Advancing Acoustic Classification of False Killer Whales Using Spectrogram-Based Machine Learning

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The false killer whale (Pseudorca crassidens), one of Hawai?i's most endangered marine mammals, is difficult to monitor visually because of its deep-sea distribution and behavioral avoidance of vessels. Passive acoustic monitoring provides a viable alternative; however, classifying their whistles remains challenging due to overlapping frequency ranges among sympatric intra- and inter-species populations and limited labeled data. This study developed a reproducible, spectrogram-based deep learning framework dedicated to improving the classification of false killer whale whistles and to evaluating the impact of targeted signal filtering. Two datasets were compared: an unfiltered baseline and a 1.5 kHz high-pass-filtered version that reduced low-frequency vessel noise while preserving biologically relevant tonal contours. Both used a MobileNetV2 convolutional neural network trained on 224×224 Mel-spectrograms with Adam optimization, label smoothing, and early stopping. Multi-seed replication and bootstrapped 95% confidence intervals quantified reproducibility. The unfiltered baseline achieved a mean test accuracy = 0.883 ± 0.011 and macro-F1 = 0.879 ± 0.015; the high-pass-filtration achieved 0.854 ± 0.010 and 0.839 ± 0.015. Although filtering reduced absolute accuracy, it yielded smoother convergence and less overfitting. Receiver-operating-characteristic analysis confirmed strong discriminative capacity, and Grad-CAM heatmaps revealed saliency concentrated along whistle contours, indicating biologically meaningful feature learning. The multi-seed methodology establishes a framework for scalable, ecologically grounded acoustic monitoring of false killer whales and other marine mammal datasets, advancing machine learning's role in conservation bioacoustics.

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