Smart Aquafarm Feeder and Monitoring System in Highly Turbid Condition (SAqFeeder)

Background :

The Project **SAqFeeder** tackles the persistent problem of inefficient feed management in aquaculture, especially in highly turbid water where feed wastage is common. This inefficiency threatens food security by limiting sustainable fish production. By leveraging AI, sensor technology, and automation, **SAqFeeder** optimizes feeding, reduces waste, and supports more reliable and sustainable aquafarming to enhance food security.

Targets:

- Optimize feed distribution and enhance aquafarm productivity through improved monitoring and health management.
- Advance aquaculture technology via research, development, and user-centric field validation.
- Promote sustainable, energy-efficient operations while supporting capacity building and technology adoption.

Speaker: **Eduardo Jr D. Piedad**, *Project Leader, DOST – Advanced Science and Technology Institute*

Smart Aquafarm Feeder and Monitoring System in Highly Turbid Condition (SAqFeeder)

Project Members :

Name	Institution	Name	Institution
Dr. Franz Asunta de Leon	ASTI, Philippines	Mr. Gershom Defe	TUPV, Philippines
Dr. Meryl Regine Algodon	ASTI, Philippines	Mr. Gregorio Crisostomo	TUPV, Philippines
Mr. Gerwin Guba	ASTI, Philippines	Mr. Jovel Young	TUPV, Philippines
Ms. Vanesa Osiana	ASTI, Philippines	Dr. Eric Malo-oy	TUPV, Philippines
Dr. Tiong Hoo Lim	UTB, Brunei	Dr. Farhan Bin Mohamed	UTM, Malaysia
Dr. Nurun Najeebah Tashim	UTB, Brunei	Dr. Mohd Shafry Bin Rahim	UTM, Malaysia
Mr. Muhammad Wafiq Zariful	UTB, Brunei	Mr. Chan Vei Siang	UTM, Malaysia
Ms. Norhafizah Binti Muhammad	UTB, Brunei	Dr. Kazutaka Kikuta	NICT, Japan
Mr. Ace Zander Antonio	TUPV, Philippines	Dr. Ken Murata	NICT, Japan

Project Duration : 2 years (1st April 2024 – 31st March 2026)

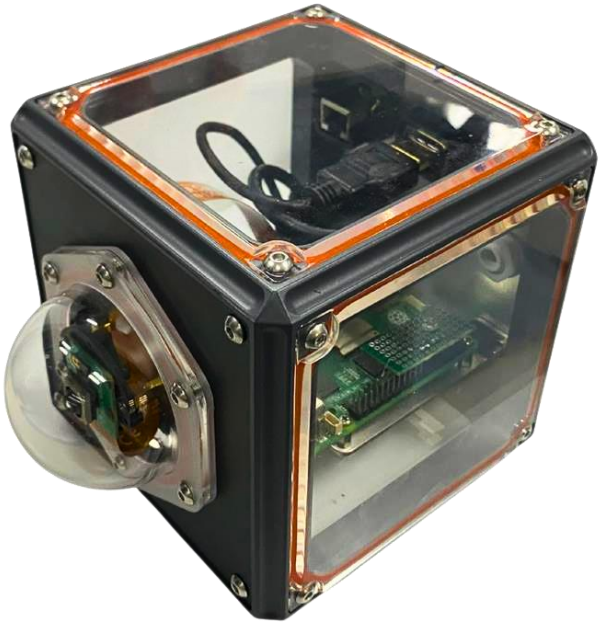
Project Budget: 80,000 USD

Associate Members :

MARMI Agricultural Corp., Philippines
Kathleen P. Trebol

O.D.E Aquaculture & Agriculture Co., Brunei
Zuhairi Hj Azahari

Project Activities > Technology Development > DOST-ASTI

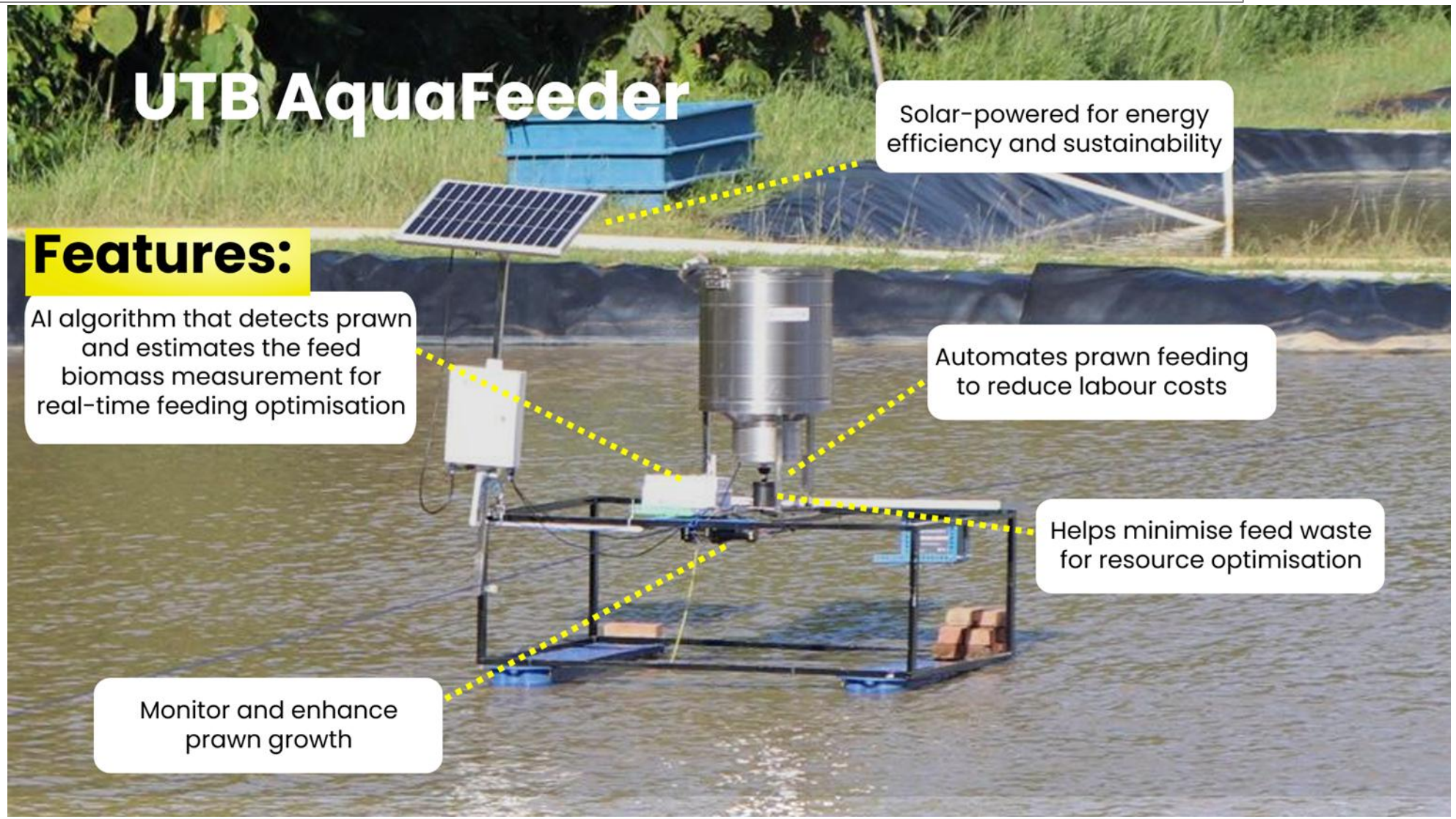


Waterproofed Cube Case for Multisensor Data Collector

Aquafarm Automated Shrimp Feeder

Portable Multisensor Data Collector

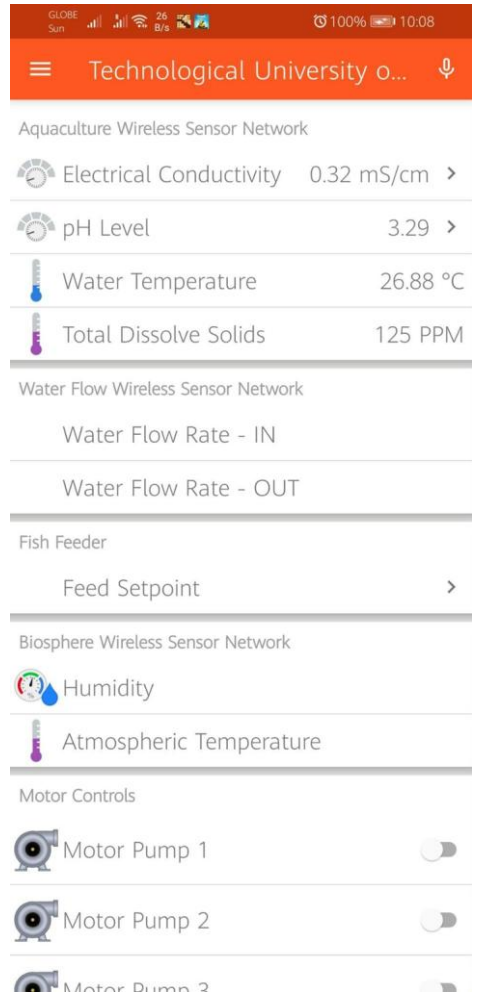
Project Activities > Technology Development > UTB



Project Activities > Technology Development > TUP-V

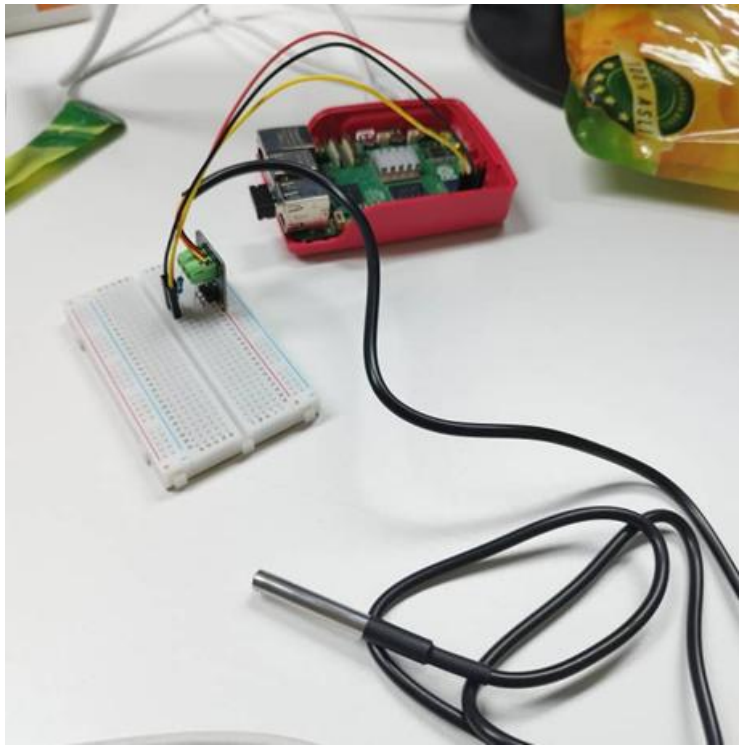
Testing Laboratory Pond

Sensor Platform Asembly



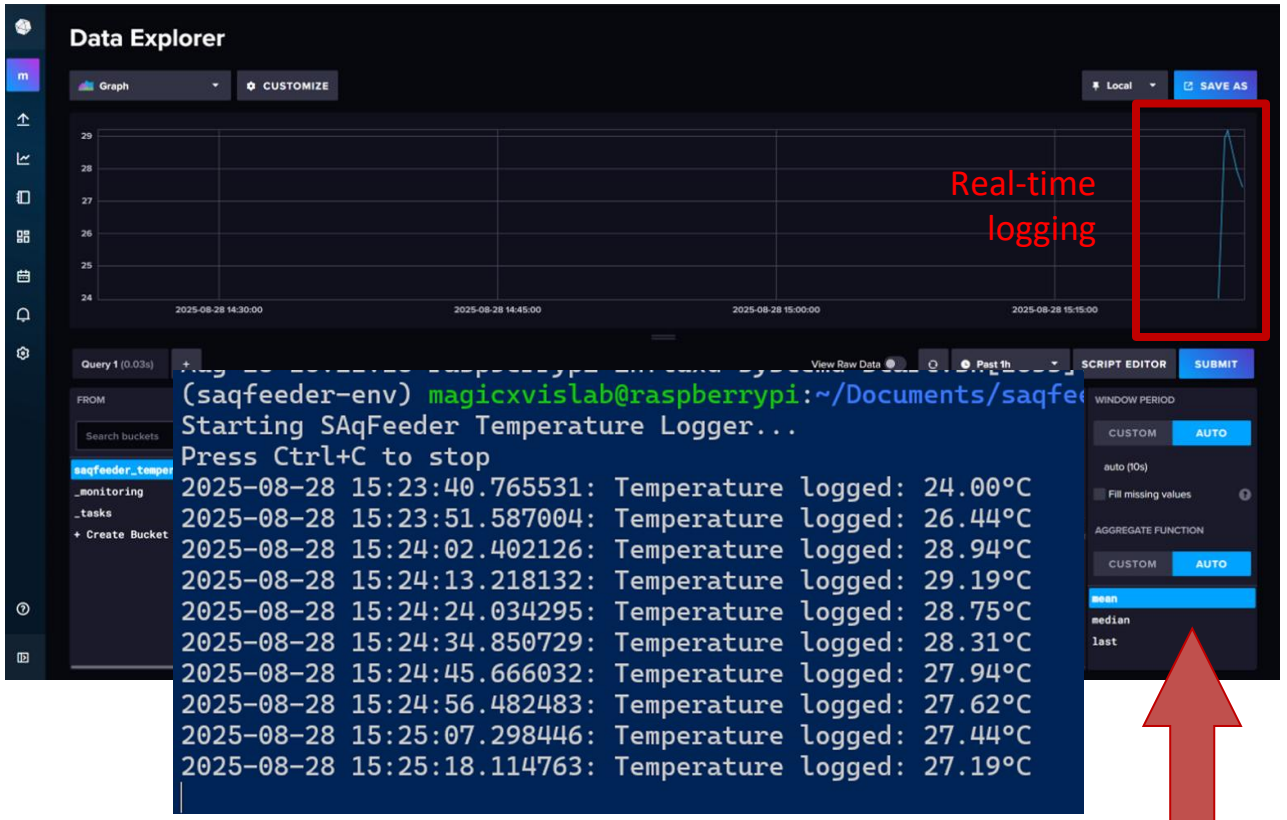
Software App GUI

Project Activities > Technology Development > UTM



1. Setup Exepriment IoT Device

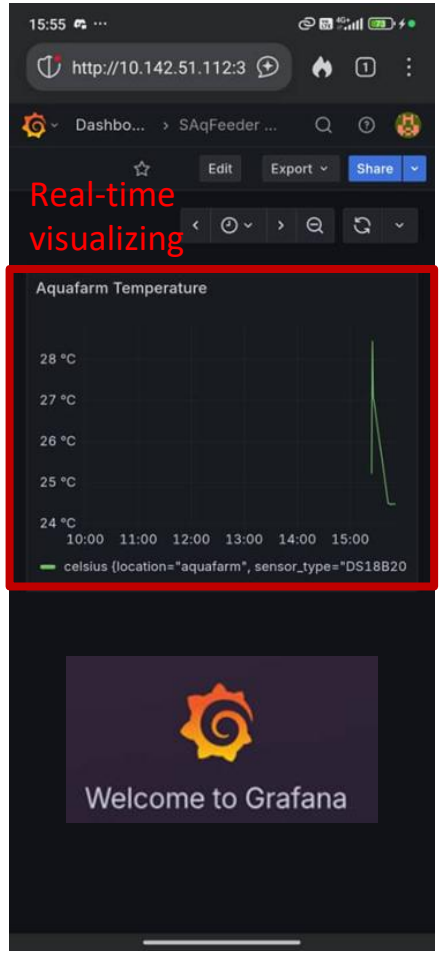
Raspberry Pi + DS18B20 temperature sensor



2. Logging the Real-time Data

Write data to InfluxDB

Read data in InfluxDB UI



2. Dashboard

Multi-platform dashboard visualization

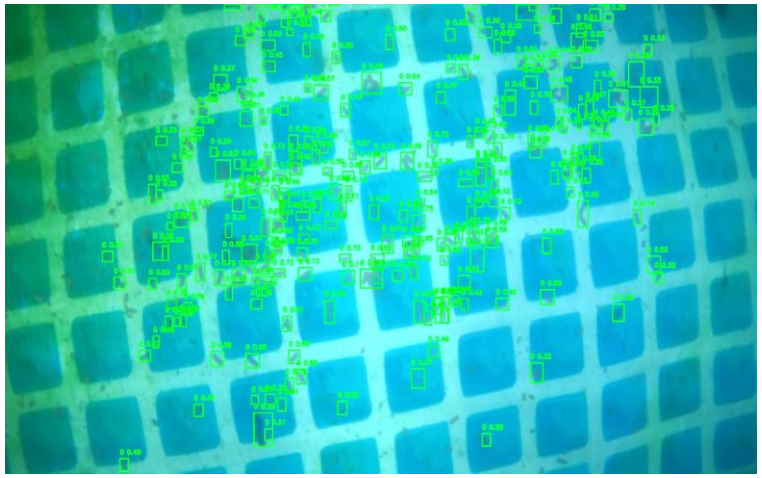
Project *SAqFeeder* Activities

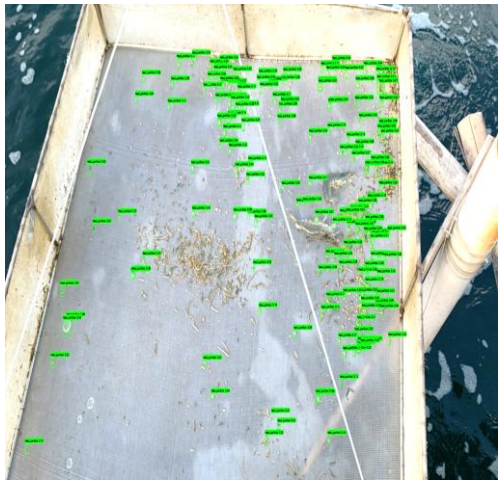
Project Activities > Field Visits & Data Collection

29 October 2024
at MARMI Agricultural Corp.

30 October 2025
at Siason Farm
(cancelled at MARMI Agricultural Farm due to flooding a incident)

Project Activities > Experiments > AI Model Development



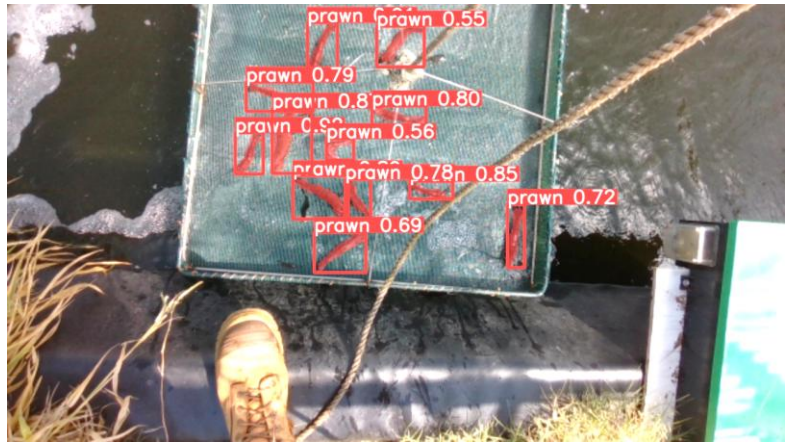


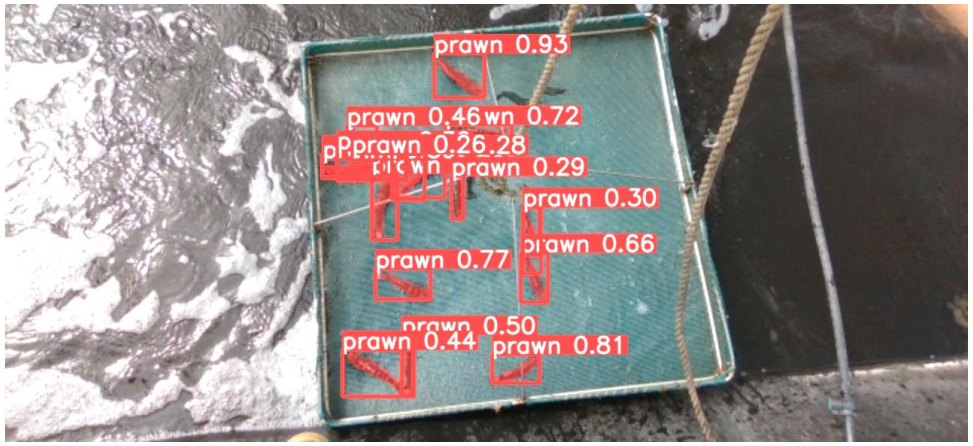
Development of AI Algorithm for feeds detection and estimation

- Initial data collection from an ideal pond (without turbidity)
- Performed data annotations
- Fine-tuned YOLOv9 Object Detection Model and demonstrated the prototype's capability to detect feeds from images using the updated model.

Project *SAqFeeder* R&D Results

Project Activities > Experiments > AI Model Development

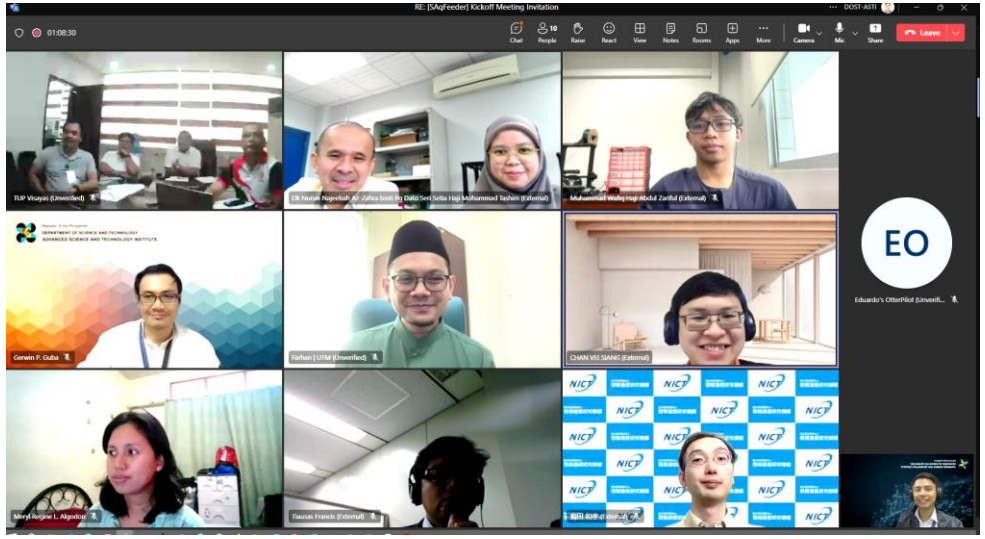




Detector	mAP	mAPIoU=.50	mAR
ResNet50 + Mask RCNN	0.556	0.883	0.619
ResNet101 + Mask RCNN	0.552	0.881	0.613
ResNeXt101 + Mask RCNN	0.574	0.889	0.639
ResNeXt101 + Cascade RCNN	0.575	0.885	0.639
Swin-Small + Mask RCNN	0.545	0.887	0.611
Swin-Tiny + Mask RCNN	0.543	0.892	0.618
Detector ResNet101 + HTC	0.569	0.898	0.632
YOLOv8n	**0.883**	**0.937**	**0.691**

Instant segmentation of shrimps using **yolov8n-seg**

Project Activities > Benchmarking > Virtual & Onsite Meetings



Virtual Meetings

First Onsite Meeting at Bacolod City, Philippines on Oct. 28 and Oct. 30, 2024

Project Activities > Benchmarking > Virtual & Onsite Meetings

Second Onsite Meeting at Quezon City, Philippines on 24 & 25 June 2025

Third Onsite Meeting at Bacolod City, Philippines on Oct. 29 & 30, 2025

Project Activities > Others > Attendance to conferences

Project Activities > MOU signing with MARMI Agricultural Corporation

National Radio Interview

Project Budget > April 2024 – October 2025

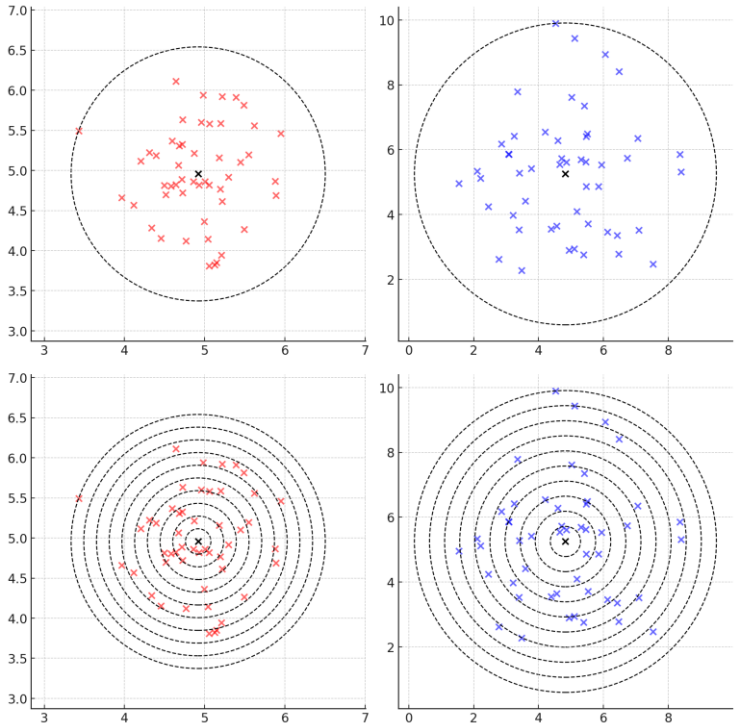
	Year 1	Year 2 (Apr-Oct 2025)	Total	Remarks
Utilized Budget	$7,181.33	$17,258.95	**$24,440.28**	
Reserved Budget	-	$27,213.85	**$27,213.85**	
Total	**$7,181.33**	**$44,473.40**	**$51,654.73**	**64.56%** utilization as of 28 Oct 2025
Remaining Balance			**$28,345.27**	*estimated as of 28 Oct 2025

Project Budget > November 2025 – March 2026

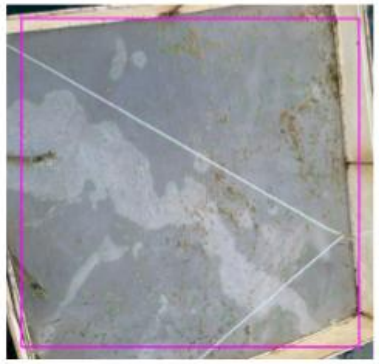
Expenses	Allocated (USD)	Remarks
4th Onsite Meeting at UTB & UTM on 26-30 Jan 2026	11,500.00	accom., flight & transpo expenses
ASTI	5,000.00	autofeeder dev't expenses
UTB	3,000.00	edge computing device/s
UTM	3,820.00	web app dev, autofeeder dev't
ASTI	4,200.00	autofeeder dev't expenses
Final field visit in Bacolod City in Feb 2026	1,825.00	accom., flight & transpo expenses

R&D Result > Scientific activities > Contribution 1

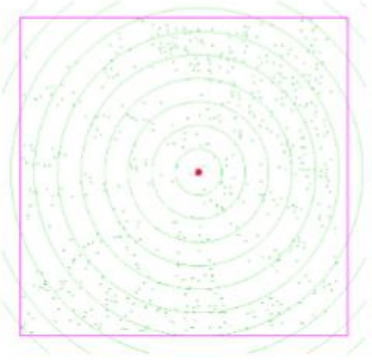
Concentric Cluster Analysis: A Radial Approachfor Quantifying Clustering and Scatter inTwo-Dimensional Data



Developed Concentric Cluster Method



(a) Original image with detected feeds and tray border.



(b) Masked feeds, centroid, CCA rings, and tray border.

Fig. 6: Spatial analysis of feeds in a shrimp tray.

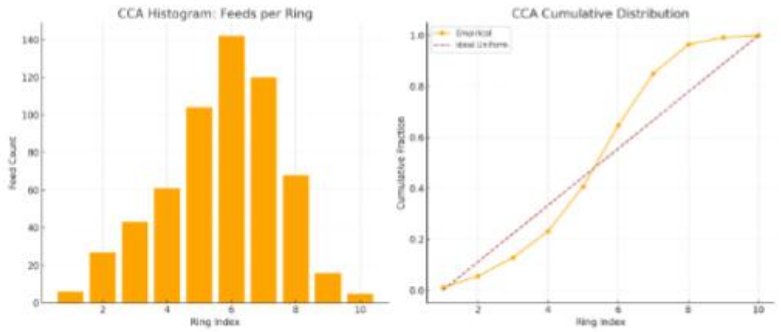


Fig. 7: CCA results for the shrimp tray image. Left: Histogram of feed counts per ring. Right: Cumulative distribution of feeds (orange) versus ideal uniform (brown dashed).

Applied to feed cluster analysis

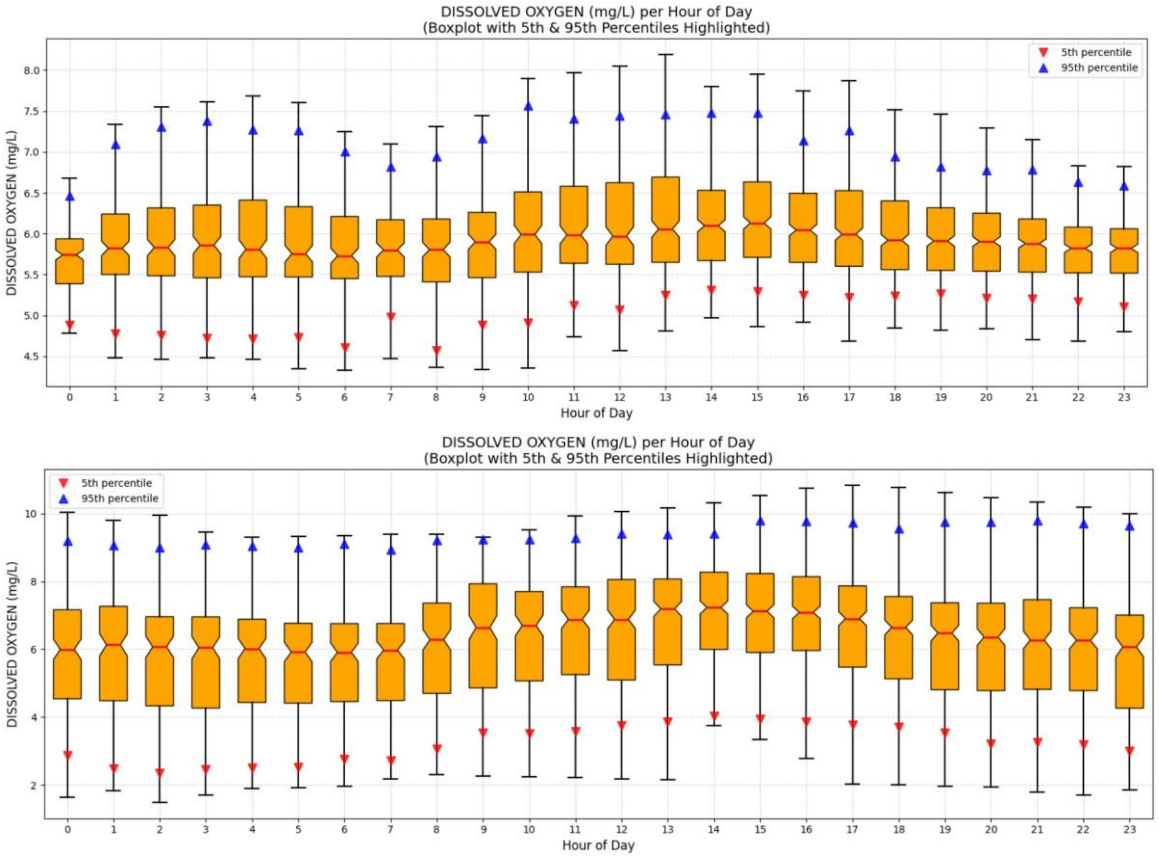
TABLE III: Comparative spatial metrics for feed distribution in the shrimp tray image.

Metric	Value	Interpretation
Variance (radial)	13,571	Overall radial dispersion
Avg Pairwise Distance	450.0	Global feed scatter (pixels)
Convex Hull Area	328,545	Spread of feed envelope (pixels^2)
Silhouette Score	0.29	Weak clustering (single group)
DBSCAN Clusters	1	One primary cluster (parameters: eps=30, min_samples=4)
DBSCAN Outliers	7	Few spatial outliers detected
K-means Inertia (k=2)	170,044	Dispersion relative to cluster centroids
Histogram-based CCA		
Entropy	1.97	Moderate radial spread
Weighted Avg Ring	5.71	Feeds concentrated in mid-outer rings
Peak Ring Index	6	Highest density at ring 6
Cumulative-based CCA		
SSE	0.111	Moderate deviation from uniform
RMSE	0.105	Consistent with SSE
Best-fit Slope	1.19	Outer-heavy distribution
KS Distance	0.19	Some non-uniformity present
KS Distance (CCA)	0.19	Some non-uniformity present

Comparison to the standard or conventional clustering methods under the same setup or data

R&D Result > Scientific activities > Contribution 2

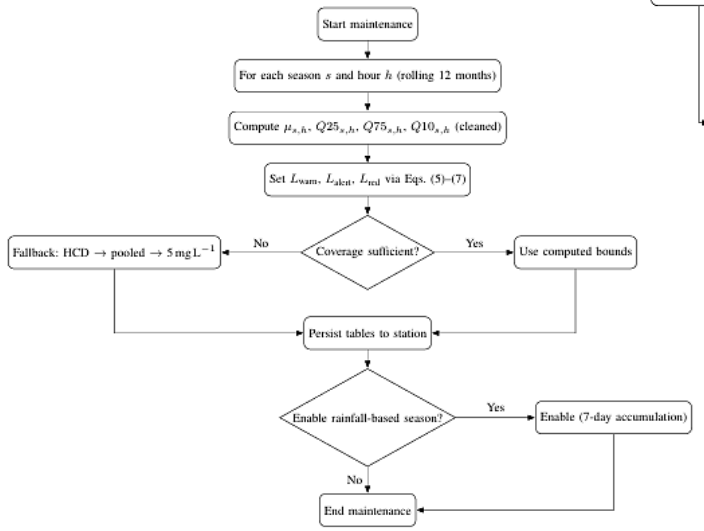
Data Analysis and Seasonal-Calibrated Dissolved Oxygen Thresholding for Real-Time Alerts on METBUOY at Taal Lake, Philippines

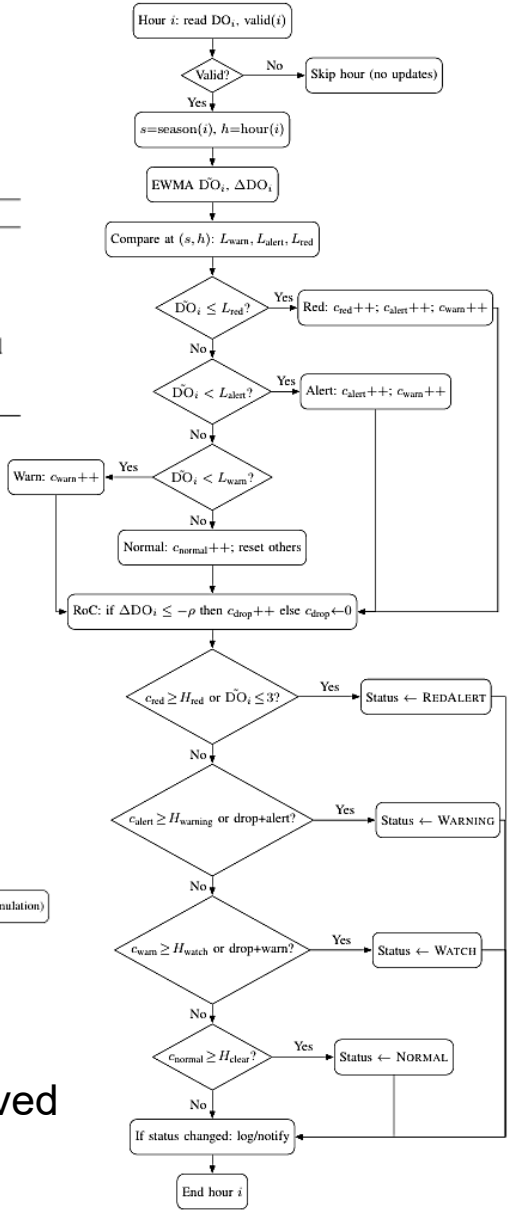


Seasonal DO thresholds for rainy and dry seasons

TABLE II
DECISION PARAMETERS AND RECOMMENDED DEFAULTS

Symbol	Default	Description
H_{watch}	3 h	Persistence to enter Watch
H_{warning}	6 h	Persistence to enter Warning
H_{red}	24 h	Persistence to enter RedAlert
H_{clear}	3 h	Normal hours to clear alert
ρ	0.5 mg L^{-1} h^{-1}	Rate-of-change drop threshold
M	3 h	Consecutive hours for RoC
α	$2/(N+1)$	EWMA weight, N=3 h

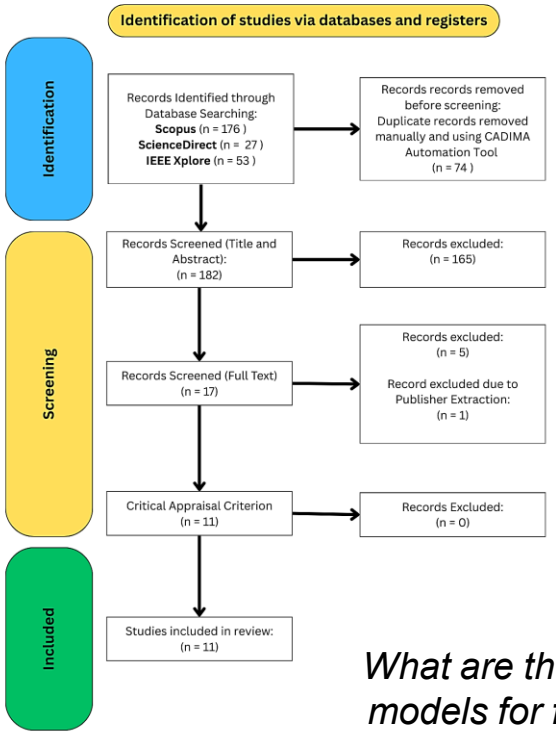




Developed flowcharts for Dissolved Oxygen (DO) thresholding

R&D Result > Scientific activities > Contributions 3 & 4

Vision-Based Granular Detection of Aquaculture Feed Pellets: A Systematic Review

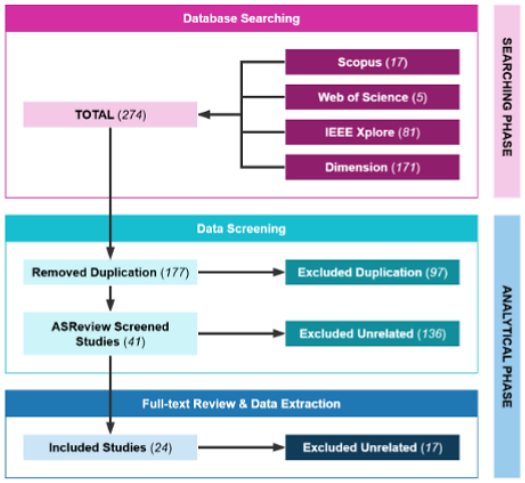


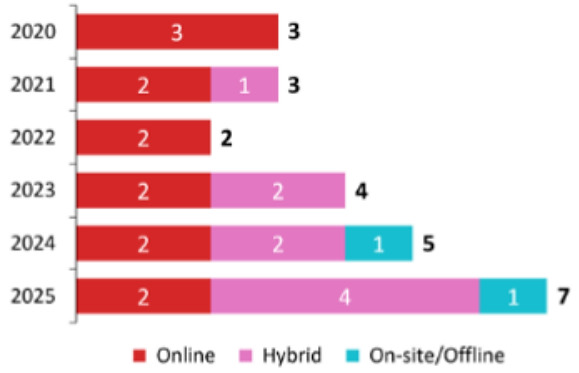
Study	Setting	Key Challenges Mentioned	Data Representation	Model Architecture	Reported Result
Hu et al. (2021) [35]	Real salmon farm	Turbidity, occlusion, blur, minus-target	(Pretraining) 175 Images; Pixel Underwater Feed Pellets and (Production Dataset) 40 Underwater Feed Pellets (Far-offshore Mariculture Cages)	Improved-YOLOv4	92.61%, Precision of 0.94(Validation), Recall of 0.89(Validation), F1-score of 0.77 (Validation)
Hou et al. (2022) [33]	Industrial Circulating Aquaculture Plant.	Small and Dense Bait Particles, Mixing of Bait Particle and Fish Swimming	800 Images (Training Set), 284 Images (Test Set)	Multi-column Feature Extractor, Density Map Generator	Mean Absolute Error (2.32), Mean Square Error (3.00)
Pradana et al. (2022) [34]	Open-net Pen Aquaculture	Tracking method for multiple small objects with dense and complex relationships	Video of Fish Feeding Process with 418 frames, MOV Format with frame rate of 30 frames/second	YOLOv4, VGG	75% Maximum mAP, 0.9 Loss Values
Wang et al. (2022) [32]	Industry Recirculating Aquaculture Workshop	Small Sizes, high pellet density, indistinguishable from cultured fish	1075 Images, 655 Images (Training Set), 179 Images (Validation Set), 241 Images (Test Set)	Multi-task Convolutional Neural Network	MAE (Density Level 1-3) 5.95, 4.73, 6.42 respectively; MSE (Density Level 1-3) 6.13, 6.47, 8.03 respectively
Hou et al. (2023) [29]	Industrial Recirculating Breeding Tank	High Density and Triviality of the Bait Particles	800 Images (Training Set), 284 Images (Test Set)	MCNN	13.99% (2 Bit), 35.31% (3 Bit), 5.86% (4 Bit,), 1.03% (5 Bit)
Xu et al. (2023) [27]	Actual Recirculating Aquaculture System	Small, Overlapping Targets, Fish and Ripple Interference, Complex Background	466 Images with 3,194 Tags - Training	YOLOv5-CAGSDL	94.1% (AP_{50}), 50.80% ($AP_{50:95}$), 12.85% (Recall), 6% (F1-score)
Hu et al. (2023) [28]	Real salmon farm	Small Target Recognition	2000 Training Samples - 50 Verification Set - 20 Test Set	YOLOv3 and Mask-RCNN	Recognition Accuracy - 96%
Zhou et al. (2023) [30]	Industrial Recirculating Aquaculture Systems	Fish Appetite Variation	1240 Images (Training Set), 400 Images (Validation Set)	YOLOv5	No written results and only graphical presentation provided
Hu et al. (2023) [31]	Experimental Outdoor Aquaculture Pond Field	Turbid and Not Clear Waters	2303 Shrimp Images (Training), 320 Bait Images (Training)	YOLOv5	0.8355 (Precision), 0.7345 (Recall), 0.7558 (mAP)
Wang et al. (2024) [26]	Experimental System	Small Volume Bait Detection	800 Images (Residual Bait Detection), 2376 Images (Feeding Activity Grading)	VGG16	Density: LOW - 1.60 (MAE), 2.32 (RMSE) — MEDIUM - 3.16 (MAE), 3.94 (RMSE) — HIGH - 5.45 (MAE), 7.85 (RMSE)
Feng et al. (2025) [25]	Indoor Recirculating Aquaculture System	Small Target, Complex Background, Fish Interference	8000 Images(Training), 500 Images (Validation), 600 Images (Test)	YOLOv8	90.5% Mean Accuracy, 0.966 (Precision), 0.883 (Recall), 0.93(F1-Score)

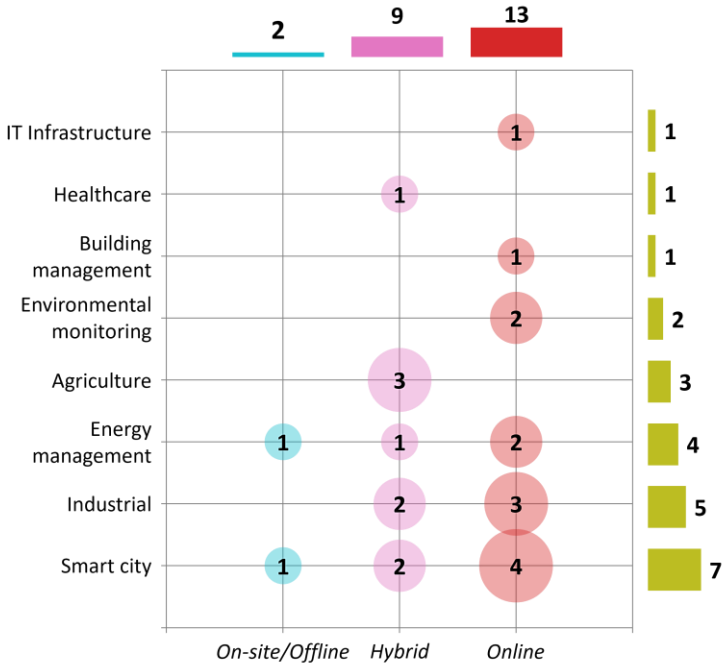
Year	Title	Ref.
2025	YOLO-feed: An Advanced Lightweight Network Enabling Real-time, High-precision Detection of Feed pellets on CPU Devices and its Applications in quantifying individual Fish Feed Intake	[25]
2024	A Graded Feeding Strategy for Aquaculture Fish	[26]
2023	A Method for Detecting Uneaten Feed based on Improved YOLOv5 Detection of Residual Feed in Aquaculture using YOLO and Mask RCNN Lightweight Fish Bait Particle Counting Method Based on Pruning and Shift Quantization A Deep Vision Sensing-based Fuzzy Control Scheme for Smart Feeding in the Industrial Recirculating Aquaculture Systems A Deep Learning-based White Shrimp Body Length and Bait Detection Methodology for Turbid Underwater Aquaculture Environment	[27]–[31]
2022	Dynamic feeding method for aquaculture fish using multi-task neural network Research on fish bait particles counting model based on improved MCNN Automatic Controlling Fish Feeding Machine using Feature Extraction of Nutriments and Ripple Behaviour	[32]–[34]
2021	Real-time detection of uneaten feed pellets in underwater images for aquaculture using an improved YOLO-V4 network	[35]

What are the known vision-based AI models for feed density estimation?

A Systematic Literature Review of AI-IoT Analytical Dashboards Within Hybrid Network Paradigm

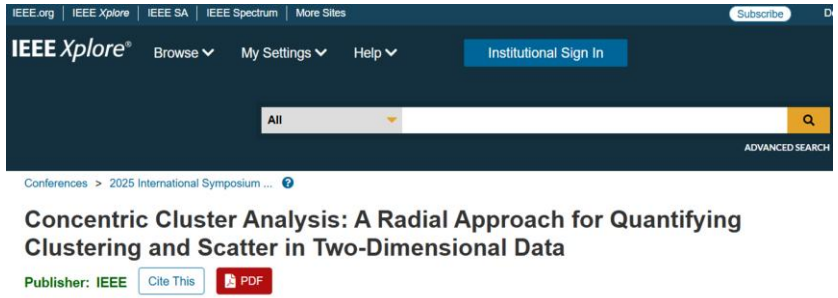






What type of network paradigm across application domains (especially in agriculture/aquaculture)?

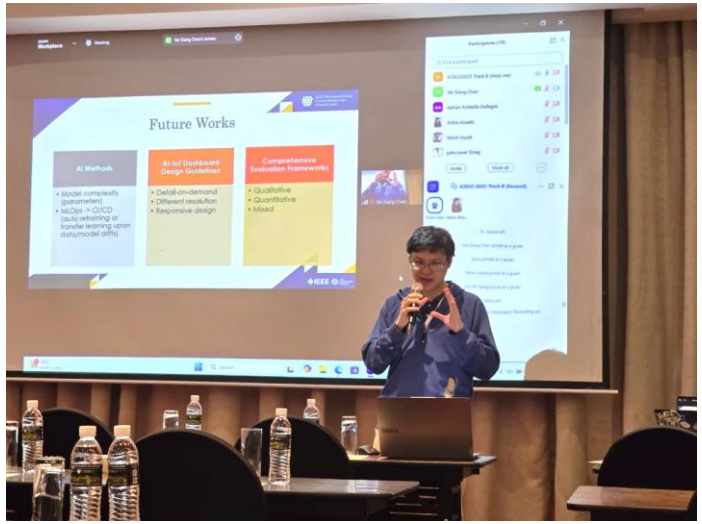
R&D Result > Scientific activities > Contributions 3 & 4



Contribution 1 was presented in **IEEE ISMAC 2025** and is already published on 29 September 2025.

ICOCO 2025 (6-8 October 2025)

Contributions 2-4 are presented hybrid in ICOCO 2025.



Best paper award was given to contribution no. 4

Presentations at International Conferences

No	Paper title:	Author names	Affiliation	Conference name	Conference Dates	Conference Venue
1	Strengthening Artificial Intelligence-On-Edge Education in the Philippines: A Teacher-Centric Curriculum Development Strategies	**[Best paper award]** Eduardo Jr Piedad	ASTI	2024 IEEE 13th International Conference on Engineering Education (ICEED)	19-20 November 2024	Kanazawa, Japan (online)
2	Concentric Cluster Analysis: Radial Approach for Quantifying Clustering and Scatter in Two-Dimensional Data	Eduardo Jr Piedad	ASTI	International Symposium on Multimedia and Communications (ISMAC 2025)	20-22 August 2025	Bohol, Philippines
3	A Systematic Literature Review of AI-IoT Analytical Dashboards Within Hybrid Network Paradigm	**[Best paper award]** Vei Siang Chan, Farhan Mohamed, Mohd Shafry Mohd Rahim, John Frederick Majan, Eduardo Jr Piedad	UTM, ASTI	2025 IEEE International Conference on Computing (ICOCO 2025)	6-8 October 2025	Kuching, Sarawak, Malaysia
4	Vision-Based Granular Detection of Aquaculture Feed Pellets: A Systematic Review	JF Majan, Eduardo Jr Piedad, Karel Pabelina, Jacqueline De Vera, Kezia Celayne Bayona, Vei Siang Chan, Farhan Mohamed, Gerwin Guba, Franz de Leon	ASTI, UTM	2025 IEEE International Conference on Computing (ICOCO 2025)	6-8 October 2025	(Online) Kuching, Sarawak, Malaysia
5	Data Analysis and Seasonal-Calibrated Dissolved Oxygen Thresholding for Real-Time Alerts on METBUOY at Taal Lake, Philippines	Eduardo Jr Piedad, John Robert Arao, Adrian Aristotle P. Dellagas, Jeanette Badong-Carlos, Joven C. Javier, John Frederick M. Majan, Ian C. Mosquera, Christine Shamah A. Cureg, Harold Bryan S. Paler, Gerwin P. Guba	ASTI	2025 IEEE International Conference on Computing (ICOCO 2025)	6-8 October 2025	(Online) Kuching, Sarawak, Malaysia

Conclusion

1) Scientific & Technological

- Fine-tuned YOLOv9 for feed detection
- Established AI–IoT stack: Raspberry Pi + DS18B20 → InfluxDB time-series → real-time dashboards
- ASTI: built waterproof data-collector cube and integrated sensor platform for turbid-water operation
- UTB: nearing the completion of their prototype
- Developed new CCA algorithm for clustering
- Set up data annotation workflow and model iteration
- Significant recent actual data collection, to be processed

2) Application / System Development

- Close to completion working prototypes: automated shrimp feeders, Phase-1 manual data collector, app GUI
- Implemented end-to-end pipeline from edge capture to database to visualization
- Coordinated multi-site builds: ASTI core prototype for data collection; TUPV sensor assembly & lab pond; UTB/UTM prototype iterations

3) Experiments & Field Testing

- Lab-pond evaluations validating real-time logging, dashboard accuracy, and feeder actuation
- Simulated-pond trials via ROV confirming feed-detection performance of the updated model
- Offline and onsite project meetings
- Field visits and data collections at MARMI & Siason
- Initial waterproofing and reliability checks on the data-collector cube in turbid environments

4) Other Outcomes (Team Contributions)

- Publications and recognition (Best Paper awards)
- Capacity building: interns trained on AI/IoT in aquaculture
- Program management: cross-institution meetings (onsite and virtual)
- Year-1/Year-2 budget planning, and aquafarm partner coordination

Societal Impact:

- Strengthens food security via AI-optimized feeding that cuts feed waste in turbid ponds.
- Boosts smallholder farm efficiency through smart feeding and continuous monitoring.
- Builds local talent—staff, interns and partner universities trained on AI/IoT.
- Speeds tech adoption with prototypes, dashboards, and validated field trials.
- Constributed scientific knowledge globally—international conference presentations and scientific publications.
- Elevates public awareness via national radio and S&T convention talks.

Future works (by all members):

- [**ALL**] To continue development and technology advancement of the feeding automation and other aquatic related food security
- [**ALL**] To perform actual deployments, iterations, and validation of the prototypes
- [**ALL**] To conduct sustainability planning for the commercialization of the developed technology
- [**ALL**] To continue engagement with the stakeholders
- [**ALL**] To process new actual dataset collected
- [**ASTI**] To resume R&D on the challenges encountered in the collected dataset
- [**UTM**] To setup a project website for better dissemination of the project details and outputs
- [**UTB**] To lead the AI model development for shrimp or prawn detection
- [**TUPV**] To optimize the autofeeding structural or mechanical design