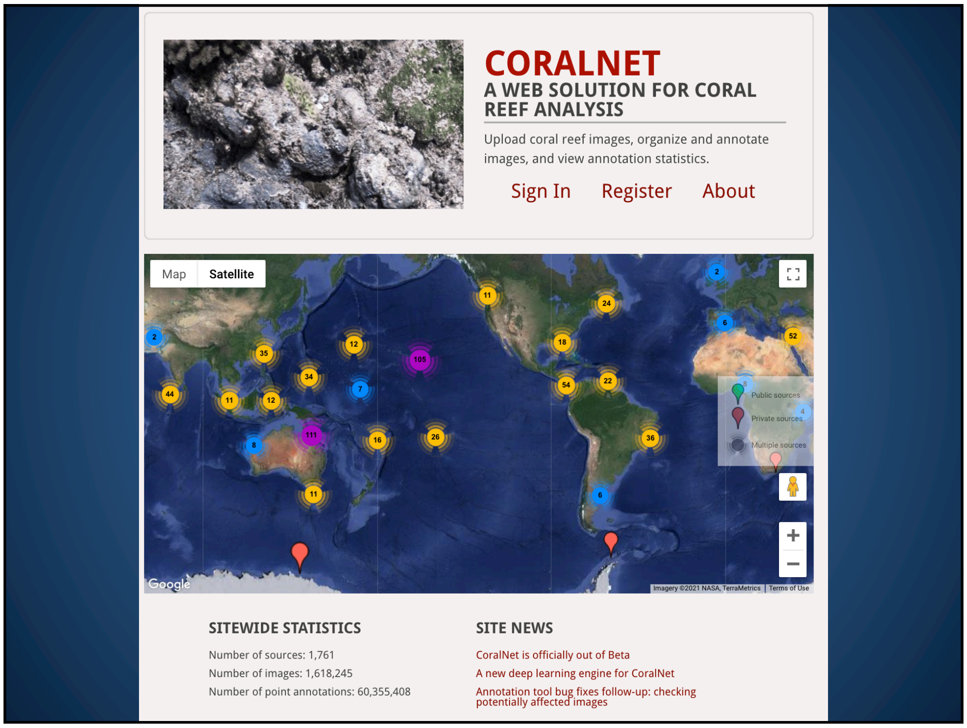
CORALNET
A WEB SOLUTION FOR CORAL REEF ANALYSIS
Upload coral reef images, organize and annotate images, and view annotation statistics.
Sign In
Register
About
Map
Satellite
Public sources
Private sources
Multiple sources
Google
SITEWIDE STATISTICS
Number of sources: 1,761
Number of images: 1,618,245
Number of point annotations: 60,355,408
SITE NEWS
CoralNet is officially out of Beta
A new deep learning engine for CoralNet
Annotation tool bug fixes follow-up: checking potentially affected images

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