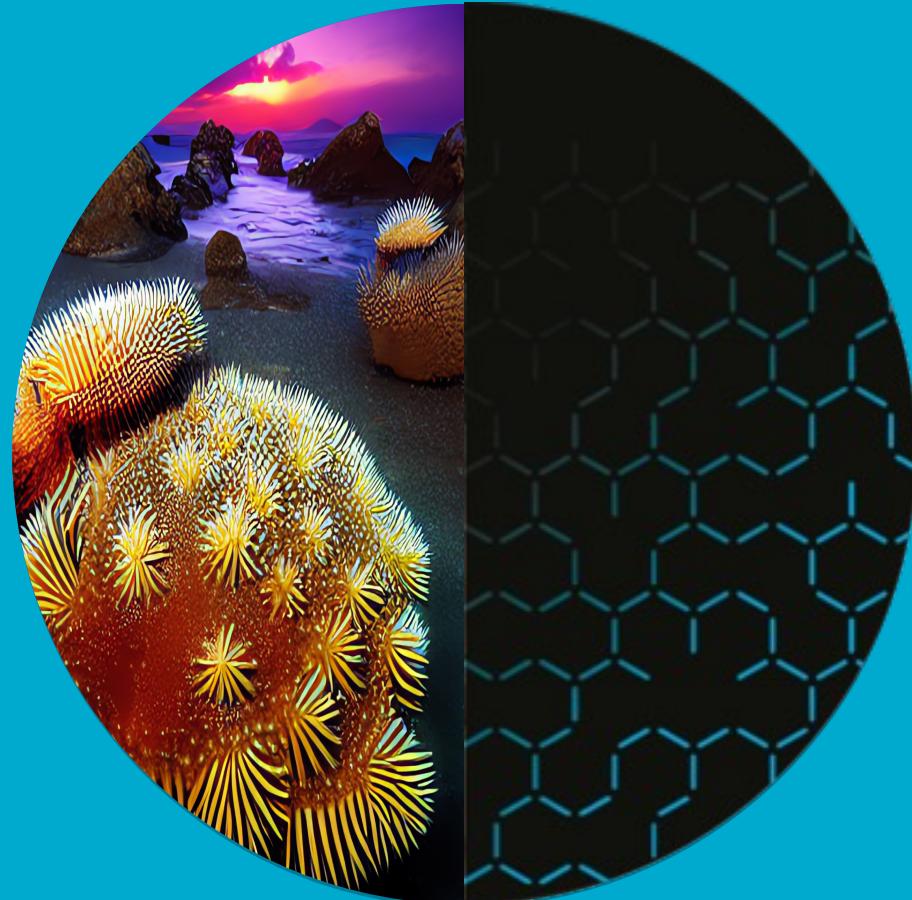




Intelligent Sensing Devices in Real World Applications

Brano Kusy
Research Group Leader
Principal Research Scientist
Distributing Sensing Systems, CSIRO
Australia's National Science Agency

| 24-Jul-2023



My Research Group: Distributed Sensing Systems

Building distributed systems consisting of small, low-power nodes capable of sensing, processing, and wireless communications

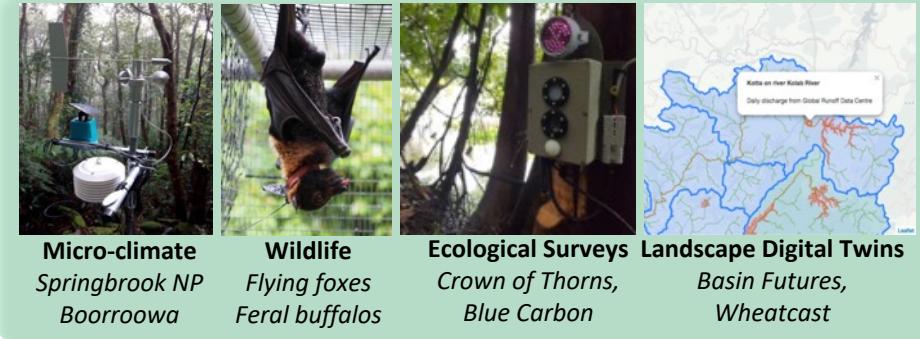
Capability

- Broad IoT technology expertise
 - IoT hardware and software, cloud, digital twins
 - IoT data analytics and models
- Applied Real-world R&D: testbeds, field work
- R&D Focus
 - Intelligence: on-device analytics/ML
 - Interactive methods: user/AI co-learning
 - Scalability and sustainability

Application Domains

- **Agriculture:** livestock management, yield forecasting
- **Biodiversity, biosecurity:** species detection/classification
- **Energy:** building systems, control
- **Terrestrial:** water management, animal-born diseases
- **Oceans:** broadscale coastal surveys, digital aquaculture

Environmental/societal Impact



Commercial Impact





What is This Lecture About?

Show you examples of real-world research impact of IoT technology.
Increasingly AI plays an important role, but not without challenges.



Quick Knowledge Review

Use-case Studies

Edge Computing vs Edge AI



IoT

IoT – network of physical objects or “things” embedded with sensors and software

Not just phones, tablets: vehicles, home appliances, machinery, ...

Make our devices smarter through connectivity and ML: help us make smart decisions, automate tasks



Edge Computing

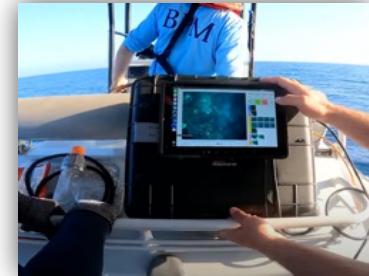
Distributed computing paradigm where data and compute are located close to data source. Sensor networks and IoT are an instance of edge computing

Benefits

Faster Response, Energy Efficiency, Scalable, Secure

Challenges

Interaction with users, Compute constraints, Unknown operating conditions / domain-shift



Edge AI

Compute efficient machine learning algorithms and compute/hardware to accelerate ML ops.



Machine learning



Artificial Intelligence (AI):

- Creating machines and software capable of intelligent behavior
- Two general methods
 - Machine learning – learn from experience, make decisions and predictions based **on data**
 - Knowledge Engineering – follow predefined rules and logic

Training:

- Understand patterns on input data, requires labels
- Adjust internal parameters to minimize prediction error

Inference:

- Trained model makes predictions on new data

Domain Shift:

- A major challenge in machine learning
- Occurs when the distribution of data changes between the training and the inference phase
- E.g., Change in lighting condition, change of camera parameters, ...

Different Types of Embedded Systems

Performance ↑

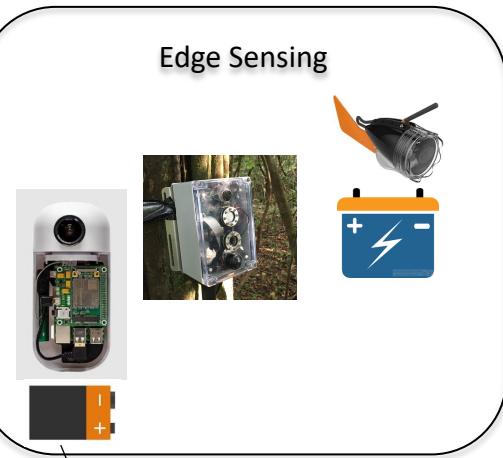
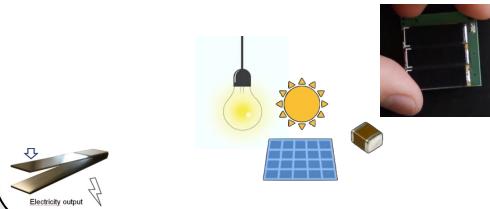
Compute: 10s μ J (simple analytics)
Comms: 10s μ J (BLE)
Sensing: μ J (solar sampling)
Duty cycling: aggressive (1 datapoint per charge cycle)

Compute: mJ (medium analytics, TF-micro)
Comms: 10s mJ (LoRaWAN, satellite)
Sensing: 10s mJ (GPS)
Duty cycling: medium (1 datapoint per sec)

Sensor Networks



Batteryless Sensors



Compute: J (CNNs, TF/TF-lite)
Comms: 100s mJ (WiFi, 4G)
Sensing: 100s mJ (cameras, audio)
Duty cycling: low (10s Hz)

Power Efficiency →

10 μ W

100 μ W

1 mW

10 mW

100 mW

1 W

10 W

innovation

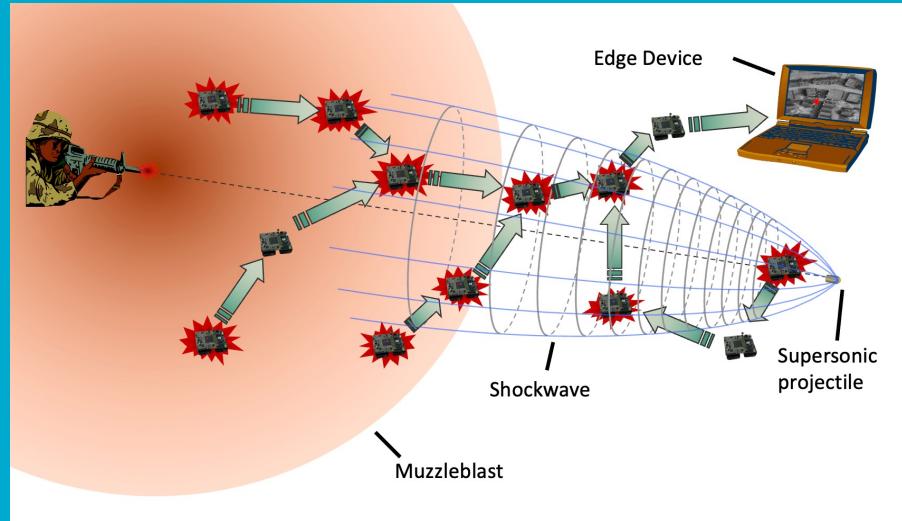
Established topic

innovation



Case Study

Shooter Localization System





Case Study: Shooter Location System



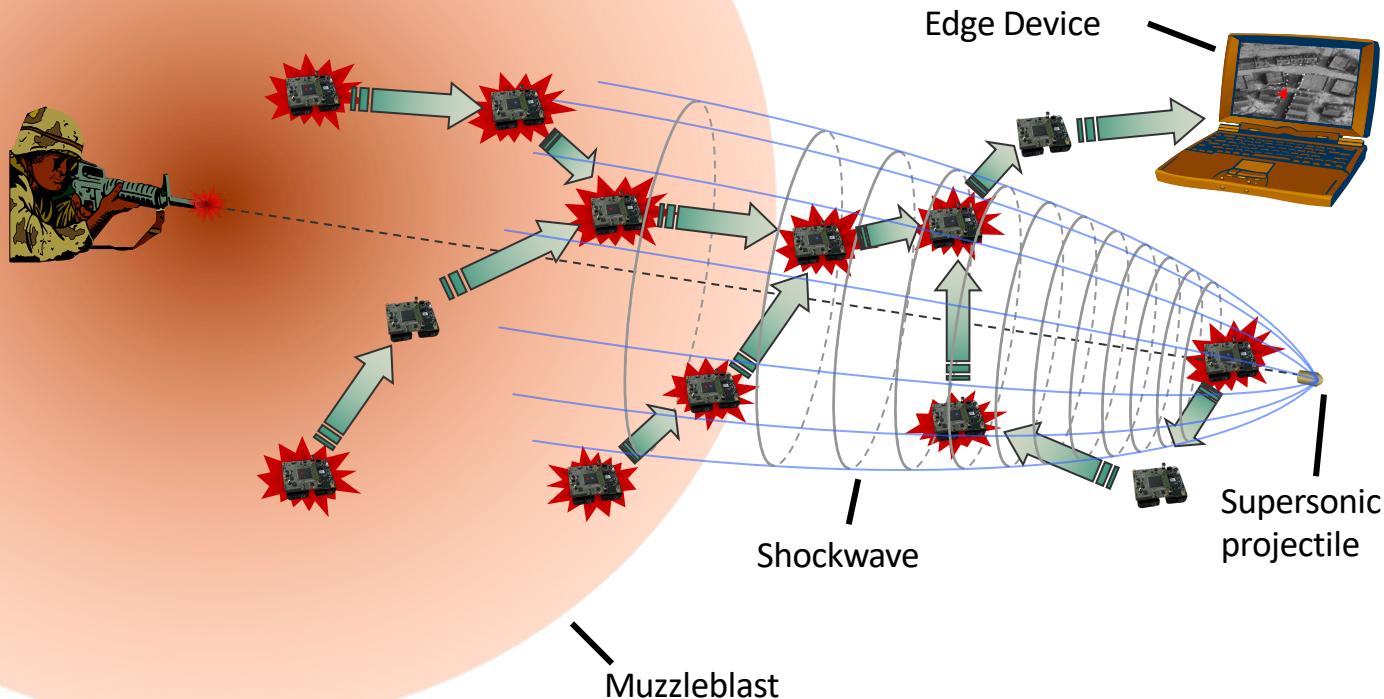
- Task:
 - Localize a shooter in urban environment in real time
 - Hard problem due to multipath and limited line of sight (shots inside buildings, behind cars, ...)
 - Deployment:
 - 60 acoustic sensors covering 100x40m
 - Ft. Benning, GA, USA
 - Performance (in 2005):
 - 1m (3D), 0.6m (2D), 2 sec latency



- Acoustic IoT sensors
 - Detect shots and record time and location
 - Proprietary acoustic board for shot detection
 - Edge device (laptop + IoT gateway)
 - Data fusion, shot location estimation

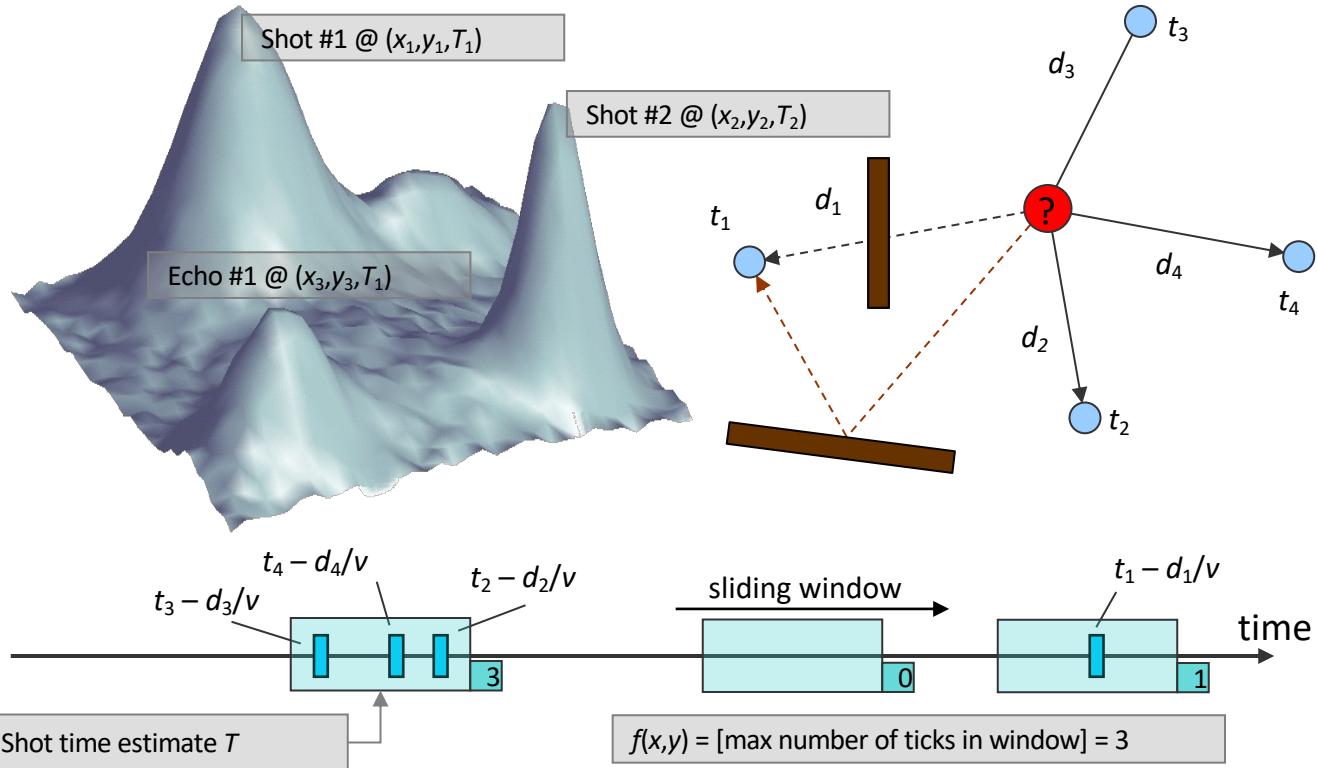


Technical Overview



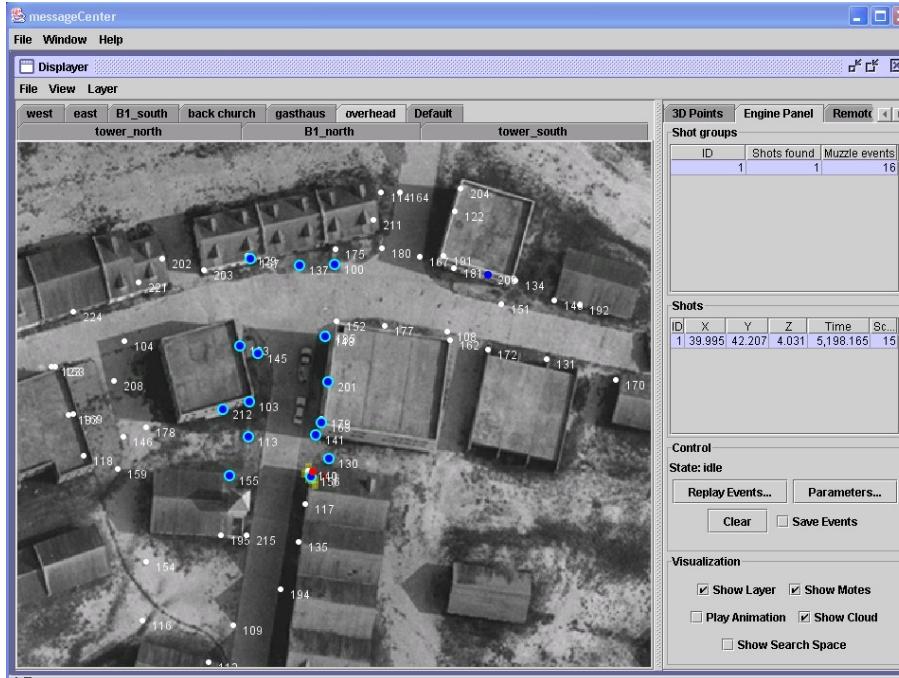


Sensor Fusion





2.5D Display, Single shot





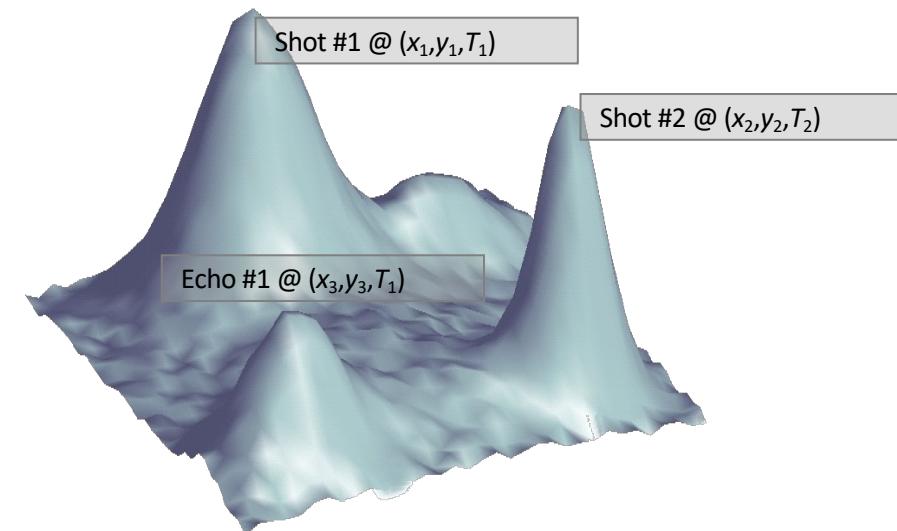
Intelligence/Summary: Mostly Knowledge Engineering

On Device – Shot Classifier



1ms/div

On Edge – Data Fusion





Case Study

Animal Behavior Classification



Use Case I: Automated Phenotyping



Task – Automate Genetic Selection in Cattle Industry

- Measure inputs: pasture intake at a location
- Against outputs: weight gain, GHG emissions

Method – Measure Detailed Food Intake

$$\text{Dry Matter Intake (DMI)} = \text{grazing}(t) \times \text{bite_rate}(t) \times \text{bite_size}(t)$$

Data

- Collar tags for cattle, deployed for 1 month
- Sensors: 9-axis IMU @50Hz, GPS @1Hz
- Manual annotations: 4 activities, bite rate

Use Case I: Intake Estimation (Shallow Classifier)

Random Forests

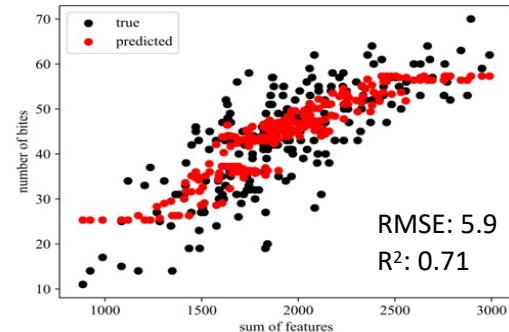
- High accuracy
- Low computation and model's size
- Higher compute required for training

Implementation

- CC2650 (cortex-m3), 48 MHz, 28 KB RAM
- Sklearn-porter (adapted to integer arithm)
- Feature calculation: ~900 CPU cycles
- Inference: ~1000 CPU cycles

=> DUTY CYCLE <0.1%

true \ predicted					precision(%)	recall(%)
	grazing	ruminating	resting	other		
grazing	2158	5	6	11	95.96	98.97
ruminating	3	679	104	1	84.00	86.28
resting	24	109	840	6	86.34	85.82
other	64	15	23	24	57.12	19.21



Use-case I: Intake Estimation (Naïve Bayes)

Histogram-based Implementation

- Good accuracy
- Allows online training

Implementation

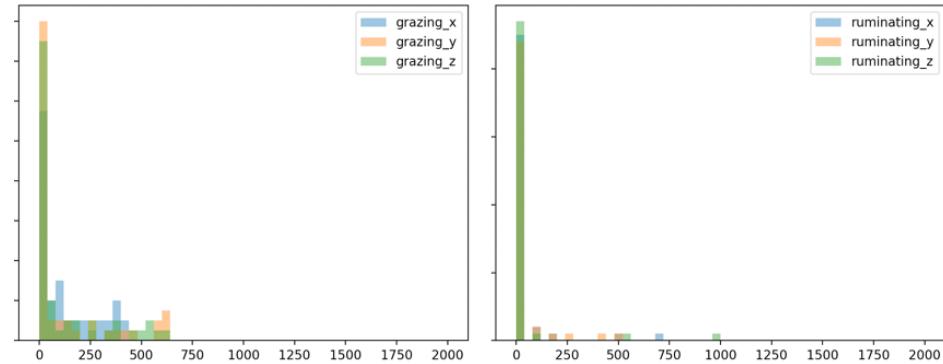
- Model size 600b per class, i.e., 2.5kb total
- Computation (CPU cycles):

Inference (float): 5969

Inference (int32): 4039

Training (int32): 869

- Error rate: 7.4%, weighted recall: 93%, weighted precision: 93%



activity	Precision (%)	Recall (%)
grazing	98	99
ruminating	91	92
resting	82	82
other	60	48

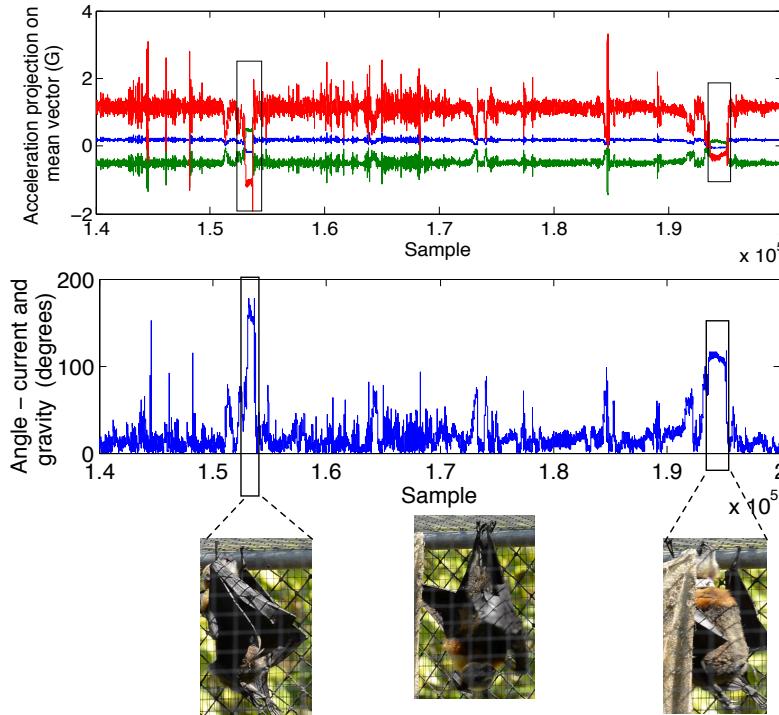
Use Case II: Behavior of Flying Foxes

Hardware Platform Constraints

- Weight limit: 20-30 g (5% of body weight)
- Long-term operation (months to years)
- Delay tolerant networking
- GPS tracking
- Context (inertial, audio, environmental)



On-board 3-axis acceleration sensor



Events of Interest:

- Flying
- Feeding
- Sleeping
- Defecating
- Urinating
- Fighting

Use Case III: In-situ Physiology of Coral Trout

Task

- Health/condition inference – linkage to stressors (climate change, industrial pollution, tourism)

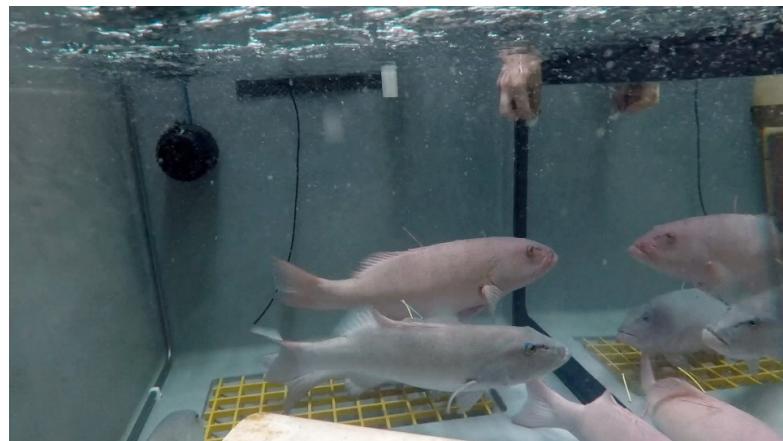


Method – Measure heart rate increase during feeding

$$\text{Energy consumed} = \text{Metabolism}/\text{Respiration}/\text{Motion} + \text{Waste} + \text{Growth}$$

Data

- Implanted sensors, deployed for 10 weeks, controlled feeding experiments
- Sensors: ECG and 3-axis ACC @50Hz, Temp/Depth @1Hz
- Manual annotations: collected paper records, video recordings of feeding



Use Case II: Feeding Classifier for Fish

Fish Feeding and Heart Rate

- Fish is exothermal, increases metabolism to digest food
- Feeding signature is different from fight/flight/etc
- Challenges - biosignals are messy, ECG reflects all motion

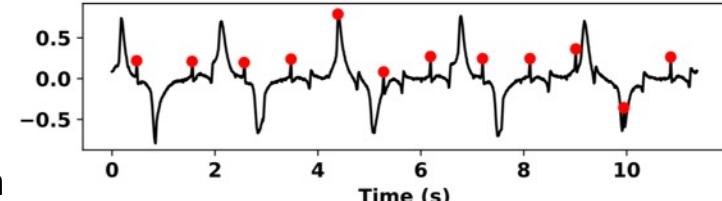
Heart Rate

- filtering, ECG peak augmentation/detection
- HR estimation, post-filtering

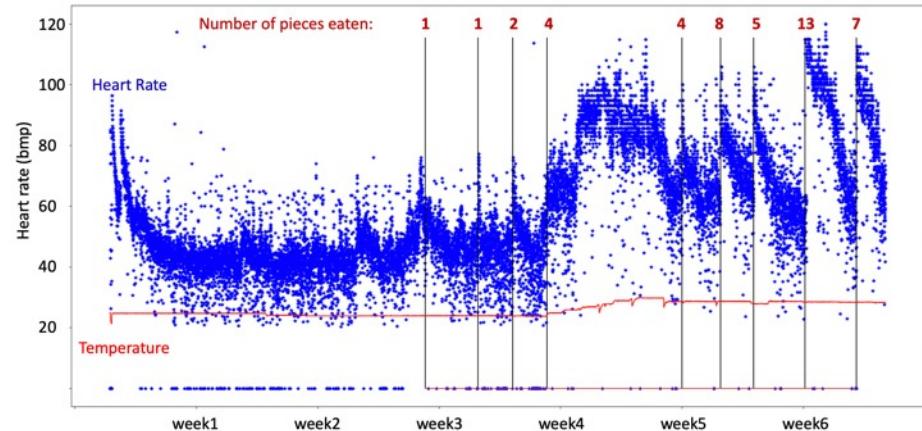
Feeding Classifier

Long-term statistical change detection

Balanced FPR/FNR of 23%, accuracy 77%



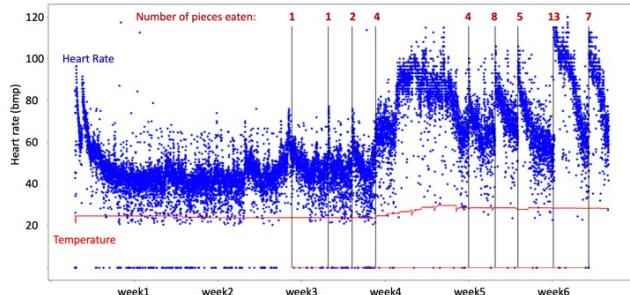
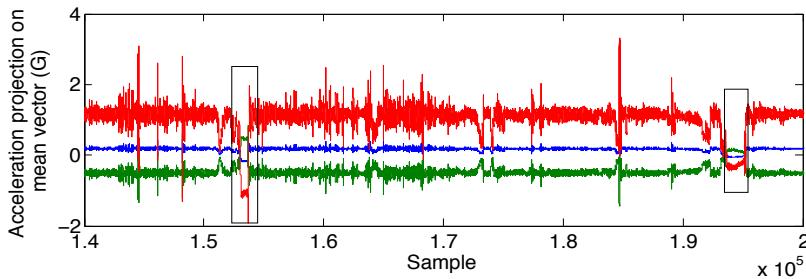
Raw ECG signal



Heart Rate, temperature, and feeding events

Intelligence/Summary: Combination of Knowledge Engineering and Machine Learning

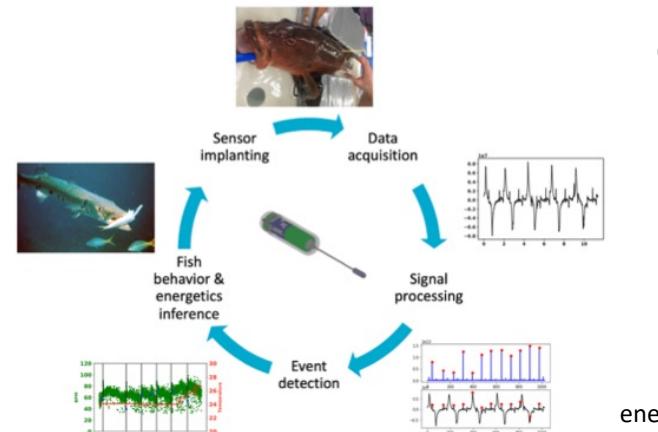
Features are Hand-Engineered



ML – Classification Algorithms



Cattle behavior



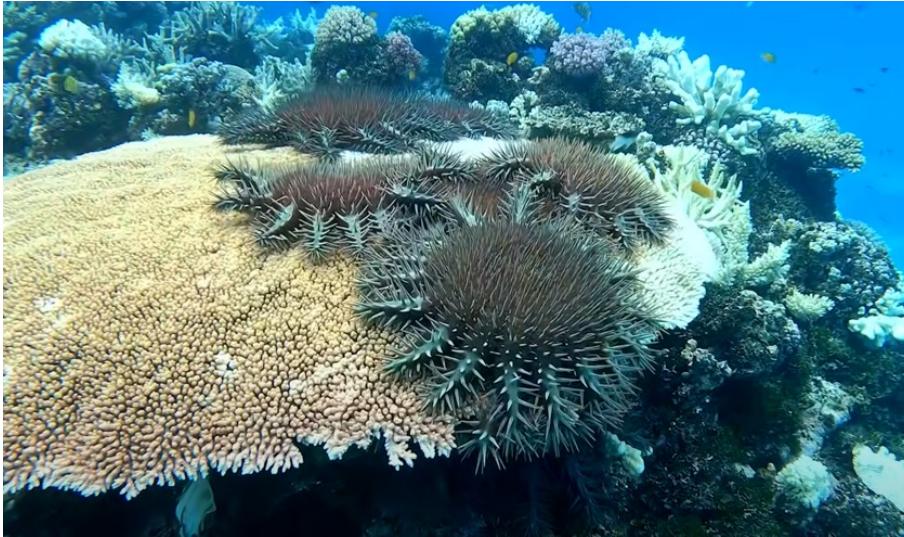


Case Study

Broadscale Coastal Surveys



Crown-of-Thorns Starfish (COTS)



Crown of Thorns Starfish (*Acanthaster planci*): a large starfish that preys on hard coral, leaving behind white carbonate skeleton

COTS population outbreaks are a major cause of coral decline.

Government-funded COTS control program actively controls starfish populations on the Great Barrier Reef. Starfish are surveyed using the Manta Tow method.



Manta Tow method

Tow No.	Coral Cover			Vis.	C O T		
	Live	Dead	Soft		No.	Size	Scars
1	3+	1-	1+		10		A
2	3-	1-	1+		0		C
3							
4							
5							

Scoring Sheet



COTS Data Dashboard

Annual manta tow surveys for CoTS:

- 5 vessels, 100 employees, 8070 in-water surveys
- 106 reefs per year, 1577km of reef-margin transects



COTS Innovation Program

Use computer vision platforms and machine learning technology to automate detection, counting, and mapping of COTS on coral reefs

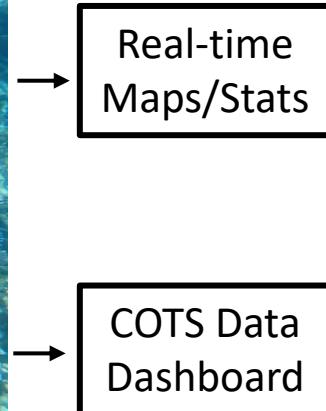


Manta Board with Cameras



Autonomous Platform

COTS ML Detector Tracker, Edge AI



Real-time
Maps/Stats

COTS Data
Dashboard



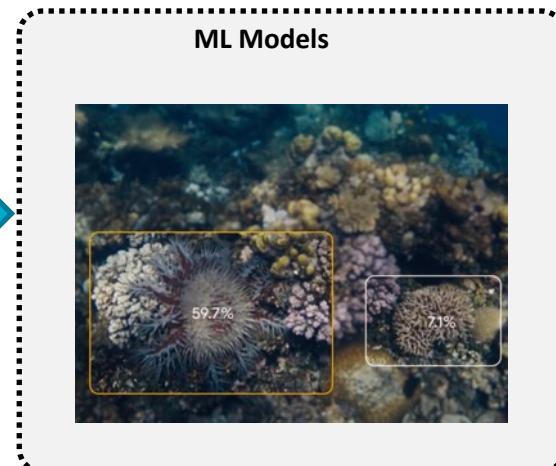
Blue Growth Project

Next generation methodologies/tools to accelerate and scale coastal surveys

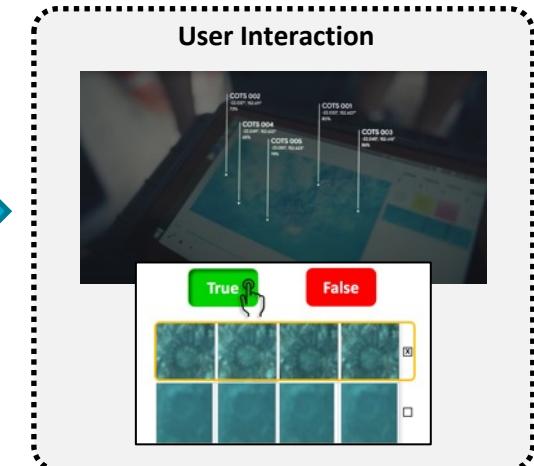
Scalable Sensing Platforms for Image Transects



Machine Learning Models for Analyzing Images



Interactive Edge AI Platform

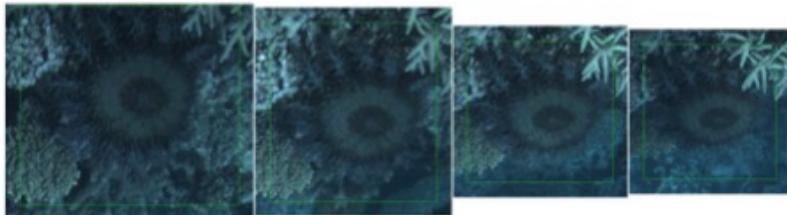


Collect Data at Scale

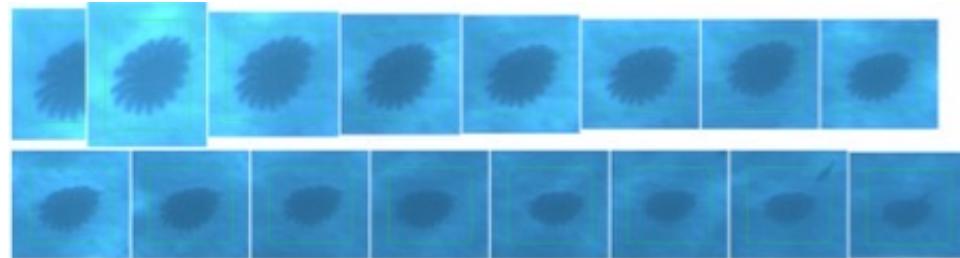
Insights in Real-time



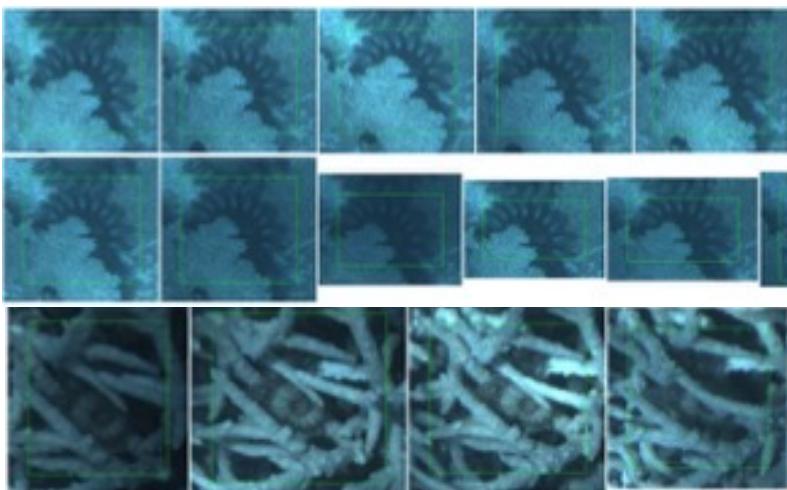
Examples: CoTS Detections by ML



Shallow



Deep



Occluded

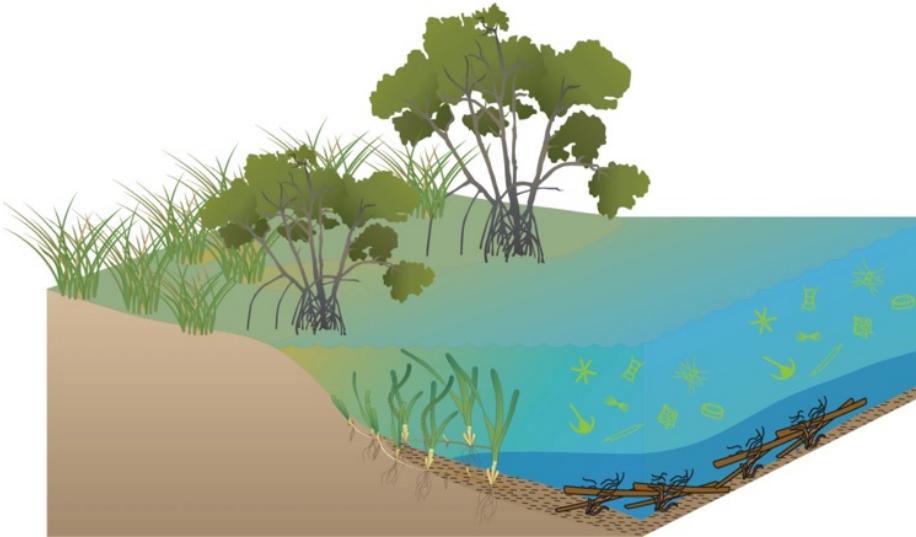


Top-down



Sideways

Blue Carbon Ecosystems



Blue Carbon coastal ecosystems provide important ecosystem services directly linked to sustainable livelihoods. For example, they can sequester carbon for millennia, through plant growth and the accumulation and burial of organic matter in the soil.

New scalable mapping and monitoring methods can provide a step change in our ability to tackle climate, prosperity, and livelihood challenges.

Existing methods for mapping and estimation of carbon sequestration potential.



Quadrat Visual Surveys



Soil samples



Drone Surveys

Seagrass Maps
Ecosystem Models



Measurement
Management
Resilience

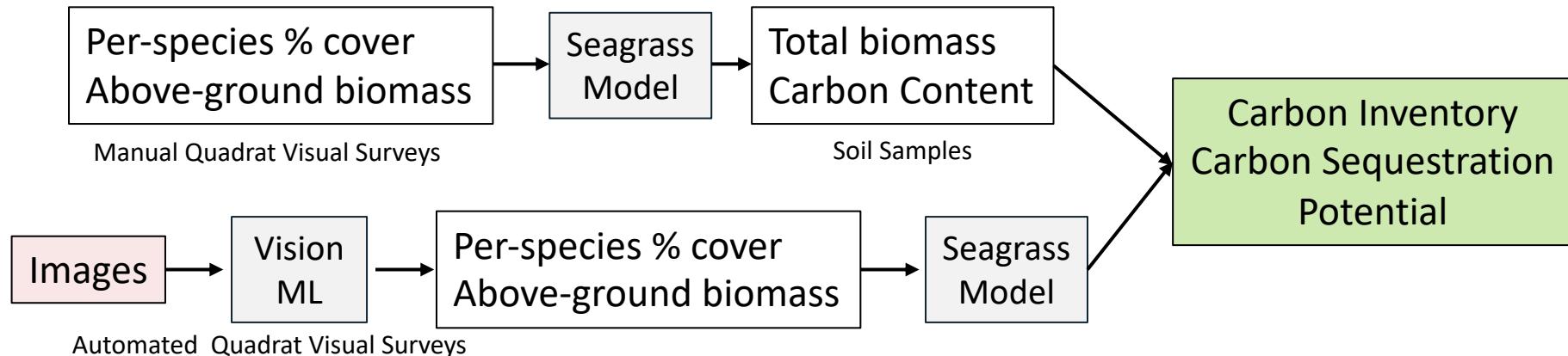
Pacific Blue Carbon Program

Motivation: Support national climate action and livelihoods through enhanced measurement, management and investment in coastal blue carbon ecosystems

Goal: Establish a blue carbon inventory and characterize controls on sequestration



Step 1: Marine Science: relationship between Seagrass Species/Biomass Data and Soil Carbon
ML Research: train ML models to automate visual data processing





Pacific Blue Carbon Program

Motivation: Support national climate action and livelihoods through enhanced measurement, management and investment in coastal blue carbon ecosystems

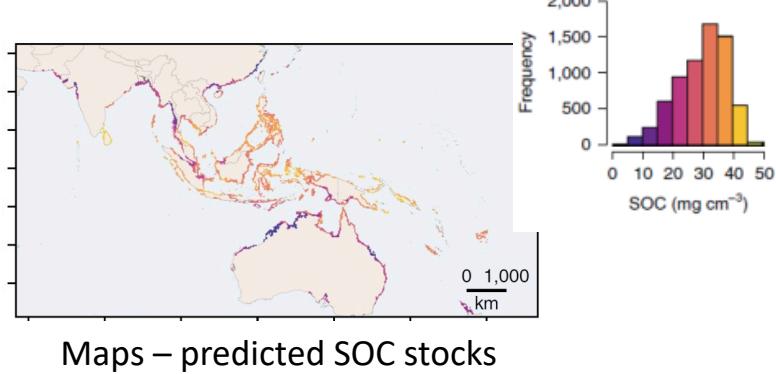
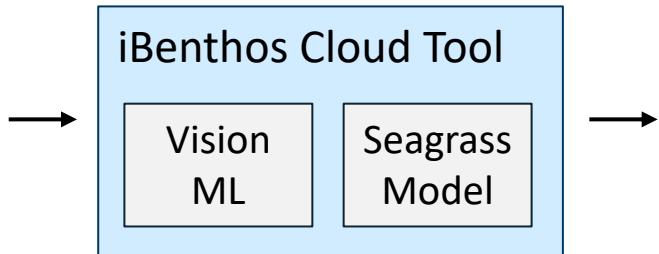
Goal: Establish a blue carbon inventory and characterize controls on sequestration



Step 2: Deploy the measurement method with in-country collaborators



Quadrat Image Surveys
(In-country Collaborators)

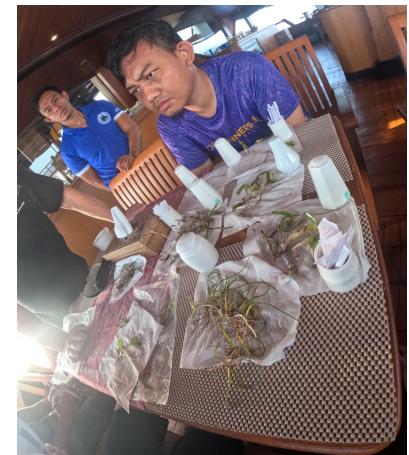




Pacific Blue Carbon Project

Characterizing carbon storage potential
of Blue Carbon ecosystems in Pacific

Fiji Lau Group Field Trip



Indonesia Komodo



Fiji Lau Group Field Trip

Fiji Sun July 25, 2022

News Sunbiz Sports World Entertainment Opinion Lifestyle Siga Karama Climate Watch E-Edition

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ADVERTISE WITH SUN

NATION

Macuata Part Of Pacific Blue Carbon Programme

Macuata has renewed its engagement with Commonwealth Scientific Industrial Research Organisation (CSIRO) Brisbane in collaboration with the University of the South Pacific's marine research program in Macuata.

By Sherika Naidu

17 Jul 2022 13:12

F T G+ S



Participants gathered at Towake Village in Macuata on July 14, 2022. Photo: Transcend Oceans

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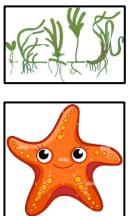


Pacific livelihoods blue carbon program



Intelligence/Summary – Machine Learning

Scalable Sensing Platforms



Commercial
Bespoke

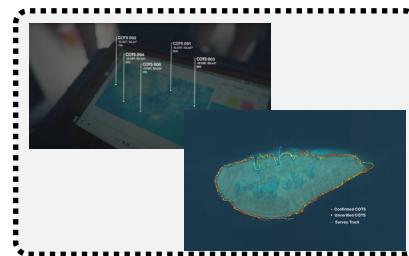
Collect Data at Scale

Machine Learning Models



Insights in Real-time

Interactive Edge/Cloud AI Platforms



- Rapid Response
- Trusted ML
- Continuous Improvement



The Key Machine Learning Challenge

ML workflow is only as good as the underlying ML models

ML Models make mistakes

Misclassification



False Positive (Model detected an object that wasn't there)

False Negative (Model hasn't detected an object that was there)

Outcomes/Insights will be wrong
(maps, stats, counts)



Edge AI Platform – Continuous Learning from Experts

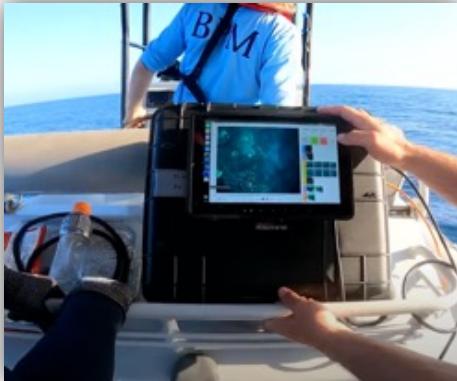


Figure 1: Live view of the camera feed super-imposed with ML outputs.

- 1) Powerful enough to run ML models in real-time (10fps HD video)
- 2) Small and efficient to carry on a small boat
- 3) Interactive GUI to learn from expert human operator

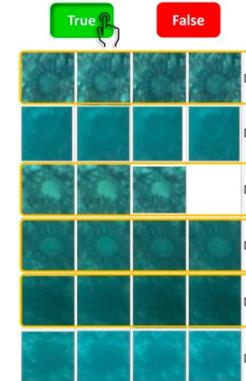


Figure 2: ML curation window: Rows correspond to objects detected over time, buttons at the top allow for quick curation of results.

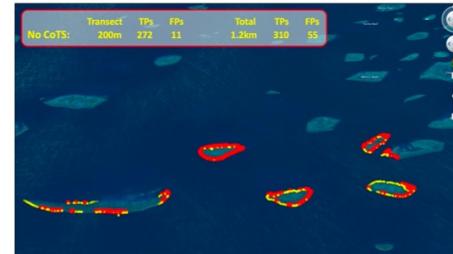
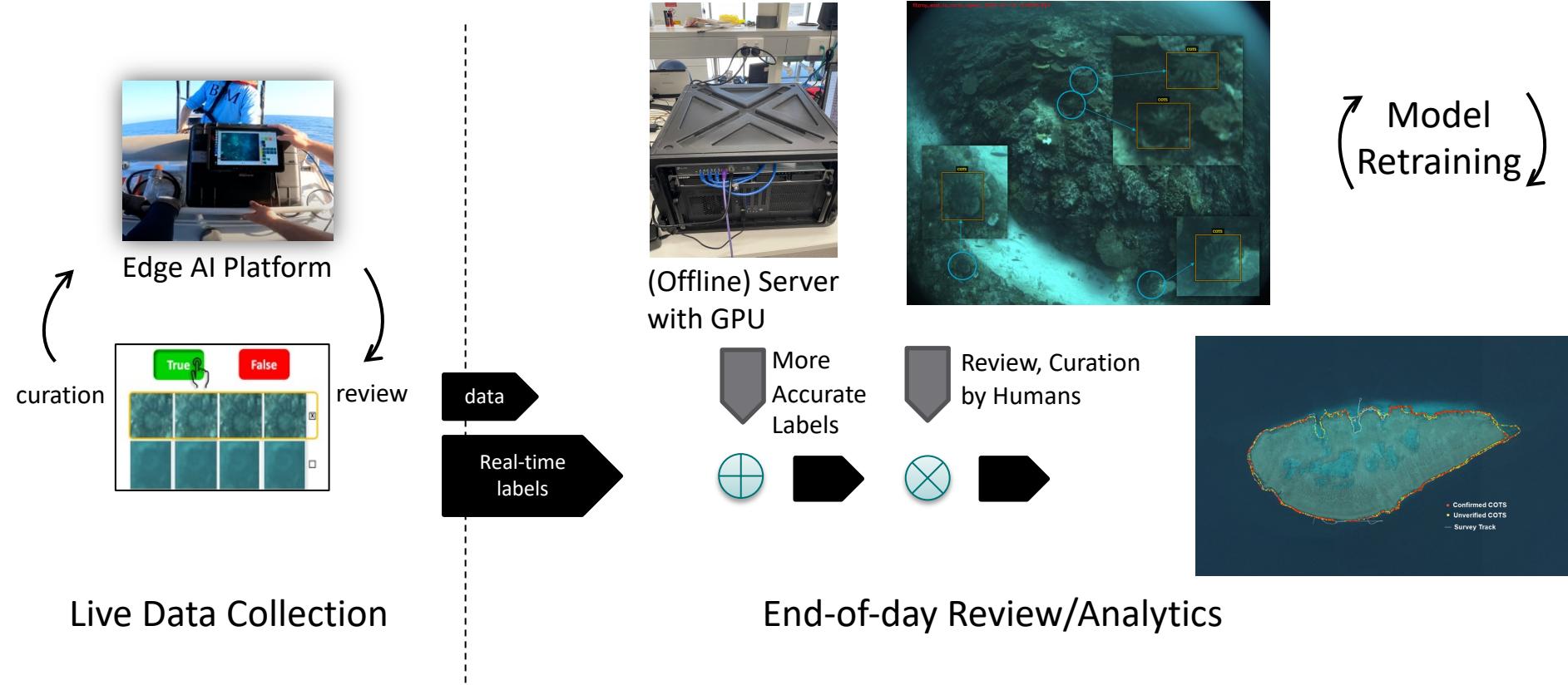


Figure 3: Map of several reefs overlaid with ML detections to show their spatial distribution.



Continuous ML Refinement Lifecycle

We continuously validate and improve performance of ML algorithms





Innovating Broadscale Surveys



Manta tow



Quadrat



Biomass/Soil Cores



Video Transects

Today: Time-consuming data collection methods
that require experts

Future: Scalable data collection by trained operators
and fast data interpretation by AI



11-point transects per day



Local Scale: higher res



Regional Scale



Impact

- COTS

- GBR Validation (2020-22): Capricorn bunkers, Swains NP
- Reef Trust Partnership (2022-24): Collaboration with AIMS, GBRF, GBRMPA, boat operators
- Google – Kaggle competition, Google I/O dev keynote

- Blue Carbon

- Fiji Lau Group (jul'22): 6 islands, 18 transects
- Indonesia Komodo (oct'22): 9 sites, 19 transects
- Indonesia Sulawesi (jun'22): 16 sites, 30+ transects
- Fiji/Indonesian government dept, academia



Google DFI Event (Nov'21)



Google-X (Sep'22, CSIRO CEO)



kaggle

Kaggle is an online community of data scientists and machine learning practitioners:

- find and publish data sets
- explore and build models in a web-based data-science environment
- work with other data scientists and machine learning engineers
- enter competitions to solve data science challenges.

The screenshot shows the Kaggle interface for the "TensorFlow - Help Protect the Great Barrier Reef" competition. The top navigation bar includes a search bar and a "Create" button. On the left, there's a sidebar with links like Home, Competitions, Datasets, Code, Discussions, Courses, and Your Work. Under "RECENTLY VIEWED", items include "TensorFlow - Help Protect the Great Barrier Reef", "Feedback: About Ac...", and "Final Great Barrier Reef...". Under "BOOKMARKS", items include "Final: Public LB Score ..." and "TensorFlow - Help Protect the Great Barrier Reef".

The main content area displays the competition details: "TensorFlow - Help Protect the Great Barrier Reef" with a "Prize Money" of "\$150,000". It shows 2,025 teams and 20 days ago. Below this is a "Leaderboard" section with tabs for Overview, Data, Code, Discussion, Leaderboard, Rules, and Host. The "Leaderboard" tab is selected. A "Late Submission" button is visible. The "Leaderboard" table has columns for #, Team, Members, Score, Entries, Last, and Code. The table lists 10 teams, with the first few including QNS, 元宵快乐, Team Hydrogen, outrunner, bestfitting, Recall Is All You Need, Three Man Works!, tk, bizard, and Where's crown-of-thorns starfish?. Each team row contains a small icon representing its members.

A video still from YouTube showing two researchers on a boat looking at a tablet displaying a map of the Great Barrier Reef. The video is titled "Help Protect the Great Barrier Reef with Machine Learning".

<https://www.kaggle.com/c/tensorflow-great-barrier-reef>

- Max team size: 5
 - **14,549** registrations, **2,613** participants on **2,026** teams
 - Submission limits: 5 per day, 4 final per team
 - Average submissions (top 100): 123.5

<https://arxiv.org/abs/2111.14311>

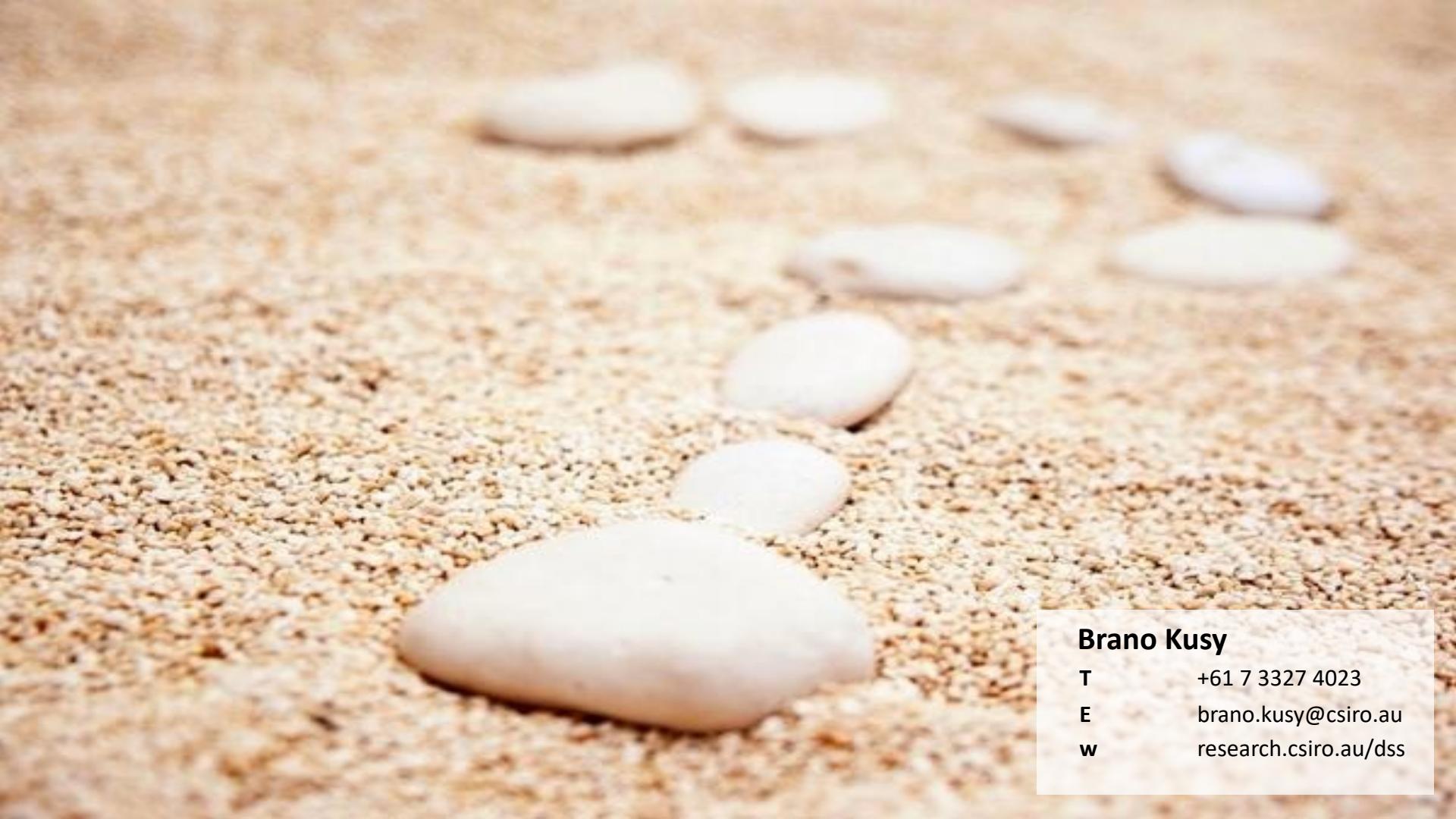


Know Our Winners

Rank	Model Ensembles	Pipeline Summary	Augmentation	Further Remarks
1	Y: 6 Yolov5 models, 3 trained on 3648 images and 3 trained on 1536 image patches	Object detection + ensemble + augmentation + re-score + attention	hflip, vflip, transpose, 45° rotation and cutout	Trust local CrossValidation
3	Y: CenterNet, FasterRCNN, FCOS, EfficientDet, YoloV5	Ensemble with different detectors plus tracker		Label refinement; Trust local CrossValidation
5	Y: YOLOv5-S6, YOLOv5-M6, YOLOv5-L6, YOLOX-L, YOLOR-P6 and HRNetV2P-W18	Ensemble with different detectors plus tracker	“Copy-paste” with Possion blending	Trust local CrossValidation

Competition is Finalized - Congratulations to our Winners; Recap

<https://www.kaggle.com/c/tensorflow-great-barrier-reef/discussion/308248>



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