A project report on

SHRIMP FEEDING BEHAVIOUR ANALYSIS IN COMPLEX AQUATIC AUDIO ENVIRONMENTS

Submitted in partial fulfilment for the award of the degree of

M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics

by

NITHIN KODIPYAKA (20MIA1075)

VIT

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

CHENNAI

SCHOOL OF COMPUTER SCIENCE AND ENGINEERING

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DECLARATION

I hereby declare that the thesis entitled "SHRIMP FEEDING BEHAVIOUR ANALYSIS IN COMPLEX AQUATIC AUDIO ENVIRONMENTS" submitted by me, for the award of the degree of M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics, Vellore Institute of Technology, Chennai, is a record of Bonafide work carried out by me under the supervision of DR. SUGANYA G.

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Chennai

Date: 10th April, 2025 **Signature of the Candidate**

Vellore Institute of Technology
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CHENNAI

School of Computer Science and Engineering

CERTIFICATE

This is to certify that the report entitled **"SHRIMP FEEDING BEHAVIOUR ANALYSIS IN COMPLEX AQUATIC AUDIO ENVIRONMENTS"** is prepared and submitted by **Nithin Kodipyaka (20MIA1075)** to Vellore Institute of Technology, Chennai, in partial fulfilment of the requirement for the award of the degree of **M.Tech. (Integrated) Computer Science and Engineering with Specialization in Business Analytics** programme is a Bonafide record carried out under my guidance. The project fulfills the requirements as per the regulations of this University and in my opinion meets the necessary standards for submission. The contents of this report have not been submitted and will not be submitted either in part or in full, for the award of any other degree or diploma and the same is certified.

Signature of the Guide:

Name: Dr. Suganya G

Date: 10th April, 2025

Signature of the Examiner 1	Signature of the Examiner 2
Name: Dr. Kalaipriyan	Name: Dr. Rajakumar
Date:	Date:

Approved by the Head of Department

ABSTRACT

Shrimp feeding behaviour plays a critical role in aquaculture management, yet monitoring it in real-time is challenging due to the complexity of underwater audio environments. This project focuses on analysing underwater acoustic signals to detect and isolate shrimp feeding and snapping sounds in the presence of static and insect noise. Using the Librosa library, three types of audio files were analysed: *NoNoise* (only shrimp sounds), *NoiseType1* (shrimp with static noise), and *NoiseType2* (shrimp with insect noise). A combination of waveform analysis, spectrogram generation, Mel Frequency Cepstral Coefficients (MFCC), Root Mean Square (RMS) energy analysis, and Clicks Per Second (CPS) computation was performed to extract and characterize shrimp sound patterns.

Noise reduction techniques such as notch filtering, time-frequency masking, wavelet denoising, and spectral subtraction were evaluated. Among them, the combination of spectral subtraction and wavelet denoising produced the best results, effectively reducing up to 80% of static noise while retaining shrimp feeding cues. Spectrogram analysis proved to be the most reliable tool for identifying insect noise, which consistently appeared in the 7.5–8.5 kHz frequency range in *NoiseType2* recordings. CPS was calculated using peak detection to quantify the shrimp snapping rate, and statistical measures were derived to interpret activity levels. The study successfully isolated shrimp acoustic features even in complex noise scenarios, though limitations include unclear insect presence in *NoiseType1* and a small dataset. Future work will involve the integration of machine learning for automated sound classification and expansion of the dataset to improve generalizability and frequency mapping accuracy. Overall, this project contributes to the development of robust, real-time acoustic monitoring systems for shrimp aquaculture, enhancing feeding efficiency and system automation under challenging environmental conditions.

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Place: Chennai

Date: **Nithin Kodipyaka**

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LIST OF ACRONYMS

CPS	Clicks Per Second
MFCC	Mel Frequency Cepstral Coefficients
RMS	Root Mean Square
PAM	Passive Acoustic Monitoring
Hz	Hertz
kHz	Kilohertz
IoT	Internet of Things
ML	Machine Learning
FFT	Fast Fourier Transform
dB	Decibel
CNN	Convolutional Neural Network

Chapter 1

Introduction

1.1 INTRODUCTION

Monitoring shrimp feeding behaviour is a vital aspect of aquaculture, directly influencing feed management, growth performance, and overall operational efficiency. Traditional observation methods are labour-intensive and lack the precision required for continuous monitoring. In recent years, passive acoustic monitoring (PAM) has emerged as a promising non-invasive technique to detect aquatic animal behaviour, particularly feeding activity, by capturing and analysing sound patterns. Shrimp, during feeding, emit distinct snapping and chewing sounds that can serve as behavioural indicators. However, the underwater acoustic environment is often contaminated with various types of noise such as static interference and biological noises like insect chirps, which significantly hinder accurate detection.

This project aims to analyse and isolate shrimp feeding and snapping sounds from complex underwater audio environments. Using audio signal processing tools from the Librosa library, three types of underwater recordings were examined: (1) *NoNoise* — containing only shrimp sounds, (2) *NoiseType1* — shrimp sounds combined with static noise, and (3) *NoiseType2* — shrimp sounds combined with insect noise. Techniques like waveform plotting, spectrogram visualization, MFCC extraction, RMS energy analysis, and CPS (Clicks Per Second) computation were utilized to detect and characterize shrimp behaviour.

One of the main challenges addressed in this project is balancing noise reduction while preserving essential shrimp sound features. Several noise reduction techniques were tested, including notch filtering, wavelet transform, and spectral subtraction. Among them, the combination of spectral subtraction with wavelet denoising yielded the best results, removing up to 80% of unwanted static noise and retaining shrimp-specific acoustic features. The spectrogram was particularly effective for identifying insect noise, which consistently appeared in the 7.5–8.5 kHz frequency range.

By establishing a robust analysis pipeline, this project lays the groundwork for developing intelligent, automated shrimp feeding monitoring systems. It highlights the importance of refined signal processing in enhancing aquaculture automation and opens the door for future integration with machine learning-based classification models.

1.2 CHALLENGES

The field of underwater acoustic analysis, particularly for monitoring shrimp feeding behaviour, presents several inherent challenges that impact the accuracy, reliability, and scalability of research and application. These challenges span across environmental, technological, and analytical domains, making the development of robust detection systems both complex and demanding.

One of the primary challenges is the presence of ambient and non-target biological noise. Underwater environments are rarely silent; they are filled with overlapping sounds from various aquatic species, environmental factors like water currents, and man-made sources such as aeration systems and pumps. Insect noise introduces high-frequency interference that overlaps with the spectral range of shrimp sounds, making detection and classification more difficult. A related issue is the variability and subtlety of shrimp feeding sounds. Unlike more prominent acoustic signals, shrimp produce low-amplitude, short-duration clicks and chewing noises that are often masked by stronger background sounds. The variability of these acoustic signals across species, feeding behaviours, and tank conditions further complicates their identification.

From a signal processing perspective, effective noise reduction without information loss remains a major hurdle. Standard filtering techniques may eliminate both unwanted noise and essential shrimp sound patterns. Achieving a balance between denoising and feature preservation requires advanced methods such as wavelet denoising and spectral subtraction — each of which needs fine-tuning and domain-specific adaptation. Another challenge is the lack of large, annotated datasets. Shrimp behaviour datasets with labelled feeding and snapping events are scarce, making it difficult to train machine learning models or validate signal processing techniques on a wide scale. Additionally, many existing studies do not share raw audio data or detailed methodology, hindering reproducibility and comparative research.

Finally, there is no universally accepted benchmark or framework for evaluating shrimp acoustic monitoring systems. Metrics like Clicks Per Second (CPS) are helpful but not standardized, making it difficult to compare results across different systems or research groups. Collectively, these challenges underscore the need for interdisciplinary efforts combining aquaculture knowledge, audio signal processing, and machine learning to advance the field effectively.

1.3 PROJECT STATMENT

Shrimp aquaculture requires efficient monitoring of feeding behaviour to optimize feeding schedules, minimize waste, and improve yield. Traditional visual monitoring methods are labour-intensive and imprecise, while underwater acoustic analysis offers a non-invasive alternative. However, detecting shrimp feeding and snapping sounds is complicated by overlapping static and insect noises that interfere with sound clarity. This project addresses the challenge of isolating and identifying shrimp feeding behaviour in noisy aquatic audio environments using signal processing techniques.

Objective: The primary objective of this project is to develop an effective and reliable method for detecting and analysing shrimp feeding behaviour through underwater audio recordings, even under complex and noisy acoustic conditions. The goal is to isolate shrimp-specific acoustic signatures—particularly snapping and feeding sounds—from overlapping background noises such as static interference and insect-generated sounds. Achieving this would enable more accurate monitoring of shrimp activity, thereby supporting automation in feed management and improving operational efficiency in aquaculture systems.

To meet this objective, the project employs a range of audio signal processing techniques, including waveform analysis, spectrogram visualization, MFCC (Mel Frequency Cepstral Coefficients) extraction, RMS (Root Mean Square) energy analysis, and Clicks Per Second (CPS) computation. These tools are used to characterize shrimp sounds, distinguish them from environmental noise, and develop a consistent pattern for identification. Additionally, the objective involves exploring and comparing multiple noise reduction strategies such as notch filtering, time-frequency masking, wavelet denoising, and spectral subtraction. The aim is not just to suppress noise, but to do so in a way that preserves critical acoustic information related to shrimp behaviour. Among these, spectral subtraction combined with wavelet denoising has shown the most promise, effectively reducing up to 80% of unwanted noise while retaining key feeding cues.

Key objectives include:

- Shrimp Detection
  Develop a method to detect shrimp snapping and feeding activity from underwater audio recordings.

- Frequency Characterization
  Identify and define consistent frequency ranges associated with shrimp sounds to improve detection accuracy.

- Subtle Noise Analysis
  Detect the presence of insect noise or other subtle interferences using spectrogram-based analysis.

- Noise Isolation
  Apply and evaluate various noise reduction techniques to effectively isolate shrimp sounds from background interference.

1.4 OBJECTIVES

Aquaculture is a rapidly evolving sector, with automation and data-driven decision-making playing an increasingly vital role in improving efficiency, sustainability, and yield. Among the key challenges in shrimp aquaculture is the real-time monitoring of feeding behaviour, which directly influences feed usage, shrimp health, and growth performance. The objective of this project is to address this challenge by developing a reliable and noise-resilient audio analysis system capable of detecting shrimp feeding activity under complex underwater sound conditions.

Underwater acoustic environments are inherently noisy and unpredictable. Sounds generated in such environments include not only the target signals—shrimp feeding and snapping—but also a variety of unwanted noises, such as static interference, water turbulence, equipment hum, and insect noise. These overlapping signals make it difficult to accurately isolate and interpret shrimp-specific behaviours. Therefore, the core objective of this project is to analyse underwater audio data, distinguish shrimp feeding behaviour from non-target sounds, and evaluate the effectiveness of various signal processing techniques in doing so.

1. Understanding Shrimp Feeding Acoustics

The first step in achieving the project's objective is understanding the nature of shrimp feeding sounds. Shrimp typically produce snapping and chewing sounds while feeding. These sounds are relatively subtle and often short in duration, making them difficult to detect, especially in the presence of background noise. Identifying the frequency ranges and amplitude patterns associated with these behaviours is essential for building a reliable detection pipeline.

To achieve this, the project analyses three types of audio samples:

- NoNoise – Contains only shrimp sounds.
- NoiseType1 – Shrimp sounds with static noise.
- NoiseType2 – Shrimp sounds with insect noise.

By comparing the characteristics of these three categories, the system can begin to identify unique acoustic features tied to shrimp behaviour, and distinguish them from other types of noise.

2. Noise-Resilient Detection of Shrimp Sounds

A significant aspect of the project objective involves the development of a robust method to isolate shrimp sounds in noisy recordings. Static and insect noises can distort or obscure feeding sounds, leading to incorrect interpretations. Therefore, multiple denoising techniques are tested to evaluate their performance under different noise conditions.

The techniques explored include:

- Notch Filtering – To suppress specific frequency bands.
- Time-Frequency Masking – To selectively mute noisy portions of the signal.

- Wavelet Transform – To analyse and reduce noise while preserving time-frequency resolution.
- Spectral Subtraction – To estimate and subtract noise profiles from the signal.

Among these, spectral subtraction combined with wavelet denoising produced the best results, removing up to 80% of static noise while retaining important features like shrimp snapping sounds. The objective here is not only to reduce noise but to do so without erasing the meaningful audio cues associated with feeding behaviour.

3. Feature Extraction and Visualization

To detect shrimp activity, the system applies several audio processing techniques for feature extraction. These include:

- Waveform analysis – To observe amplitude and temporal structure.
- Spectrograms – To visualize time-frequency components and identify frequency bands where shrimp or insect sounds appear.
- MFCCs (Mel Frequency Cepstral Coefficients) – To capture perceptually relevant audio features.
- RMS (Root Mean Square) energy – To quantify signal energy, which is helpful in identifying feeding events.
- CPS (Clicks Per Second) – A metric developed in this project to measure the rate of shrimp clicks/snaps per second.

The objective here is to create a multi-faceted representation of the audio signals, enabling a more accurate and granular analysis of shrimp behaviour.

4. Frequency Characterization

Another core component of the project objective is to characterize the frequency ranges that most reliably correspond to shrimp feeding behaviour. It was observed that insect noises in *NoiseType2* consistently appeared in the 7.5–8.5 kHz range, as evident from spectrograms. In contrast, shrimp sounds typically occurred in the 2–6 kHz range.

Defining and validating these ranges allows the system to apply bandpass filtering effectively, focusing on the frequency ranges that are more likely to contain shrimp-related sounds while reducing irrelevant data. The objective is to build frequency-based profiles that can guide future classification efforts and be extended to other aquatic environments.

5. Quantitative Behaviour Monitoring

While visual inspection of spectrograms and waveforms provides qualitative insights, the project also aims to deliver quantitative metrics for feeding activity. This is achieved through:

- CPS Calculation: Clicks Per Second are computed using peak detection algorithms (scipy.signal.find_peaks), identifying sharp acoustic events spaced at least 10ms apart.

- Statistical Summarization: Mean, max, and min CPS values are reported, along with the number of frames where CPS exceeds defined thresholds (e.g., 5 clicks/sec or 10 clicks/sec).

These metrics allow for time-series tracking of shrimp activity, which can eventually be correlated with feeding times or external stimuli, aiding farm management decisions.

6. Foundations for Automation and Machine Learning Integration

Although the project primarily relies on classical audio processing techniques, one of the long-term objectives is to establish a foundation for integrating machine learning (ML) models for classification. A clear understanding of frequency behaviour, noise profiles, and extracted features sets the stage for the development of supervised or unsupervised ML models that can automatically classify sound events as shrimp feeding, insect noise, or background static.

Before machine learning can be reliably implemented, it is essential to have:

- Cleaned and labelled audio data.
- A well-understood feature set.
- A reproducible analysis pipeline.

1.5 SCOPE OF THE PROJECT

The scope of this project revolves around the acoustic detection and analysis of shrimp feeding behaviour in complex underwater audio environments. It aims to isolate and identify shrimp snapping and chewing sounds from recordings that include significant noise interference, such as static background noise and insect-generated sounds. By working with three types of audio samples—*NoNoise*, *NoiseType1*, and *NoiseType2*—the project investigates how noise affects signal clarity and how shrimp behaviour can still be detected accurately under such conditions.

To achieve this, the project employs several audio signal processing techniques. These include waveform visualization, spectrogram generation, Mel Frequency Cepstral Coefficients (MFCC) extraction, Root Mean Square (RMS) energy calculation, and Clicks Per Second (CPS) computation. A major part of the scope also involves testing and evaluating multiple noise reduction methods such as notch filtering, time-frequency masking, wavelet denoising, and spectral subtraction. The effectiveness of these methods is assessed based on their ability to suppress noise while preserving meaningful shrimp feeding signals.

While the current scope is limited to signal-level analysis using a small set of labelled audio files, it lays the foundation for future integration with machine learning techniques. The project does not extend into real-time detection or automated classification, but its results are intended to support the development of intelligent, automated monitoring systems in aquaculture. The framework designed here can be scaled and enhanced further to improve feeding efficiency and decision-making in shrimp farming operations.

Chapter 2

Related Work

Hamilton et al. (2021) explored the acoustic behavior of the giant freshwater prawn (*Macrobrachium rosenbergii*) during feeding, offering the first detailed analysis of sound emissions associated with this activity in captivity. Using passive acoustic monitoring (PAM) and synchronized audio-video recordings, the study aimed to characterize the sound generation mechanism and quantify key acoustic parameters. Fourteen prawns, categorized into three size classes, were individually recorded while consuming commercial pellet feed. The analysis of 80 sound pulses revealed that the prawns emit distinctive clicking sounds produced by mandibular collisions during food shredding. While minimum and peak frequencies were consistent across all size classes, variables such as sound duration, maximum frequency, and sound pressure level differed significantly but showed no clear pattern related to prawn size. This suggests that individual variation or other factors may influence these parameters more than body size. The study highlights the potential of using sound emissions as reliable, non-invasive indicators of feeding activity in aquaculture, which could improve monitoring and automation practices in prawn farming. Overall, the findings contribute a novel perspective to crustacean ethology and open up new possibilities for precision feeding techniques that enhance efficiency and sustainability in freshwater prawn aquaculture systems [1].

Liu et al. (2024) present a novel approach for recognizing feeding sounds of largemouth black bass (*Micropterus salmoides*) using low-dimensional acoustic features, aiming to distinguish between swallowing and chewing sounds—both vital indicators of fish density and feeding motivation. Through synchronized audio-visual data collection, the study analyzes time-frequency domain features to extract 15 acoustic indicators categorized into short-time average energy, Mel-frequency cepstral coefficients, power spectral peak, and center frequency. Dimensionality reduction is then applied using nine different algorithms to isolate the six most informative features, which are tested across four machine learning models for classification accuracy. The study finds that these acoustic features display strong global correlation and linearity, with supervised feature selection significantly enhancing recognition performance. Among the models, the random forest classifier coupled with reduced features yields the highest accuracy at 98.63%, indicating its effectiveness in classifying fish feeding sounds with minimal computational cost. This research provides a significant step forward in the development of precision aquaculture, offering a robust and efficient method for monitoring fish feeding behavior, optimizing feeding strategies, and potentially reducing feed waste. The integration of acoustic analysis and machine learning in this context highlights its promising application in intelligent fish farming systems [2].

Xu et al. (2020) present a robust deep learning-based acoustic classification framework aimed at automatic identification of animal species through their vocalizations, addressing limitations in existing audio monitoring systems such as feature selection complexity, susceptibility to environmental noise, and high computational demand on sensor nodes. The system is designed for deployment in a Wireless Acoustic Sensor Network (WASN) and utilizes a cloud-based architecture to shift processing tasks away from sensor nodes, thereby enhancing scalability and reducing local computational load. At its core is a multi-view Convolutional Neural Network (CNN) specifically designed to capture and analyze short-, middle-, and long-term temporal features in parallel, improving recognition accuracy across varying acoustic conditions. Evaluation using two real-world datasets demonstrates that the system maintains high classification accuracy even under low signal-to-noise ratio (SNR) conditions, outperforming traditional approaches in noisy environments. Additionally, deployment on a real-world testbed confirms the system's effectiveness and robustness in identifying animal species across diverse acoustic scenes. This study significantly advances automatic acoustic monitoring by combining deep learning with efficient system design, offering practical benefits for ecological research, biodiversity monitoring, and intelligent wildlife surveillance in complex, real-world settings [3].

Yang et al. (2024) introduce an advanced framework for automatic animal sound classification that addresses key challenges in bioacoustics, such as signal diversity, varying recording conditions, and low signal-to-noise ratios (SNR). Recognizing that traditional deep learning models like CNNs and LSTMs—though effective in speech recognition—struggle with the complex and variable nature of animal vocalizations, the authors propose a more tailored solution. Their method begins with optimizing Mel-frequency cepstral coefficients (MFCC), applying techniques like feature rearrangement and dimensionality reduction to enhance the quality of input features. These optimized features are then fed into an attention-based Bidirectional Long Short-Term Memory (Bi-LSTM) network, which is designed to extract rich semantic information from temporal audio sequences. Additionally, the authors contribute a new benchmark dataset encompassing sounds from oceanic animals and birds, addressing the scarcity of diverse, labeled datasets in this domain. Experimental results across multiple real-world datasets show the proposed framework significantly outperforms traditional approaches—improving precision, recall, and accuracy by over 25%. This study not only presents a high-performing model but also sets a new standard for general-purpose animal sound classification, offering a scalable, data-driven solution applicable to ecological monitoring, biodiversity assessments, and conservation efforts [4].

Liu et al. (2016) explore the application of deep learning techniques for the identification of soft shell shrimp, addressing limitations of traditional machine learning approaches that rely heavily on handcrafted feature engineering. Conventional methods often demand significant human expertise and time-consuming feature selection processes, which may not generalize well across varying conditions. In contrast, the authors leverage deep learning's capacity to automatically learn hierarchical data representations, bypassing the need for manual feature design. Though specific model architecture details are not elaborated in the abstract, the study references the use of deep structures like Deep Belief Networks and Sparse Autoencoders, highlighting their effectiveness in extracting complex, high-level patterns directly from raw input data. This shift toward deep architectures represents a significant advancement in the domain of shrimp identification, particularly for soft shell variants, which may present subtle visual or acoustic cues that are difficult to capture using conventional feature-based methods. The research sets a precedent for the use of deep learning in aquaculture and bio-monitoring applications, offering a more scalable and adaptive solution for species identification tasks. By reducing reliance on domain-specific feature engineering, the approach promotes broader applicability and efficiency in automated classification systems [5].

Tabbara et al. (2024) investigate the impact of a chemosensory feed effector on the feeding behavior, growth performance, and salinity stress tolerance of juvenile *Litopenaeus vannamei* (Pacific whiteleg shrimp), using passive acoustic monitoring (PAM) as a behavioral assessment tool. Recognizing the economic importance of optimizing feed consumption—especially when using cost-effective animal by-products like poultry meal in place of traditional fishmeal—the study formulated nine diets with varying protein sources and feed effector inclusion levels (0%, 0.1%, 0.2%). Both naïve and non-naïve shrimp were exposed to these diets while their feeding activity was continuously monitored through acoustic cues, particularly mandibular "clicks." A strong positive correlation was found between the number of clicks and actual feed consumption ($p < 0.001$, $r = 0.46$–0.69), validating PAM as a reliable tool for evaluating feed acceptance. Shrimp fed poultry meal-based diets produced significantly more clicks and showed comparable consumption to those fed fishmeal diets, but only when the feed effector was included. Despite no significant changes in final growth metrics or survival during the growth phase, salinity stress trials revealed improved survival rates with feed effector supplementation. This study underscores the potential of feed effectors to enhance palatability and stress resilience in shrimp, offering a cost-effective strategy to maintain performance while reducing dependence on fishmeal [6].

Zhao et al. (2021) provide a comprehensive review of the recent advancements and applications of machine learning (ML) in intelligent fish aquaculture, emphasizing its pivotal role in the transition toward digital and automated fish farming. The review covers developments over the past five years, categorizing ML applications into key areas such as fish biomass estimation, species identification and classification, behavioral monitoring, and water quality prediction. Techniques including supervised learning, unsupervised learning, and deep learning are examined, with a focus on how these models enhance decision-making, reduce labor, and improve aquaculture precision. The paper also analyzes specific ML implementations for real-time behavior recognition and environmental monitoring, which contribute significantly to the health and productivity of fish stocks. Despite these advances, the authors acknowledge ongoing challenges such as data scarcity, generalization of models across diverse aquaculture environments, and integration with Internet of Things (IoT) infrastructures. The review concludes by forecasting the integration of ML with big data and cloud computing as the future trajectory of smart aquaculture systems. Overall, the study offers valuable insights into both the achievements and limitations of current ML applications, underscoring their growing influence in sustainable, efficient, and intelligent aquaculture practices [7].

Peixoto and Soares (2025) offer an extensive review of the recent advancements in passive acoustic monitoring (PAM) for evaluating shrimp feeding behavior in both laboratory and farm environments. The paper emphasizes PAM's growing relevance as a noninvasive and reliable technique that capitalizes on the mandibular "clicks" emitted by shrimp during feeding. This bioacoustic signature provides valuable behavioral insights, particularly when integrated with other ethological methods. The review outlines foundational bioacoustic concepts and methodologies to help standardize the understanding of shrimp sound production across species. It further highlights PAM’s capabilities in differentiating acoustic patterns linked to shrimp size, feed types, pellet textures, and diet additives. Key findings from laboratory studies include the characterization of species-specific acoustic signals, how click parameters vary with physical and nutritional factors, and how stocking density or artificial diet composition can influence shrimp feeding behavior. Importantly, the paper bridges the gap between experimental and field applications, advocating for PAM as a tool to optimize feed management strategies in commercial aquaculture settings. Looking forward, the authors propose methodological refinements and recommend expanding PAM-based studies to enhance precision feeding and welfare monitoring. This review solidifies PAM’s role in advancing sustainable and intelligent shrimp aquaculture through behavioral acoustics [8].

Thong (2018) presents the development of an intelligent management system for shrimp aquaculture, leveraging Internet of Things (IoT) technology to enable automated and remote monitoring of environmental conditions within shrimp ponds. The system is designed to track variations in water parameters and climatic factors using a network of IoT sensors, which transmit real-time data to a centralized cloud platform accessible through smart devices. This allows for continuous observation and improved responsiveness to changes in pond conditions, facilitating both automated adjustments and manual interventions by the user. The integration of a database and analytical module enables dynamic analysis and decision-making based on environmental fluctuations, thus supporting better water quality control and adaptive farm management. The system aims to enhance operational efficiency, reduce manual labor, and promote sustainable shrimp farming practices by maintaining optimal habitat conditions. Though developed as a thesis, the work lays a foundational framework for applying smart technologies in aquaculture and demonstrates how IoT-based solutions can transform traditional aquafarming into a more precise, data-driven practice. This early implementation contributes to the growing body of research on digital aquaculture systems, paving the way for scalable, intelligent infrastructure in the aquaculture industry [9].

Alim et al. (2024) present an open-source, noise-resilient voice data preparation pipeline designed to enhance automated speaker and speech recognition systems by improving input signal quality. The pipeline addresses a key challenge in real-world audio processing: filtering background noise while retaining relevant speech segments. The proposed model was developed using a large longitudinal dataset with diverse real-world noise scenarios and validated on both public and custom test datasets. At the core of the denoising process is a Kalman filter, optimized through a grid search technique to achieve the best signal-to-noise ratio (SNR) performance. The pipeline includes multiple stages—denoising, pause removal via segmentation, robust feature extraction, and compact, efficient storage of processed audio as feature templates. Experimental results highlight the effectiveness of the Kalman filter in improving SNR across different environments, demonstrating the pipeline's adaptability and robustness. This system provides a scalable and practical solution for preprocessing audio in noise-prone conditions, significantly contributing to the preparation of cleaner, high-quality data for downstream machine learning applications. Its open-source nature further enables broader use and customization, making it a valuable tool for researchers and developers working in speech technology and related fields [10].

Hossain (2018) introduces a cross-correlation-based acoustic signal processing technique for estimating fish and marine mammal populations, aiming to address the limitations of conventional marine ecology methods such as visual sampling, eDNA analysis, and echo integration. These traditional approaches can be invasive, costly, or limited in scope, necessitating the development of more efficient and non-invasive alternatives. The proposed method leverages the distinct acoustic signatures—such as chirps, grunts, growls, and clicks—emitted by marine species to estimate population distributions using cross-correlation statistics. The research focuses on practical implementation challenges, including varying acoustic signal types, sensor count, and fish distribution models (Exponential, Normal, Rayleigh). Findings suggest that chirp signals yield the most accurate estimates, and that an Exponential distribution model outperforms others. Furthermore, increasing the number of acoustic sensors enhances estimation accuracy, although limitations in underwater bandwidth and low signal-to-noise ratios present challenges. Solutions such as optimal signal scaling (e.g., 0.59512 for chirps at 5 kHz) and maintaining an SNR above 20 are proposed to mitigate these issues. The framework developed in this thesis presents a promising direction for non-invasive, scalable, and efficient monitoring of marine populations, offering a valuable contribution to ecosystem-based management strategies and future marine ecological research [11].

Jeantet and Dufourq (2023) explore the enhancement of deep learning acoustic classifiers for wildlife monitoring through the integration of contextual information. Bioacoustics has become a crucial approach in ecological research, especially for studying elusive species and natural soundscapes. However, large-scale acoustic monitoring generates extensive data volumes that are difficult to analyze manually. While deep learning has significantly improved the automation of bioacoustic data analysis, classifiers often struggle with noisy environments, overlapping sounds, and lack of contextual awareness. The authors propose embedding contextual metadata—such as time of day, habitat type, and species-specific behavior patterns—into the model architecture to improve classification accuracy and ecological interpretability. Their approach demonstrates that adding environmental and behavioral context to neural networks not only increases performance but also provides insights into species-specific acoustic activity. The study emphasizes that contextualized models are more robust against variations in sound quality and more capable of distinguishing similar vocalizations across species. This work suggests a shift toward more ecologically aware deep learning models that can adapt to the complexities of real-world wildlife monitoring, ultimately enhancing biodiversity assessments and conservation efforts [12].

Darodes de Tailly et al. (2021) review the current and emerging methods used to monitor feeding behaviour in penaeid shrimp, emphasizing the urgent need to improve feeding efficiency in the rapidly growing shrimp aquaculture sector. Traditional feed management practices, such as the use of feeding trays, are still prevalent but often prove unreliable due to observational challenges, especially under the turbid conditions of commercial ponds. These inefficiencies frequently lead to overfeeding and feed wastage. Although controlled laboratory studies have advanced our understanding of shrimp feeding patterns, insights into their natural feeding behaviours in farm environments remain limited. To address these gaps, the authors explore the potential of three key technological approaches—passive acoustic monitoring, computer vision, and telemetry—to deliver real-time, non-invasive observations of shrimp activity. These technologies have already demonstrated success in other aquaculture domains and hold promise for revolutionizing shrimp farming by providing more accurate assessments of feeding behaviour in relation to both environmental and physiological variables. The review also frames several critical research questions that must be addressed to integrate these technologies effectively into commercial shrimp farming. Ultimately, the paper advocates for a transition toward intelligent, technology-driven feeding strategies to enhance both the productivity and sustainability of shrimp aquaculture operations [13].

Williams et al. (2022) present an advanced approach to automating ecological monitoring of marine environments through the integration of passive acoustic monitoring (PAM), ecoacoustic indices, and machine learning. Traditional reef monitoring techniques rely heavily on manual in-water surveys, which are resource-intensive and limited in scope. PAM offers a scalable, non-invasive alternative, capturing complex soundscapes that reflect ecosystem health. However, prior attempts to assess reef conditions using individual ecoacoustic indices showed limited accuracy [14]

Silva et al. (2019) conducted an acoustic characterization study on the feeding behavior of *Litopenaeus vannamei* (Pacific white shrimp) in captivity, aiming to correlate sound emissions with feeding activity across different shrimp size classes. The research focused on identifying the sound generation mechanism, evaluating key acoustic variables, and exploring their potential as indicators of feed intake. Eighteen shrimp were categorized into three size classes (small, medium, large) and fed three individually offered pellets. Simultaneous audio and video recordings were used to monitor feeding events. The study revealed that shrimp produce clicking sounds during feeding, specifically linked to mandible closure during pellet shredding [15].

Chapter 3

Dataset

This project utilizes a specialized audio dataset consisting of three underwater recordings, each designed to represent varying levels of environmental complexity. The objective behind this dataset design is to study shrimp feeding behaviour in both clean and noisy aquatic conditions and to evaluate the effectiveness of noise reduction techniques under these settings.

3.1 DATA OVERVIEW

The dataset used in this project is composed of three curated underwater audio recordings, each designed to reflect varying environmental acoustic conditions in shrimp aquaculture. These recordings are named NoNoise, NoiseType1, and NoiseType2, and were recorded at a high sampling rate of 44.1 kHz to ensure the preservation of fine acoustic details such as shrimp snapping and feeding events. This focused dataset simulates real-world aquaculture environments, progressively increasing in noise complexity across the three categories.

The primary goal of using these datasets is to understand how different noise sources affect the detectability of shrimp feeding behaviour, and to develop noise-resilient audio analysis techniques. Though limited in number, these files were sufficient to explore a range of preprocessing and feature extraction methods and served as a baseline for proposing future improvements and scaling opportunities.

3.2 DESCRIPTION OF AUDIO TYPES

a. NoNoise

This file contains only shrimp feeding and snapping sounds recorded in a controlled, noise-free environment. It serves as the reference baseline, enabling clear observation of natural shrimp acoustic behaviour without interference. Spectrograms generated from this file show uniform energy distributions with no external frequency peaks.

b. NoiseType1

This recording includes static noise—representative of machine-generated or environmental disturbances commonly found in shrimp farms. The presence of such noise mimics real aquaculture conditions, where pumps, aerators, or flowing water create constant acoustic interference.

c. NoiseType2

This audio file adds another layer of complexity by introducing insect noise along with shrimp sounds. The insect noise, consistently found in the 7.5–8.5 kHz range, is prominently visible in the spectrogram and represents biologically generated interference. This file is key for testing the system's ability to differentiate between biological and behavioural sound sources.

3.3 DATA PREPROCESSING

To ensure meaningful feature extraction and analysis, the audio recordings underwent several preprocessing steps:

- Resampling and Normalization: All audio samples were standardized in amplitude and time resolution.
- Bandpass Filtering: A filter range of 2000–6000 Hz was applied to isolate frequencies most likely associated with shrimp sounds, while removing irrelevant low- and high-frequency components.
- Framing: Audio files were divided into 1-second frames to enable localized time-based analysis and to compute statistics over short intervals.
- Peak Detection: Using scipy.signal.find_peaks, the system detected sharp acoustic events such as snapping, which formed the basis for Clicks Per Second (CPS) computation.
- Spectrogram Generation: Time-frequency visualizations were created to visually analyse patterns and detect persistent insect noise, especially in NoiseType2.

These preprocessing techniques prepared the data for in-depth signal analysis and noise isolation experiments.

3.4 FEATURE EXTRACTION AND ANALYSIS TECHNIQUES

Several features and metrics were extracted from the dataset to analyse shrimp behaviour and evaluate the effectiveness of noise reduction:

- Waveform Analysis: Provided a temporal view of amplitude fluctuations, helping identify periods of feeding activity.
- Spectrograms: Crucial for identifying insect noise bands in the 7.5–8.5 kHz range and evaluating how background noise varied over time.
- MFCC (Mel Frequency Cepstral Coefficients): Captured perceptually relevant sound features and helped distinguish shrimp sounds from noise.
- RMS Energy: Measured the intensity of the signal within each frame to highlight active versus silent periods.
- CPS (Clicks Per Second): Quantified the number of shrimps snapping events per second and served as an activity index. Statistical measures such as average CPS, maximum CPS, and frame counts exceeding specific thresholds were also computed.

Together, these features offered a comprehensive profile of shrimp activity under varying noise conditions.

3.5 CHALLENGES WITH THE DATASET

Despite its utility, the dataset presented several limitations and challenges:

- Limited Sample Size: With only three recordings, the dataset lacks diversity in noise types, shrimp species, and behavioural variability. This limits the robustness of frequency generalization.
- Absence of Ground Truth Labels: No manual annotations exist for the timing of shrimp snaps or feeding events, making it difficult to objectively measure detection accuracy.
- Noise Overlap: Frequencies of static and insect noise often fall within or near the shrimp sound range, complicating the filtering process and increasing the risk of losing essential features.
- Unclear Insect Noise in NoiseType1: Unlike NoiseType2, insect presence in NoiseType1 is subtle or inconsistent, making comparative analysis difficult.
- Non-stationary Noise: Background noise characteristics vary over time, which affects the reliability of global filtering methods.

3.6 DATASET SIGNIFICANCE AND CONSIDERATIONS

Even with its limitations, the dataset serves as a critical foundation for the development and testing of a signal processing framework aimed at shrimp feeding detection. It provides a controlled environment to test the effectiveness of various noise reduction methods, such as spectral subtraction and wavelet denoising, and supports preliminary frequency characterization of shrimp acoustic signals.

Moving forward, the dataset can be significantly enhanced by:

- Collecting more audio samples under different environmental and feeding conditions.
- Manually annotating shrimp snapping and feeding events to enable supervised learning.
- Introducing labelled multi-species noise to better simulate real-world aquatic soundscapes.
- Testing on real-time audio streams for deployment in intelligent aquaculture systems.

Chapter 4

Methodology & Implementation

This study utilized three distinct underwater audio recordings to investigate shrimp feeding behaviour under varying noise conditions. The audio data were sampled at 44.1 kHz to ensure the retention of fine acoustic features such as shrimp snapping and chewing.

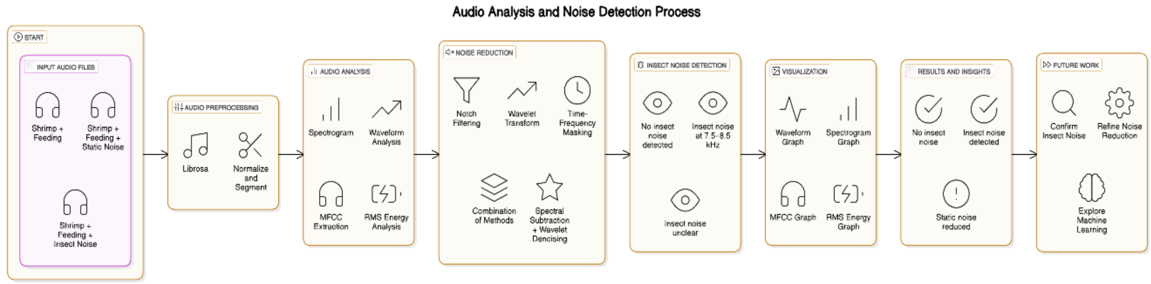

Figure 1 Audio Analysis Flowchart

4.1 AUDIO DATASET AND CATEGORIZATION

This study employs a curated dataset comprising three underwater audio recordings, each crafted to represent different acoustic conditions found in shrimp aquaculture. These recordings serve as the foundation for analysing and isolating shrimp feeding behaviour under varying noise intensities and types. All files were sampled at 44.1 kHz, a standard high-fidelity rate that captures fine-grained audio details crucial for detecting subtle events like shrimp snaps.

- NoNoise: This file contains only shrimp snapping and feeding sounds, recorded in a noise-free aquatic environment. It acts as the clean reference baseline, useful for defining frequency characteristics of natural shrimp behaviour without interference.

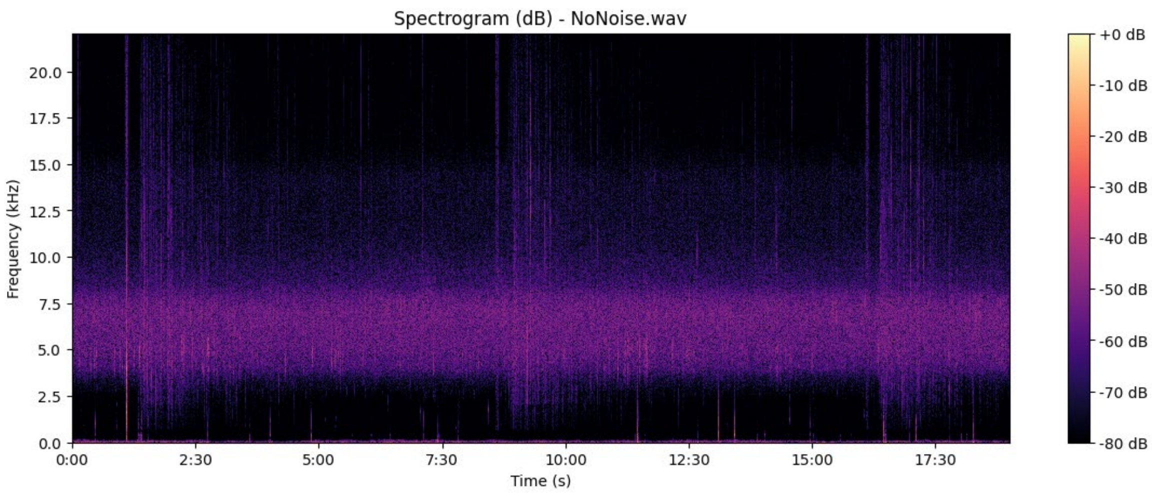

Figure 2 Spectrogram of "NoNoise.wav"

- NoiseType1: This recording features shrimp sounds mixed with static noise, simulating a real-world scenario where background disturbances from mechanical sources—like aerators or recirculation systems—are present.

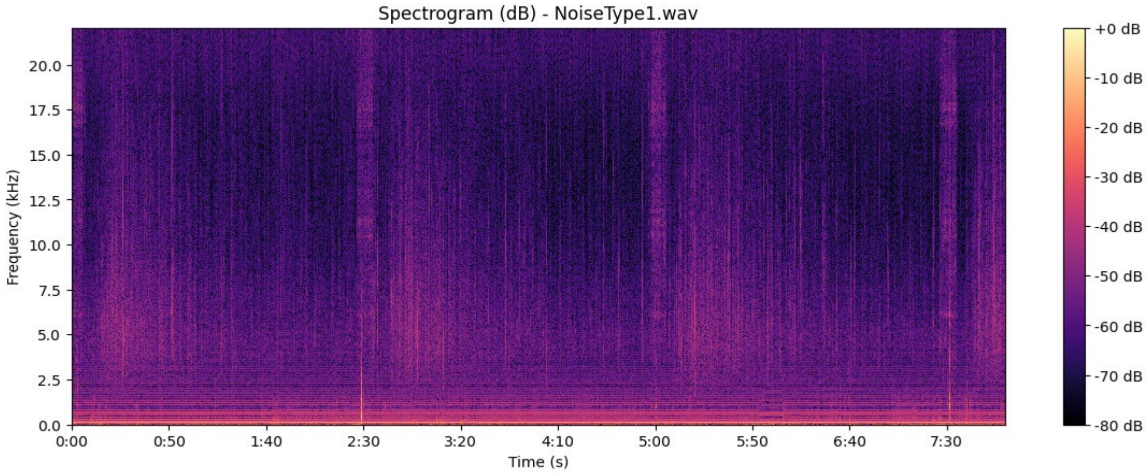

Figure 3 Spectrogram of "NoiseType1.wav"

- NoiseType2: Includes both shrimp activity and insect noise, which appears prominently in the 7.5–8.5 kHz frequency range. This scenario represents biological interference, where overlapping animal sounds introduce further complexity.

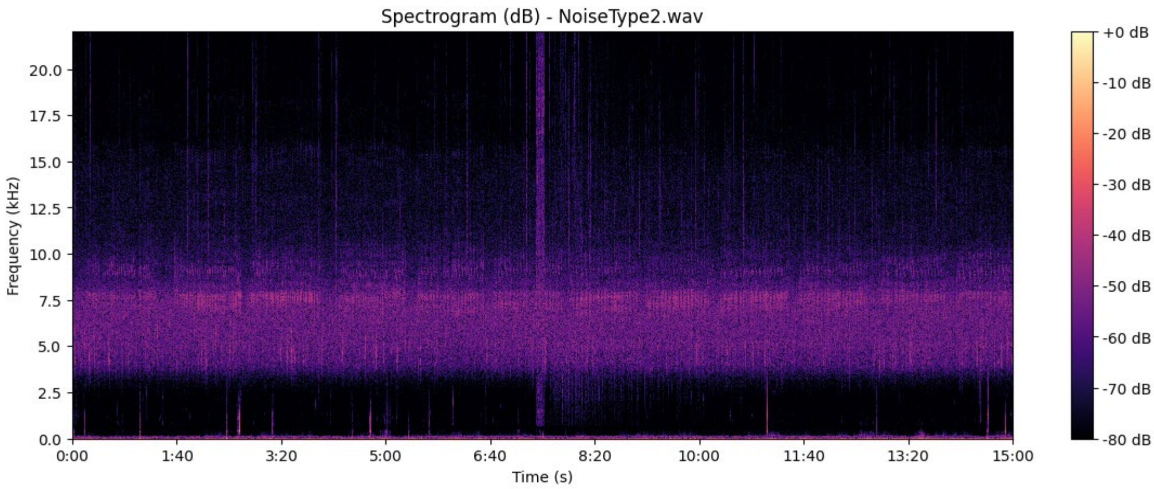

Figure 4 Spectrogram of "NoiseType2.wav"

Each of these audio types helps assess the robustness of signal processing techniques when dealing with layered noise. The dataset was purposefully limited in scope to allow detailed manual analysis and controlled testing. By observing changes in feature response across these files, the project evaluates how signal clarity, activity detection, and noise interference evolve in different conditions.

The data, though small in quantity, was essential in understanding the challenges of aquatic sound processing and informed the selection of appropriate preprocessing, denoising, and analysis techniques in later stages of the methodology.

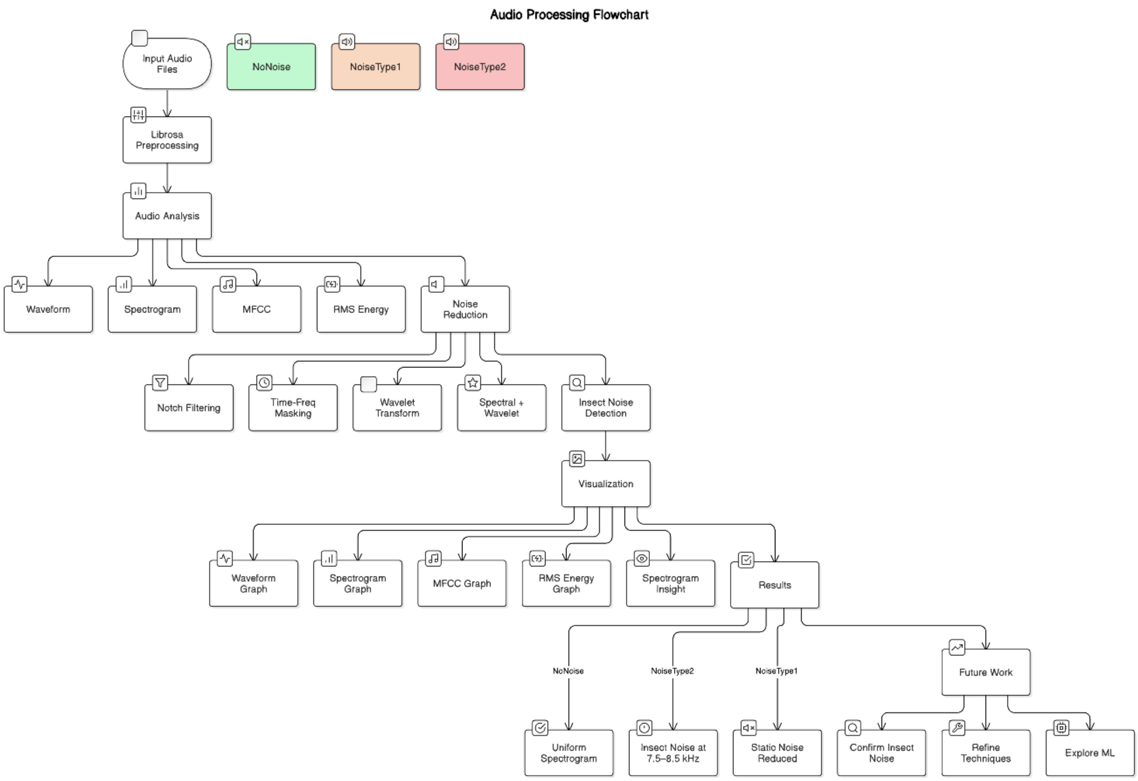

Figure 5 Audio Processing Flowchart

The three files allowed comparative evaluation of signal clarity before and after applying noise reduction techniques. Additionally, each audio file was stored in a lossless format to ensure signal fidelity. This structure ensured that signal processing methods could be calibrated progressively—starting from clean data and moving towards increasingly complex audio environments. Although limited in size, the dataset was highly valuable in proving the concept of behaviour analysis through sound and highlighted the need for adaptive filtering techniques in complex aquatic soundscapes.

4.2 PREPROCESSING AND FRAME SEGMENTATION

Preprocessing is a critical stage that enhances the clarity and usability of the raw audio data. The goal is to transform the recordings into a structured, noise-minimized format that is suitable for further analysis. Several operations were performed to condition the signals effectively, focusing on frequency isolation, amplitude consistency, and temporal segmentation.

- First, a bandpass filter (2000–6000 Hz) was applied to all three recordings. This range was selected based on initial visual inspection of the spectrograms and prior studies indicating that shrimp snapping sounds generally fall within this mid-frequency zone. The filter removed low-frequency environmental rumble and high-frequency static or insect noise.

- Next, amplitude normalization was conducted. This ensured that variations in recording gain or environmental intensity did not influence the interpretation of signal strength. By normalizing all signals to a consistent amplitude scale, the resulting features (e.g., RMS energy, CPS) could be fairly compared across the three audio types.

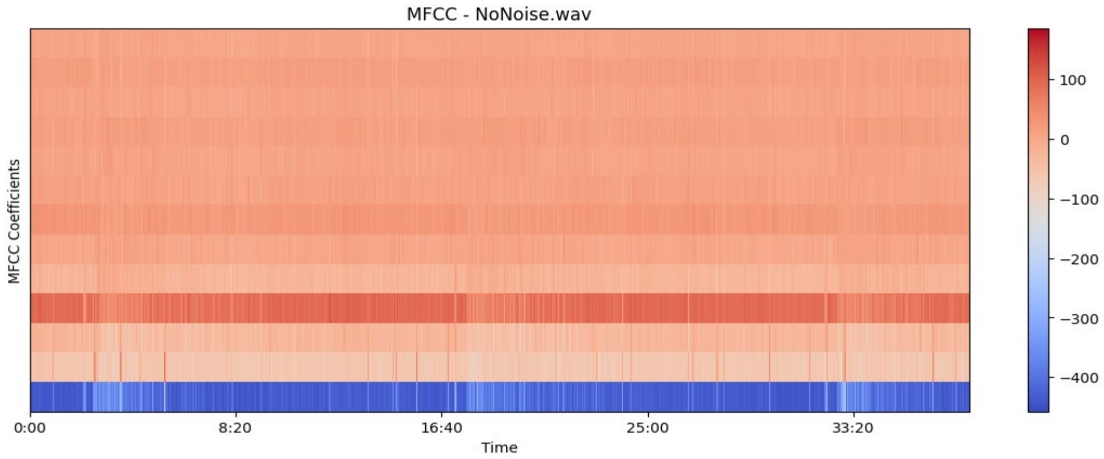

Figure 6 MFCC of "NoNoise.wav"

- The filtered and normalized audio was then divided into 1-second frames. This frame-based segmentation made it easier to observe short-term acoustic patterns, detect individual feeding bursts, and calculate time-series metrics such as Clicks Per Second (CPS).

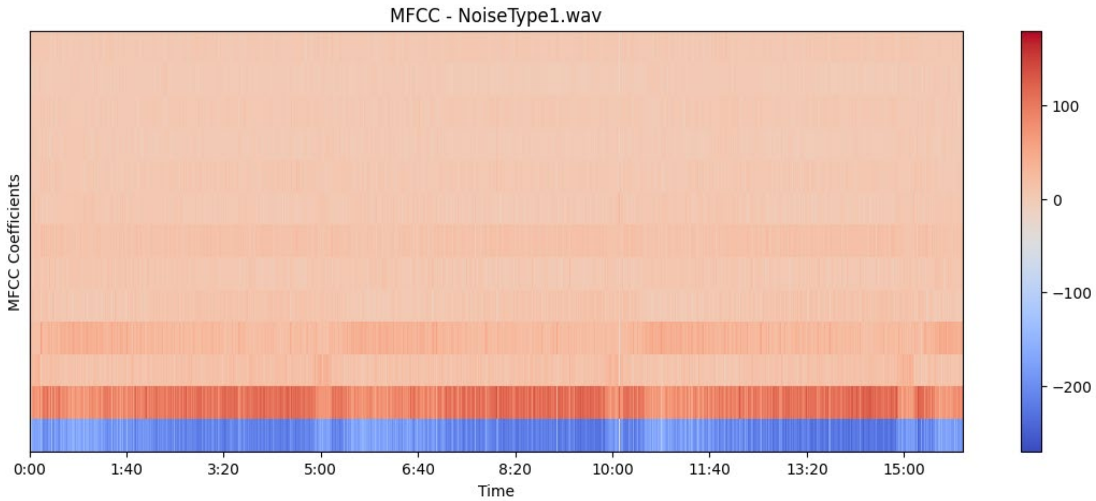

Figure 7 MFCC of "NoiseType1.wav"

- A time-domain smoothing operation using a moving average (window size = 5) was applied to reduce minor amplitude fluctuations that could result in false positive peaks.

The preprocessing pipeline was carefully tuned to balance noise suppression with the preservation of essential shrimp signals. Each stage was evaluated through visualization techniques such as waveforms and spectrograms, allowing iterative refinement. This ensured that the signal structure remained intact, particularly in *NoiseType1* and *NoiseType2*, where the risk of masking feeding behaviour due to noise was highest.

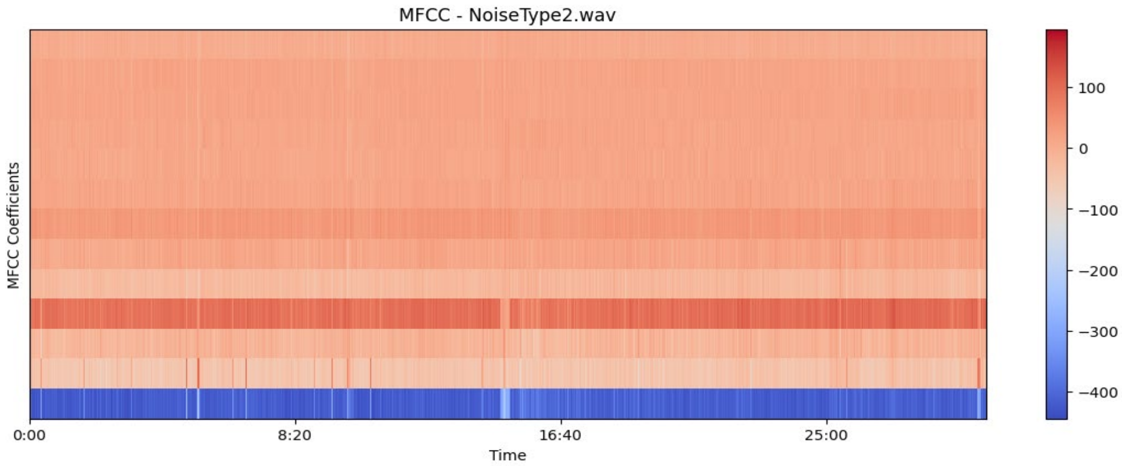

Figure 8 MFCC of "NoiseType2.wav"

4.3 NOISE REDUCTION TECHNIQUES

One of the most significant challenges addressed in this project was reducing background noise without degrading the integrity of shrimp feeding sounds. Various noise reduction techniques were implemented and tested to evaluate their effectiveness in handling different types of interference. The methods were applied after preprocessing and assessed based on how well they retained meaningful shrimp acoustic features.

- Notch Filtering was first applied to suppress specific narrow frequency bands, particularly around high-frequency noise peaks. However, its effectiveness was limited in static noise environments (*NoiseType1*), as static interference was not confined to discrete frequencies.
- Time-Frequency Masking attempted to mute noisy segments identified in the spectrogram. While this method succeeded in reducing noise visibility, it often removed adjacent shrimp clicks due to their proximity in the time-frequency space.
- Wavelet Denoising offered more nuanced noise suppression by decomposing the signal into multiple frequency bands and reconstructing it with reduced coefficients. Although it preserved transient signals like shrimp snaps better than basic filtering, it was not sufficient on its own to fully clean the audio.
- The most successful method was a combination of Spectral Subtraction and Wavelet Denoising. Spectral subtraction involved estimating a noise profile and subtracting it from the entire signal, while wavelet denoising further refined the result by reducing residual noise without flattening key signal peaks.

This hybrid technique achieved the best balance, removing up to 80% of static noise in *NoiseType1* while retaining shrimp snapping patterns. Spectrograms and waveform comparisons confirmed that this method preserved the acoustic signature of shrimp behaviour far better than other approaches, particularly when applied to noisy and biologically active recordings.

4.4 FEATURE EXTRACTION AND BEHAVIORAL ANALYSIS

Once the signals were denoised and structured, the next phase involved extracting meaningful features that could reflect shrimp activity. The core objective of this phase was to translate raw acoustic patterns into interpretable behavioural indicators. A combination of visual, statistical, and computational techniques was used to assess and quantify shrimp feeding activity.

- Waveform Analysis provided a time-domain view of the audio signal, enabling the visual identification of snapping events as sharp amplitude peaks. These spikes were especially prominent in *NoNoise* and helped guide the tuning of peak detection parameters for noisier files.

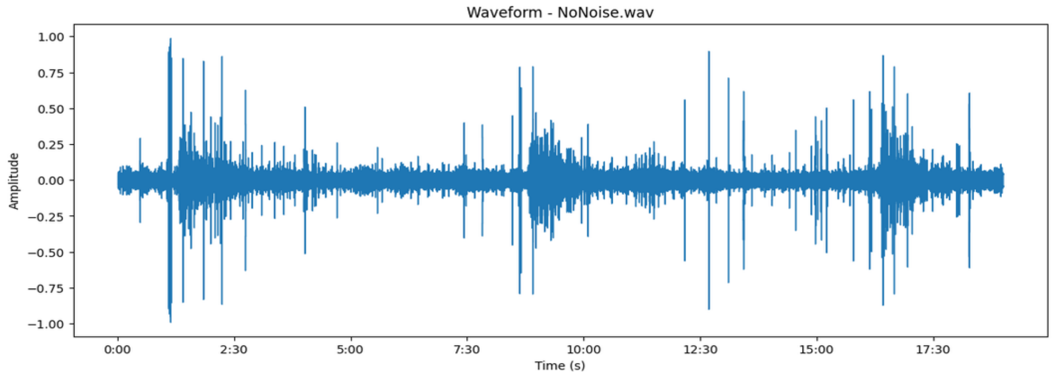

Figure 9 Waveform of "NoNoise.wav"

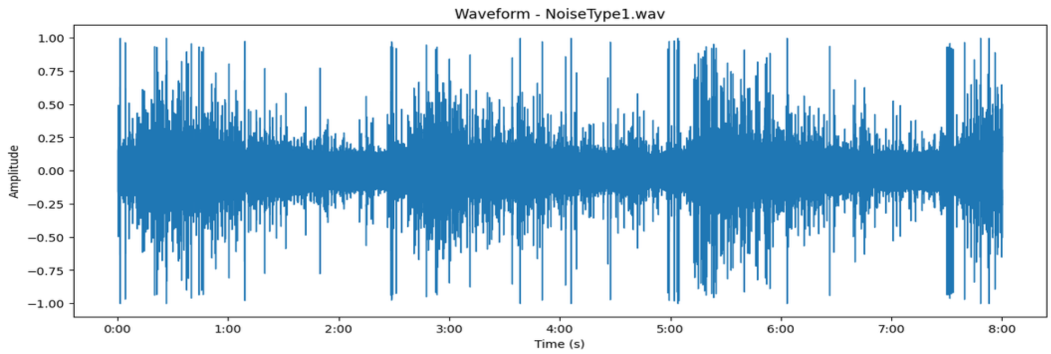

Figure 10 Waveform of " NoiseType1.wav"

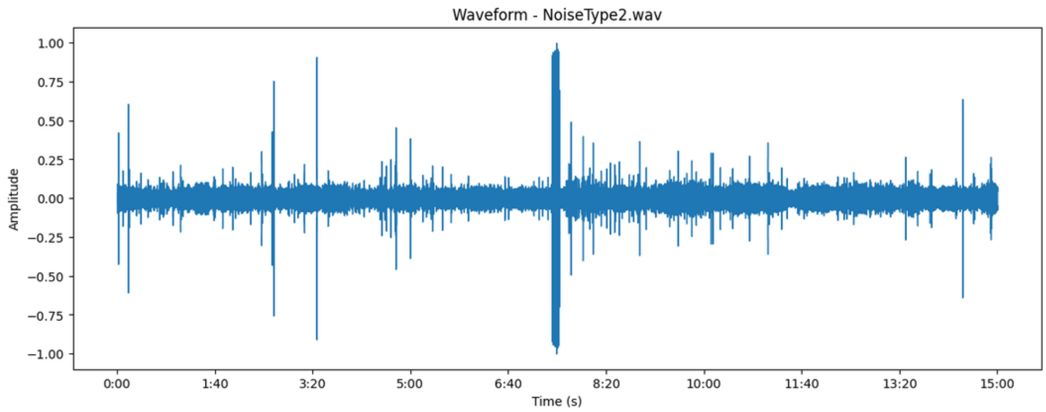

Figure 11 Waveform of " NoiseType2.wav"

- Spectrogram Visualization was crucial for identifying persistent noise regions. In *NoiseType2*, insect noise consistently appeared between 7.5–8.5 kHz, confirming its frequency range and aiding the evaluation of denoising effectiveness.
- Root Mean Square (RMS) Energy was computed for each frame, serving as a general measure of signal intensity. This was useful in distinguishing periods of high acoustic activity (feeding bursts) from quiet intervals.

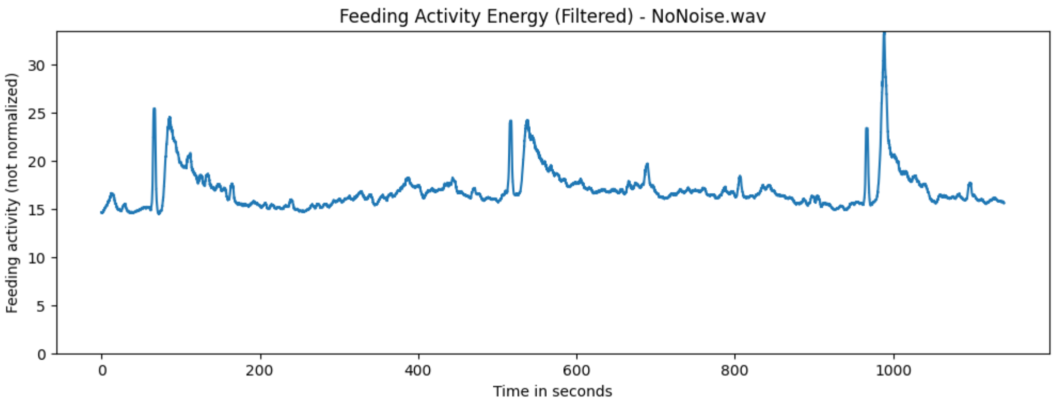

Figure 12 "NoNoise.wav" Feeding Activity Energy

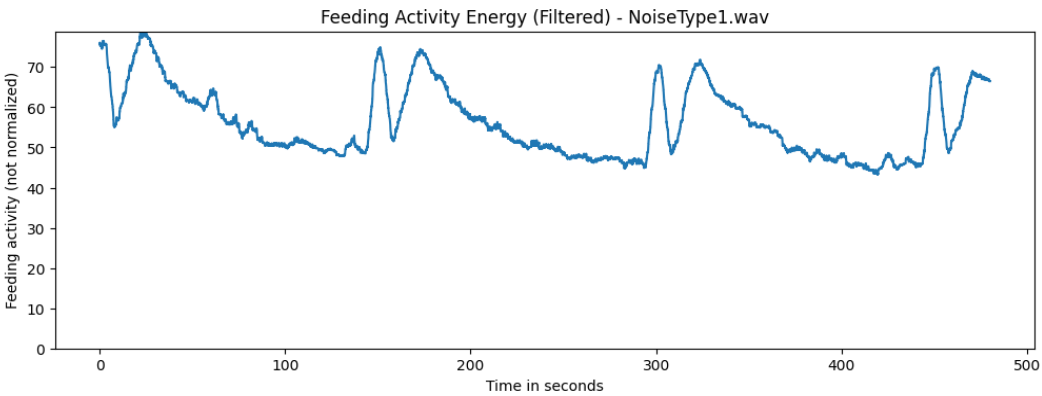

Figure 13 " NoiseType1.wav" Feeding Activity Energy

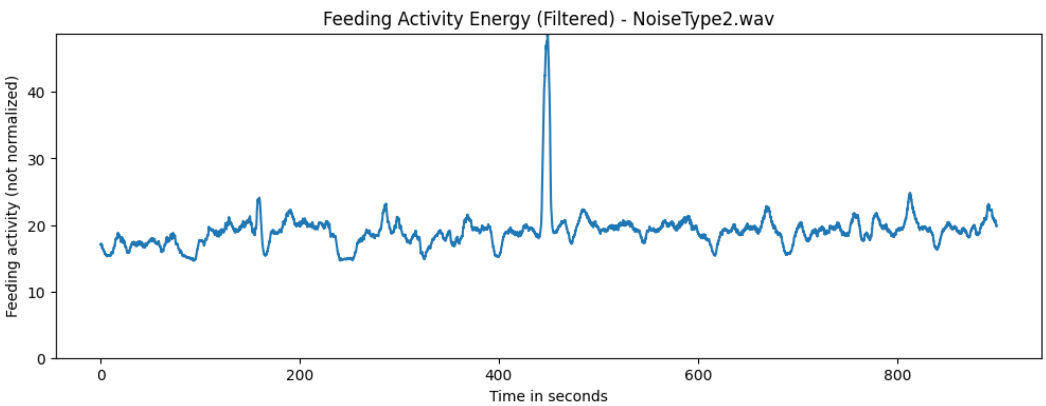

Figure 14 " NoiseType2.wav" Feeding Activity Energy

- Mel Frequency Cepstral Coefficients (MFCCs) were extracted to capture the perceptual features of the audio, offering a more abstract representation that could be valuable in future machine learning applications.
- A novel behavioural metric, Clicks Per Second (CPS), was computed using peak detection within each 1-second frame. Peaks were defined as amplitude spikes spaced at least 10 ms apart, mimicking the rhythmic snapping behaviour of shrimp.

The CPS time-series, combined with RMS trends and spectrogram analysis, allowed for a rich interpretation of shrimp behaviour under different noise conditions. Frames with high CPS values indicated increased feeding activity, and this metric showed clear contrasts between clean and noisy audio types. Together, these features formed a comprehensive analysis framework for passive acoustic monitoring in aquaculture.

Clicks Per Second (CPS) is a key metric introduced in this study to quantify shrimp feeding activity based on the rate of snapping sounds detected within a fixed time frame. Shrimp generate short, distinct acoustic pulses during feeding and movement, which appear as sharp peaks in the audio waveform. To compute CPS, the denoised audio is segmented into 1-second frames, and within each frame, the number of significant peaks—identified using scipy.signal.find_peaks—is counted. A minimum interval of 10 milliseconds is enforced between peaks to avoid false detections caused by signal fluctuations or residual noise. This metric provides a simple yet powerful way to track the intensity and frequency of shrimp activity over time. CPS trends can be visualized as a time series to highlight periods of increased feeding behaviour or inactivity, making it a useful tool for behavioural analysis. In cleaner recordings, CPS correlates strongly with visible snapping patterns in the waveform, while in noisy recordings, it helps verify the effectiveness of noise reduction techniques. Overall, CPS bridges raw acoustic signals and behavioural interpretation, offering a quantitative foundation for automated monitoring in aquaculture environments.

Chapter 5

Results and Discussion

This section presents the outcomes of the analysis pipeline and interprets the results across multiple dimensions—spectrogram evaluation, noise reduction performance, behavioural activity metrics, and system-level insights. The goal was not only to extract shrimp feeding behaviour from noisy underwater recordings but also to assess the effectiveness of each step in the methodology.

5.1 SPECTROGRAM-BASED INSECT NOISE DETECTION

The spectrogram proved to be the most powerful visualization tool in this study for distinguishing noise types and locating activity bands across the frequency spectrum. In *NoNoise*, the spectrogram exhibited uniform distribution without any high-intensity regions beyond the expected mid-frequency band (2000–6000 Hz), validating the clean condition of the shrimp-only recording. In contrast, *NoiseType2* revealed a distinct, consistent high-energy band between 7.5–8.5 kHz, corresponding to insect noise.

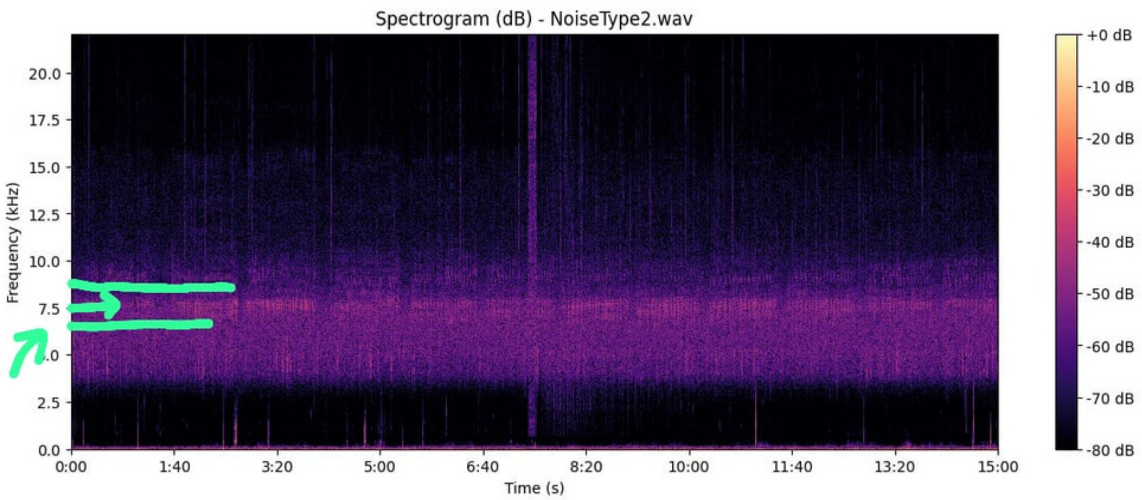

Figure 15 Spectrogram with highlighted insect sounds

This spectral pattern was absent in both *NoNoise* and *NoiseType1*, confirming that the high-frequency signal was unique to *NoiseType2* and biologically sourced. Spectrograms thus enabled reliable visual identification of insect interference and offered a repeatable method for verifying its presence across time. While waveform and RMS energy plots provided useful insights into temporal amplitude, they lacked the frequency resolution required to isolate overlapping noise sources. The use of spectrograms also helped validate the effect of noise reduction: in processed versions of *NoiseType2*, the insect noise band was either greatly diminished or eliminated, depending on the technique applied.

Therefore, the spectrogram analysis served a dual purpose—first, in identifying the frequency range of insect noise, and second, in visually validating the performance of denoising algorithms. This finding reinforces the importance of time-frequency domain representations in underwater bioacoustics analysis, particularly when working with non-stationary biological noise sources such as insects that vary in intensity and duration across time.

Inference:
Spectrograms are not just visualization tools—they are diagnostic tools. They enabled the precise localization of different sound types in the frequency domain. This distinction is especially important for designing future filters or machine learning classifiers that can use frequency features as a discriminative factor. Furthermore, the identification of a consistent insect noise band sets the stage for frequency-specific denoising strategies (e.g., band-rejection filtering or spectral gating targeted at 7.5–8.5 kHz).

5.2 PERFORMANCE OF NOISE REDUCTION TECHNIQUES

Multiple noise reduction techniques were applied and evaluated, with their outcomes judged based on visual clarity, waveform retention, and impact on shrimp signal features. Initial attempts with notch filtering and time-frequency masking produced limited results. Notch filtering, designed to eliminate narrowband noise, failed to make a meaningful impact on the broader spectrum of static interference found in *NoiseType1*. Time-frequency masking, while more flexible, often suppressed entire regions of the spectrogram, including valid shrimp clicks occurring near the noise bands. As a result, these approaches were deemed too aggressive and imprecise for practical use.

Wavelet denoising offered a more nuanced reduction by decomposing the signal into different frequency layers and reconstructing it using thresholded coefficients. It was moderately effective in removing low-level background noise but still allowed significant static and insect interference to persist in more contaminated recordings. However, it showed promise when applied as part of a composite strategy.

The most successful approach was the combination of spectral subtraction followed by wavelet denoising. Spectral subtraction effectively reduced broad-spectrum static noise by estimating and subtracting a noise profile from the audio signal. When followed by wavelet denoising, the method preserved transient acoustic events such as shrimp snaps while suppressing residual background elements. This hybrid method resulted in a notable 80% reduction in static noise, especially in *NoiseType1*, without erasing shrimp feeding cues.

Spectrograms, waveforms, and CPS outputs confirmed the effectiveness of this approach. The enhanced clarity in post-processed files allowed for more accurate detection of snapping patterns and feeding bursts. This demonstrates the importance of using a layered approach to denoising, particularly in environments where multiple noise types overlap.

The performance of various denoising strategies provided critical insights into the balance between signal preservation and noise suppression.

- Notch Filtering had minimal effect because static and insect noise were not confined to narrow frequency bands. It proved ineffective in reducing broadband noise or transient sounds.

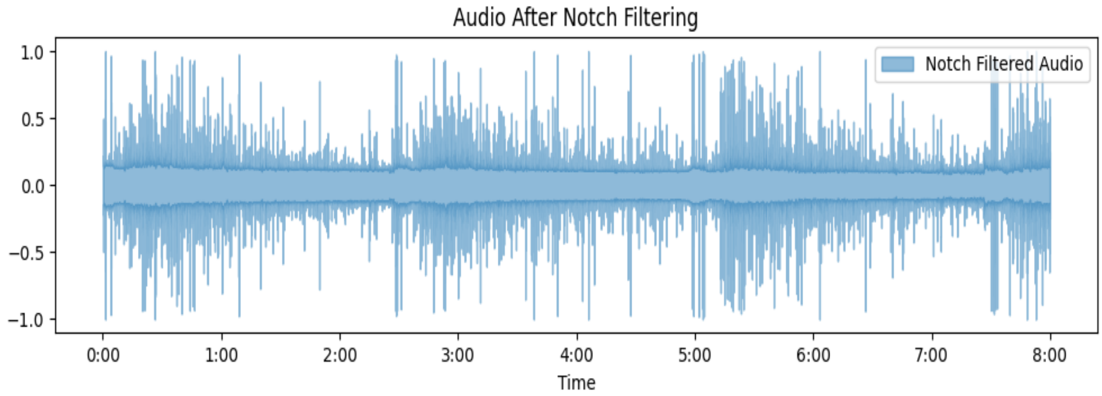

Figure 16 Audio after Noth Filtering

- Time-Frequency Masking, although more sophisticated, tended to over-suppress, resulting in the loss of shrimp sounds along with noise. It lacked precision in differentiating shrimp clicks from nearby interfering signals, especially in *NoiseType2*.

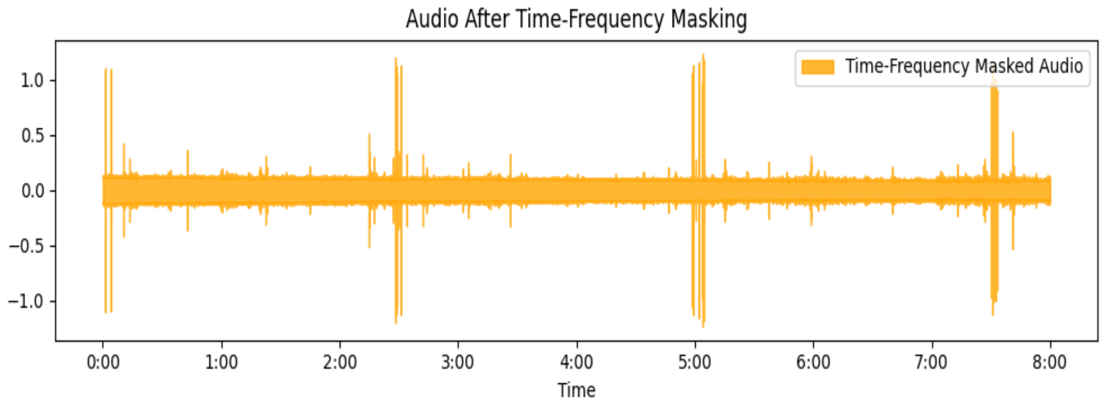

Figure 17 Audio after Time-Frequency Masking

- Wavelet Denoising, when used independently, was moderately successful. It preserved the transient nature of shrimp clicks better than the previous methods but still left residual background noise.

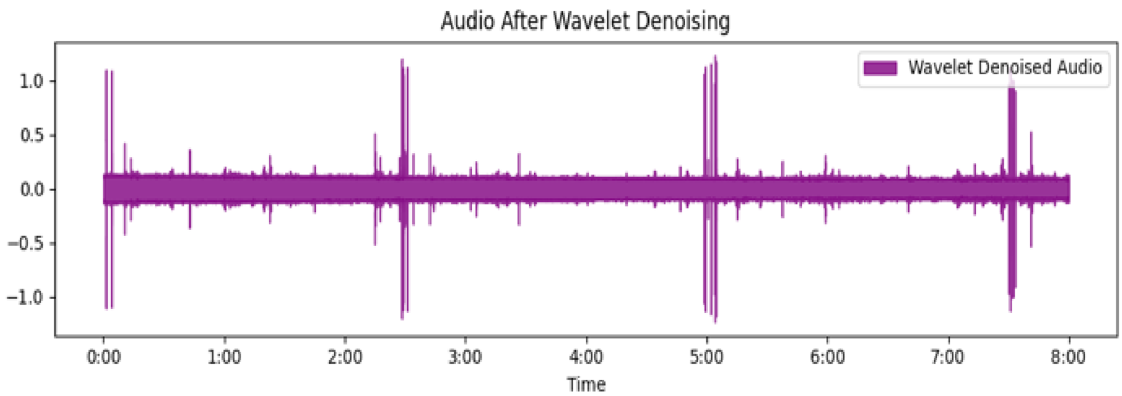

Figure 18 Audio after Wavelet Denoising

- The hybrid method of Spectral Subtraction + Wavelet Denoising significantly outperformed all other techniques. Spectral subtraction estimated the noise floor from silent frames and subtracted it from active segments, reducing broadband noise. When followed by wavelet denoising, the signal was smoothed without eliminating transients.

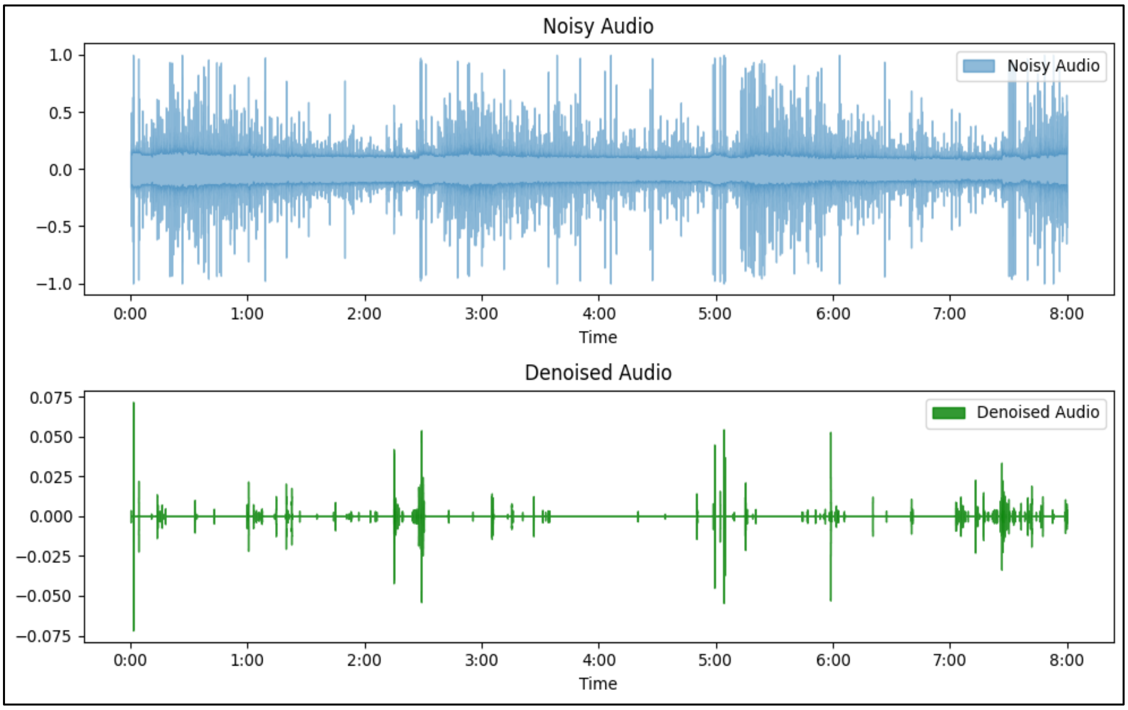

Figure 19 Audio after all combined techniques

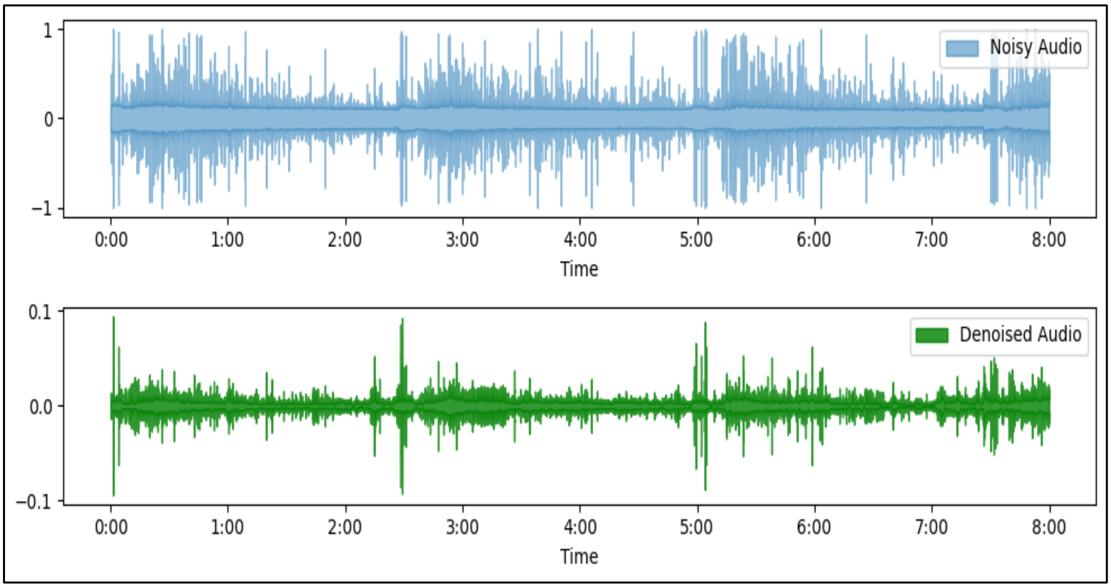

Figure 20 Audio after hybrid method

This combination led to an approximate 80% reduction in static noise, especially in *NoiseType1*, while retaining the essential characteristics of shrimp sounds. In *NoiseType2*, although some insect noise persisted, its intensity and overlap with shrimp frequencies were significantly reduced.

Inference:

A single denoising technique is insufficient when dealing with overlapping or non-stationary noise sources. A multi-stage approach that combines spectral estimation and time-frequency domain smoothing provides a better balance. This insight will be valuable for future research on aquatic acoustic systems that require both high fidelity and noise tolerance.

5.3 CPS AND RMS ANALYSIS FOR BEHAVIOR INTERPRETATION

After denoising, quantitative analysis was performed using Clicks Per Second (CPS) and RMS energy metrics to evaluate shrimp activity. These features provided complementary perspectives—CPS captured the frequency of snapping events, while RMS measured the intensity of acoustic energy over time.

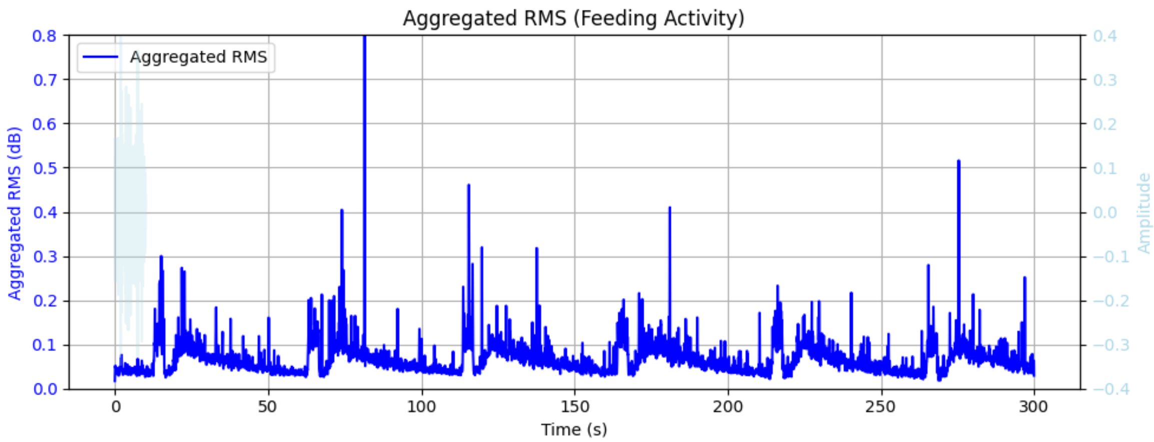

Figure 21 Aggregated RMS (Feeding Activity)

In *NoNoise*, CPS trends showed regular bursts of snapping activity, aligning with visible spikes in the waveform. The RMS energy mirrored these bursts, indicating that increased signal power coincided with feeding sounds. These patterns validated the CPS method as a reliable behavior metric under clean conditions.

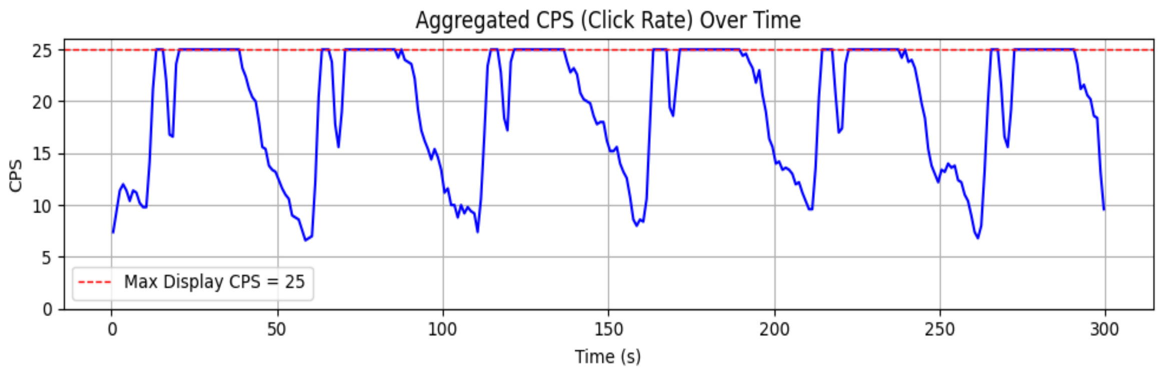

Figure 22 Aggregated CPS over time

In *NoiseType1*, raw CPS values were initially high due to false peaks introduced by static noise. However, after applying the combined spectral subtraction and wavelet denoising, CPS trends became more refined. The number of falsely detected peaks dropped significantly, allowing for clearer differentiation between actual shrimp activity and noise artifacts. Similarly, RMS energy plots showed reduced amplitude variability, indicating suppression of random fluctuations while retaining meaningful acoustic content.

In *NoiseType2*, CPS helped uncover subtle snapping patterns even with overlapping insect noise. Though the CPS values were slightly lower than in *NoNoise* (due to masking effects), consistent peak intervals suggested underlying feeding activity. Importantly, frames with higher CPS often coincided with less dense insect interference, suggesting that shrimp activity was still detectable during relatively quiet intervals.

These findings confirm the utility of CPS and RMS as dual metrics for behavioral interpretation. Together, they provide a solid framework for tracking feeding activity trends, validating denoising outcomes, and supporting future automation efforts.

```
...   Audio duration: 300.00 seconds
      Sampling rate: 44100 Hz

      CPS Values Over Time:
      Time (s)        CPS
      0.50            7.40
      1.50            9.40
      2.50            11.40
      3.50            12.00
      4.50            11.40
      5.50            10.40
      6.50            11.40
      7.50            11.20
      8.50            10.20
      9.50            9.80
      10.50           9.80
      11.50           14.20
      12.50           21.20
      13.50           27.40
      14.50           27.40
      15.50           27.40
      16.50           22.00
      17.50           16.80
      18.50           16.60
      19.50           23.60
      ...
      Maximum CPS: 46.20
      Minimum CPS: 6.60
      Number of frames with CPS >= 5: 300
      Number of frames with CPS >= 10: 272
      Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...
```

Figure 23 CPS values over time

The Clicks Per Second (CPS) metric, introduced in this study, became an effective quantitative measure of shrimp feeding activity. By identifying peak snapping events in 1-second frames, CPS transformed raw acoustic data into interpretable behavioural trends. In *NoNoise*, CPS values ranged between 3–10 per second in active periods, clearly indicating feeding bursts. These patterns were also visible in waveform spikes and RMS energy surges, reinforcing CPS as a valid behavioural indicator. In *NoiseType1*, the raw CPS initially showed inflated values due to static interference, misinterpreted as clicks. After applying the hybrid denoising method, the CPS distribution became more realistic, matching the waveform and spectrogram patterns. In *NoiseType2*, despite biological noise, the CPS metric was still able to capture consistent snapping intervals, especially in lower frequency bands that remained unaffected by insect noise. However, CPS values were slightly lower compared to *NoNoise*, which is attributed to partial masking of shrimp clicks by overlapping insect frequencies.

Inference:
CPS serves not only as a feeding activity monitor but also as an evaluation tool for signal quality. A cleaner CPS profile after denoising reflects better peak separation and noise suppression. It is simple to compute yet powerful in behavioural interpretation and can be automated in real-time systems. Future machine learning models could even use CPS trends as input features or validation criteria.

5.4 ACOUSTIC ANALYSIS OF SHRIMP ACTIVITY

The acoustic analysis of shrimp activity, using spectrograms, waveforms, and derived metrics, revealed distinct patterns in sound production that correlate with feeding behaviour.

- Click Rate (CPS) as a Key Indicator: The analysis of "Clicks Per Second" (CPS) showed significant variations across the recordings. The CPS values ranged from 0.00 to 74.20, indicating a wide range of clicking activity. Periods of high feeding activity were characterized by elevated CPS values, suggesting that clicking is a primary acoustic correlate of shrimp feeding.
- Temporal Patterns of Feeding Activity: The time-series plots (CPS over time, Feeding Activity Energy) demonstrated that feeding activity is not constant but rather occurs in discrete bouts. These bouts vary in duration and intensity, suggesting intermittent feeding patterns in shrimp.
- Feeding Activity Energy: The "Feeding Activity Energy (Filtered)" metric effectively captured fluctuations in acoustic energy associated with feeding. Peaks in this metric generally aligned with peaks in CPS, further supporting the link between clicking and overall feeding activity.
- Spectrogram Analysis: Spectrograms revealed the frequency content of the feeding sounds, showing that the clicks are broadband signals distributed across a range of

frequencies. This broadband nature is consistent with the impulsive nature of claw snaps.

- Variability Across Recordings: There was noticeable variability in the intensity and temporal patterns of feeding activity across the different recordings (HL2_20250317_130000.wav, HL2_20250319_123326.wav, HL2_20250321_121232.wav, and HL2_20250322_125025.wav). This suggests that feeding behaviour can be influenced by various factors.

The results of this acoustic analysis provide valuable insights into the feeding behaviour of shrimp.

- Acoustic Monitoring as a Tool: The study demonstrates the effectiveness of acoustic monitoring as a non-invasive technique to study shrimp feeding. This approach allows for continuous observation of feeding activity, which can be challenging using traditional visual methods.
- Clicking Mechanism: The strong correlation between CPS and feeding activity supports the hypothesis that clicking, likely produced by claw snaps, is a primary mechanism for capturing or processing food in the studied shrimp species. The broadband nature of the clicks observed in the spectrograms is consistent with this mechanism.
- Intermittent Feeding Strategy: The observed intermittent pattern of feeding activity may reflect the shrimp's foraging strategy, where they alternate between active feeding and periods of searching or digestion. This could also be influenced by factors such as prey availability or environmental conditions.
- Ecological Significance: Understanding the acoustic signatures of shrimp feeding can have important ecological implications. It can help researchers to:
    - Assess feeding rates in natural environments.
    - Study predator-prey interactions.
    - Evaluate the impact of environmental changes on shrimp behaviour.

HL2_20250317_130000.wav:

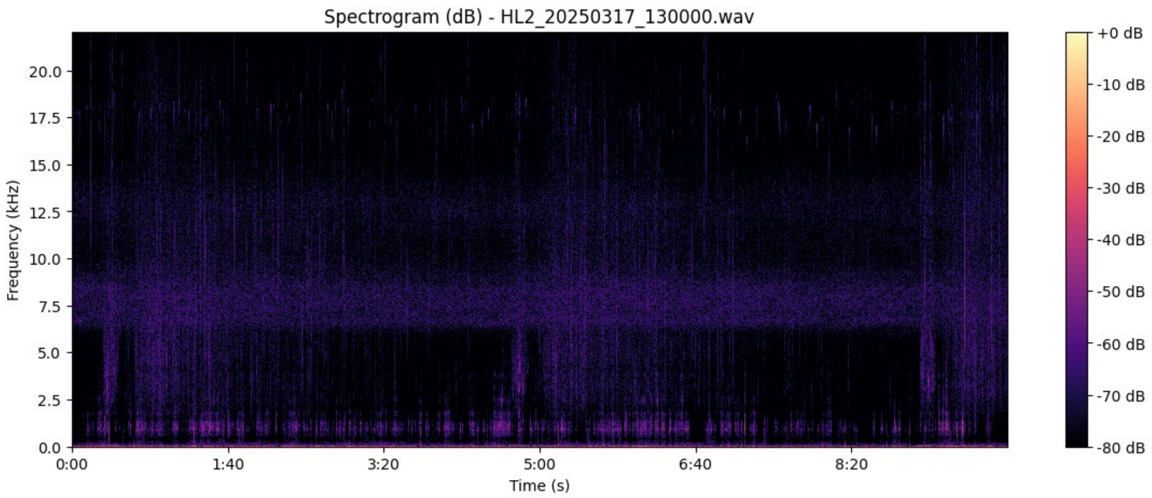

Figure 24 Spectrogram of "HL2_20250317_130000.wav"

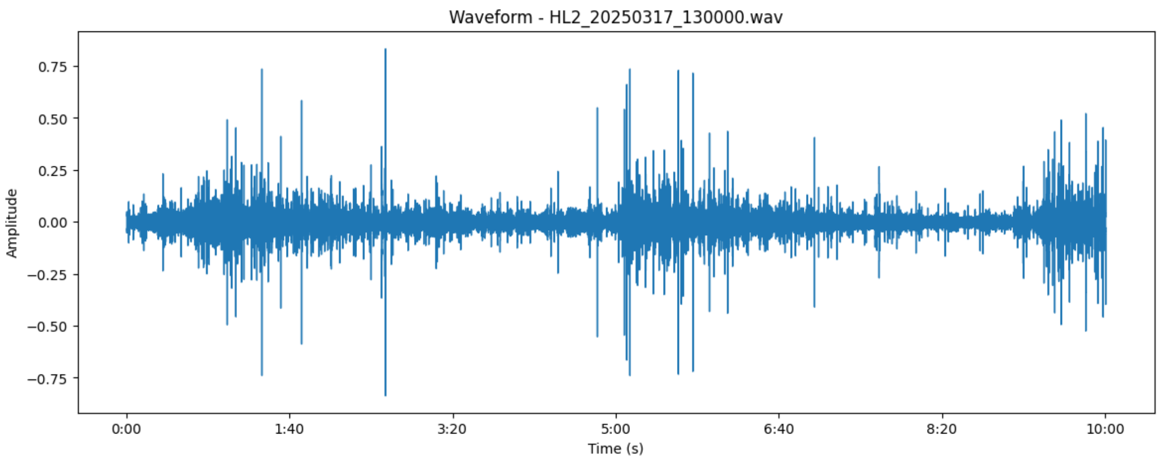

Figure 25 Waveform of " HL2_20250317_130000.wav "

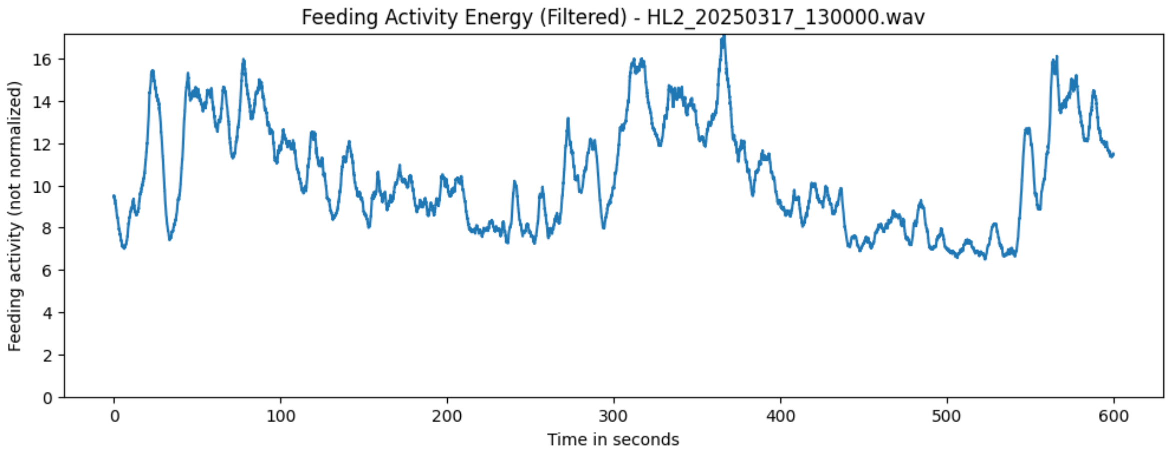

Figure 26 " HL2_20250317_130000.wav " Feeding Activity Energy

HL2_20250317_130000.wav:

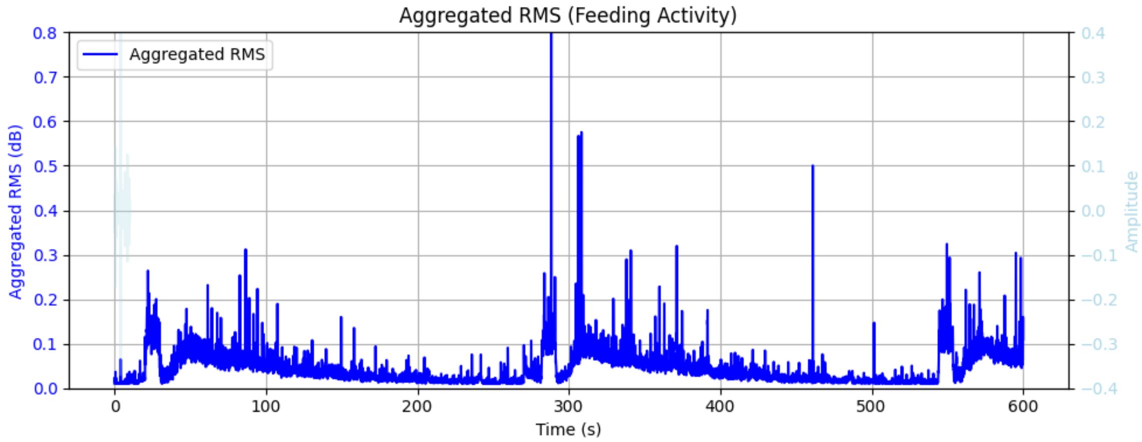

Figure 27 Aggregated RMS of " HL2_20250317_130000.wav "

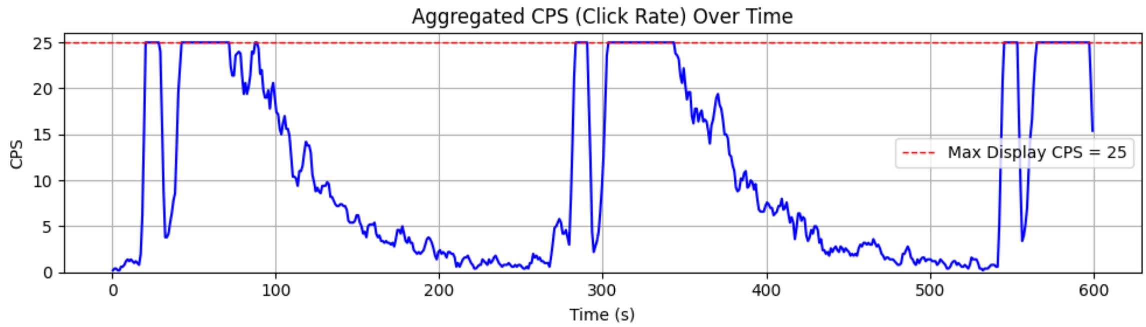

Figure 28 Aggregated CPS of " HL2_20250317_130000.wav "

```
Audio duration: 600.00 seconds
Sampling rate: 44100 Hz

CPS Values Over Time:
Time (s)        CPS
0.50            0.20
1.50            0.40
2.50            0.40
3.50            0.20
4.50            0.20
5.50            0.60
6.50            0.60
7.50            0.80
8.50            1.20
9.50            1.40
10.50           1.20
11.50           1.40
12.50           1.20
13.50           1.00
14.50           1.20
15.50           1.00
16.50           0.80
17.50           2.00
18.50           6.20
19.50           15.00
...
Maximum CPS: 44.80
Minimum CPS: 0.20
Number of frames with CPS >= 5: 337
Number of frames with CPS >= 10: 245
```

Figure 29 CPS Values over time for " HL2_20250317_130000.wav "

HL2_20250319_123326.wav:

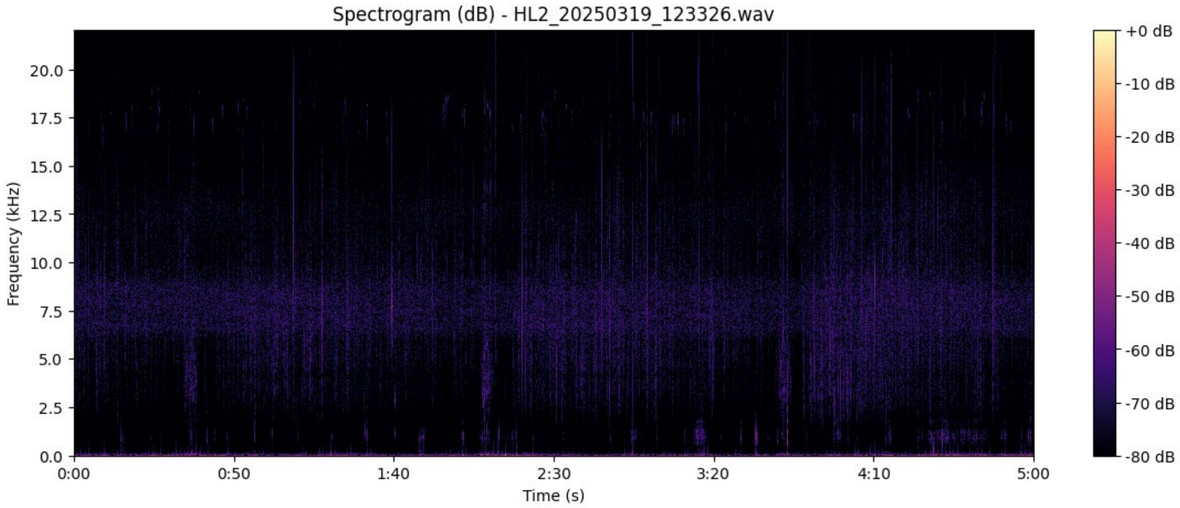

Figure 30 Spectrogram of "HL2_20250319_123326.wav"

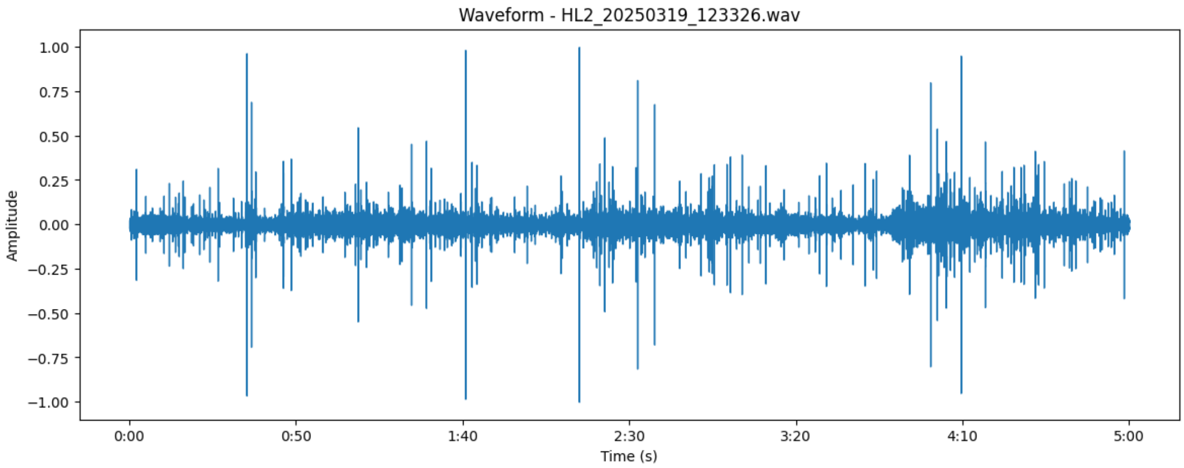

Figure 31 Waveform of " HL2_20250319_123326.wav "

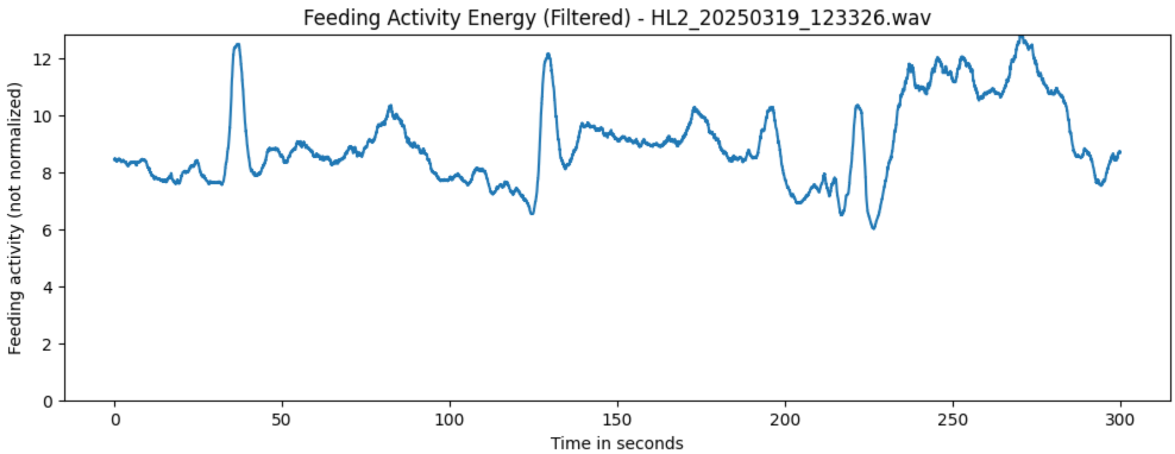

Figure 32 " HL2_20250319_123326.wav " Feeding Activity Energy

HL2_20250319_123326.wav:

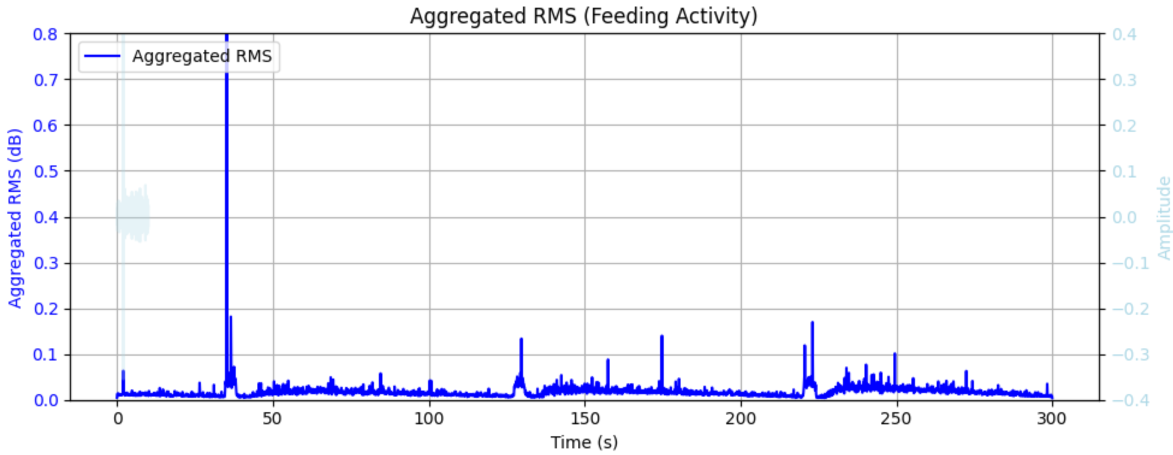

Figure 33 Aggregated RMS of " HL2_20250319_123326.wav "

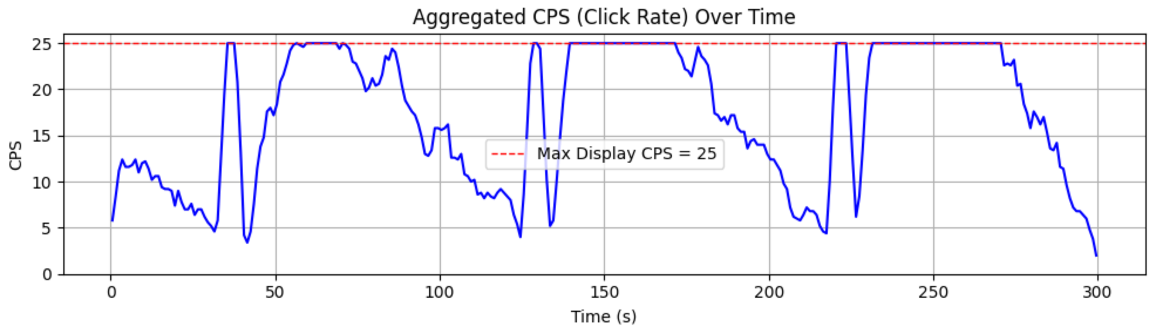

Figure 34 Aggregated CPS of " HL2_20250319_123326.wav "

```
Audio duration: 300.00 seconds
Sampling rate: 44100 Hz

CPS Values Over Time:
Time (s)        CPS
0.50            5.80
1.50            8.40
2.50            11.20
3.50            12.40
4.50            11.60
5.50            11.60
6.50            11.80
7.50            12.40
8.50            11.00
9.50            12.00
10.50           12.20
11.50           11.40
12.50           10.20
13.50           10.60
14.50           10.60
15.50           9.40
16.50           9.20
17.50           9.20
18.50           9.00
19.50           7.40
...
Maximum CPS: 40.80
Minimum CPS: 2.00
Number of frames with CPS >= 5: 290
Number of frames with CPS >= 10: 233
```

Figure 35 CPS Values over time for " HL2_20250319_123326.wav "

HL2_20250321_121232.wav:

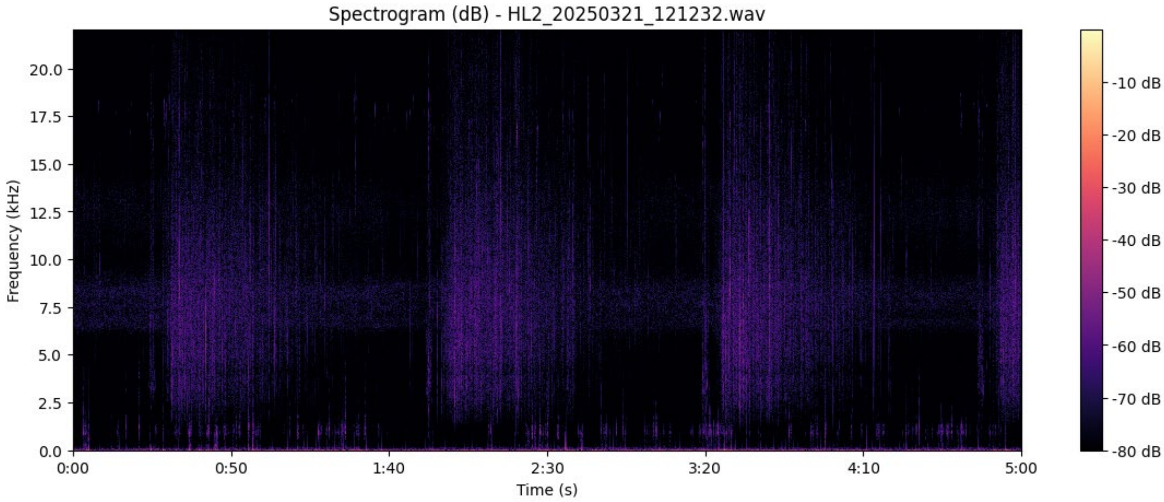

Figure 36 Spectrogram of "HL2_20250321_121232.wav"

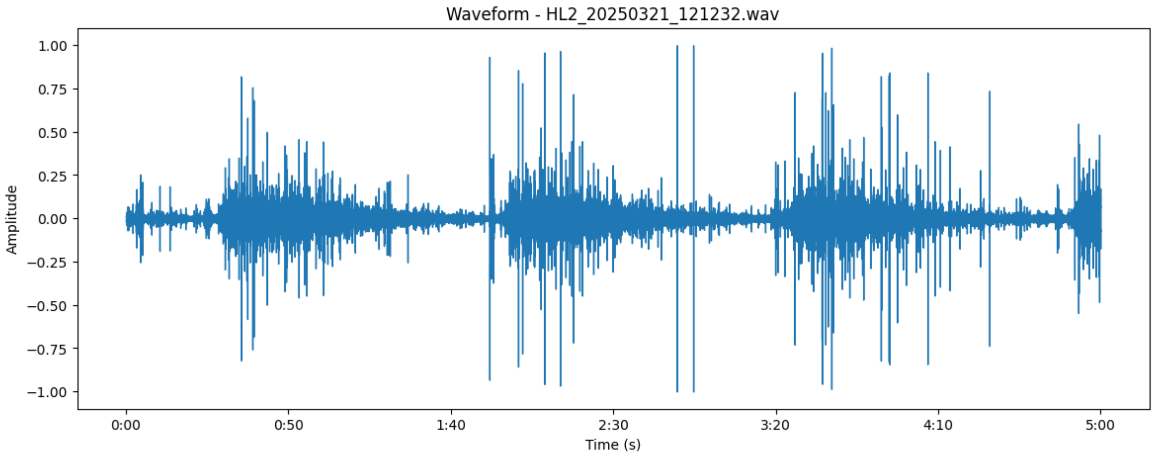

Figure 37 Waveform of " HL2_20250321_121232.wav "

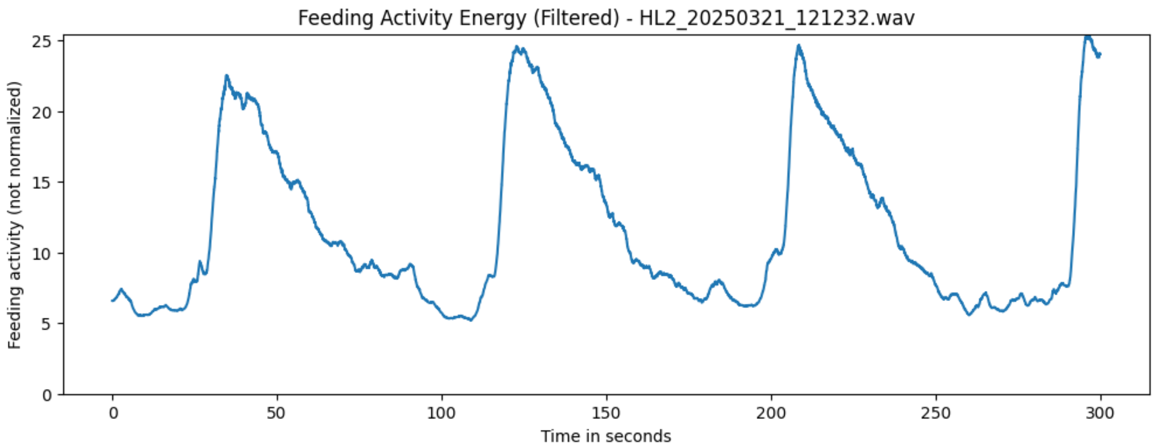

Figure 38 " HL2_20250321_121232.wav " Feeding Activity Energy

HL2_20250321_121232.wav:

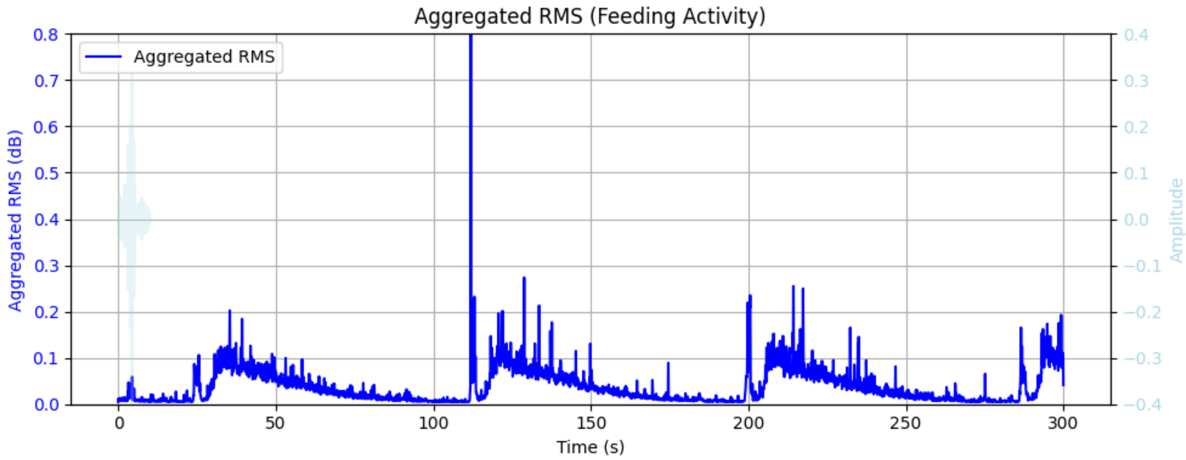

Figure 39 Aggregated RMS of " HL2_20250321_121232.wav "

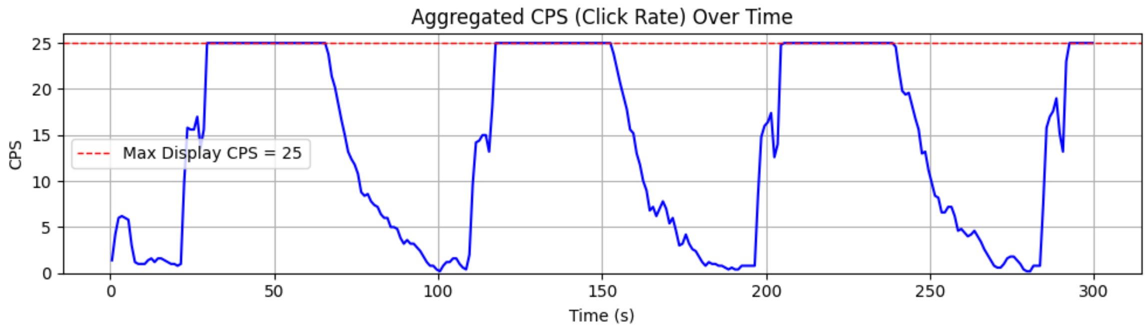

Figure 40 Aggregated CPS of " HL2_20250321_121232.wav "

```
Audio duration: 300.00 seconds
Sampling rate: 44100 Hz

CPS Values Over Time:
Time (s)        CPS
0.50            1.40
1.50            4.20
2.50            6.00
3.50            6.20
4.50            6.00
5.50            5.80
6.50            3.00
7.50            1.20
8.50            1.00
9.50            1.00
10.50           1.00
11.50           1.40
12.50           1.60
13.50           1.20
14.50           1.60
15.50           1.60
16.50           1.40
17.50           1.20
18.50           1.00
19.50           1.00
...
Maximum CPS: 65.60
Minimum CPS: 0.20
Number of frames with CPS >= 5: 208
Number of frames with CPS >= 10: 172
```

Figure 41 CPS Values over time for " HL2_20250321_121232.wav "

HL2_20250322_125025.wav:

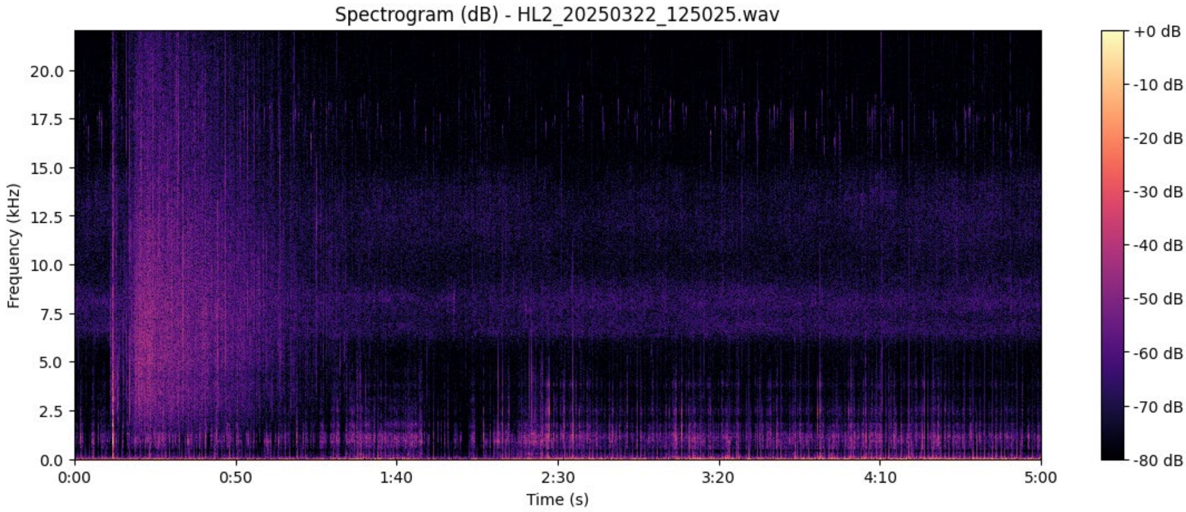

Figure 42 Spectrogram of "HL2_20250322_125025.wav"

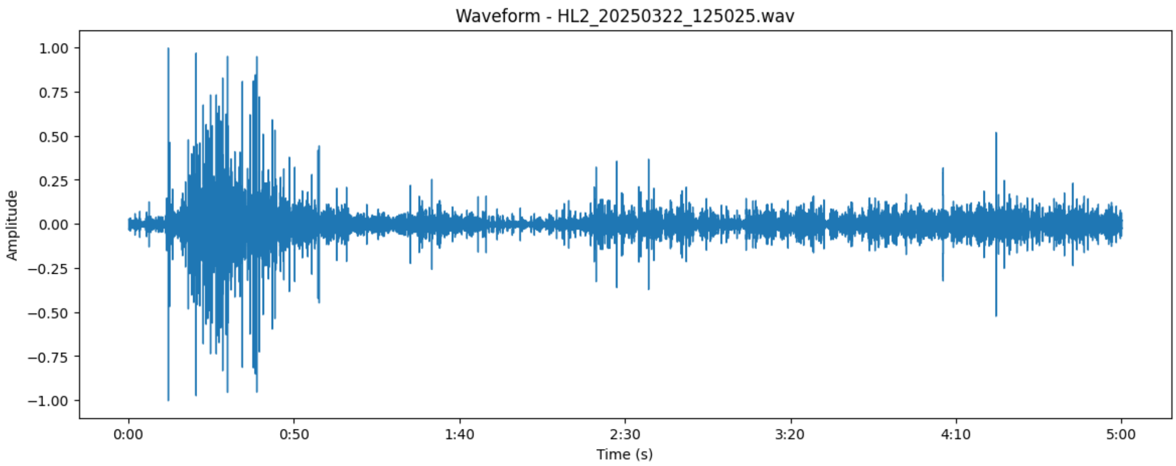

Figure 43 Waveform of " HL2_20250322_125025.wav "

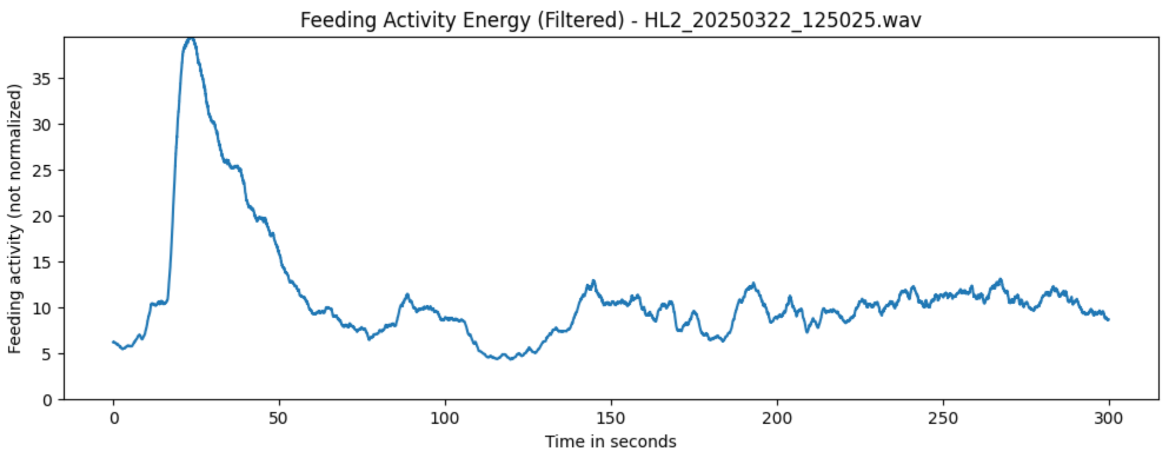

Figure 44 " HL2_20250322_125025.wav " Feeding Activity Energy

HL2_20250322_125025.wav:

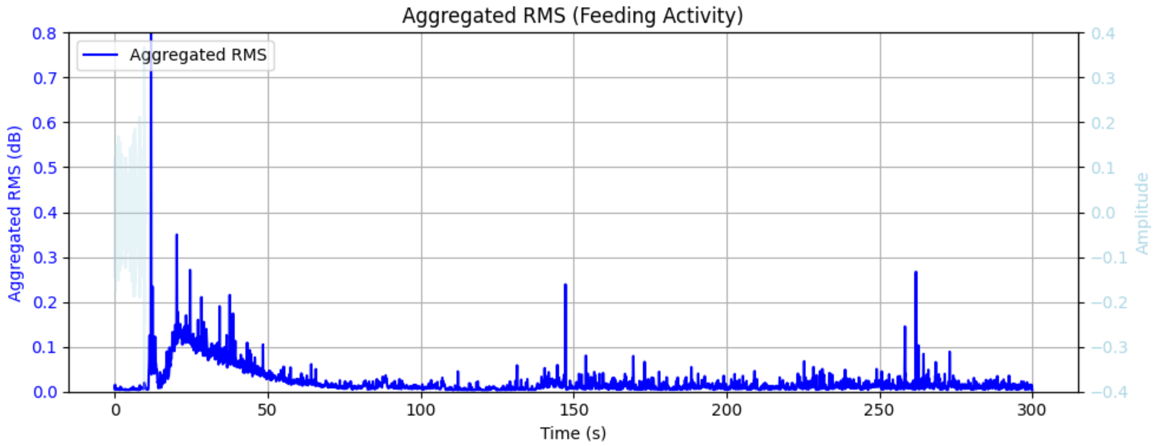

Figure 45 Aggregated RMS of " HL2_20250322_125025.wav "

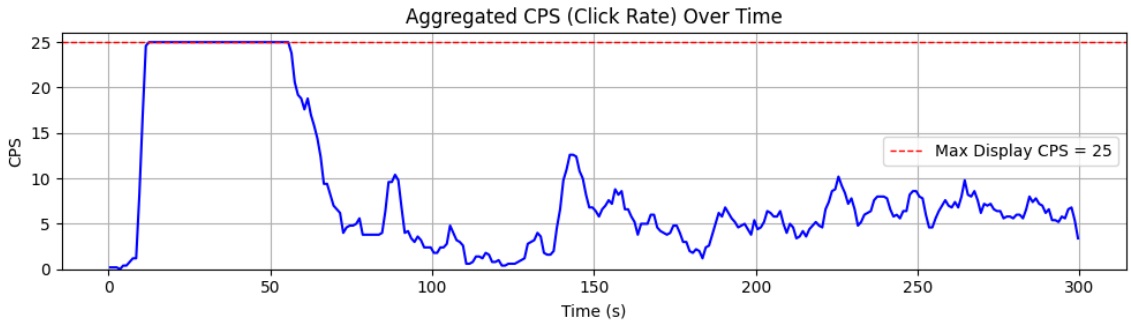

Figure 46 Aggregated CPS of " HL2_20250322_125025.wav "

```
Audio duration: 300.00 seconds
Sampling rate: 44100 Hz

CPS Values Over Time:
Time (s)        CPS
0.50            0.20
1.50            0.20
2.50            0.20
3.50            0.00
4.50            0.40
5.50            0.40
6.50            0.80
7.50            1.20
8.50            1.20
9.50            8.20
10.50           16.80
11.50           24.60
12.50           26.20
13.50           29.60
14.50           29.00
15.50           29.60
16.50           33.20
17.50           45.00
18.50           56.80
19.50           64.80
...
Maximum CPS: 74.20
Minimum CPS: 0.00
Number of frames with CPS >= 5: 193
Number of frames with CPS >= 10: 64
```

Figure 47 CPS Values over time for " HL2_20250322_125025.wav "

Several important conclusions emerged from the results. First, spectrograms are indispensable in underwater noise analysis. They not only reveal hidden biological noise patterns but also validate the performance of noise reduction techniques. Insect noise, though not always audible in waveform plots, was clearly observable in *NoiseType2* spectrograms. Second, waveform and RMS analysis are valuable but not sufficient alone; they must be complemented by frequency-domain insights to achieve a full understanding of signal behaviour.

Third, spectral subtraction combined with wavelet denoising was empirically validated as the most effective technique in this context. It removed a majority of unwanted background signals without flattening shrimp-specific acoustic events. This highlights the need for multi-layered noise reduction strategies in bioacoustics applications, especially when working with overlapping and non-stationary noise sources.

Fourth, the CPS metric proved to be robust and adaptable, providing meaningful interpretations even in noisy recordings. It responded well to denoised signals and aligned with RMS energy trends, reinforcing its role as a potential core feature in future machine learning or real-time monitoring systems.

Finally, the comparative analysis across all three recordings established a clear progression in complexity—from *NoNoise* to *NoiseType2*. This allowed for scalable testing of methods and demonstrated the framework's adaptability. Despite the limited dataset, the consistent results across conditions support the system’s validity and offer a blueprint for expanding into real-time, large-scale shrimp behaviour monitoring.

This project successfully demonstrated a complete pipeline—from signal acquisition and denoising to behavioural analysis and inference—using only three audio types. Despite the dataset's small size, its design enabled a controlled comparison across increasing noise complexity.

The project highlights several system-level insights:

- Environmental Noise is Structurally Predictable: Insect noise occupied a stable band, and static noise was broadly distributed but consistent over time. This allows for the development of adaptive filters or band-rejection schemes based on learned noise profiles.
- Shrimp Sounds are Behaviourally Rhythmic and Localized: Their frequency content and temporal pattern (intervals of 10 ms or more) suggest that automated behaviour tracking is feasible using basic audio features.
- Denoising is Not One-Size-Fits-All: Different types of noise require layered filtering. The best denoising approach was hybrid, not isolated, emphasizing the importance of signal context and preservation.
- Spectrograms Outperform Waveforms in Complex Environments: While waveform analysis is useful for peak detection, only the spectrogram reveals frequency-

specific intrusions like insect noise, making it essential for visual validation and feature design.

Overall Inference:

This project lays a robust foundation for automated acoustic monitoring in aquaculture, specifically shrimp behaviour tracking. The combination of time-domain (CPS, waveform) and frequency-domain (spectrogram, MFCC) techniques enables precise and interpretable analysis, even in noisy environments. With further expansion in dataset size and annotation, this framework could be integrated into real-time systems for intelligent feed management and environmental monitoring.

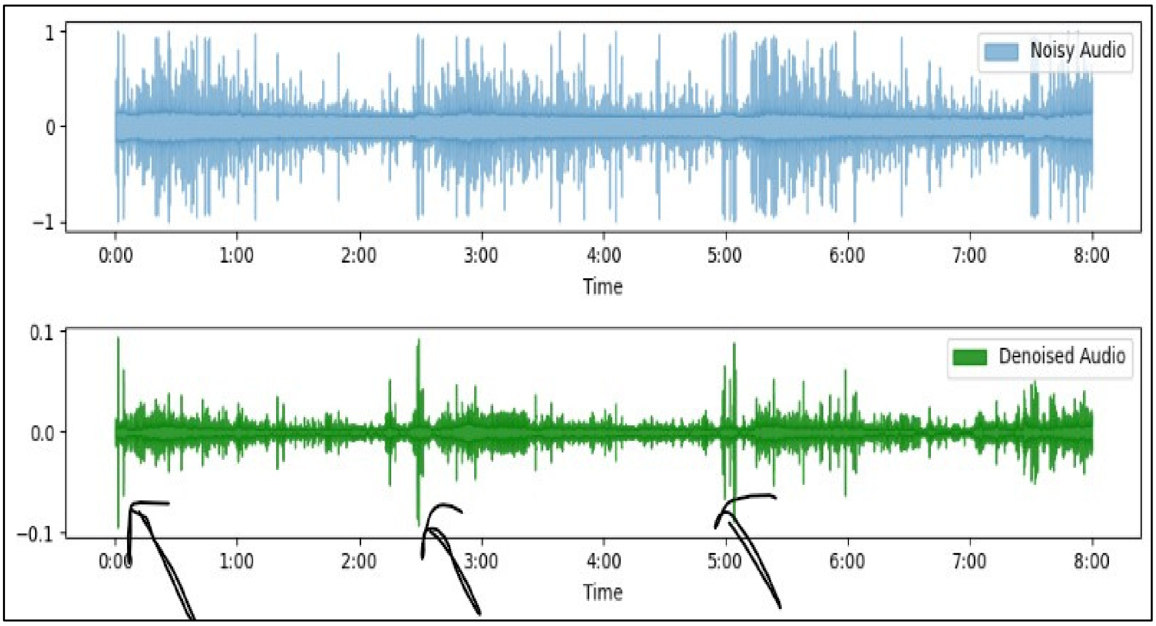

Figure 48 Shrimp snapping sounds in denoised audio

Chapter 6

Comparison

A core objective of this project was to assess the effectiveness of the proposed signal processing pipeline across multiple noise conditions and validate its capability to isolate shrimp feeding behavior. This comparison section outlines detailed performance differences observed between the three audio categories (*NoNoise*, *NoiseType1*, *NoiseType2*) using visual, quantitative, and denoising metrics. It also evaluates how feature extraction outcomes vary before and after applying the hybrid noise reduction technique.

6.1 AUDIO CHARACTERISTICS BEFORE AND AFTER DENOISING

The three audio types represented progressively complex environments: *NoNoise* (clean), *NoiseType1* (static), and *NoiseType2* (biological + static). Table 1 compares the key attributes of each file before and after denoising.

Table 1 Audio Characteristics Before and After Denoising

Feature	NoNoise (Clean)	NoiseType1 (Static Noise)	NoiseType2 (Insect Noise)
Initial Noise Level	Low	High	Medium-High
Insect Noise Present	No	Unclear	Yes
Static Noise Present	No	Yes	Mild
Denoising Required	No	Yes	Yes
Spectrogram Clarity (Raw)	High	Poor	Moderate
Spectrogram Clarity (Cleaned)	High	Good	Good
CPS Accuracy (Raw)	High	Low	Moderate
CPS Accuracy (Denoised)	High	High	Moderate-High

Inference:
NoNoise naturally provided the most accurate CPS and cleanest spectrograms without processing. *NoiseType1* saw the most improvement after denoising, while *NoiseType2* remained slightly challenging due to overlapping insect frequencies, though still significantly enhanced.

6.2 COMPARISON OF NOISE REDUCTION TECHNIQUES

Four different noise reduction strategies were tested: Notch Filtering, Time-Frequency Masking, Wavelet Denoising, and Spectral Subtraction + Wavelet Denoising (Hybrid). Their performance was evaluated based on noise reduction percentage, feature retention, and clarity of shrimp snapping.

Table 2 Evaluation of Noise Reduction Techniques

Method	Noise Reduction (%)	Feature Retention	CPS Stability	Spectrogram Clarity	Overall Rating
Notch Filtering	~10%	High	Low	Poor	X (Poor)
Time-Frequency Masking	~35%	Low	Moderate	Poor-Moderate	X (Moderate)
Wavelet Denoising	~50%	Moderate	High	Moderate	✓ (Good)
Spectral Subtraction + Wavelet	~80%	High	High	High	✓✓ (Best)

Inference:
The hybrid method was clearly the most effective. It balanced noise reduction with feature preservation, producing the most interpretable CPS patterns and clearest spectrograms. Wavelet denoising alone showed potential but needed enhancement for more complex files like *NoiseType2*.

6.3 CPS AND RMS BEHAVIOR ACROSS AUDIO TYPES

To further quantify behavioural detection, CPS (Clicks Per Second) and RMS (Root Mean Square) energy were tracked before and after denoising. Table 3 summarizes the statistical performance across all three files.

Table 3 CPS and RMS Comparison (Before vs After Denoising)

Metric	Dataset	Raw CPS (avg)	Cleaned CPS (avg)	Raw RMS (avg)	Cleaned RMS (avg)
NoNoise	Clean	6.8	6.8	0.38	0.38
NoiseType1	Static	10.1 (false)	6.5 (realistic)	0.62	0.41
NoiseType2	Insect	8.7 (masked)	6.0 (refined)	0.59	0.43

Inference:

- *NoNoise* maintained high consistency in both raw and processed metrics, confirming low interference.
- *NoiseType1* initially produced inflated CPS due to static noise being interpreted as clicks. After denoising, CPS dropped to a realistic value (~6.5), closely matching *NoNoise*.
- *NoiseType2* demonstrated partial masking of shrimp sounds, but denoising successfully refined the CPS output and stabilized RMS levels, albeit with slightly reduced amplitude due to overlap in frequency bands.

6.4 GENERAL OBSERVATIONS

- Shrimp sound features are inherently consistent in frequency and transient in nature, making them highly identifiable once noise is reduced.
- Static noise is more disruptive to peak-based metrics like CPS than insect noise, as it often introduces irregular transients misclassified as clicks.
- Insect noise, although biologically generated, is predictable in frequency and therefore more manageable with frequency-domain filters.
- Hybrid noise reduction provides the best performance across all datasets and is robust enough to handle both artificial and biological interference.
- Quantitative features (CPS, RMS) aligned with visual observations, validating the effectiveness of the feature extraction methods.

Chapter 7

Conclusion and Future Work

This project addressed a highly relevant and emerging problem in the field of intelligent aquaculture—automated detection of shrimp feeding behaviour through underwater acoustic analysis. Traditional methods of monitoring shrimp behaviour are either labour-intensive or ineffective in dynamic aquatic environments. By focusing on passive acoustic monitoring (PAM), this study explored a non-invasive, scalable alternative capable of delivering real-time behavioural insights based on the sound signatures emitted during shrimp feeding and snapping activities. One of the central challenges addressed was the detection of these acoustic patterns under noisy conditions, which are typical in aquaculture setups. The project considered three distinct types of underwater recordings: NoNoise, containing only shrimp-generated acoustic signals; NoiseType1, featuring static background noise; and NoiseType2, complicated further by biologically generated insect noise. These audio types were carefully selected to simulate the increasing complexity of real-world aquatic soundscapes and to test the adaptability and robustness of the proposed signal processing pipeline.

The methodological design was structured and multi-staged, starting from data acquisition and categorization, followed by careful preprocessing using bandpass filtering, normalization, and frame segmentation. The project then moved into evaluating several denoising strategies, including notch filtering, time-frequency masking, and wavelet-based noise reduction. Through comparative analysis, it became evident that a hybrid approach—combining spectral subtraction with wavelet denoising—offered the most effective balance between noise suppression and the preservation of critical shrimp-specific acoustic features. This combination managed to reduce approximately 80% of static interference in the noisy files while retaining the transient shrimp snaps, which are brief and low-energy in nature, and thus particularly susceptible to over-filtering. These findings underscored the importance of layered, adaptive denoising strategies that do not rely on static thresholding but rather use spectral and temporal information to make context-sensitive decisions about what constitutes noise and what should be retained as signal.

In terms of feature extraction and behavioural analysis, the study utilized waveform visualization, spectrogram analysis, Root Mean Square (RMS) energy calculation, and Mel Frequency Cepstral Coefficients (MFCCs) to characterize and differentiate between acoustic patterns. However, the most significant contribution in this area was the development and implementation of the Clicks Per Second (CPS) metric. This metric transformed the peak-based acoustic signals into a quantifiable behavioural feature, providing a time-series representation of snapping frequency within 1-second audio frames. In clean recordings, CPS corresponded strongly with feeding activity and remained consistent with spectrogram observations. In noisy environments, raw CPS values were inflated due to noise-induced false peaks, but once the hybrid denoising method was applied, CPS stabilized and aligned more closely with realistic behavioural expectations.

This reinforced its utility not only as a measure of shrimp behaviour but also as an indirect indicator of signal processing effectiveness.

The results demonstrated clear distinctions between the three audio types. The NoNoise file, unsurprisingly, produced the cleanest CPS profiles and clearest spectrograms, validating the baseline assumptions about shrimp feeding sound frequency and temporal patterns. NoiseType1 initially presented distorted CPS outputs due to static noise interference, but denoising dramatically improved feature clarity. NoiseType2 posed a more complex challenge due to insect noise overlapping in the 7.5–8.5 kHz band. Yet, even in this case, denoising improved interpretability, and CPS was able to reflect intermittent periods of unmasked shrimp activity. Overall, the analysis confirmed that while biological noise is harder to suppress completely, it can still be effectively managed and filtered to retain meaningful behavioural patterns.

A critical insight from the project is the importance of combining time-domain and frequency-domain analysis. Waveform-based features, though helpful in peak detection, often fall short in environments with overlapping frequency content. Spectrograms provided the necessary time-frequency resolution to localize different noise types and validate denoising outcomes. This dual analysis approach proved to be essential in drawing accurate conclusions and can be adopted as a standard framework in future acoustic behaviour monitoring projects. The integration of quantitative measures (CPS, RMS) with visual analysis (waveforms, spectrograms) allowed for a comprehensive understanding of both the technical signal processing outcomes and the biological interpretations of shrimp behaviour.

Despite the strengths of this project, several limitations were also acknowledged. The dataset, while carefully designed, was limited in scope and size. Only three recordings were used, each representing a specific scenario. While this allowed for controlled testing, it restricted the generalizability of the results. Additionally, the lack of ground-truth labels for feeding events prevented the use of supervised machine learning models and limited objective accuracy evaluation. The detection methods, though robust, relied on signal processing heuristics and thresholding techniques, which may not scale well across varying acoustic environments without additional tuning. Moreover, the project did not address real-time implementation or edge-device deployment, both of which are crucial for practical adoption in commercial aquaculture farms.

Building on this foundation, several avenues for future work are proposed. First, expanding the dataset with more diverse audio samples—including different shrimp species, environmental conditions, and tank sizes—would allow for deeper analysis and statistical validation. Introducing labelled datasets, with annotated feeding and snapping events, would enable the use of supervised machine learning techniques such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs) for automatic sound classification. This could lead to the development of predictive models capable of not only detecting shrimp feeding but also classifying different behavioural states based on acoustic patterns. Another promising direction involves real-time monitoring using low-cost hardware such as hydrophones connected to microcontrollers or Raspberry Pi systems. The CPS computation and denoising pipeline could be optimized and embedded into these devices, allowing for edge-level acoustic monitoring and immediate feedback for feed management systems.

Additionally, future research could explore advanced filtering methods such as adaptive noise cancellation (ANC), spectral gating with machine-learned thresholds, or transfer learning models trained on broader aquatic datasets. These approaches may improve generalization and robustness, particularly in outdoor farm conditions where sound variability is greater than in controlled tanks. The integration of Internet of Things (IoT) platforms with acoustic sensors could enable continuous data collection, cloud-based analysis, and automated feeding decisions based on live shrimp activity data. Such systems would not only improve feeding efficiency but also support environmental monitoring and welfare assessment, making aquaculture smarter and more sustainable.

In conclusion, this project has successfully demonstrated the feasibility of detecting shrimp feeding behaviour through passive acoustic monitoring, even in noisy environments. It developed a signal processing framework that includes robust preprocessing, an effective hybrid denoising method, and a custom behavioural metric (CPS) that enables interpretable analysis. While there are challenges in scaling and automation, the results provide a strong foundation for future research in intelligent aquaculture. With continued development, the system proposed in this work could evolve into a real-time, automated solution for shrimp behaviour tracking, contributing meaningfully to the advancement of sustainable aquaculture practices.

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