Optimized Aquaculture Feeding Through Matched Filter Audio Signal Processing and Machine Learning

Dror Ettlinger-Levy[a], Shai Kendler[a], Iris Meiri Ashkenazi[b], Shay Tal[b,**], Barak Fishbain[a,*]

[a]*Technion - Israel Institute of Technology, Faculty of Civil and Environmental Engineering, Haifa, Israel*
[b]*Israel Oceanographic & Limnological Research Ltd., National Center for Mariculture, Eilat, Israel*

Abstract

Accurate feeding in marine aquaculture is essential for optimizing fish growth while minimizing adverse impacts on the surrounding ecosystem. Previous studies have successfully used acoustic signals and neural network-based classification models for monitoring feeding. This work builds on these efforts by addressing the continuous variability of fish behavior and enhancing sensitivity to subtle changes, offering a complementary and efficient approach. In this study, matched filtering and domain knowledge are applied to detect and quantify feeding intensity using continuous numerical labels. A template from a single gilthead seabream (*Sparus aurata*) bite acoustic signature was used, and matched filter response detections were aggregated with a sliding window into a continuous intensity label, advancing data reduction. To validate label values based on environmental and biological variables, the analysis applies machine learning regression models. eXtreme Gradient Boosting (XGBoost) and Random Forest results indicate that the variables explain 98% and 96% of label variation, respectively. The methodology presented in this paper provides a simple, precise, and scalable tool for optimizing feeding using acoustic monitoring. The use of domain knowledge paves the way for the further development and application of data-driven methods to utilize acoustic signal monitoring for improving marine aquaculture practices.

Keywords:
Audio Signal Processing, Aquaculture Monitoring, Machine Learning, Passive Acoustic Monitoring, Fish Feeding Intensity, Matched Filter.

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[*]Corresponding author at Technion - Israel Institute of Technology, Faculty of Civil and Environmental Engineering, Haifa, Israel. Email: fishbain@technion.ac.il (B. Fishbain).

[**]Corresponding author at Israel Oceanographic & Limnological Research Ltd., National Center for Mariculture, Eilat, Israel. Email: shay.tal@ocean.org.il (S. Tal).

[1]Email addresses: dror.e@campus.technion.ac.il (D. Ettlinger-Levy), sk-

1. Introduction

Aquaculture is expanding rapidly, with mariculture emerging as a key sector driven by the urgent need to meet the rising global demand for sustainable seafood (FAO, 2024). Its expansion presents new challenges and opportunities to improve efficiency and environmental monitoring, particularly in high-value species such as gilthead seabream (Mhalhel et al., 2023). Accurate monitoring of feeding is a key factor in optimizing growth while minimizing environmental impact (Price et al., 2015). Excess feed releases nutrients, creating anoxic conditions that support anaerobic processes. This nutrient loading degrades water quality and causes eutrophication, harmful algae blooms, and greenhouse gas emissions (Fadum et al., 2024). Thus, overfeeding remains a major challenge, with trials in seabream and seabass showing that up to half of the feed may go uneaten (Ballester-Moltó et al., 2017). In addition, a decrease in appetite and feed intake is common when fish are sick and often serves as an early indicator of disease (Roberts, 2012). With the intensification of aquaculture systems, disease outbreaks have become a major threat, leading to significant financial losses and severely affecting fish welfare (Naylor et al., 2021). Continuous feeding monitoring could enable early detection of disease onset, thereby minimizing economic losses and improving fish well-being.

Acoustic signals are a promising tool for monitoring feeding behavior in aquaculture (Li et al., 2024). Passive acoustic methods capture characteristic sound patterns, providing a non-invasive approach to assess feeding behavior (Li et al., 2020). Recent studies have used passive acoustic monitoring to classify the intensity of fish feeding. Zeng et al. (2023) applied acoustic signals with an audio spectrum Swin Transformer to classify feeding intensity into four levels: strong, medium, weak, and none. Du et al. (2023) used Mel spectrograms and a lightweight network to group feeding sounds into three classes: strong, medium, and none. Ma et al. (2024) used six-axis inertial sensor data and also proposed a method for classifying feeding intensity across similar categorical levels. Although classification models have demonstrated high accuracy in identifying feeding levels, they can rely on manual labeling, which might introduce bias and inconsistency (Haliburton et al., 2025). More importantly, by forcing feeding behavior into fixed categories, they fail to reflect variance across different feeding events. The wide range of feeding intensities within a single class might lead to substantial errors in feeding estimation. By contrast, a regression approach captures feeding intensities on a continuous scale, enabling more precise, data-driven decisions about feeding.

One notable application of acoustic-based regression modeling in aquaculture is reported in studies of shrimp species such as *Litopenaeus vannamei.* Silva et al. (2019) studied the acoustic characteristics of feeding activity in *Litopenaeus vannamei.* In their research, a regression models based on feeding clicks

endler@technion.ac.il (S. Kendler), imeiri@ocean.org.il (I. Meiri Ashkenazi), shay.tal@ocean.org.il (S. Tal), fishbain@technion.ac.il (B. Fishbain).

were sought. The underlying assumption was that these clicks were associated with mandible closures during feeding. However, in that study, click counts were obtained manually from audio recordings, making the process cumbersome and less efficient compared to an automated workflow. Building on this, Peixoto et al. (2020) examined the relationship between the number of clicks per pulse train and the signal duration, revealing a significant exponential correlation between these variables. The above regression models show that while these models may offer greater precision than classification for modeling feeding behavior, they are constrained by non-automated tools to quantify feeding intensity.

Quantifying feeding intensity through regression holds strong potential, highlighting the need for an efficient and automated approach. This paper addresses this need by applying matched filtering (MF) analysis to the processing of audio signals. MF is an optimized signal detection method to detect known signal patterns in Gaussian noise (Yaroslavsky, 2004), making it ideal for automated regression-based quantification of feeding intensity. The Stochastic Matched Filter (SMF) extends the standard matched filter to handle non-white noise in open ocean environments. Bouffaut et al. (2018) combined SMF with MF to improve passive detection of Antarctic blue whale calls. Caudal and Glotin (2008) used SMF to track multiple sperm whales in 3D with high accuracy using hydrophone arrays.

Living organisms generate distinct acoustic signatures corresponding to specific behaviors, which can serve as reliable templates for the automated detection and monitoring of such events. In aquaculture setups, gilthead seabream (*Sparus aurata*) are typically fed industrially processed sinking pellets, which produce a distinct cracking sound as they move during feeding. This consistent acoustic signature across individuals provides a reliable biological template, making it well-suited for use in matched filtering. This prior biological knowledge of the gilthead sea-bream is an example of domain knowledge, thus shifting from machine learning to machine education (Kendler et al., 2022; Geltman et al., 2025), a method in Deep Learning (DL) and Machine Learning (ML) that uses expert, problem-specific information, beyond raw data (Barzamini et al., 2022). Domain knowledge can improve the generalization of our method across real-world conditions (Kendler et al., 2022).

This study presents a method for detecting and quantifying fish feeding intensity as a continuous numerical value, based on passive audio signals processed through matched filtering with knowledge domain approach. Given the distinct acoustic signature produced by gilthead seabream during feeding, this signal was used as a template for MF. To further validate this approach, machine learning regression models were applied using key environmental and biological variables, revealing strong alignment between predicted feeding intensity and these variables. This study introduces a novel methodology that uses matched filtering to derive a continuous numerical label of fish feeding intensity from audio signals. The approach produces and leverages explainable domain knowledge, enabling a simple, scalable assessment of hunger levels. It also demonstrates strong alignment with environmental and biological variables, further enhancing the reliability and interpretability of the feeding label.

2. Methodology

To monitor feeding behavior using audio signals, a 19-day audio recording of gilthead seabream was conducted under fixed feeding schedules. Audio signals were preprocessed in the frequency domain using spectral gating and high-pass filtering to reduce background noise and enhance relevant features. Feeding events were detected and quantified using a matched filter in combination with a sliding window technique. To evaluate the robustness of the resulting feeding intensity label, supervised machine learning models, Random Forest and eXtreme Gradient Boosting (XGBoost), were applied to explain the label based on environmental and biological variables. A schematic overview of the process is presented in Figure 1, where block (A) represents the data acquisition methodologies. ; (B) depicts signal preprocessing using STFT (Short-Time Fourier Transform), spectral gating, and high- pass filtering to reduce noise; (C) detects and quantifies feeding events using a matched filter; and (D) validates the methodology based on environmental and biological variables using regression machine learning models, XGBoost, and Random Forest.

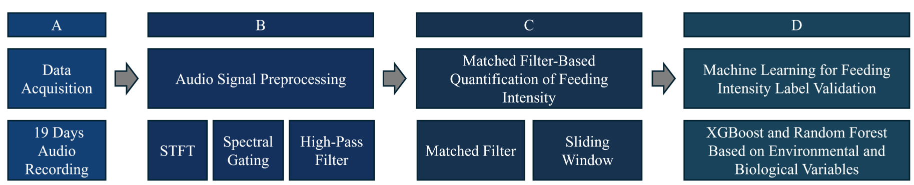

Figure 1. Methodology workflow: (A) represents data acquisition of a continuous audio signal recorded over 19 days; (B) involves signal preprocessing using STFT (Short-Time Fourier Transform), spectral gating and high-pass filtering to reduce noise; (C) detects and quantifies feeding events using a matched filter combined with a sliding window; and (D) validates the methodology based on environmental and biological variables using regression machine learning models, XGBoost, and Random Forest.

2.1. Data Acquisition

The study was conducted in three identical flow-trough tanks (2.0 × 1.0 × 1.0 m) with constant aeration, each stocked with 30 gilthead seabream *(Sparus aurata)*, as shown in Figure 2. All fish were 3 months old at the beginning of the experiment (estimated average weight 40 gr), collected from the same hatching batch. Each tank was equipped with two hydrophones (AS-1 hydrophone, Aquarian Audio & Scientific, Anacortes, WA, USA) connected to phantom-powered preamplifiers (PA6, Aquarian Audio & Scientific, Anacortes, WA, USA). The fish were fed daily at consistent times and with fixed amounts of commercial 3 mm sinking pellets (Raanan Fish Feed LTD., Israel). Artificial lighting simulated constant day-night cycles, with lights on at 06:00 and off at 17:00. Continuous acoustic signals were recorded to a memory card using a Zoom F8n Pro recorder (Zoom North America, Hauppauge, NY, USA) at a sampling rate of 48 kHz and a bit depth of 24 bit, resulting in 19 days of recordings.

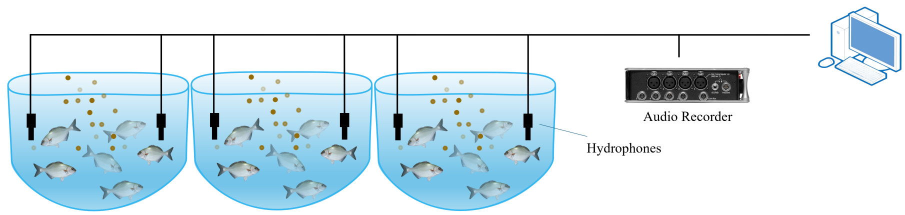

Figure 2. Experimental system.

2.2. Audio Signal Prepossessing

The recorded audio signal contained background noise from electronic equipment and the continuous inflow of water and oxygen into the tanks. As gilthead seabream feeding sounds occur in a specific frequency range, targeted signal processing was needed to extract the relevant information. The signal was first transformed into the frequency domain using the Short-Time Fourier Transform (STFT). Spectral gating reduces noise across all frequencies, followed by a high-pass filter to remove low-frequency components and enhance higher-frequency feeding signals.

2.2.1. Short-Time Fourier Transform for Time-Frequency Analysis

The Short-Time Fourier Transform (STFT) is a common method for converting time-domain signals into the frequency domain. It generates a spectrogram by dividing the signal into overlapping windows and applying a Fourier Transform to each, showing how spectral energy changes over time. This representation enables the detection of short-duration acoustic events, such as feeding events. In this study, STFT was implemented using the Python *scipy* library. This transformation is formally expressed in Equation 2.

$$\hat{S}[f,t] = \mathrm{STFT}[f,t] = \sum_{n=0}^{L-1} s[n] \cdot w[n-t]\, e^{-j2\pi fn} \tag{1}$$

where $s[n]$ is the input signal, $w[t]$ the analysis window centered at time t, f the frequency bin, n the time index within the window, and L is the window length.

The inverse transform is given by:

$$s[t] = \mathrm{iSTFT}[f,t] = \frac{\sum_{f=0}^{L-1} \hat{S}[f,t] \cdot e^{-j2\pi f(L-t)/L} \cdot w[L-t])}{\sum_t w^2[L-t]} \tag{2}$$

2.2.2. *Spectral Gating*

Spectral gating is a noise reduction technique that reduces noise in each frequency band. For each band, the signal's amplitude standard deviation is calculated, and a threshold of three standard deviations filters out lower components. This thresholding operation is formally defined in Equation 3, where frequency bins below the threshold are set to zero, enhancing acoustic signal clarity while minimizing noise.

$$\hat{X}(f,t) = \begin{cases} X(f,t), & \text{if } |X(f,t)| \geq \theta(f) \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where $\hat{X}(f,t)$ is the gated spectrogram, $X(f,t)$ is the original spectrogram, and $\theta(f)$ is the threshold set to three standard deviations of the amplitude in each frequency band. This process was implemented using the Python library *noisereduce* (version 3.0.3), which applies spectral gating based on frequency-wise amplitude thresholds.

2.2.3. *High-pass Filter*

Following spectral gating, residual low-frequency noise remained, mostly from equipment and the tank's surroundings. As feeding sounds for Gilthead seabream occurred at higher frequencies, a high-pass filter at 2048 Hz was applied to further isolate the relevant signal. This removed irrelevant low-frequency components and enhanced the acoustic features linked to feeding events. The final preprocessing result, showing the enhanced signal after spectral gating and high-pass filtering, can be seen in Figure 3. The Mel spectrogram, a visual representation of sound that captures how the intensity of different frequencies evolves over time, was used to represent the signal and was computed using a Python library. *Librosa*.

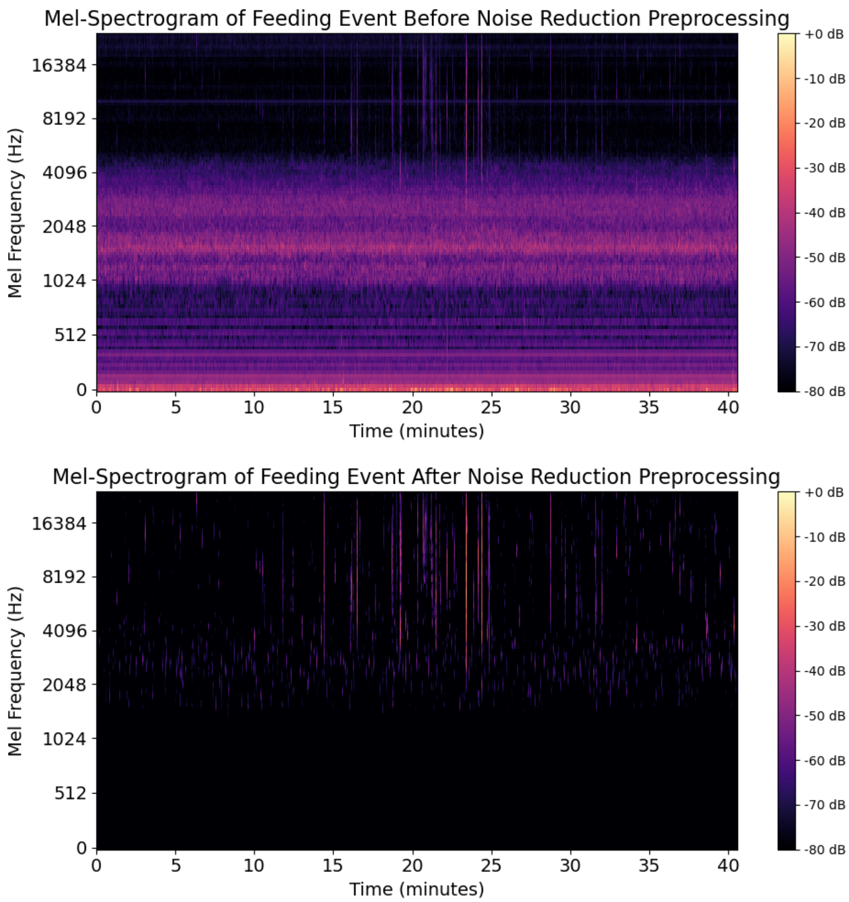

Figure 3. Mel-spectrograms of feeding event before (top) and after (bottom) noise reduction. Spectral gating and high-pass filtering improve audio clarity by reducing background noise.

2.3. Matched Filter-Based Detection and Quantification of Feeding Events

Feeding intensity was measured using a matched filter, a signal processing method optimized to detect known patterns with high accuracy. In this study, the pattern was defined as a single "click" bite sound produced by gilthead seabream during feeding, followed by a sliding window technique to aggregate bite detections into feeding events.

2.3.1. Matched Filter

The matched filter technique identifies signal patterns by optimally aligning a template with the signal input. The template, shown in the time domain in Figure 4, has a max power frequency of 4462 Hz and a spectral centroid of 5138 Hz.

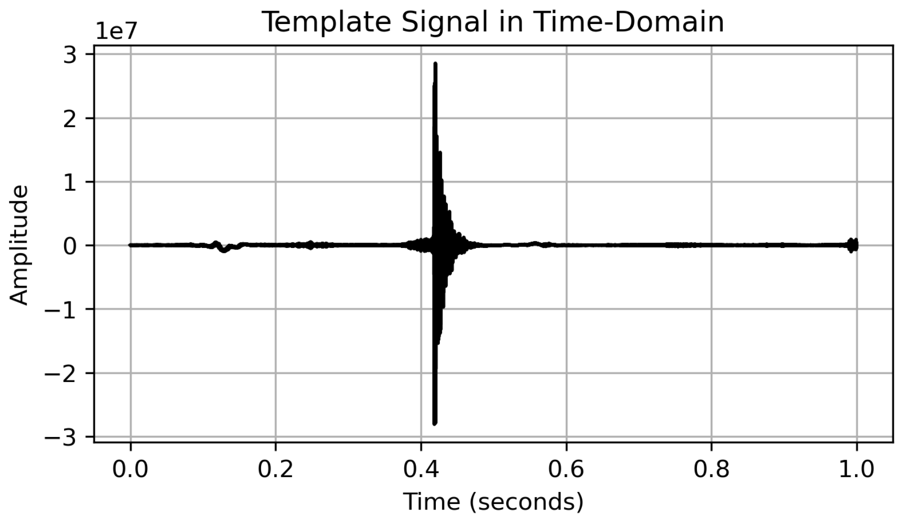

Figure 4. Time-domain waveform of a single bite sound produced by the gilthead seabream, used as the template in the matched filter analysis.

Both the template and the signal are transformed into the frequency domain using the STFT method (Equation 1), with a window sizes of 1024 and a hop size of 512, as described below in Section 2.2.1. The template in the frequency domain is then conjugated and element-wise multiplied with the signal's frequnecy respond.

The matched filter output, computed as shown in Equation 4, emphasizes segments of the signal that closely resemble the template.

$$y_{\text{out}}(t) = ||iSTFT\{STFT\{s[t]\} \cdot STFT\{w[t]\}^*\}|| \tag{4}$$

where $s(t)$ is the input signal, $w(t)$ is the matched filter template, $STFT\{w[t]\}^*$ is the complex conjugate of the template. The norm applied in Equation 4 ensures the output's magnitude is returned.

To convert segments of the signal that strongly resemble the template into meaningful feeding events, a sliding window approach was applied. This method aggregates peaks occurring within a defined time range, allowing isolated detections to be grouped into continuous feeding event. An example of a matched filter result during a feeding event is shown in Figure 5.

Specificity of the matched filter template was assessed by comparing its performance to 20 randomly selected templates. For each template, the matched filter output was used to calculate the signal-to-noise ratio (SNR) as defined in Equation 5. The value of $k = 48{,}000$ corresponds to one second of signal at a 48 kHz sampling rate.

$$\text{SNR} = \left(\frac{\mu_{\text{sig-top}}}{\mu_{\text{noise}}}\right) \cdot \sigma_{\text{sig}} \tag{5}$$

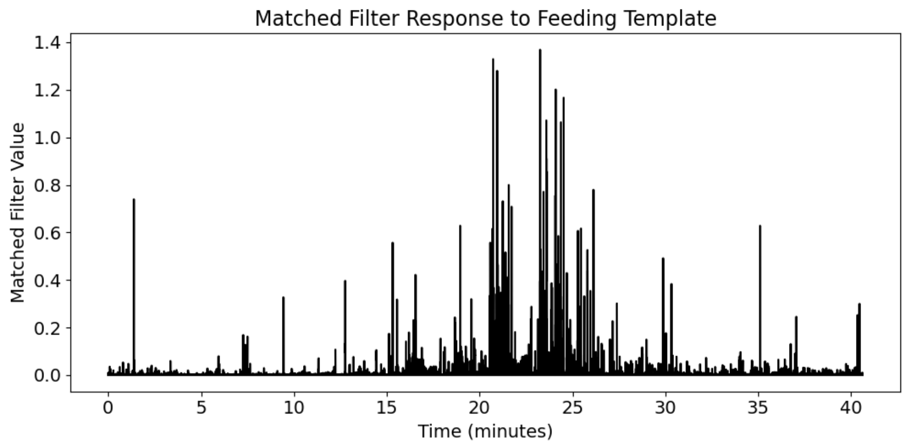

Figure 5. Matched filter response showing peak values corresponding to the bite sound template of the gilthead seabream.

where $\mu_{\text{sig-top}}$ is the mean of the top k values in the signal window, μ_{noise} is the mean of the noise window, and σ_{sig} is the standard deviation of the signal window.

Results showed that the selected bite template yielded up to 16 times higher SNR than random templates.

2.3.2. Sliding Window

Sliding window analysis is a common method for processing time series data, using a fixed-length window that slides over the signal with a defined step size. In this study, it was applied to the matched filter output. At each step, the algorithm sums the values within the window that exceed a defined threshold, producing aggregated values that reflect the intensity of feeding events, as defined in Equation 6. To enable continuous processing of the 19-day dataset, the signal was downsampled by averaging every 1,000 samples. Each daily time series was normalized by its maximum value to produce a relative measure of feeding intensity. Here, a 10-minute sliding window with a 6-second step size was used, with a threshold of 0.1. Thresholds from 0.05 to 0.2 were tested; lower values introduced excessive noise, while higher ones missed relevant activity. The final output is a continuous quantitative label suitable for integration into regression-based machine learning models. An example of sliding window aggregation is shown in Figure 6.

$$I(t) = \sum_{i=0}^{W-1} [M(t+i) > \theta] \tag{6}$$

where $I(t)$ is the feeding intensity score at time t, $M(t+i)$ is the matched filter output at time $t+i$, W is the window length, and θ is the detection threshold.

The expression $[M(t+i) > \theta]$ evaluates to 1 if true and 0 otherwise, effectively counting the number of matched filter values that exceed the threshold within the window.

Figure 6. Sliding window aggregation of matched filter results, reflecting the temporal distribution of feeding event.

2.3.3. Machine Learning for Feeding Intensity Label Validation

To test the robustness of the feeding intensity label and its alignment with environmental and biological variables, machine learning algorithms XGBoost and Random Forest regression models were applied. The environmental and biological variables used to explain the label were fish age, expressed as the number of days since the start of the experiment, categorized feeding time (morning, noon, or evening), and time elapsed since the previous feeding.

3. Results

3.1. Detection and Quantification of Feeding Intensity

An example of the results from a single experimental day, obtained using the proposed methodology, are shown in Figure 7. Feeding events are clearly marked by distinct peaks in the signal, showing more than a tenfold difference between feeding and non-feeding activity. These peaks closely correspond to the feeding times recorded in the experimental log.

A statistical analysis of feeding events across tanks revealed clear variation in feeding intensity throughout the day, as shown in Figure 8. Morning feedings were most intense, with a mean value of 1.00 ± 0.01. Noon and evening feedings showed similar average values around 0.68 ± 0.20 and 0.62 ± 0.20, respectively. This pattern aligns with the environmental context, as morning feeding occurs after the longest fasting interval, likely reflecting increased hunger.

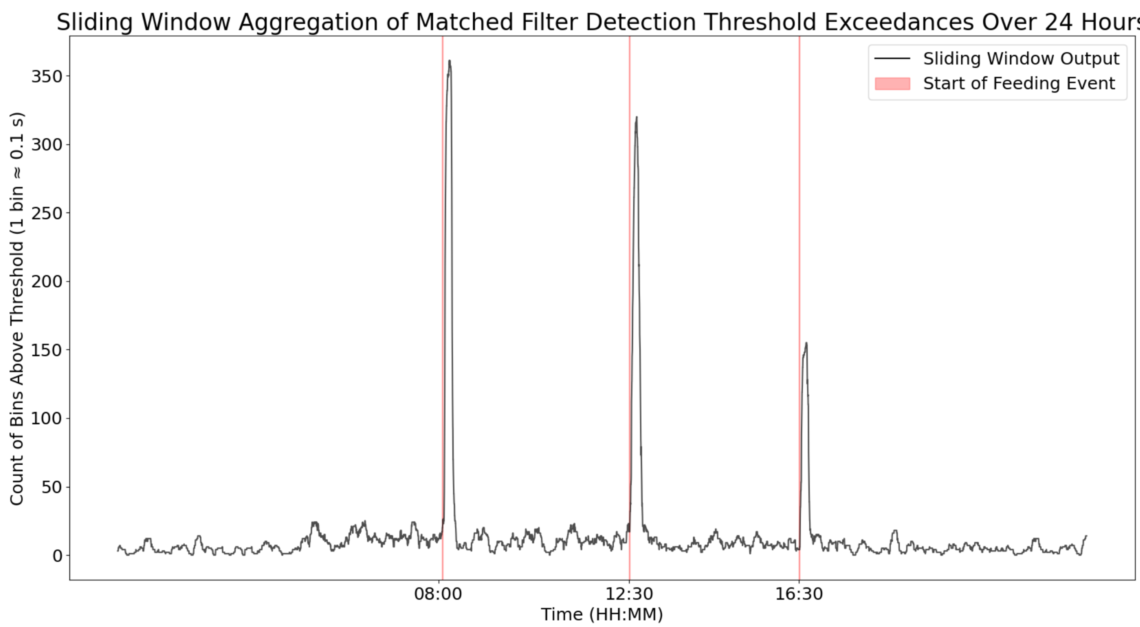

Figure 7. Sliding window aggregation showing the count of bins above the detection threshold across a 24-hour period. Red vertical lines indicate the scheduled start times of feeding events.

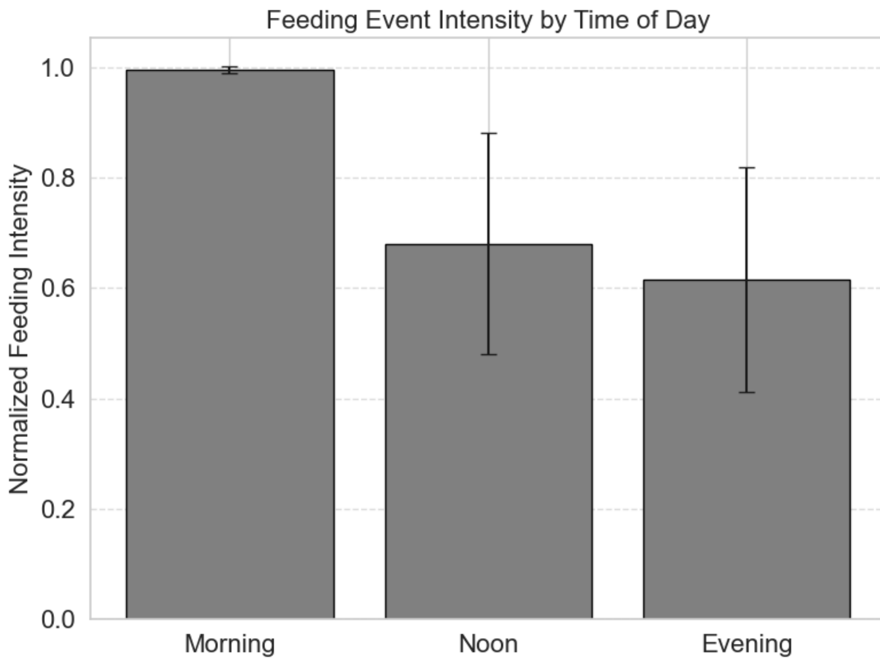

Figure 8. Feeding intensity across times of day, with labels normalized per day. Error bars are also marked in the figure. Note that the daily results were normalized to the most intense signal of that day—typically the morning feeding—so the error for the morning result is often close to zero

3.2. Machine Learning Validation of Feeding Intensity Label

Regression models using XGBoost and Random Forest examined the correspondence between the feeding intensity label and environmental and biological variables. Both showed strong predictive performance, as summarized in table 1, with R^2 values of 0.9803 for XGBoost and 0.9664 for Random Forest. The prediction error was low, with RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) values of 0.0352 and 0.0194 for XGBoost, and 0.0460 and 0.0236 for Random Forest, respectively. Models trained with 100 estimators using the Python *Scikit-learn* library.

Table 1. Regression Performance Metrics for XGBoost and Random Forest

Model	$\mathbf{R^2}$	**RMSE**	**MAE**
XGBoost	0.9803	0.0352	0.0194
Random Forest	0.9664	0.0460	0.0236

Feature importance analysis showed that in the normalized daily data, the most influential variable was time since previous feeding, with importance scores of 0.7160 and 0.6116 for XGBoost and Random Forest, respectively. In unnormalized data, the age of the fish was the dominant feature, with scores of 0.6640 and 0.4753 for XGBoost and Random Forest, respectively. These findings align with aquaculture practices, where feeding amounts increase with fish age, while within each day, feeding behavior is influenced by time since last feeding, as summarized in Table 2.

Table 2. XGBoost Feature Importance Scores

Data Type	Time from Feeding	Days Passed	Time of Day
Normalized	0.7160	0.1259	0.1580
Unnormalized	0.0208	0.6640	0.3152

4. Conclusion

This study presents a simple and robust methodology for detecting and quantifying fish feeding intensity using audio signals and domain knowledge. A matched filter algorithm with a sliding window enables high sensitivity in detecting species-specific feeding events, using the bite sound of gilthead sea bream as a reliable template. ML regression models were used to evaluate how biological and environmental parameters explain variation in the feeding label, with feature importance ranking confirming a strong explanatory value.

Our work demonstrates an advance in data reduction by transforming raw acoustic input on the order of 10^8 samples into a single representative value of feeding intensity. This serves as proof of concept, supporting the potential integration of our methodology into hardware-based data conversion which is highly desirable for field applications.

The method presented in this study lays the groundwork for automated feeding monitoring based on audio signals. It supports the development of advanced artificial intelligence models by leveraging optimal data reduction techniques informed by domain knowledge.

It is important to note that this study was conducted in a controlled environment, using a single species and a uniform fish age for a specific monitoring application. In contrast, real-world aquaculture—whether in land-based tanks or open-sea cages—presents greater complexity due to population diversity, environmental variability, and dynamic feeding behaviors.

Future work will focus on further developing the method and expanding its applications to more complex scenarios, including early disease detection and performance assessment across different species, age groups, environments, and feeding regimens. Ultimately, such approaches can help farmers optimize fish cultivation, increase yield, reduce overfeeding, and support environmental sustainability.

5. Acknowledgments

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