With an exponential growth in global sea-bound activities, ranging from naval shipping to recreational boating and underwater construction, the world's oceans are becoming busier than ever. However, this increasing hustle and bustle beneath the waves carries with it a less visible, but significant consequence: noise pollution. Underwater noise pollution, an often overlooked by-product of maritime activities, presents complex challenges that ripple through diverse sectors.

These challenges directly affect areas such as national defense, where persistent underwater noise can mask the sound signatures of potential threats, and ocean policing, where distinguishing illicit activities amidst the cacophony of oceanic noise becomes a daunting task.
Unintentionally, the resounding echoes of human activities interfere with environmental preservation efforts, as these noises can disrupt delicate marine ecosystems and impede scientific research, particularly in marine biology, where tracking migratory patterns can be confounded by conflicting audio signals.

Furthermore, excessive noise pollution underwater can disrupt the efficiency of shipping operations, necessitating the need for more optimized ship design to reduce noise emissions, thus benefiting fuel efficiency and potential top speeds.

This growing recognition of the far-reaching impacts of underwater noise pollution has precipitated the urgent need for technological innovations and solutions that go beyond monitoring to proactive management and control of marine acoustic footprints.

Previous research in this domain has used several techniques, each with its own pros and cons. For instance, Azimi-Sadjadi et al. utilized adaptive feature mapping for underwater target classification. Similarly, Pezeshki et al. used canonical correlation analysis for the same. Filho et al. applied neural classification processes to passive sonar signals, while Wu et al. relied upon Wigner-Ville distribution for extraction and classification of acoustic scattering from underwater targets.

Nonetheless, a common theme among these approaches was their reliance on complex preprocessing techniques, intricate dimensionality reductions, and deep models, which added substantial computational overhead to the classification process. These methods predominantly furnished binary outputs, falling short of providing a classification of the type of ship being detected, let alone furnishing further details regarding its properties.

I have created a baseline in order to compare future results I created a simple logistic regression. I collected audio data, converted it into Mel-Frequency Cepstral Coefficients for easy input into a model, and then grouped the data according to ship type. A logistic regression model trained on the above-mentioned data and features yielded some intriguing results. For the tug category, my model achieved perfect precision and recall. However, it failed to identify passenger ships and cargo ships correctly. The model performed significantly better on tankers, accurately predicting them 70% of the time.

While my model does not perfectly solve the problem of identifying type of ship based on its noise, it provides a simple and efficient approach for a baseline model. In specific categories such as tugs and tankers, the model demonstrates promising potential. In next phase I will be implementing additional preprocessing techniques, feature extractions, and more highly tuned models. From the previous research contained in the previously mentioned articles I will implement and comparing the results of:

1. Wavelet packet decomposition - To analyze non-stationary signals and ensure that the model can capture multi-resolution characteristics of the sound data.
2. Linear Predictive Coding (LPC) - To better model the spectral envelope of the time-domain signal.
3. Fisher Criterion for feature selection - This can be instrumental in determining which attributes contribute most significantly to the classification task.
4. And a few more promising techniques found by Muhammad Irfan et al: Cepstrum, Mel spectrogram, MFCC, Constant Q Transform (CQT),

Gammatone Frequency Cepstral Coefficients (GFCC), and additional Wavelet packets.

5. Finally different models to Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) which can more effectively handle time-series data like audio signals compared to my baseline logistic regresssion.

I will be doing comparisons between different techniques to find the best model that not only has the highest accuracy scores, but is the most comprehensible, efficient, and applicable for a wide variety of potential applications.

Sources:

1. **Underwater target classification in changing environments using an adaptive feature mapping**
    - By: M.R. Azimi-Sadjadi; D. Yao; A.A. Jamshidi; G.J. Dobeck
2. **Undersea Target Classification Using Canonical Correlation Analysis**
    - By: Ali Pezeshki; Mahmood R. Azimi-Sadjadi; Louis L. Scharf
3. **Preprocessing passive sonar signals for neural classification**
    - By: Filho, W.S., De Seixas, J.M., De Moura, N.N.
4. **Extraction and classification of acoustic scattering from underwater target based on Wigner-Ville distribution**
    - Yushuang Wu a b, Xiukun Li a b, Yang Wang c
5. **Individual Ship Detection Using Underwater Acoustics**
    - Damianos Karakos; Jan Silovsky; Richard Schwartz; William Hartmann; John Makhoul
6. **Acoustic Classification of Surface and Underwater Vessels in the Ocean Using Supervised Machine Learning**
    - Choi, J., Choo, Y., & Lee, K.
7. **DeepShip: An underwater acoustic benchmark dataset and a separable convolution based autoencoder for classification**
    - Muhammad Irfan, Zheng Jiangbin, Shahid Ali, Muhammad Iqbal, Zafar Masood, Umar Hamid

Criteria	Description	Score
Introduction	Clearly defines the problem, its relevance, and importanc	
Previous Work Review	Adequately discusses and critiques related works in the problem space	
Methodology	Explanation of your approach, tools, techniques, and data used	
Results	Detailed discussion of your experiment results	
Future Work	Clearly states next steps and future improvements	
Writing Style	Clarity, readability, grammar and punctuation, and essay structure	
Overall Content	Cohesiveness, relevance to the topic, depth and breadth of coverage	

Used ChatGPT