DRIFTER BUOY LOW FREQUENCY ANALYSIS PROJECT

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Table of Contents

Project Introduction & Objectives

The "Drifter Buoy Low Frequency Analysis Project" is driven by the need to gain a deeper understanding of select marine mammal populations, particularly the distribution of Fin whales (*Balaenoptera physalus*)/Sei whales (*Balaenoptera borealis*), and possibly Bryde's whales (*Balaenoptera brydei*), within the Pacific Ocean study area. Fin whales and Sei whales produce acoustically similar signals, and thus are not differentiated in terms of pulsed/downsweep calls in this effort. To accomplish this, the focus of this effort included processing an extensive archival drifter buoy dataset collected during intermittent drift surveys conducted from 2016 to 2023. The primary objective was to identify and annotate periods containing the distinct calls of these whale species, thereby shedding light on their distribution and behavior. This endeavor holds significance in the broader context of marine ecology and conservation efforts.

Passive acoustic data, acquired from drifter buoys, presents its own unique set of challenges. Identifying whale calls within low-frequency data can be particularly demanding due to the presence of instrument noise and ambient sounds. The frequencies of interest, ranging from 10 Hz to 200 Hz, often overlap with the spectrum of various environmental noises, making it essential to employ specialized techniques for call detection and annotation. Compounded to this was the occurrence of instrument noise, which ranged from intermittent to pervasive within each drifter buoy dataset. This project addresses these challenges head-on by leveraging the processing capabilities of the software program PAMGuard, and through the development of deep neural networks aimed specifically at detecting signals of interest within noisy datasets.

At the core of this project report, two distinct yet interconnected analytical objectives shaped our approach to the project need. The first objective involved the annotation of whale calls within the dataset, with a specific emphasis on call types from these species. The semi-automated annotation process using PAMGuard involved leveraging automated detectors, and assignment of calls from target species to acoustic event groups during a post-processing stage. The second objective was to develop an improved method of detecting for Fin whale low-frequency calls within obscure acoustic environments using a deep learning approach. Using a deep learning network development and detection tool DeepAcoustics, we iteratively tested ideal image and network parameters for the calls procured from the data review process. Network development encompassed training with both 20 Hz and 40 Hz whale call types, given the likelihood of co-occurrence of these call types (Širović et al., 2013). In addition to calls from this dataset, we leveraged annotated data from another 20 Hz pulse dataset to increase sample sizes. Both objectives were met successfully within the project timeframe.

Methods

Analysis Methods: Acoustic Events

The following methods were used to detect and annotate calls of interest from target species within all drifter buoy datasets. Processing drifter data was prefaced by research into call types and variability within the study area, and analysts were prepared with example data prior to processing. The following elements constitute the process of reviewing all drifter buoy data.

A. Data Analysis Prep & Management

Configuration files were developed and tested with known example call data prior to processing. These data were obtained from Scripps Institution of Oceanography (SIO), and enabled optimization of configuration files prior to processing any drifter data. Examples of calls and literature used to guide identification can be found in the "PacNW_Baleen_Whale_Calls.pptx" file. During the course of preparing data and establishing data management practices and protocols, we identified the following details to incorporate in the processing of all data:

1. Species: The call types from species indicated below were annotated within the dataset. If other calls were observed or heared within the dataset, they were noted for reference and context but not annotated.
    - **Fin whale 40 Hz calls**: this was a primary target species for this effort, specifically this call type. Review of SIO datasets indicated that these calls can range from 40-60 Hz and are differentiated from D calls through call structure and duration:

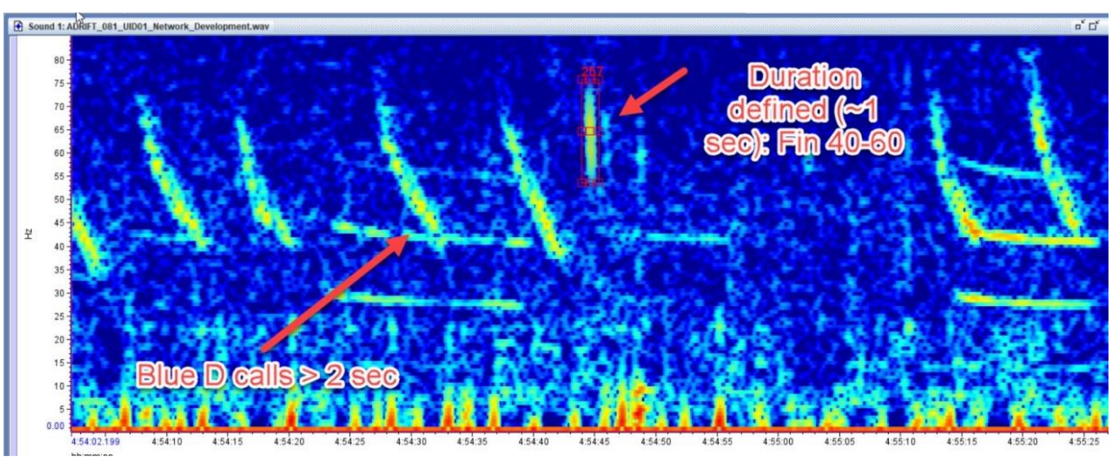

Figure 1: Spectrogram example of differentiation between blue whale D calls and fin whale 40 Hz calls.

Note: 40 Hz calls can be challenging to detect using standard PAMGuard detectors. Detectors frequently miss these calls and the closest detection is used for noting the date/time stamp of these calls. This means that in the PAMGuard annotations, there is an underestimate of the number of calls within the dataset, so absolute values should not be used to quantify call counts for 40 Hz detections. For a an explanation of this please review the following: Fin whale 40 Hz calls

- **Fin whale 20 Hz calls**: Although not initially identified as a target, due to the relationship between 20 Hz pulses, and because 20 Hz pulses provide context for potential 40 Hz pulse identification, we additional annotated 20 Hz pulses in the dataset. This decision was approved by Cory Hom-Weaver ahead of processing.

- **Bryde's whale calls**: We were tasked with specifically annotated Be4 calls within the dataset, or any other call type encountered.

- **Gray whale calls:** Although we did not expect to regularly encounter calls from this species, we anticipating annotating those calls opportunistically should they be identified within reasonable confidence.

- **Blue whale D calls**: These calls are not produced from the target species, but their structure overlaps considerably with the 40 Hz fin calls at times. To allow for consideration in identification by the analyst, we decided to annotate these calls as well, as it provided context during review.

- Species/sounds we noted, but did not annotate: Additional call types were encountered in the 10-200 Hz bandwidth of our review. We noted these in the summary but did not annotate them given it was indicated that these calls were already annotated:
    i. Blue whale A/B calls
    ii. Humpback whales
    iii. Minke whales
    iv. Passing vessels

2. **Acoustic Events**: Typically, when annotating a baleen whale acoustic event, we define it as calls of the same nature and type that are grouped when there are two hours or less duration between calls. Calls usually occur in bouts, or a series of calls with a short time interval between the first and last call. We combine multiple bouts into an acoustic event usually given that time criteria of two hours. If a new call of the same

type starts three hours after the last call, it is given a new acoustic event identification. This largely assists in data management and identifying potentially different call types of a similar nature and is not reflective of a count of animals. For the drifters, as they are continuously moving, we sometimes did not adhere to a two-hour cutoff and would group very the same call types over longer periods.

3. Bout Minimums: We conservatively approach annotation and only assigned called to a group if there were 10 or more calls for Fin and Blue whales. Or three or more calls for Gray or Bryde's whales. We provided annotation notes regarding call quality in the comments section of the "Detection Grouper Localiser" table in each database and indicated "Possible" when less confident in the species assignment.

4. Noise: As the client is aware, pervasive noise exists in many of the drifter buoy datasets. However, noise was also intermittent and often concentrated in low enough frequencies that we could evaluate the data for target species calls. We therefore processed all data in the automated stage of PAMGuard, and reviewed in order to identify if calls were present during periods of the datasets with lower noise. Therefore, unless the data were completely indicated as corrupt in the dataset inventory, we processed in PAMGuard.

B. Inter-analyst Comparison

Comparing analyst annotations is crucial for the review of large passive acoustic datasets because it helps ensure data accuracy and reliability by identifying potential discrepancies or uncertainties in the annotations. This process enhances the overall quality of the dataset and minimizes the risk of misinterpretations, thus contributing to more robust and trustworthy scientific analysis and conclusions. For this analysis, we conducted a comparison of review and annotation for two drifters, the ADRIFT 001 and ADRIFT 018 datasets. An expert bioacoustician (ELF) was compared to the analyst selected for this project (JP). Blue whales were present in the ADRIFT 001 dataset and no acoustic calls were detected in the ADRIFT 018 dataset by either analyst. For ADRIFT 001, the density of detections is compared in this figure, demonstrating the similarity in the annotation practices for both analysts:

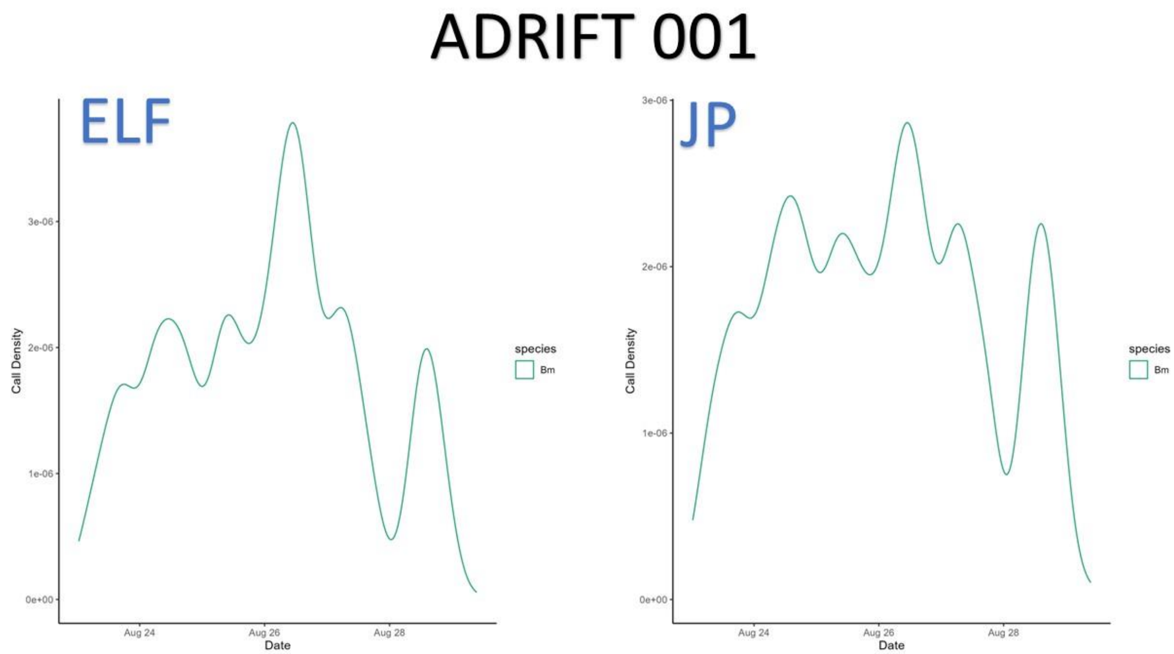

Figure 2: Inter-analyst comparison of blue whale AB call annotation for ADRIFT 001. This represents the quantity of automated detections that were attributed to the annotation of this species, resulting in a similar trend in annotation of the acoustic event.

C. PAMGuard Processing

The acoustic dataset was processed using PAMGuard (version 2.01.09; Gillespie et al., 2009) during a two-stage process. PAMGuard is a widely used, open access software program that includes automated and semi-automated modules for the detection and localization of marine mammals. Stage 1 of data processing included using PAMGuard's standard mode and involved automated detection of calls from several marine mammal species using the whistle and moan detector. Stage 2 involved using PAMGuard's ViewerMode for the post-automation annotation of the automated detections. During annotation, several modules are used to expedite the review of automated detections and parse out true detections from noise (e.g., the clip generator, the long-term spectral average; LTSA). Calls attributable to marine mammals that occur within close proximity to each other are then grouped into "acoustic events" according to species or species group (e.g., Delphinid species, fin whale). The following PAMGuard tools were used for each stage:

- **Stage 1**: PAMGuard Automated Processing Mode
  Raw audio (.wav) files were organized and processed by drifter dataset and included tested parameters for inbuilt "Whistle and Moan Detector" that would serve to detect calls from a variety of species. Automated detections were clipped and stored in a

clip folder in order to allow for review in the clip generator. These were housed outside of the binary to maintain lower binary file size for later processing/copying of data. An LTSA module was added to all configuration files to assist with rapid identification of noise and marine mammal vocal activity periods, but largely only leveraged with continuous data.

- Stage 2: PAMGuard Viewer Mode Review and Annotation
  The binary and database files are used in the manual annotation process through PAMGuard Viewer Mode. An experienced data analyst used the 'Detection Group Localiser' to mark the start and end of each acoustic event (defined by a minimum elapsed time between the end of a series of continuous calls and beginning of another, e.g., 120 minutes). A custom logger form is used to collect the analyst initials, species, call type and comments regarding the acoustic event. If an analyst was not confident in a species identification, an association of "Possible" and the whale name was indicated. If the calls were not possible to identify to species, a label of "Unknown whale" (if thought to be a whale) or "Unknown sound" (if unsure if it was a whale or fish) was used.

Example Video: Demonstration of PAMGuard annotation process

All binary and database files that contained annotations were placed in a folder so that they could be further processed using PAMpal by the client.

Analysis Methods: Deep Neural Network Development

Deep neural networks are revolutionizing underwater bioacoustic research by leveraging advanced machine learning techniques to automate the detection and classification of marine species' vocalizations. Their ability to process vast amounts of acoustic data with remarkable accuracy and efficiency significantly accelerates the analysis of underwater soundscapes. This transformative technology not only enhances our understanding of marine ecosystems but also plays a pivotal role in conservation efforts by providing valuable insights into the behavior and distribution of marine life. The following processes were used to develop a set of deep neural networks for the specific task for detecting either only 40 hz pulses, or 20 and 40 Hz pulses.

A. Fin whale call Data Preparation

We selected several audio files across multiple available detections throughout the ADRIFT dataset. Training and test data from separate audio files were selected for the network development process. We annotated all files in Raven, and ended up iteratively needing to revisit annotation when sample rate changes or changes in the spectrogram FFT size were made. This resulted in a very fine-tuned network of annotations used in training. We created separate annotation files for 40 Hz only training when there was a mixture of calls, in order to also test out a 40 Hz only network.

In addition to drifter buoy data, we incorporate data from our analysis of Ocean Observatories Initiative (OOI) hydrophone data. This includes 20 Hz calls from the coast of Newport, Oregon, and was intended to provide a larger dataset for training, given the calls had been previously annotated. These calls also provide a different ambient soundscape for incorporation in training, which could either help or hinder performance. Finally, with the example data provided by Scripps Institution of Oceanography (SIO) for 40 Hz files, we were able to include a test file of annotated 20 and 40 Hz files from their southern California site. These data were not annotated in Raven, and thus could not be used in network training, as we had not budgeted time for that dataset annotation aside from a test file.

B. Network Development

YOLO (You Only Look Once) employs a convolutional neural network (CNN) architecture, which is specialized in processing images and extracting features at various scales. In a single forward pass, YOLO predicts bounding boxes and class probabilities directly from the input image. It's trained through supervised learning, where both input data and desired output (ground truth) are provided. The model adjusts its internal weights based on the training dataset, which contains images with annotated objects, class labels, and bounding box coordinates.

In the context of DeepAcoustics, pre-trained YOLO v4 models like ResNet-50, CSP-DarkNet-53, and Tiny YOLO are used. ResNet-50, a 50-layer CNN, was trained on a vast ImageNet database. CSP-DarkNet-53 (53 layers) and Tiny YOLO (29 layers) networks were pre-trained on COCO, a dataset for object detection, segmentation, and captioning. While ImageNet is larger and widely used, COCO stands out for its object segmentation approach, outlining objects rather than creating bounding boxes like ImageNet. These pre-trained networks expedite training and enhance performance in object detection tasks.

Modifications to the sampling rate, window length, and image file duration were all evaluated in an initial stage of development. Once the ideal parameters were identified for image creation, we tested values such as pixel size, batch size, and optimizer algorithm, incorporating knowledge gain from previous testing. For instance, an epoch size of 10 was used for all training due to DeepAcoustics commonly reaching optimal performance by that number of epochs. Additionally, our testing of several parameters such as batch size and pixel size is limited to the capabilities of our desktop computer used for deep learning. Most of the initial training occurred with the lighter weight tiny YOLO, and once ideal settings identified was used going forward with CSP-DarkNet-53 and ResNet-50 training.

C. Performance Evaluation

We tested each network with a set of test files that were not used in training. These included a Drifter dataset file with only 20 Hz and one with a combination of 20 and 40 Hz calls, an OOI test file, and a test file from the SIO example. Noise files were also evaluated and compared in order to understand how well each network performed when there were no calls in the dataset. For those files with calls, we calculated precision, recall and an f-score for the testing datasets. Precision is the ratio between the true positives and all of the positives and indicates how good the model is at detecting.

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives + False positives}} = \frac{\text{Calls correctly detected}}{\text{Calls correctly detected + noise incorrectly detected as calls}}$$

Recall relates to the sensitivity of the model and indicates how correct it is at identifying true positives.

$$\text{Recall} = \frac{\text{True positives}}{\text{True positives + False negatives}} = \frac{\text{Calls correctly detected}}{\text{Calls correctly detected + calls not detected as calls}}$$

An f-score combines the precision and recall of a classifier into a single metric to compare different models.

$$\text{F1 score} = 2 * \frac{\text{Precision * recall}}{\text{Precision + recall}}$$

We use this instead of a simple average as it is a more balanced in terms of assessing model performance. A classifier with a precision of 1 and recall of 0 has a simple average of 0.5 but an F1score of “0”. When creating a detection network with the optimal balance of recall and precision, we try and maximize the F1 score. Collectively, these values provide a means of evaluating detector performance, and are provided in the results for all of the best performing networks.

Results

Marine Mammal Acoustic Detection Event Summary

The results of the analysis from the drifter datasets for species or call type is indicated in **Table 2** and summarized from the DRIFTER_Summary_and_Tracking.xlsx spreadsheet. This table summarizes the number of drifters that contained calls, with additional details of the call frequency available in the PAMGuard database for each drifter. Acoustic detections found within the drifter datasets were heavily weighted towards fin whale 20 Hz and D calls, with regular occurrence of 40 Hz calls in the ADRIFT dataset.

Table 2: Number of drifter buoy datasets that contained acoustic events from each species/call type. These counts include “possible” assignments in the detection events.

Species/Call Types	ADRIFT	CCES	PASCAL
Fin whale – 20 Hz call type	18	11	16
Fin whale – 40 Hz call type	18	2	3
Blue whale – D calls	20	6	17
Bryde’s whale – Be4 calls	0	0	0
Unidentified whale	3	1	1
Unidentified sound/Possible fish	2	0	0

All data products explained in this video: Drifter Buoy Analysis Files Tour

Fin whale 40 Hz Data

The Fin whale 40 Hz data proved to be more prevalent than expected within the drifter dataset, particularly in the ADRIFT files. Detection of calls is challenging, as mentioned above and when files are duty cycled, the likelihood of detecting these calls is reduced due to a combination of complexity of detection in short audio and detection false positives at the start of each file in the dataset. It is highly likely that the acoustic events for this call type are an under representation in the dataset.

Figures 3-6 indicate some of the observations of these calls within the dataset. Many of the calls were lower intensity, however several examples stood out as exceptional in the dataset including the example in **Figure 3** from ADRIFT 063. In **Figure 4**, the variability in the call frequency bandwidth and intercall interval is evident. Low quality calls intermixed in these acoustic events were not included in network training to minimize false positive detection.

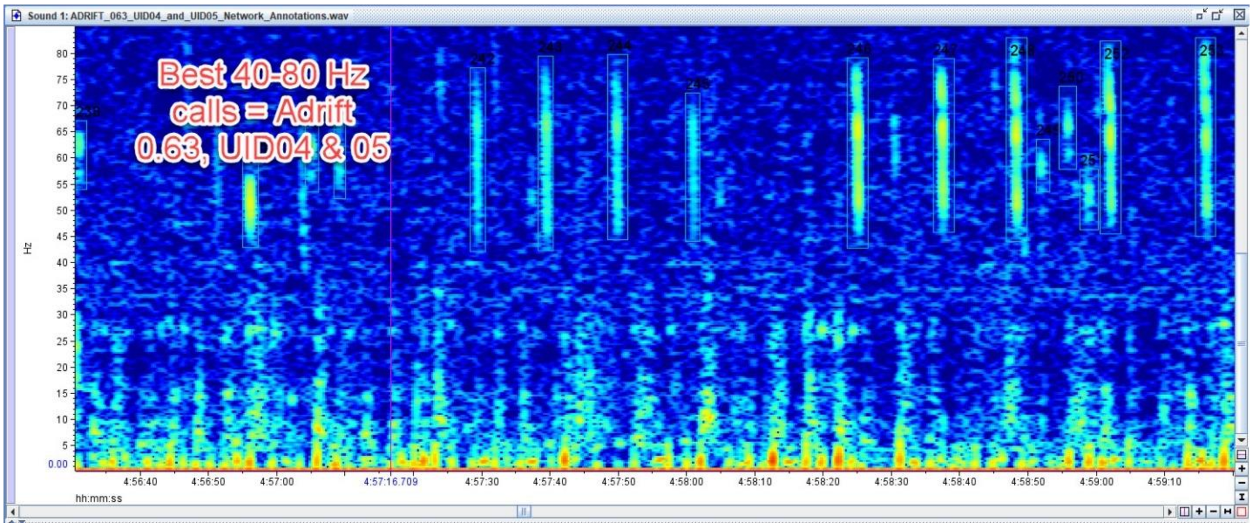

Figure 3: High quality example of fin whales within the drifter buoy dataset.

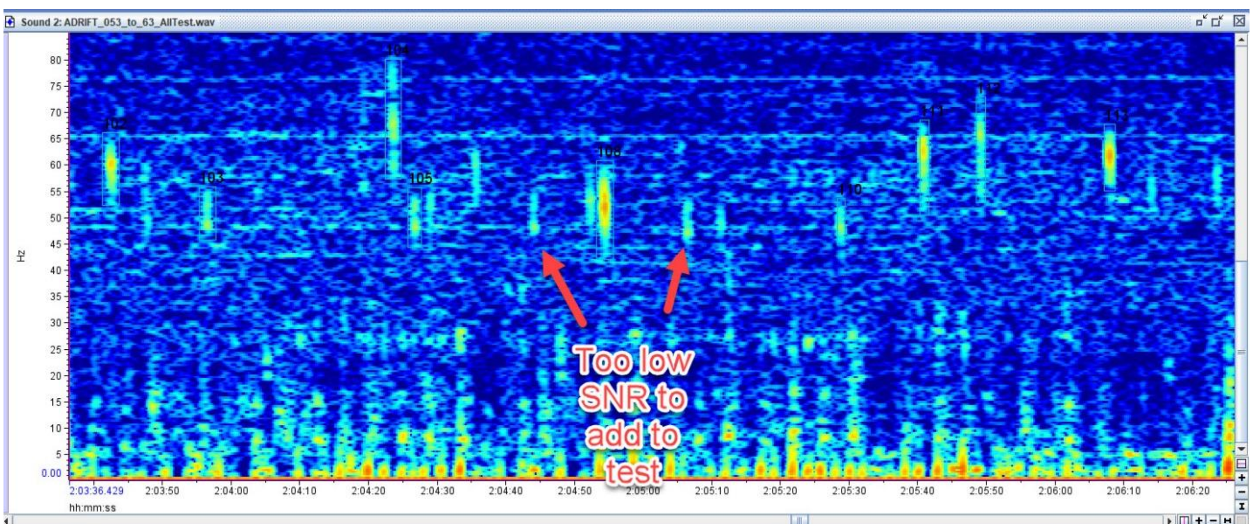

Figure 4: This image demonstrates the variability of the call frequencies and intervals within the dataset. Additionally, often low quality calls were intermixed in an acoustic event. These lower quality calls were excluded from anntoations for deep learning networks due to the possible indiscrimiation with noise.

The frequency bandwidth of the “40 Hz” varied in terms of the peak frequency from approximately 40 Hz to 70 Hz in our observations. **Figure 5** provides a clear example of how these calls can exhibit variability spectrally. Finally in **Figure 6** we show how Fin whale 40 Hz calls were sometimes co-occurring with blue whale AB and/or D calls.

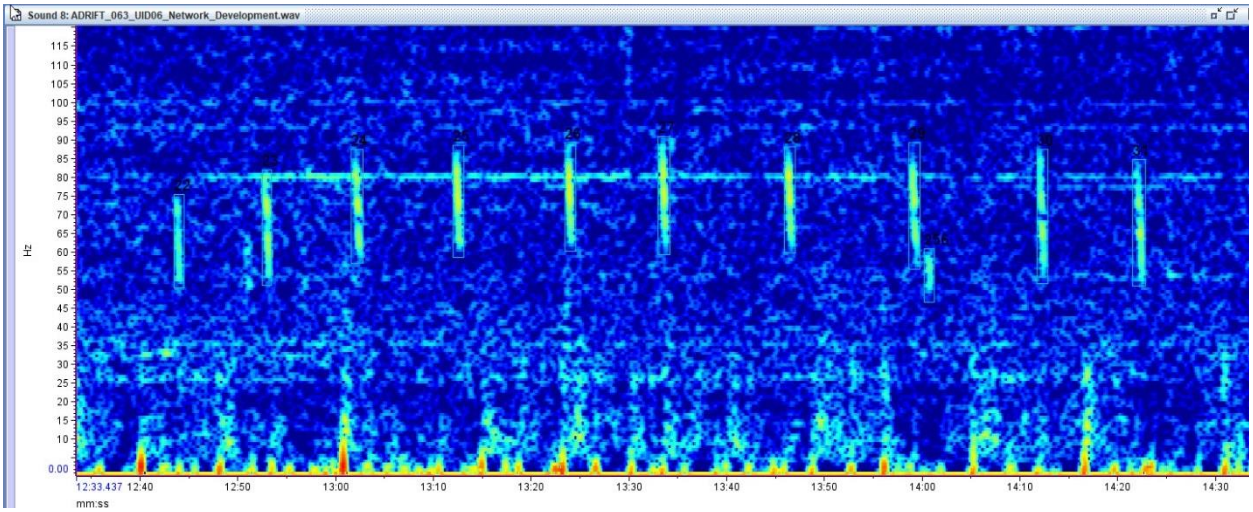

Figure 5: This high quality crescendo of “40 Hz” pulses clearly demonstrates the variability in the bandwidth of these calls. We identified “40 Hz” as calls that could have a peak at anywhere from 40 to 70 Hz, but retained the short duration (~1 second) characteristic identified by SIO.

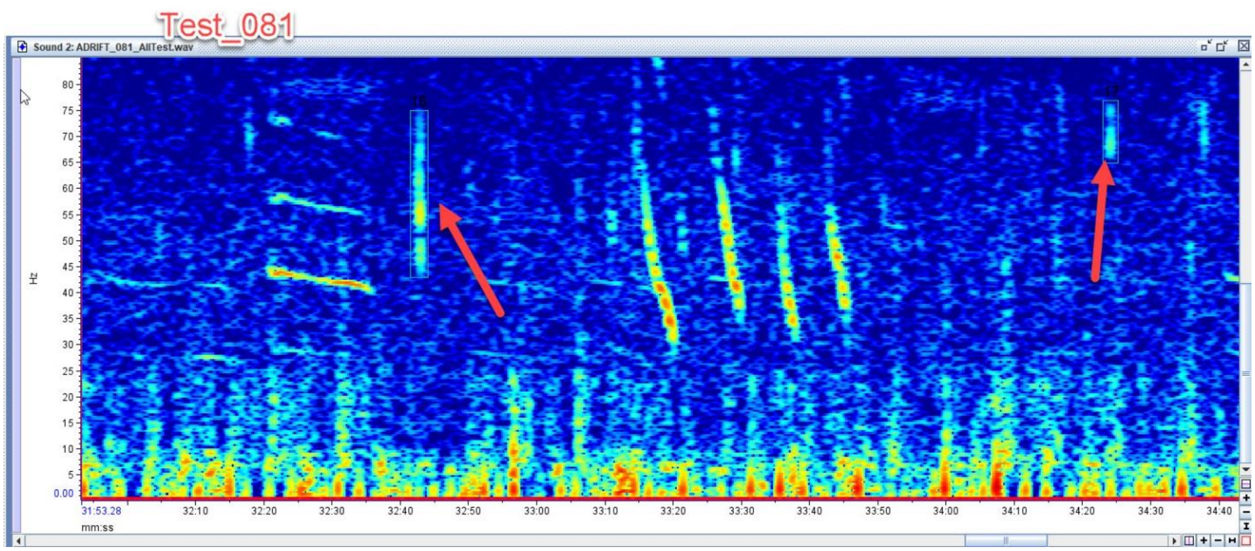

Figure 6: Fin whale 40 Hz calls sometimes occur during periods of blue whale D calls and/or AB calls.

Unique Acoustic Encounters

Although not the explicit target of the dataset, we encountered several unique unidentified calls within the dataset. In addition to aurally observed social sounds from humpbacks and other species noted in the comments, we encountered some unidentified whale calls within ADRIFT 060. In **Figure 7** below, unique calls from a possible sei whale (but also possible blue whale) were detected over multiple days. This dataset is presumed to have followed the path of the animal given the consistency in calls over time.

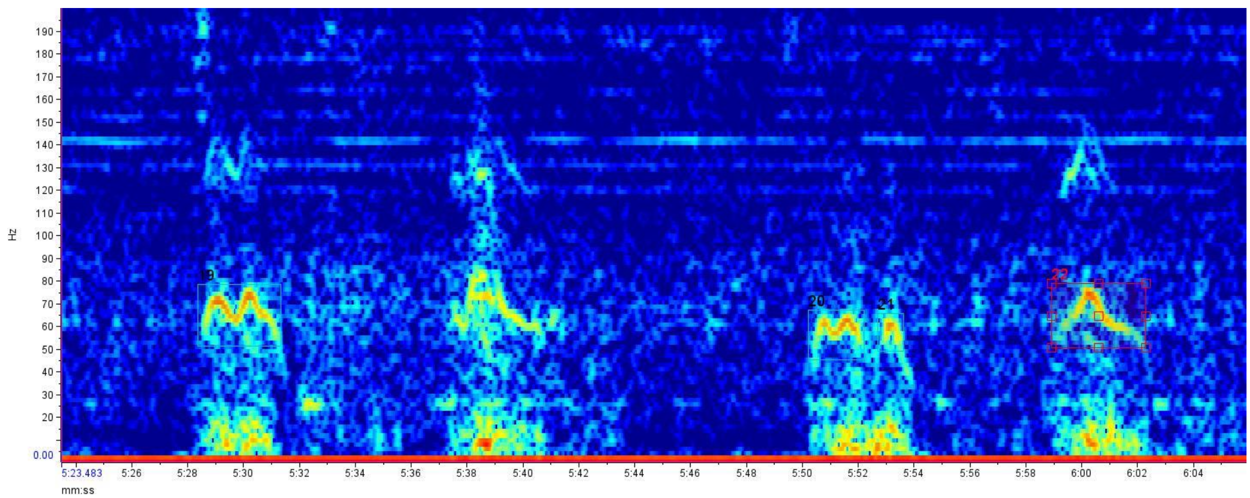

Figure 7: Unidentified whale calls in ADRIFT 060.

Variability in downsweeps also lead to several “possible” instances and are exemplified in the clips associated with each event in each drifter folder.

Deep Learning Network Results

We conducted a comprehensive analysis by testing the influence of various dataset combinations and evaluating the best results across the three network architectures. This rigorous exploration allowed us to optimize our models for improved performance. The deep learning network results provide a promising outlook for the detection of these calls in future endeavors. We successfully demonstrated the detection of calls and achieved a notable reduction in the false positive rate in our best-performing networks, highlighting the effectiveness of our approach in enhancing call detection accuracy.

Dataset Testing

Initial tests into different combinations of datasets were performed in order to identify the most effective network for detected Fin whale 40 Hz pulse calls. We used the Tiny YOLO framework for this testing due to the speed at which this powerful, yet lightweight network can be trained. **Table 3** indicates the details associated with developing networks with different combinations of the training datasets. Notably our sample sizes are low, and an increase in these would increase performance. We incorporated 20 Hz data from both the drifter buoys and the OOI dataset to elicit better performance with call detection. Although not indicated in this table, network version 12, which included all data 20 and 40 Hz data from drifter buoys and OOI datasets performed best and was selected as the training dataset moving forward.

Table 3: Testing of different training dataset and associated image parameters Note that the number of annotations differs from images because some images have more than one training sample.

Tiny YOLO Network Version	Training Data	Image Duration (s)	Window Length (s)	File Sample Rate (Hz)	Number of Annotations*	Number of Training Images**
9	20 Hz DATA (DRIFTER/OOI)	8	0.64	200	1,494 (Drifter =345, OOI = 1,149)	4407
10	DRIFTER 20/40 All Data	8	0.64	200	1,426	3999
11	DRIFTER 40-80 Hz Only	5	0.32	200	724	2172
12	ALL DATA - DRIFTER / OOI	8	0.64	200	2,575 (Drifter =1,426, OOI = 1,149)	7428

** Unique annotations, all files included two augmented duplicate datasets for training*

*** A small number of training images contain more than one annotation*

Best Performing Networks

The best performing network resulting from above was then used for comparing the ResNet-50 and CSP-DarkNet-53 networks. Training variables identified in an earlier stage were used in this final development. This included a 200 Hz sampling rate, as a 400 Hz sampling rate was insufficient. It also included a lower than anticipated window length of 0.64 for 8 second files (20 Hz only and 20Hz + 40 Hz) and of 0.32 for 40 Hz only files. These elements greatly influenced the results of networks, so it is important to note. In **Table 4** we provide information on each of the test files that were used. **Table 5** provides the metrics for each of the test files for each network. In terms of precision, tiny YOLO performed best whereas CSP-DarkNet-53 performed better with recall or identifying more of the true positives. Both Tiny YOLO and CSP-DarkNet-53 networks produced lower false positive rates, which is important given the noise in the dataset. The ResNet-50 performed worst of the three but in our experience, limited sample size can be the cause of this.

Table 4: Test file description including the call types and number of true positives. In addition to drifter data, we included OOI test files and an SIO test file.

Test File	Call Types in Test File	Number of True Positives in File
ADRIFT 027	20 Hz	95
ADRIFT 053-063	20 & 40 Hz	217
OOI 2018	20 Hz	181
SIO - SOCAL 34M	20 & 40 Hz	236

Table 5: Performance metrics for each network architecture with all four test files.

	Tiny YOLO				CSP-DarkNet-53				ResNet-50		
Test File	Precision	Recall	F-Score		Precision	Recall	F-Score		Precision	Recall	F-Score
ADRIFT 027	0.80	0.55	0.65		0.58	0.80	0.67		0.45	0.72	0.55
ADRIFT 053-063	0.73	0.69	0.71		0.63	0.82	0.72		0.48	0.79	0.60
OOI 2018	0.76	0.24	0.36		0.86	0.32	0.47		0.33	0.38	0.35
SIO - SOCAL 34M	0.78	0.46	0.58		0.80	0.54	0.64		0.30	0.52	0.38

Performance is also critical when no calls are present within a dataset. The drifter buoy dataset often contains pervasive noise, which can greatly impact the false positive rate. We tested four different audio files that were not observed to contain calls of interest but did contain varying degrees of noise (**Figure 8**).

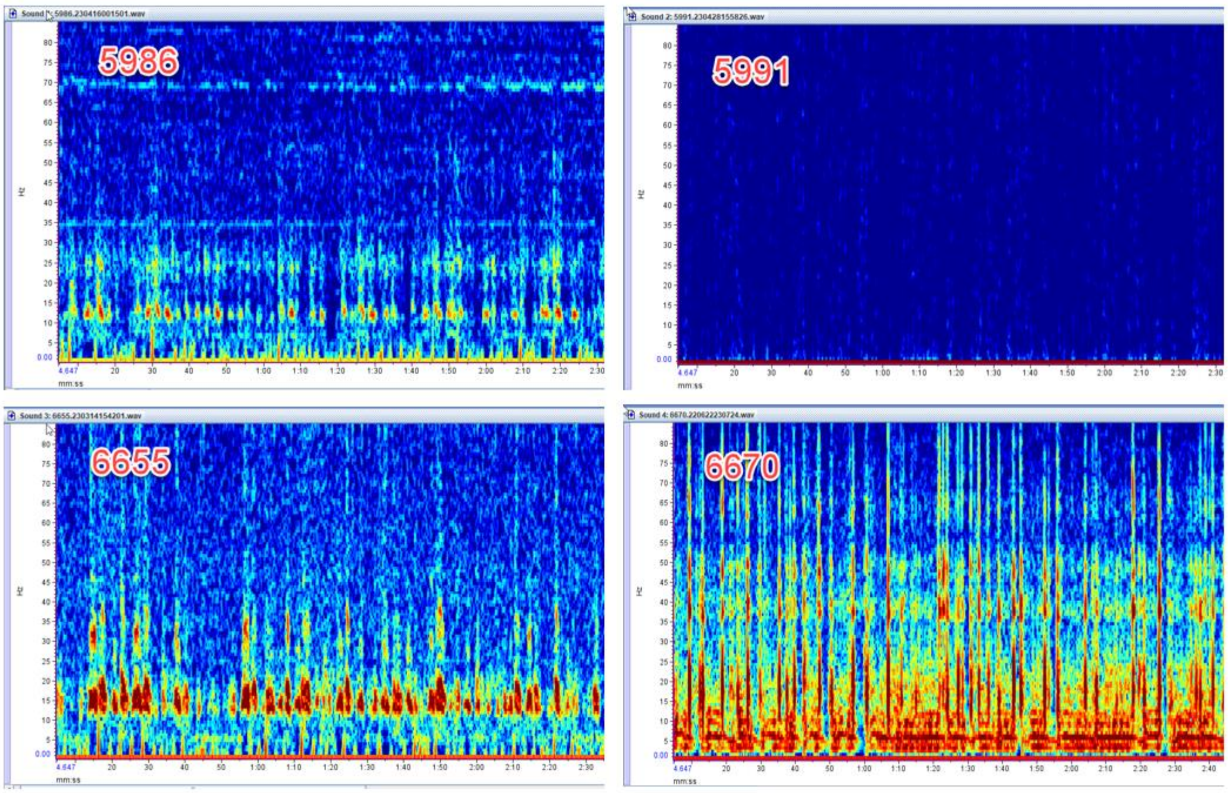

Figure 8: Sample noise from several drifter buoys representing the variability in noise throughout the datasets. Each network was tested with these datasets to get an idea of false positive rate.

We ran each of the best performing networks on these noisy files to obtain an idea of how the noise would influence detection. Table 6 indicates the rate of false positives in each of these noise files. Perhaps not surprising is that 6670 results in a greater number of false positives, but given the poor quality, the tiny YOLO and CSP-DarkNet-53 results are reasonable. With a larger sample size training dataset, the ResNet-50 would likely increase in performance.

Table 6: Number of false positives resulting when detecting calls with each of the best performing networks. File numbers correspond to images above.

		Number of False Positives in Noise Only File			
Network	Version	5986	5991	6655	6670
Tiny YOLO	12.1 (All Drifter/OOI Data)	2	0	1	17
CSP-DarkNet-53	12.1 (All Drifter/OOI Data)	5	2	8	35
ResNet-50	12.1 (All Drifter/OOI Data)	20	33	17	128

The performance of the Tiny YOLO and CSP-DarkNet-53 in this dataset were comparable, with a higher number of true positives being correctly identified by CSP-DarkNet-53 but at the sacrifice of more false positives. We believe the combination of 20 and 40 Hz files could perform better due to allowing the discrimination of calls from noise in both bands during training. We also note that performance results of the OOI dataset are not as good as expected, which might be a result of the missing 40 Hz representation in that dataset. If speed in training new networks is required, Tiny YOLO would be sufficient, but if a greater number of true positives is desired, the CSP-DarkNet-53 is the best architecture.

Example Dataset for Evaluation in DeepAcoustics

We compiled a dataset from ADRIFT 087 that contains 20 Hz and 40 Hz pulses to allow for evaluation of the best performing networks. These files are available in the "04_DeepAcoustics_Networks" folder. A recorded demonstration of these steps is also available for stepping through detection of calls.

Video: Example of DeepAcoustics Test Dataset

To get started, download the current version of the DeepAcoustics software program from the OSA GitHub Repository: DeepAcoustics. You can then follow the steps in the video. We recommend using GitHub Desktop for accessing the program as we are actively making improvements. We are currently developing a tutorial which will be shared when available soon.

Concluding Thoughts

The project represents a significant step forward in the field of underwater bioacoustic research. Through the meticulous annotation of whale calls and the development of advanced deep neural network architectures, we have not only enhanced our understanding of marine mammal populations but also demonstrated the potential for more efficient and accurate call detection in large passive acoustic datasets. Our findings indicate that the combination of precise annotation methods and well-tailored deep learning networks can significantly reduce false positives, offering promising prospects for future studies in marine ecology and conservation efforts. We appreciate the opportunity to work on this project and demonstrate the capabilities of using both PAMGuard for large dataset analysis and DeepAcoustics for neural network development.

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