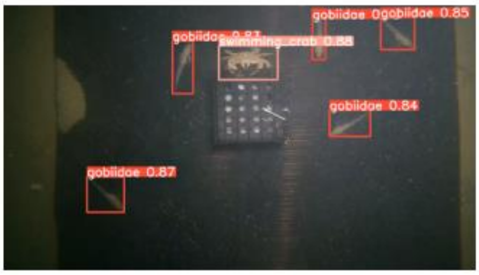
UNIVERSITY OF GOTHENBURG

**DEPARTMENT OF MARINE SCIENCES**

# ASSESSING BENTHIC BIODIVERSITY IN LOW-TROPHIC AQUACULTURES USING COMPUTER VISION AND DEEP LEARNING



Xhoni Dalipi

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Supervisor: **Matthias Obst – Department of Marine Sciences**
Examiner: **Gunilla Toth – Department of Marine Sciences**

# Abstract

Aquaculture has been identified as one of the key contributors to future food security. Low trophic aquaculture (LTA) is an emerging sector in the field of blue bioeconomy and it includes species such as seaweed and shellfish, holds promise for significantly expanding production volumes while, if managed appropriately, minimizing environmental impacts. Although mussel aquaculture has gained favor as a means to improve water quality, in shallow coastal areas with relatively low dispersal capacity, mussel farms may induce changes to macrobenthic diversity due to biodeposition. Utilizing the latest technological advancements such as computer vision and Deep Learning (DL), we assessed and compared the benthic biodiversity beneath mussel aquacultures across the farming season, using a Baited Remote Underwater Video system (BRUV). Analysis revealed no statistically significant difference in species composition between the farm and control sites. We found that our method integrating DL with BRUV is an effective approach to survey benthic mobile fauna communities and monitor the effects of aquaculture practices.



Keywords: deep learning, bruv, low-trophic aquaculture, ecological impact

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# List of Abbreviations

**BRUV** – Baited Remote Underwater Video system

**DL** – Deep Learning

**LTA** – Low Trophic Aquaculture

# 1. Introduction:

## 1.1. Importance of Aquaculture

The emergence of aquaculture has gained significant attention in the recent years due to its capability to address food security (Visch et al., 2020). Despite the economic benefit of production of high trophic level species (e.g. Salmon), it is not sustainable the growth of the sector to depend solely on that (Slater & James, 2023). Instead, focusing on species that occupy lower trophic levels (e.g. bivalves) holds promise for significantly increased production while, if managed appropriately, minimizing environmental impacts (Slater & James, 2023).

## 1.2. Low-Trophic Aquaculture

Low-trophic aquaculture (LTA) is an emerging sector within the blue bioeconomy that focuses on the cultivation of species such as seaweed and shellfish (Krause et al., 2022). These species offer several ecological and economic benefits, including providing a sustainable source of protein and reducing pressure on wild fisheries. Unlike high-trophic species, LTA species draw their nutrients directly from the surrounding water, eliminating the need for supplemental feed (Visch et al., 2020). Additionally, low-trophic species play crucial roles in marine ecosystems: seaweed creates three-dimensional habitats that attract biodiversity and filter harmful elements from the water column, while shellfish, through their filter-feeding activities, enhance water quality and contribute to nutrient cycling (Krause et al., 2022; Visch et al., 2020).

On the other hand, such practices also raise concerns about their effect on marine biodiversity (Hartstein & Rowden, 2004). When shellfish is cultured on large scale, some adverse effects may arise, such as accumulation of biodeposits in the benthic seafloor (Callier et al., 2006; Hartstein & Stevens, 2005). Such an occasion may affect the benthic species that are found beneath and in the surrounding of the farm location (Hartstein & Rowden, 2004). Modifications to local ecosystems and potential habitat alternation are some of the challenges that need to be addressed (Visch et al., 2020). One approach to address these challenges involves analyzing the distribution and composition of marine benthic fauna, which vary according to the different environmental conditions each species can tolerate (Carrier-Belleau et al., 2021).

### 1.2.1. Environmental Benefits

Shellfish not only offer significant nutritional benefits but also provide valuable ecosystem services like nutrient remediation, which are advantageous to both the environment and society (Van Der Schatte Olivier et al., 2020). Additionally, mussels modify their habitats by increasing physical heterogeneity and habitat diversity and reinforce the reputation of mussels as ecosystem engineers (Borthagaray & Carranza, 2007). Furthermore, by filter feeding at high rates, mussels remove considerable amounts of particulate matter and sequester nitrogen from the water column by converting this material into their tissue mass (Lüskow & Riisgård, 2018). They also contribute to phytoplankton growth dynamics through the facilitation of ammonia cycling in the water column (Petersen et al., 2014). For this reason, mussel farms have been evaluated for their mitigation potential against eutrophication as stand-alone coastal aquaculture systems (Carlsson et al., 2012; Petersen et al., 2014).

### 1.2.2. Environmental Impacts

Even though bivalve aquaculture is known to contribute to the improvement of water quality, it is still linked to some ecological concerns (Ferreira et al., 2014). Cultured bivalves have the risk of contributing to organic enrichment of the local area because they might compete with other filter feeders that occur there naturally (McKindsey et al., 2011). However, Petersen (2014) persisted that these are reasonably insignificant considering the nutrient remediation services provided by the mussels. However, studies have shown significant yet contrasting effects in underlying benthic communities as an outcome of mussel farming (Suplicy, 2020). Mussel aquacultures, due to large amounts of biodeposition, may cause hypoxic sediments in shallow coastal areas with low dispersal capacity, which may result in adverse changes to the benthic macrofauna diversity (Carlsson et al., 2012; Gallardi, 2014). Typically, benthic communities composed of species that feed by suspension will be replaced by small opportunistic deposit feeders due to their high tolerance to anoxic conditions caused by large amounts of deposition (Gallardi, 2014).

## 1.3. The shift towards automation in ecological research

Baited Remote Underwater Video (BRUV) is a non-invasive monitoring technique applied in marine biodiversity monitoring research due to its ability to sample multiple taxa across diverse habitats and depths (Whitmarsh et al., 2017). By attracting species with bait, BRUVs allow for the assessment of species abundance, diversity, and behavior without the need for divers, thereby minimizing safety risks and reducing observer bias (Langlois et al., 2018; Stobart et al., 2015). A key metric used in BRUV research is MaxN, which records the maximum number of individuals observed within a single video frame, offering a conservative estimate of species abundance while minimizing the risk of double counting (Campbell et al., 2015; Stobart et al., 2015). BRUVs have proven particularly useful in marine protected areas and zones difficult to access through traditional survey methods (Currey-Randall et al., 2020).

Computer Vision technology, utilizing underwater cameras, can assist us in understanding and managing marine fish communities (Saleh et al., 2024). However, most of the data that is generated creates a lot of manual workload, which is impractical in terms of time and cost (Da Silva et al., 2023). Deep Learning (DL) is a technique (see Figure 1) that is utilized in monitoring fish communities and is a very valuable approach for understanding the ecology and biodiversity of marine ecosystems (Saleh et al., 2024). DL amplifies the monitoring of fish by providing accurate methods for fish classification, detection, counting, and tracking (Marrable et al., 2023; Saleh et al., 2024).

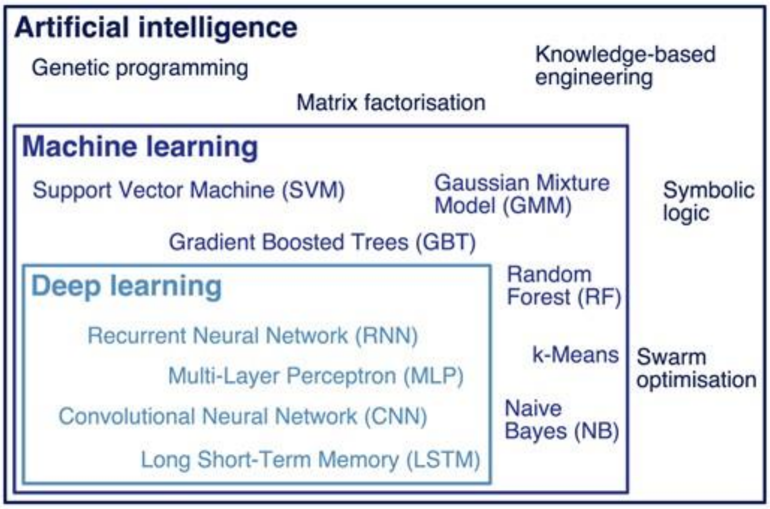


*Figure 1: Deep learning is a subdomain of machine learning, which on its own is a subdomain of artificial intelligence, as illustrated. Specific methods are mentioned in each subdomain (Rubbens et al., 2023).*

## 1.4. Objective

The study aspires to develop and test new methods for automated monitoring by combining in-situ technology with deep learning (DL) with the goal of assessing the effect of low-tropic aquacultures (LTA) on benthic diversity. More specifically, I focus on the following objectives:

i) Design and develop a low-cost BRUV, to effectively monitor the seafloor beneath LTA.
ii) Assess and compare abundance, species richness and community composition in the proximity of LTA, with the reference sites, using a BRUV.
iii) Develop and train deep learning (DL) models, to automatically detect and classify species from the video footage, focusing on up to 5 benthic species.

## 1.5. Hypothesis

It is hypothesized that LTA practices lead to:

i) changes in species richness
ii) changes in species abundance
iii) changes in community composition

# 2. Materials & Methods

## 2.1. Study Area

We examined the presence of marine mobile benthic biodiversity along the Swedish west coast (see Figure 2) at 5 different locations. The samples were collected between the 20$^{th}$ of November 2023 and 5$^{th}$ of May 2024 between 11am and 3pm. Out of the five locations studied, only two underwent sampling for both aquaculture and control sites. In the remaining three locations, only one site was sampled, either aquaculture or control. Despite this partial sampling across locations, data obtained from these sites were used in training object detection models, ensuring the efficient utilization of all available data.

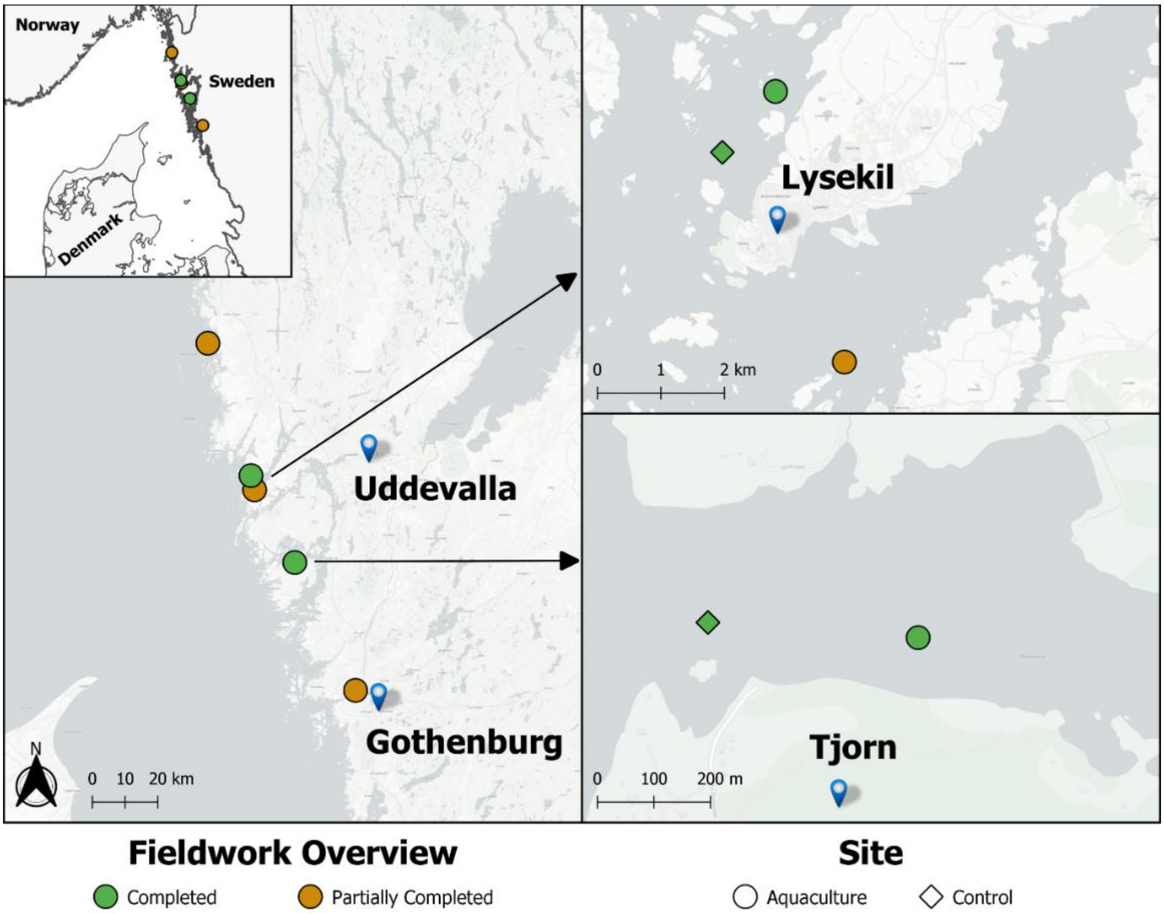


*Figure 2: Map of study region showing the 5 sampled locations along the west coast of Sweden. The green dots depict the locations where samples were successfully taken at both sites. The orange dots depict the locations where samples were taken at 1 of the site.*

## 2.2. BRUV setup

### 2.2.1. Hardware

The BRUV system used in this study was a custom-built design (see Figure 3). It was equipped with a GoPro HERO 9 camera positioned to face downward toward the bait box. The camera settings were standardized to 1080p resolution, wide-angle view, and 100 FPS. The bait box was filled with frozen shrimp, which had slits cut through them to enhance the dispersal of their scent plume, attracting mobile fauna to the camera trap more quickly (Hardinge et al., 2013). A light was mounted alongside the camera, facing the same direction, and a black mat was placed at the bottom of the BRUV. This mat provided a contrasting background to improve species identification during the training of the DL model by reflecting the light. The entire system was tethered using a polypropylene rope.


*Figure 3: The components of the Low-Cost BRUV setup are as follows: 1 - camera Tripod; 2 - GoPro 9; 3 - underwater lights; 4 - ankle weights; 5 - trunk mat; 6 - bait box.*

### 2.2.2. Sampling Method

During the sampling conducted at Tjörn, the sites were spaced 300 meters apart, while the sampling at Lysekil had sites spaced 1 kilometer apart. After deployment, the BRUV was let to film the sea floor for 30 minutes at each site. For each deployment, the date and time were recorded, along with the GPS coordinates of each site. Video analysis began after the BRUV reached the seafloor. Mobile benthic fauna was observed and identified to the lowest taxonomic level possible. The conservative measure of maximum number observed at a point in time (MaxN) was recorded for each species, to avoid double counting individuals (Langlois et al., 2020).

During sampling at Tjörn, the sites were spaced 300 meters apart, while at Lysekil, the spacing was 1 kilometer between sites. At each location, the BRUV was deployed to film the seafloor for 30 minutes. For each deployment, the date, time, and GPS coordinates were recorded. Video analysis began once the BRUV reached the seafloor, with mobile benthic fauna being observed and identified to the lowest possible taxonomic level. The conservative MaxN measure, representing the maximum number of individuals observed at a given time, was used for each species to avoid double counting (Campbell et al., 2015; Langlois et al., 2020).

## 2.3. DL-based Model Development

### 2.3.1. Data preprocessing

After storing the acquired footage from the fieldwork, we proceeded with the workflow as shown in Figure 4.

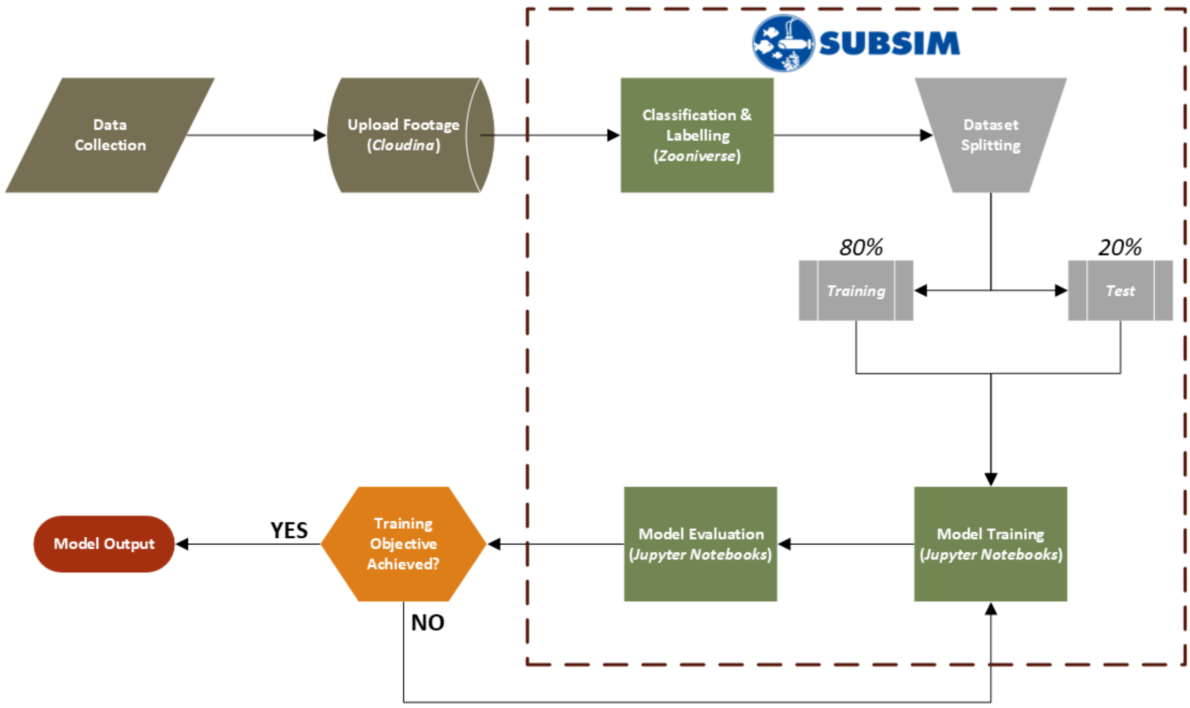


*Figure 4: Flowchart of workflow for Deep Learning algorithms.*

Firstly, we uploaded the footage to Cloudina (https://console.cloudina.org/). From there, using the tutorials from SUBSIM platform (https://subsim.se/), we extracted frames (see Figure 5A) from the video. These frames were then made available on Zooniverse platform (https://www.zooniverse.org/), where the next step of labelling (see Figure 5B) would take place. After manually annotating all the species observed in the extracted frames, we proceeded to the model training phase.

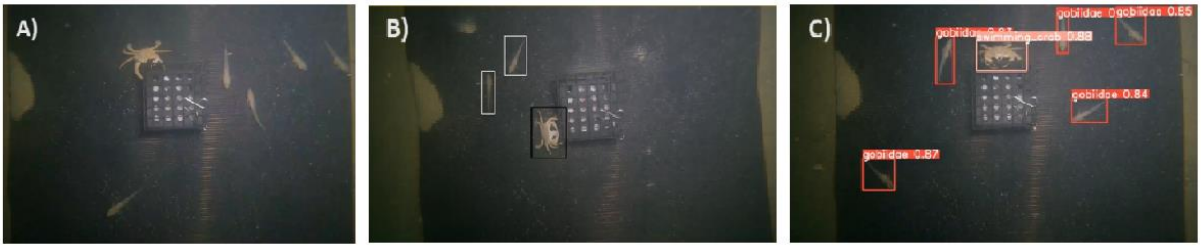


*Figure 5: A) Displays frame during raw footage B) Displays frame during the annotation process; C) Displays frame during the deep learning (DL) model prediction.*

### 2.3.2. Model Training & Evaluation

For model training, we used the YOLOv8 algorithm (Jocher et al., 2023). The annotated data was split into 80% for training and 20% for testing. The training configurations were set as follows: batch size = 8 and epochs = 75. Once the training was complete, we evaluated the performance of the model using the test dataset. The performance metrics obtained, such as precision, recall, F1-score, and mean Average Precision (mAP), provided insight into how well the model was able to detect and classify species in the frames. This evaluation helped in identifying any weaknesses in the model and informed further adjustments to enhance its performance.

### 2.3.3. Processing Model Output

We ran the trained model on footage, which generated an output CSV file containing raw annotation data. This data included the detected species, frame number, bounding box coordinates of where the species is in the frame, and the confidence level of the predicted species. The raw annotation data was then processed in R Statistical Software (v4.4; R Core Team 2021) to compute the abundance and species richness. This detailed information from the raw annotations allowed us to assess the biodiversity in the study area comprehensively.

## 2.4. Statistical Analysis

To test the hypothesis that LTA activities lead to changes in species composition near farm sites compared to control sites, we employed a combination of Principal Coordinates Analysis (PCoA) and Permutational Multivariate Analysis of Variance (PERMANOVA). All analyses were performed using R Statistical Software (v4.4; R Core Team, 2024).

To statistically test differences in species composition between the sites, we conducted a PERMANOVA using the vegan package (v2.6; Oksanen, J. et al., 2024). PERMANOVA, based on Anderson (2017), is a non-parametric method that partitions the dissimilarity matrix among sources of variation and uses permutation to assess statistical significance.

PCoA was conducted to visualize the patterns of species composition among the sampled sites. The Bray-Curtis dissimilarity index was used to construct the dissimilarity matrix, which is appropriate for ecological data as it considers the differences in species presence and abundance between sites. The analysis was performed using the vegan package (Oksanen, J. et al., 2024)

# 3. Results

## 3.1. Species Richness and Abundance

The results indicate that when data from both sampling locations were combined and analysed, no significant differences were found in two key ecological metrics: mean species richness and relative MaxN (maximum number of individuals observed), which measure abundance. The analysis of data from both the Control and Farm sampling locations across all months, revealed no significant differences in two key ecological metrics: mean species richness and mean MaxN (relative abundance). Specifically, the overall mean MaxN for the Control site was 7.25 ($\pm$ 2.43 SE), while the Farm site recorded a slightly higher value of 7.63 ($\pm$ 1.52 SE). Despite this small difference in MaxN, the results were not statistically significant, indicating that both sites support similar abundance levels. In terms of species richness, the overall mean for the Control site was 2.25 ($\pm$ 0.45 SE) and for the Farm site, the mean was 2.13 ($\pm$ 0.44 SE). No significant differences were detected between the two sites, suggesting comparable levels of biodiversity, as measured by the number of different species observed at each site.

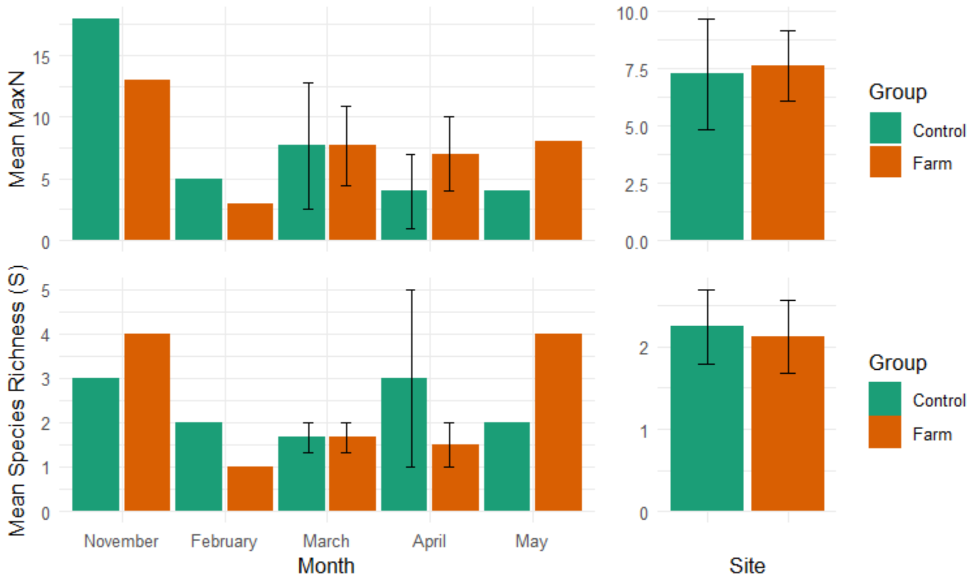


*Figure 6: Site-based analysis of species richness and abundance at control and farm sites over time.*

## 3.2. Species Composition Analysis

The PERMANOVA results indicate no statistically significant difference in species composition between the farm and control sites ($p > 0.05$). As shown in Table 1, the p-value of 0.501 indicates that any observed differences in species composition between the sites are not statistically meaningful and could likely be attributed to random variation rather than actual ecological differences. This implies that the sites are highly similar in terms of the species they support.

*Table 1: PERMANOVA analysis comparing species compositions between the sites.*

| Source | Df | SumOfSqs | R2 | F | Pr_F |
|---|---|---|---|---|---|
| **Group** | 1 | 0.1954 | 0.0475 | 0.6981 | 0.501 |
| **Residual** | 14 | 3.9197 | 0.9525 | NA | NA |
| **Total** | 15 | 4.1151 | 1.0000 | NA | NA |

Further support for this conclusion comes from the PCoA (Principal Coordinates Analysis) plot, which confirms the PERMANOVA findings. The plot shows a high degree of overlap between the farm and control sites, indicating that species compositions are not clustered separately by site type. This lack of distinct grouping reinforces the conclusion that the differences between the farm and control sites in terms of species composition are insignificant.

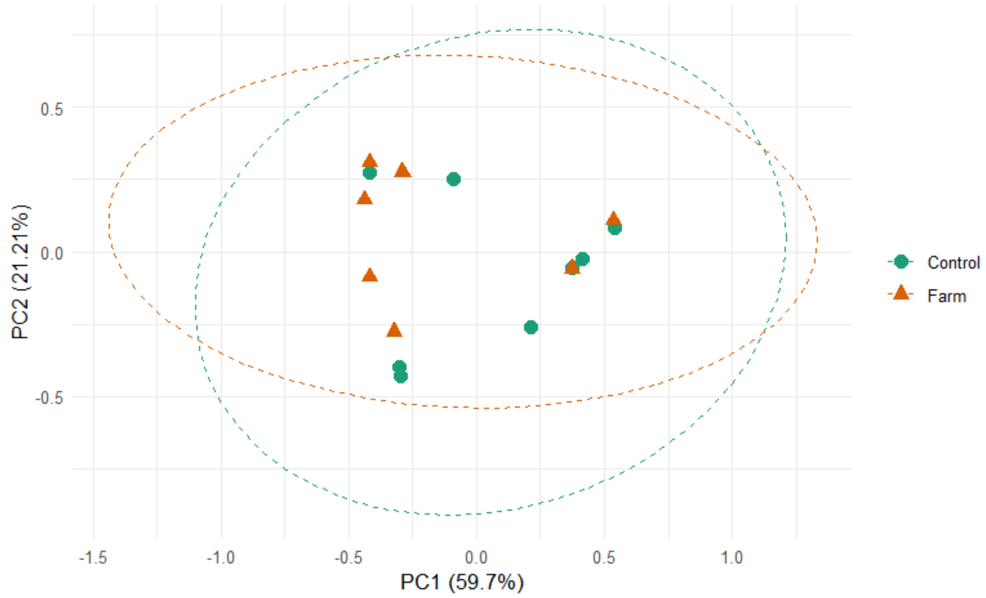


*Figure 7: Results of PCoA showing the first two principal coordinates that, combined, explain 80.9% of the observed species composition variation.*

## 3.3. DL Performance

In evaluating the performance of the DL object detection model, the F1 confidence curve (see Figure 8: A) F1 Curve depicting the harmonic mean of precision and recall scores across varying thresholds. B) Dataset class instances detailing the distribution of class labels within the dataset.) was used as a key metric for assessing the balance between precision and recall. This curve demonstrates the relationship between the confidence threshold of the model's predictions and the F1 score across all classes. The model achieves an F1 score of 0.92 at a confidence threshold of 0.651, and is able to detect 5 species. This means that when the model classifies detections with a confidence level of 65.1% or higher, it strikes an optimal balance between precision and recall, resulting in a high overall performance. This F1 score suggests that the model is highly effective at both correctly identifying species (high recall) while maintaining a low rate of false positives (high precision).

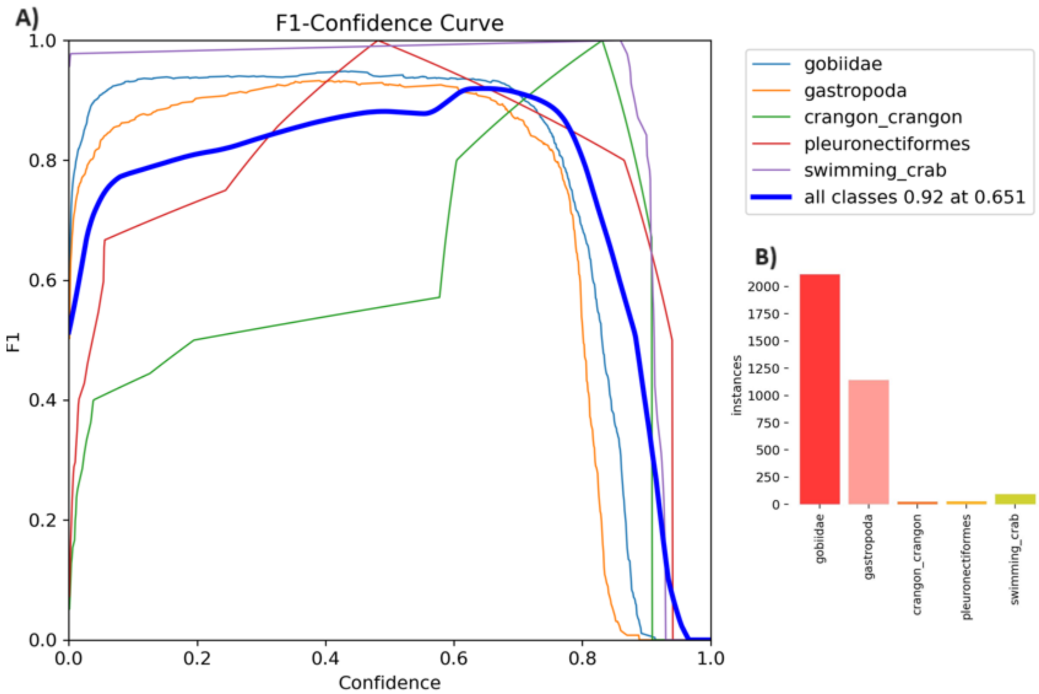


*Figure 8: A) F1 Curve depicting the harmonic mean of precision and recall scores across varying thresholds. B) Dataset class instances detailing the distribution of class labels within the dataset.*

## 3.4. DL vs Human

The DL object detection model and human observation were compared over three months (March, April, and May) at both farm (F) and control (C) sites for the *gobiidae* class, as it was the species that was encountered the most during the video analysis (see above). The method involved pausing the video at the frame of each minute up to 30 minutes and then comparing my observation with the DL model's prediction for the same minute. This approach allowed for a fixed minute-by-minute MaxN comparison.

In March and April, the DL model demonstrated strong alignment with human observation. At both F and C sites during these months, the correlation between observed and predicted values was high, with R-values ranging from 0.74 to 0.95 ($p < 0.05$), showing minimal deviations between the observed and predicted MaxN values over time. This strong performance indicates that the model was well-trained on the species present in these months, accurately identifying species and detecting similar numbers of individuals as human observer. However, in May, the model's performance declined, particularly at the farm site, where the correlation was weak ($R = 0.22$, $p = 0.25$). The control site in May performed moderately better with an R-value of 0.62 ($p < 0.05$).

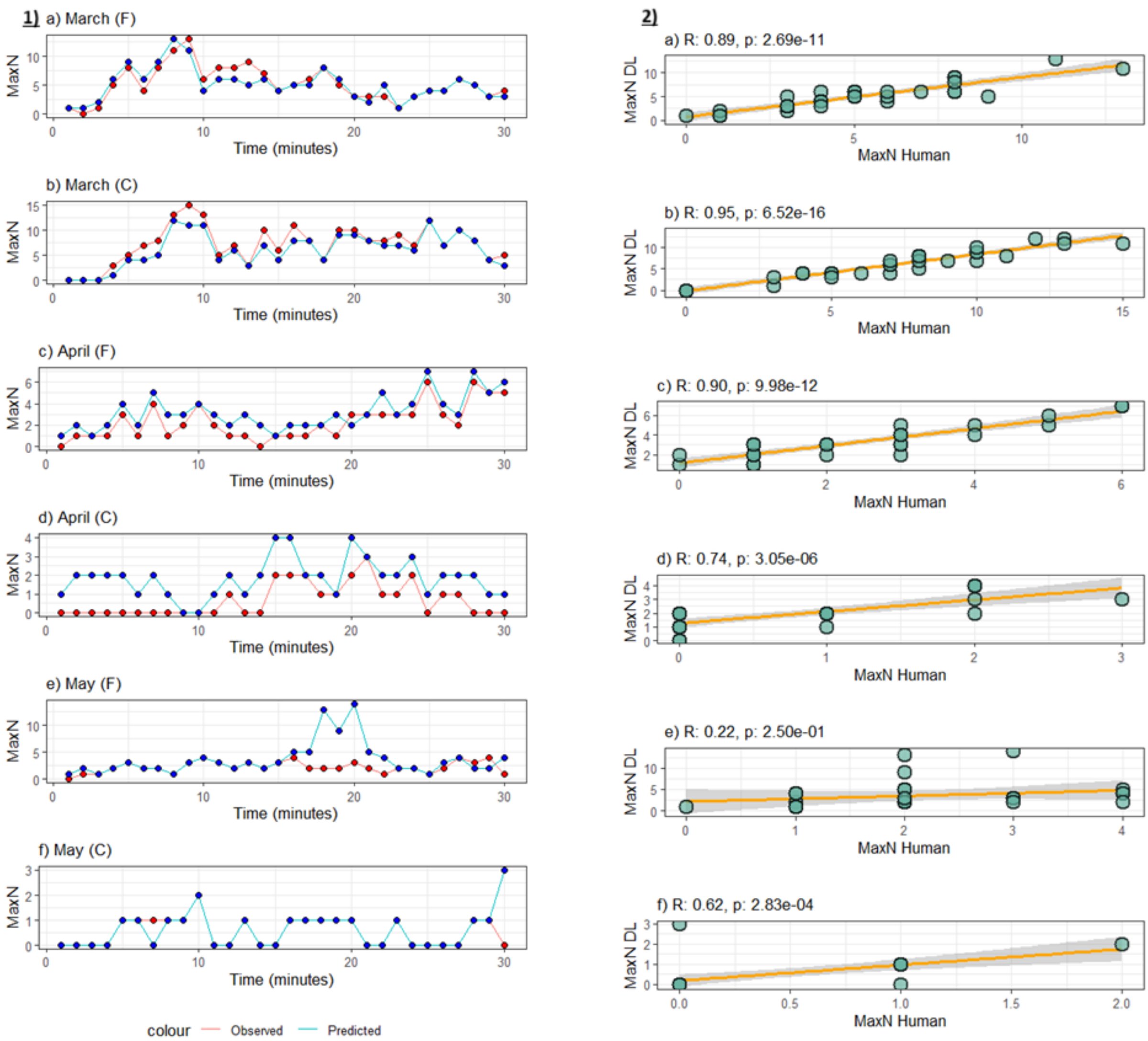


*Figure 9: 1) shows MaxN values per minute, comparing observed data against DL predictions; 2) presents the correlation between human-observed and DL-predicted MaxN values, with the R value indicating relationship strength and the p-value signifying statistical significance.*

# 4. Discussion

## 4.1. Biodiversity Metrics (Species Richness, Abundance, and Species Composition)

The analysis of biodiversity metrics, revealed no significant differences between the farm and control sites. The control site had a mean MaxN of 7.25, and the farm site recorded a slightly higher value of 7.63, though this difference was not statistically significant. Similarly, species richness was nearly identical between the two sites, with values of 2.25 and 2.13 for the control and farm sites, respectively, suggesting that both sites support similar levels of biodiversity.

The PERMANOVA analysis of species composition further supports these findings, showing no statistically significant difference between the two sites ($p = 0.501$). The PCoA plot reinforces this, with both sites exhibiting a high degree of overlap in species composition, explaining 80.9% of the total variation. This indicates that the species composition at both the farm and control sites is largely the same.

Hedberg (2018) highlights that the effects of mussel farming on ecosystems are highly dependent on the size and density of farms relative to the size of the surrounding water body. In cases of intensive farming practices, significant ecosystem changes, such as increased sedimentation, have been observed particularly in regions with larger-scale aquacultures (Hartstein & Rowden, 2004; Hartstein & Stevens, 2005; Hedberg, N. et al., 2018). In contrast, the small-scale aquacultures in the Baltic Sea, similar to the site in this study, show fewer negative effects (Hedberg, N. et al., 2018). This comparison aligns with the findings of the present study, which also observed no significant impact from aquaculture practices activities at the farm site to the benthic mobile biodiversity.

## 4.2. Evaluation of DL performance and comparison vs Human

The DL object detection model performed remarkably in terms of balancing precision and recall, achieving an F1 score of 0.92 at a confidence threshold of 0.651. This indicates that when the model is sufficiently confident (≥ 65%), it is highly effective at detecting species while maintaining a low rate of false positives. The ability to detect five species in the dataset suggests that the DL model can be a reliable tool for identifying multiple species in ecological monitoring, reducing the need for time-consuming manual annotations in the future.

The comparison between DL predictions and human observations in this study shows that the DL model closely aligns with human observation in March and April, with R-values ranging from 0.74 to 0.95, indicating strong correlations. This suggests that the model was well-trained on accurately locating and correctly identifying the individuals of *gobiidae* class. However, the model’s performance declined in May, when there was a decline in accuracy with R-value ranging from 0.22 to 0.62. The deviations in May were mainly because new species were observed during the last month, for which the DL model had not been trained yet on that new class. This resulted in the overestimation of the *gobiidae* class prediction by the DL model. This issue can be addressed by training models to recognize the new species, which will further expand our DL model library for more accurate class prediction in future encounters.

While this study focuses on species localization, classification and abundance, no research currently directly compares DL models with human observations in this specific context of ecological monitoring. However, a similar study by Marrable (2023) compared DL and human accuracy in fish length approximation using BRUV image processing. Marrable's study showed that DL methods can achieve near-human accuracy in fish length measurement, with an R-value of 0.99 for 3,954 measurements. Although the DL model in Marrable's study occasionally over- or under-estimated as well the fish length, repeated measurements resulted in alignment between DL and human estimates.

## 4.3. Recommendations for future research

The results of this study demonstrate that DL models can serve as valuable tools for ecological monitoring, offering high accuracy in detecting species when sufficiently trained. However, the model's performance in May highlights the need for continuous updating and retraining, especially when species compositions change over time. These findings are in line with other studies that emphasize the importance of retraining machine learning models in maintain high accuracy (Marrable et al., 2023).

To further improve the accuracy and consistency of DL models in species localization and classification, several key areas could be addressed in future research:

1. *Expand Training Data:* As observed in May, the appearance of new species that the model had not been trained on led to inaccuracies in predictions. Expanding the training dataset to include the newly encountered species will ensure the model will reduce overestimation issues.
2. *Annotation Protocol:* A standardized annotation protocol should be developed to ensure high-quality data for model training. This will help minimize errors and improve model performance.

    - *Label only high-quality images*: Annotating blurry individuals will degrade the performance of the DL model.
    - *Annotate full body:* Only annotate species when their entire body is visible in the frame, rather than parts like the head, to reduce the risk of false positives in predictions.

## 4.4. Limitations

While the study demonstrates the potential of Artificial Intelligence (AI) used in ecological monitoring research for species detection and classification, there are several limitations to consider.

1. *Seasonality*: The data acquisition for this study was conducted during the cold months (November till early May) for Sweden, a period when gobies typically migrate to deeper waters (Behrens et al., 2022). This migration likely contributed to the lower species diversity observed in the shallow waters where the LTA were located (Tjorn - 10m; Lysekil - 20m). From my own experience, having started

sampling on the west coast of Sweden since September, species abundance tends to decline from November and does not recover until May.

2. *Short Time Frame*: The duration and timing of the study was relatively short, capturing only a limited period. Long term monitoring, especially during the Summer months, would provide a more comprehensive understanding of how biodiversity metrics for mobile benthic taxa fluctuate throughout the year beneath the LTA, potentially revealing seasonal trends that were missed in the present study.

# 5. Conclusion

The research found no significant differences in species richness, abundance, or composition between farm and control sites, suggesting that LTA practices, particularly mussel farming, have minimal ecological impact when managed appropriately and emphasizes the potential of LTA as a sustainable approach within the aquaculture industry.

The integration of BRUV technology with DL models proved to be an effective method for assessing benthic marine biodiversity, achieving a high level of accuracy species detection and classification. The DL model accuracy of detecting closely aligned with human observation, though performance declined when new, untrained taxa was encountered. This approach of combining scientific expertise with advanced AI technologies, offers a promising pathway for sustainable marine resources management. This study provides baseline data for future studies and highlights the need for integrating DL with BRUV, which appears to be a promising method to survey mobile benthic fauna communities.

# 6. Acknowledgements

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