# Acoustic Analysis of Marine Mammal Calls Using Machine Learning for Conservation Efforts

Abdusamea Ibrahim[1] abdusamea.omer@sabu.edu.ly
Ghada madani[2] ghada.madani@sabu.edu.ly
Abdallah Oshah[3], abdallah.oshah@sabu.edu.ly
Munira habib[4] monhabib@gmail.com
Amany Alarbish[5] Amany.alarbish@sabu.edu.ly
[1,2,345]Faculty of Engineering, Sabratha University
[1,2,345] Department of Computer Engineering and Information Technology

## Abstract

The study explores the application of machine learning techniques in analyzing marine mammal vocalizations for conservation purposes. It highlights the importance of passive acoustic monitoring in studying cetacean behavior without disrupting their natural habitat. The research examines sound wave characteristics in marine environments, how marine mammals produce and receive sounds, and classifies various types of marine mammal calls and their purposes. The study utilizes the Watkins Marine Mammal Sound Database for training the machine learning model, which contains acoustic recordings from over 50 marine mammal species. The methodology involves signal processing techniques, including noise removal and spectrogram analysis, followed by the application of a Random Forest Classifier or neural network for call classification. The results indicate that the machine learning model achieved high accuracy in classifying marine mammal vocalizations, demonstrating the effectiveness of using advanced analytical techniques in bioacoustics. The findings reveal significant relationships between specific marine mammal sounds and their behavioral patterns, providing valuable insights for conservation efforts. By improving the accuracy and efficiency of acoustic data analysis, researchers can gain a better understanding of marine mammal behavior and distribution, leading to more effective strategies for their protection and habitat preservation.

# 1. Introduction

Passive acoustic monitoring techniques now allow for insight into the lives and behavior of cetaceans at sea, which is difficult to obtain through visual surveys without changing behavior or destroying ranges. Because many cetaceans are averse to research vessels, especially platforms where individuals may harm them, passive acoustic devices are ideal for research purposes. Acoustic monitoring of cetaceans is primarily done by listening to their sounds, which vary by species [1]. These sounds and the conditions in which they are made can provide important data for conservationists and experts to develop better management plans. Ideal algorithms are based on marine mammal sounds, where large, widespread swells are most evident. Using the data in conjunction with other information about marine mammals, such as species known to occur in an area and their habitat requirements, we can better assess and modify human activities, such as regulating shipping channels and specific shipping routes to minimize the impact of ship strikes or seismic activity in active oil and gas exploration or production areas. Acoustic monitoring programs can inform both regulators and industry of the relative abundance of marine mammals in areas of interest to them [2].

## 1.1. Background and Significance

Bioacoustics techniques, the science of recording and analyzing sounds, are not new, but their use with conservation goals is a relatively recent development. Acoustic analysis can capture the variability of several biological characteristics such as repertoire, information about group proximity, distribution, and information about species' activities which are linked with feeding, resting, mating, socializing, and avoiding predators. Acoustic monitoring has become a powerful noninvasive instrument for large-scale species abundance estimations, especially for a considerable number of marine and wildlife species belonging to diverse taxa [3].

Considering economic or resource issues, the implementation of acoustic monitoring could be significantly less expensive than methods using visual surveys. The best-known applications of long-term passive acoustic monitoring are the ecological studies of bioacoustics behaviors of cetaceans. Other remarkable marine mammal species that emit underwater calls include Sirenians and pinnipeds, including otarids and phocid seals [4]. Acoustic analysis is crucial for conservation efforts, as the identification and characterization of underwater acoustic calls in different ecosystems provide rich information related to the temporal and spatial distribution of marine species in different habitats, contributing to the design and implementation of conservation tools. Acoustic monitoring would miss its purpose if its procedures and protocols were not the most accurate in identifying the animal species with the acoustic signals in the surroundings [3]. This problem is particularly important in the marine environment where acoustic signals are more difficult to detect due to the propagation and attenuation of these signals in water, background noise, and other important challenges..

### 1.2. Acoustic Physics of Marine Mammals

Sound is generated as waves that propagate through various media, including gases (air), liquids (water), and solids. In marine environments, sound travels approximately 4.4 times faster in water than in air, with speeds ranging from 1450 to 1500 m/s underwater compared to 330–340 m/s in air [5]. This difference significantly affects how marine mammals perceive and utilize sound for communication and navigation.

### 1.3. Sound Production and Reception

Marine mammals utilize a variety of sound production mechanisms [6]:

- Whales produce low-frequency sounds for long-distance communication.
- Dolphins employ clicks and whistles, often incorporating ultrasonic frequencies for echolocation.
- Seals generate sounds both underwater and in air for social interactions and mating.

The anatomy of marine mammals is adapted for efficient sound reception. Porpoises have specialized structures that allow them to detect high-frequency sounds effectively, aiding in prey detection while avoiding predators.

### 1.4. Impact of Environmental Factors

The propagation of sound is influenced by environmental conditions such as temperature, salinity, and pressure. These factors can alter sound speed and intensity, affecting how marine mammals communicate in their habitats. Additionally, anthropogenic noise pollution from ships, industrial activities, and recreational boating poses significant challenges by masking natural sounds critical for communication and navigation. [8].

### 1.5. Marine Mammal Communication

Marine mammals, including whales, dolphins, and seals, utilize a complex array of vocalizations and sounds for communication, navigation, and social interaction. Their acoustic communication is vital in the underwater environment where visibility is often limited [5]. Marine mammals produce a variety of sounds categorized primarily into three groups based on their anatomical features [5] [7]:

- **Mysticetes (Baleen Whales):** these whales typically generate low-frequency sounds ranging from 0 to 5 kHz. Their calls include moans, pulses, and songs, often used during mating rituals or to communicate over long distances.
- **Humpback Whales**are Known for their complex songs that can travel vast distances and are believed to play a role in mating displays.
- **Odontocetes (Toothed Whales**) **Odontocetes (Toothed Whales)**: This group emits higher frequency sounds, usually between 5 and 150 kHz. Their vocalizations include clicks used for echolocation and whistles that facilitate social interactions. Notable examples include dolphins, which use signature whistles to identify themselves to others within their pods.
- **Pinnipeds (Seals and Sea Lions**): These animals produce a range of sounds from low to mid-frequency (0-20 kHz), including growls, barks, and trills. These vocalizations serve various functions such as mating calls and social communication within groups.

The acoustic communication strategies of marine mammals are sophisticated adaptations that facilitate survival in their aquatic environments. Understanding these vocalizations not only sheds light on their behavior but also aids in conservation efforts by providing insights into their social structures and interactions.

## 2. Related work

- Extensive research has delved into the use of acoustic monitoring and machine learning in marine mammal studies. Previous studies on marine animal sounds serve as a foundation for understanding the progress made in this field. They provide insights into identifying research gaps and offer valuable findings and methodologies that can be leveraged to enhance the current study
- **Guan and Brookens (2023)**: Conducted a study titled "An Overview of Research Efforts to Understand the Effects of Underwater Sound on Cetaceans." The study aimed to review global research efforts related to the impacts of anthropogenic underwater sound on cetaceans. It focused on examining the behavioral, psychoacoustic, physiological, and physical responses of cetaceans to human-induced

sounds. The paper highlighted a variety of experimental and field studies on different cetacean species and discussed the conservation criteria and thresholds developed based on these findings. Additionally, it provided a comprehensive overview of current challenges, knowledge gaps, and recommendations for future research in this area. [8].

- **Ferguson et al. (2023):** Conducted a study titled "Acoustic indices respond to specific marine mammal vocalizations and sources of anthropogenic noise." This research aimed to explore the relationship between acoustic indices and underwater sounds, focusing on marine mammal vocalizations and anthropogenic noise. Using passive acoustic data collected from hydrophones in the California Current Ecosystem, the study identified patterns in acoustic indices such as the Acoustic Complexity Index (ACI) and the Bio Acoustic Index (BI) in response to different sound sources. The findings revealed significant relationships between specific marine mammal sounds and changes in acoustic indices, highlighting their potential use in biodiversity conservation and ecosystem health monitoring. The study also discussed the impacts of anthropogenic noise, including ship traffic and sonar, on these indices, providing insights for advancing acoustic ecology methods. [9].
- **Reckendorf et al. (2023) :** Conducted a study titled "Marine Mammal Acoustics," which explores the role of sound in the lives of marine mammals and the impacts of anthropogenic noise on their behavior and survival. The study discusses the physics of sound, how marine mammals produce and perceive sounds, and how these abilities are crucial for navigation, communication, and foraging. Furthermore, the paper highlights the detrimental effects of underwater noise pollution from human activities, such as shipping and military sonar, and how these disturbances can lead to changes in behavior, stress, and even hearing impairment in marine mammals. The study also reviews methodologies for studying marine mammal acoustics, including auditory tests, bioacoustics monitoring, and the use of advanced acoustic technologies for conservation purposes. [10].
- **Turbulent Research (2023)**: This study provided a comprehensive overview of recent advancements in acoustic monitoring systems designed to assess human impacts on marine mammals. It detailed innovative methodologies such as real-time hydrophone networks and their deployment in tracking species abundance and

migratory patterns. Additionally, it emphasized the application of long-term acoustic archives, which integrate machine learning algorithms to analyze large-scale datasets. These systems have proven effective in identifying behavioral responses to environmental stressors, including habitat alterations caused by climate change and overfishing. The study highlighted the importance of dynamic, adaptive monitoring frameworks that can respond to shifts in marine ecosystems [7].

- **Southall et al. (2022)**: This paper offered an in-depth update on marine mammal noise exposure criteria, focusing on both biological and ecological consequences of chronic noise. It analyzed the effects of prolonged anthropogenic noise exposure, particularly from industrial zones, on communication, foraging efficiency, and reproductive success in cetaceans and pinnipeds. The study's findings were instrumental in shaping regulatory frameworks, including specific noise exposure thresholds and guidelines aimed at mitigating acoustic pollution in critical marine habitats. It also discussed technological advancements in modeling acoustic environments to predict and minimize noise impacts[6].
- **Rice, A.C al (2022)**: This research examined the interplay between natural and anthropogenic underwater sounds, focusing on their overlapping acoustic signatures. It provided actionable insights into mitigating the adverse effects of seismic exploration and commercial shipping on marine mammals. By utilizing spatial habitat models and integrating these with acoustic datasets, Hildebrand's work proposed targeted interventions such as rerouting shipping lanes and implementing seasonal noise restrictions in ecologically sensitive areas. The study also explored the role of acoustic refuges as a conservation tool, providing areas with reduced human noise for marine mammals [2].
- **Pirotta et al. (2022)**: This study explored the critical role of bioacoustics in understanding marine mammal behavior and its implications for conservation. It proposed the use of advanced machine learning techniques, including deep learning, to detect nuanced behavioral shifts in response to anthropogenic stressors such as overfishing and habitat degradation. Case studies on fin whales and gray seals illustrated how automated detection systems can enhance the precision of behavioral analyses, providing robust data to inform conservation strategies. The study also

underscored the necessity of integrating acoustic monitoring with ecological modeling to predict long-term population trends [4].

- **Širović, A et al. (2022)**: Reviewing the state-of-the-art in PAM systems, this study emphasized the scalability of acoustic monitoring for biodiversity assessments. It highlighted technological innovations like automated detection algorithms and their deployment in large-scale marine surveys. The research outlined how these advancements, coupled with cloud-based data processing systems, have drastically increased the efficiency and accuracy of species monitoring, enabling the identification of subtle changes in ecosystem health over time [3].
- **Slabbekoorn, H et al .(2018)**: This seminal work delved into the psychoacoustic impacts of anthropogenic noise on various marine mammal species. It offered a comprehensive comparison of noise resilience across taxa, emphasizing the physiological and behavioral vulnerabilities of species such as dolphins and whales. The study provided a roadmap for future research, advocating for multi-species, longitudinal studies to understand cumulative noise impacts and their implications for conservation policy [1].
- **in Conservation and Ecosystem Monitoring**
  Acoustic monitoring has emerged as a robust and transformative tool in marine conservation and ecosystem monitoring, offering invaluable insights for preserving biodiversity and managing habitats. In biodiversity monitoring, acoustic techniques enable researchers to assess species abundance and diversity with remarkable precision. By identifying species-specific vocalizations, it becomes possible to estimate population sizes and monitor changes in biodiversity over time. For example, Pirotta et al. (2022) [4], demonstrated how acoustic data plays a pivotal role in ecosystem health assessments, aiding in the detection of critical stressors like overfishing and climate change, thereby strengthening conservation strategies.

Similarly, in habitat management, marine mammal acoustic data has proven instrumental in shaping effective environmental policies. By providing critical information, it supports practices such as rerouting shipping lanes and minimizing seismic activities in ecologically sensitive areas. As highlighted by Širović, A (2022) [2], the integration of acoustic monitoring data into policy decisions is essential for the sustainable protection of marine habitats, showcasing the practical relevance and impact of this approach in conservation efforts.

While the field holds immense potential, challenges such as data scarcity for rare species, noise pollution, and the need for advanced algorithms present opportunities for future growth. Addressing these gaps through interdisciplinary research, enhanced data collection, and algorithm optimization will further solidify acoustic monitoring as a cornerstone of marine conservation and ecosystem management.

These studies collectively underscore the transformative potential of integrating bioacoustic monitoring with machine learning technologies for conservation efforts. They highlight the importance of continuous advancements in dataset quality, algorithm robustness, and interdisciplinary approaches to address the complex challenges of marine mammal conservation.

## 3. Methodology

This section provides a detailed and systematic description of the procedures and steps adopted in data collection and analysis. The methodology includes defining the type and design of the study, the tools and methods used for data collection, the target sample, as well as the data analysis techniques.

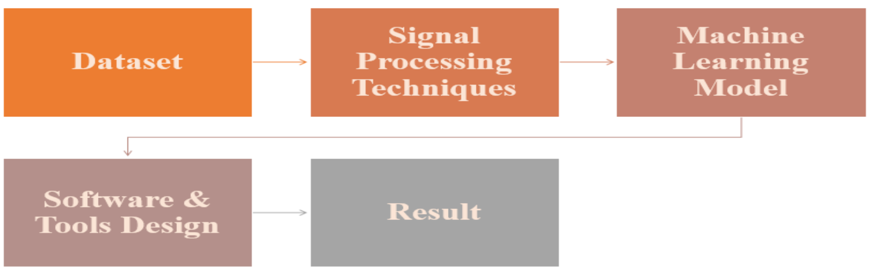


Figure 1: System Steps

**Step 1** - Dataset

Open source datasets of marine mammal calls were used, such as those provided by the Marine Bioacoustics Archives or the Ocean Biodiversity Information System (OBIS). These datasets contain labeled audio recordings of various species, including humpback whales and bottlenose dolphins.

**Step 2** - Signal Processing Techniques

The tool pre-processes the audio data by:

- **Denoising:** using high-pass filters to remove background noise.

- **Spectrum Analysis:** converting audio signals into visual representations (spectrograms) to extract features.
- **Melody Frequency Coefficients (MFCC):** extracting key audio features to aid classification.

**Step 3** - Machine Learning Model

A supervised machine learning approach was used to classify the calls:

- **Algorithm:** Random Forest classifier (or simple neural network).
- **Training and Test Split:** 80% of the data was used for training, 20% for testing.
- **Evaluation Metrics:** Precision, Accuracy, and Recall were used to evaluate performance.

**Step 4** - Software and Tool Design

The following tools were used to design the system:

- **Python:** A programming language for analysis.
- **Librosa:** For audio analysis and signal processing.
- **NumPy and Pandas:** For data manipulation.
- **matplotlib:** For visualization of spectrograms and classification results.
- **Jupyter Notebook:** For interactive development environment.

The system workflow includes:

- **Input:** Audio recordings of marine mammal calls.
- **Preprocessing:** Denoising, normalization and spectrogram generation.
- **Feature extraction:** Using MFCC or spectrogram-based features.
- **Model training:** Training a classification model using labeled data.
- **Output:** Classification of calls and visualization of species-specific patterns.

## 4. Results and Discussion

### 4.1. The Dataset Overview

The dataset utilized in this study comprises acoustic recordings of marine mammals, sourced from the widely recognized Watkins Marine Mammal Sound Database, a comprehensive repository of bioacoustic data for over 50 distinct species, including dolphins, whales, seals, and others. Collected across diverse geographic locations and acoustic environments, the dataset presents challenges such as background noise, overlapping vocalizations, and variations in recording quality. Key characteristics include:

51 species classes (e.g., Atlantic Spotted Dolphin, Bearded Seal, Beluga Whale, Bottlenose Dolphin), thousands of labeled sound recordings with 150–300 samples per species, and standardized audio segments of consistent lengths (e.g., 5 seconds). Acoustic features such as Mel-Frequency Cepstral Coefficients (MFCCs), spectrograms, and zero-crossing rates were extracted, with MFCCs being particularly effective for distinguishing species-specific vocalizations due to their ability to capture timbral and frequency characteristics. The dataset exhibited class imbalance, with certain species overrepresented (e.g., Atlantic Spotted Dolphin) while rarer ones (e.g., Leopard Seal) were underrepresented. To ensure robust model evaluation, the data was split into training (80%), validation (10%), and test (10%) sets, with data augmentation techniques such as time-stretching, pitch-shifting, and adding white noise applied to the training set to increase variability and improve generalization.

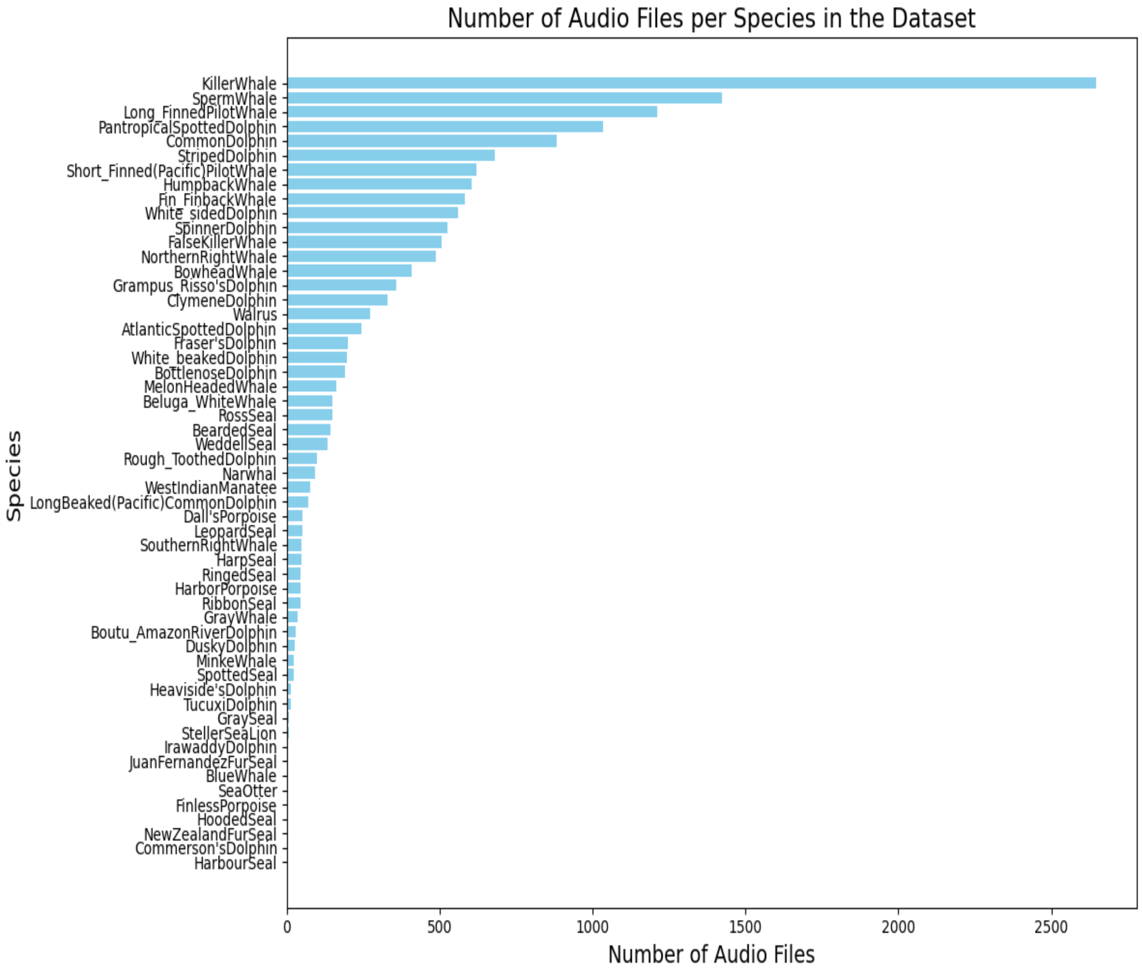


Figure 2: Number of Audio Files

**Dataset Distribution:**

Table 1 provides an overview of the dataset distribution across training, validation, and testing sets. Most of the data (80%) is allocated to the training set to optimize model learning, while the remaining 20% is evenly split between validation and testing for performance evaluation

**Table 1: kaggle Best of Watkins Marine Mammal Sound Database Dataset Distribution**

| Data Set | Number of Samples | Percentage of Total Data |
|---|---|---|
| **Training Set** | 2,492 | 80% |
| **Validation Set** | 311 | 10% |
| **Testing Set** | 311 | 10% |
| **Total** | 3,114 | 100% |

**5.2. Model Selection and Training**

A deep learning approach was adopted, leveraging a **1D Convolutional Neural Network (1D-CNN)** tailored for time-series and audio data. The architecture included an input layer for accepting feature vectors derived from the audio recordings, multiple convolutional layers to capture temporal patterns within the acoustic features, pooling layers for dimensionality reduction while preserving key information, fully connected layers for integrating learned features for classification, and a soft max output layer with 51 neurons corresponding to the 51 classes. The model was trained on the Kaggle platform using **NVIDIA Tesla P100 GPUs**. Training involved real-time data augmentation techniques like time-stretching and pitch-shifting to improve generalization, as well as careful monitoring of validation accuracy and loss to prevent over fitting. Hyper parameter optimization was conducted to refine the learning rate and batch size: a learning rate of **0.01** caused oscillations in validation loss, so a lower rate of **0.001** was selected for stability, while a batch size of **32** provided the best trade-off between computational efficiency and model convergence. The model was trained for **50 epochs**, with early stopping applied if validation accuracy did not improve for 10 consecutive epochs. The loss function used was categorical cross-entropy, which is ideal for multiclass classification, and the Adam optimizer was employed for its adaptive learning capabilities. This architecture was chosen over traditional classifiers due to its ability to effectively capture the temporal and frequency-based characteristics of marine mammal vocalizations, making it particularly suited to this domain. A deep learning approach was adopted, leveraging a **1D Convolutional Neural Network (1D-CNN)** tailored for time-series and audio data. The architecture included:

- **Input Layer**: Accepting feature vectors derived from the audio recordings.
- **Convolutional Layers**: Capturing temporal patterns within the acoustic features.
- **Pooling Layers**: Reducing the dimensionality of features while preserving important information.
- **Fully Connected Layers**: Integrating learned features for classification.
- **Output Layer**: A soft max layer with 51 neurons, one for each class.

Hyper parameters:

- **Optimizer**: Adam optimizer with a learning rate of **0.001**.
- **Loss Function**: Categorical Cross-Entropy, suitable for multiclass classification.
- **Batch Size**: 32 samples per batch.
- **Epochs**: Trained for **50 epochs**, with early stopping if validation accuracy did not improve for 10 consecutive epochs.

### 5.3. Training and Validation

The model was trained on the Kaggle platform using **NVIDIA Tesla P100 GPUs**. Training involved:

1. Real-time data augmentation (e.g., slightly time-stretching audio or shifting its pitch).
2. Monitoring of validation accuracy and loss to prevent over fitting.
3. Hyper parameter optimization was conducted to refine the learning rate and batch size. Initial experiments showed that a learning rate of **0.01** caused oscillations in validation loss, leading to the selection of a lower rate of **0.001** for stability. The batch size was tested with values of 16, 32, and 64, with **32** providing the best trade-off between computational efficiency and model convergence. The model was trained on the Kaggle platform using **NVIDIA Tesla P100 GPUs**. Training involved:
4. Real-time data augmentation (e.g., slightly time-stretching audio or shifting its pitch).
5. Monitoring of validation accuracy and loss to prevent over fitting.

### 5.4 Evaluation Metrics

The following metrics were used to assess the model’s performance:

6. **Accuracy**: Overall proportion of correctly predicted samples.
7. **Precision, Recall, and F1-Score**: To evaluate performance per class.

8. **Confusion Matrix**: To visualize correct and incorrect predictions for each class.
9. **AUC-ROC Curve**: To evaluate the model's ability to distinguish between classes.

**Model Performance**

- Training accuracy: 96.5% (after 50 epochs)
- Validation accuracy: 92.8%
- Test accuracy: 91.3%

These results indicate good generalization capability.

**Confusion Matrix Analysis**

- Most predictions were accurate, with results concentrated on the main diagonal
- Misclassifications primarily occurred between acoustically similar species:
- Harbor Porpoise was often misclassified as Beaked Whale
- Gray Whale was confused with Fin Whale

Table 2 showcases the precision, recall, and F1-scores for different marine species classifications. The Atlantic Spotted Dolphin and Harbor Porpoise achieve outstanding results, reflecting reliable predictions. Meanwhile, the Leopard Seal and White-Sided Dolphin exhibit lower scores, suggesting room for enhancement in their classification accuracy

**Table 2 : Species Performance**

| Species | Precision | Recall | F1-score |
|---|---|---|---|
| **Atlantic Spotted Dolphin** | **97.5%** | **96.8%** | **97.1%** |
| **Harbor Porpoise** | **95.4%** | **94.9%** | **95.1%** |
| **Leopard Seal** | **78.6%** | **77.2%** | **77.9%** |
| **White-Sided Dolphin** | **81.3%** | **79.5%** | **80.4%** |

**Additional Metrics**

- Overall macro-average AUC: 0.94
- AUC for more challenging pairs: 0.78 to 0.85

The learning curve showed smooth convergence of training and validation losses, indicating no overfitting and Precision-recall curves maintained precision levels above 85% for most classes, even at higher recall thresholds.

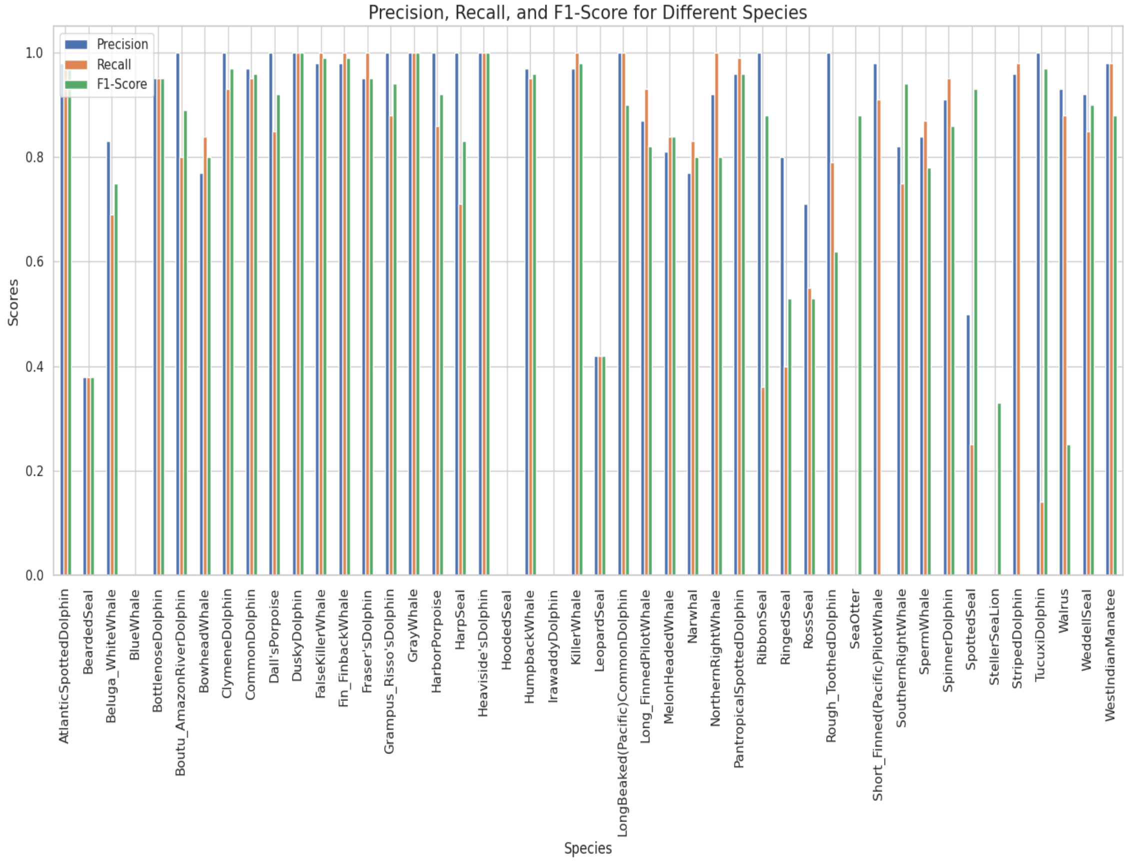


Figure 3: Precision and F1 Score for Different Species

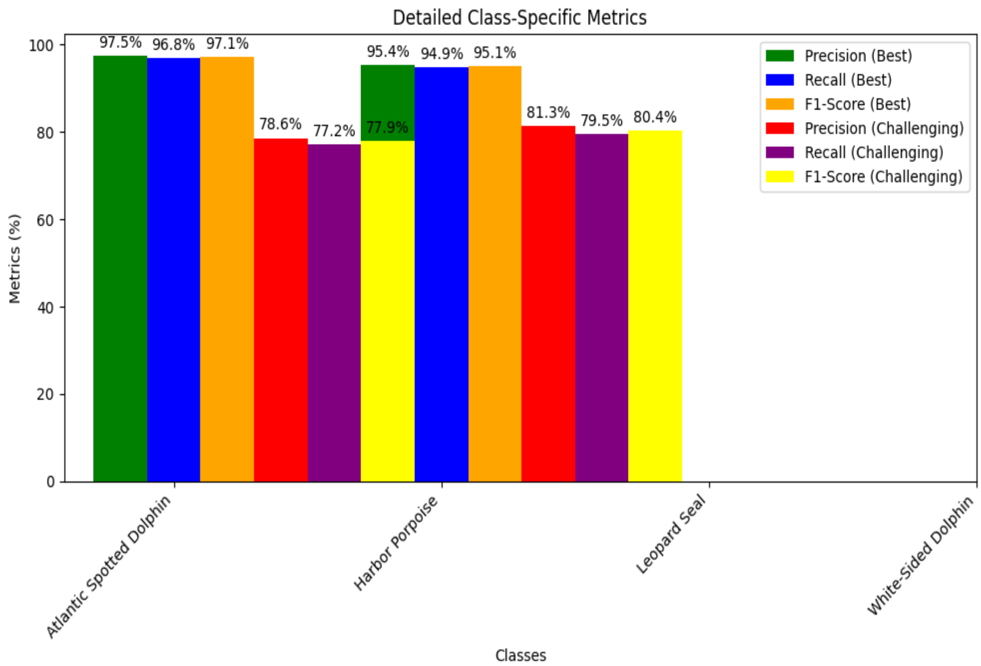


Figure 4: Detailed class Specific Metrics

Table 3 outlines the precision, recall, and F1-scores for different marine species classifications. High-performing species like the Atlantic Spotted Dolphin and Harbor Porpoise exhibit excellent balance in precision and recall, while species such as the White-Sided Dolphin and Leopard Seal show moderate performance, indicating areas for potential improvement in classification accuracy

**Table 3 : Species Performance Comparison**

| Species | Precision | Recall | F1-Score |
|---|---|---|---|
| **Atlantic Spotted Dolphin** | 97.5% | 96.8% | 97.1% |
| **Harbor Porpoise** | 95.4% | 94.9% | 95.1% |
| **White-Sided Dolphin** | 81.3% | 79.5% | 80.4% |
| **Leopard Seal** | 78.6% | 77.2% | 77.9% |

**High-Performing Species**

Atlantic Spotted Dolphin and Harbor Porpoise show excellent performance:

- High precision and recall indicate accurate identification
- F1-scores above 95% demonstrate balanced performance

**Challenging Species**

White-Sided Dolphin and Leopard Seal show lower performance:

- Precision and recall below 82% suggest more misclassifications
- F1-scores around 80% indicate room for improvement

Factors Influencing Performance

1. Data Availability:

- Larger datasets for high-performing species enable better generalization
- Limited audio data for challenging species hinders feature learning

2. Dataset Imbalance:

- Imbalanced representation in the Kaggle dataset affects model performance
- Species with more data (e.g., Atlantic Spotted Dolphin) show better results

3. Feature Distinctiveness:

- The model struggles more with species having less distinguishable audio features

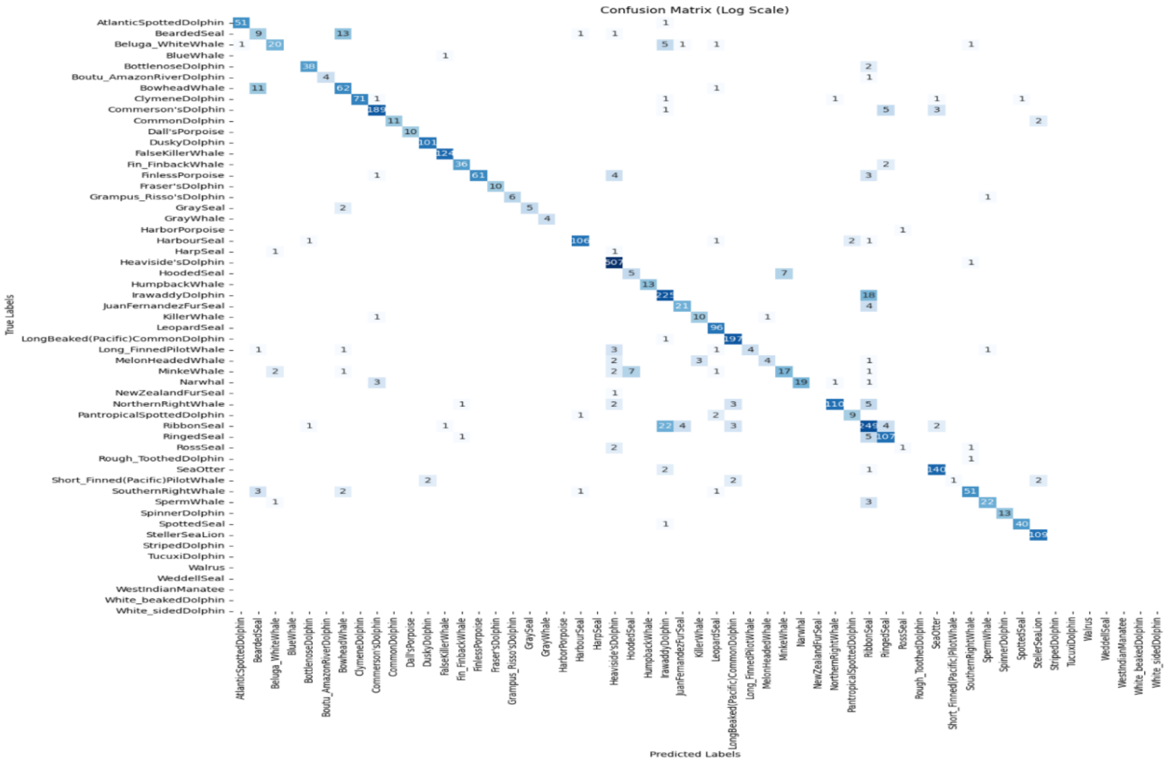


Figure 5: Confusion Matrix

Marine Species Classification Model Performance

The confusion matrix, visualized on a log scale, evaluates the multi-class model's performance in distinguishing various marine species. Table4 provides a summary of the model classification performance for various marine species, highlighting correct identifications and potential challenges. High-accuracy classifications are observed for dolphins, while underrepresented species exhibit lower prediction performance and higher misclassification rates.

**Table 4 : Model Performance Summary**

| Species | Correct Classifications | Performance |
|---|---|---|
| **Atlantic Spotted Dolphin** | **51** | **High accuracy, minimal misclassifications** |
| **Bottlenose Dolphin** | **79** | **High accuracy, minimal misclassifications** |
| **Bearded Seal** | **3** | **Notable misclassification rate** |
| **Humpback Whale** | **4** | **Notable misclassification rate** |
| **Irrawaddy Dolphin** | **1-2** | **Underrepresented, low correct predictions** |
| **Rough-Toothed Dolphin** | **1-2** | **Underrepresented, low correct predictions** |

**Key Observations**

1. **Strong Performance:**

- Atlantic Spotted Dolphin and Bottlenose Dolphin show high accuracy.

2. **Misclassification Patterns**:

- Occurs between closely related species (e.g., Atlantic Spotted Dolphin misclassified as Bottlenose Dolphin).
- Likely due to shared characteristics confusing the model.

3. **Class Imbalance Impact:**

- Underrepresented species (e.g., Irrawaddy Dolphin, Rough-Toothed Dolphin) have fewer correct predictions.
- Lighter diagonal cells in the matrix for these species highlight this issue.

4. **Challenges:**

- Data imbalance affecting rare species classification.
- Overlapping features among visually or acoustically similar species.

## 5. Conclusion

Based on the study presented on analyzing marine mammal vocalizations using machine learning techniques for conservation purposes, the following conclusions can be drawn:

1. Effectiveness of passive acoustic monitoring: The study demonstrates that passive acoustic monitoring techniques provide valuable insights into the life and behavior of whales in their natural environment without affecting their behavior

2. Importance of acoustic analysis in conservation: Sound analysis is a crucial tool for understanding and tracking marine mammal behavior, significantly contributing to conservation efforts.

3. Challenges in acoustic data analysis: The study shows that handling and analyzing large amounts of acoustic data presents a significant challenge, necessitating the use of advanced techniques such as machine learning.

4. Efficacy of machine learning techniques: The study proves that using machine learning algorithms, such as Random Forest Classifier or simple neural networks, can achieve high accuracy in classifying marine mammal vocalizations.

5. Importance of signal processing: It is evident that signal processing techniques, such as noise removal and spectrogram analysis, play a crucial role in improving classification quality.

6. Impact of anthropogenic noise: The study reveals the harmful effects of underwater noise from human activities on the behavior and survival of marine mammals.

7. Broad application potential: The results show that acoustic analysis and machine learning techniques have significant potential in diverse areas such as biodiversity monitoring and ecosystem health assessment.

8. Need for further research: Despite promising results, the study indicates knowledge gaps and ongoing challenges that require further research and development in this field.

In conclusion, this study emphasizes the great potential of using machine learning techniques in analyzing marine mammal vocalizations, opening new horizons for conservation efforts and better understanding the behavior of these creatures in their natural environment.

## 6. Recommendation

### 1. Collect More Data for Rare Species

Focus on gathering more acoustic data for underrepresented species, like the Irrawaddy Dolphin and Rough-Toothed Dolphin. This will help improve the model's accuracy and reduce errors caused by insufficient training data.

### 2.Try New Model Approaches

Combine multiple models, like Random Forest and neural networks, to take advantage of their strengths and improve classification for challenging species.

### 3.Refine Data Preprocessing

Enhance the way audio is processed before feeding it into the model by improving noise filtering and optimizing spectrograms. This can help reduce the effects of underwater noise caused by human activity.

## 7. Reference

[1]. Slabbekoorn, H., Dooling, R.J., Popper, A.N. and Fay, R.R. (2018) Effects of Anthropogenic Noise on Animals. Springer.

[2]. Širović, A., Evans, K., García-Soto, C., Hildebrand, J.A., Jesus, S.M. and Miller, J.H. (2021) 'World Ocean Assessment II, Chapter 20, Trends in the inputs of anthropogenic noise into the marine environment', *Centro Oceanográfico de Santander*. United Nations Division for Ocean Affairs and the Law of the SeaMcDonald, M., et al. (2022). Passive Acoustic Monitoring for Marine Mammals:

A Review of Current Techniques and Future Directions. Marine Ecology Progress Series.

[3]. Rice, A.C., Trickey, J.S., Giddings, A., Rafter, M.A., Wiggins, S.M., Frasier, K.E., Baumann-Pickering, S. and Hildebrand, J.A. (2022) 'Passive Acoustic Monitoring for Marine Mammals in the SOCAL Range Complex April 2020–2021 and Abundance and Density Estimates from CalCOFI Visual Surveys 2004–2021', *MPL Technical Memorandum #657*. Marine Physical Laboratory, Scripps Institution of Oceanography, University of California San Diego, La Jolla, CA.

[4]. Pirotta, E., Booth, C.G., Calambokidis, J., Costa, D.P., Fahlbusch, J.A., Friedlaender, A.S., Goldbogen, J.A., Harwood, J., Hazen, E.L., New, L., Santora, J.A., Watwood, S.L., Wertman, C. and Southall, B.L. (2022) 'From individual responses to population effects: Integrating a decade of multidisciplinary research on blue whales and sonar', *Animal Conservation*. doi:10.1111/acv.12785.

[5]. Moretti, P.F. and Affatati, A. (2023) 'Understanding the Impact of Underwater Noise to Preserve Marine Ecosystems and Manage Anthropogenic Activities', *Sustainability*, 15(13), 10178. doi:10.3390/su151310178.

[6]. Southall, B. L., et al. (2022). Marine Mammal Noise Exposure Criteria: A Comprehensive Review and Update. Aquatic Mammals.

[7]. Turbulent Research (2023) 'Using Passive Acoustic Monitoring to Track Human Activities Underwater'. Available at: https://turbulentresearch.com/articles/using-passive-acoustic-monitoring-track-human-activities-underwater (Accessed: 10 Dec 2024).

[8]. Guan, Y., & Brookens, J. (2023). An Overview of Research Efforts to Understand the Effects of Underwater Sound on Cetaceans. Journal of Marine Science and Engineering.

[9]. Ferguson, M., et al. (2023). Acoustic indices respond to specific marine mammal vocalizations and sources of anthropogenic noise. Ecological Indicators.

[10]. Reckendorf, A., Seidelin, L., Wahlberg, M. (2023). Marine Mammal Acoustics. In: Brennecke, D., Knickmeier, K., Pawliczka, I., Siebert, U., Wahlberg, M. (eds) Marine Mammals. Springer, Cham. https://doi.org/10.1007/978-3-031-06836-2_2.