



COMPARING WITHOUT CLASSIFYING: EVALUATING EMBEDDINGS FROM BIOACOUSTIC DEEP LEARNING FEATURE EXTRACTORS

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ABSTRACT

In computational bioacoustics, deep learning models are composed of feature extractors and classifiers. The feature extractors generate vector representations of the input sound segments, called embeddings. While benchmarking of classification scores provides insight into specific performance statistics, it is limited to species that are included in the models training data. Furthermore, it makes it impossible to compare models trained on very different taxonomic groups. This paper aims to address this gap by analyzing the embeddings generated by the feature extractor of more than 15 bioacoustic models spanning a wide range of setups (model architectures, training data, training paradigms). We evaluate and compare different ways how models structure embedding spaces through clustering and linear classification, which allows us to focus our comparison on feature extractors independent of classifiers. We believe that this approach lets us evaluate the adaptability and generalization potential of models going beyond the classes they were trained on.

Keywords: *deep learning, bioacoustics, embeddings*

1. INTRODUCTION

Human-driven climate change and deforestation have caused a rapid decline in global biodiversity [1]. Using sensor arrays for biodiversity monitoring, ecologists can

gather information on environments and investigate how human pressures affect biodiversity and how we can halt its decline [2]. Passive acoustic monitoring (PAM) is one method that provides a low-cost and non-invasive way to monitor biodiversity [3]. The vast amount of data generated by PAM sensors has led to the rapid development of bioacoustic deep learning models to help researchers reduce the annotation effort [4]. The use of these state-of-the-art models has proven valuable in ecological studies, for example in general species assessments [5,6] or detection of endangered species [7].

While bioacoustic deep learning models are a useful asset in ecology, it is crucial to understand the model's limitations based on their training setup. The two main training strategies to develop bioacoustic deep learning models are supervised learning and self-supervised learning. Supervised learning models require large amounts of annotated data to be trained [8]. The models classify sounds based on a fixed number of predefined classes representing annotated sounds in the dataset. While supervised learning can have the benefit of instructing models to differentiate between species vocalizations, it requires annotated datasets. This limits supervised learning models to known and annotated classes and makes them sensitive to class imbalance and label quality. Self-supervised learning can be executed in different ways. In a paradigm referred to as masked prediction, the model is trained to predict a masked portion of the audio, thereby modelling bioacoustic characteristics without supervision [9, 10]. With growing annotated databases supervised learning models like Birdnet [11] improve in performance, yet recent developments in self-supervised learning on models like animal2vec [12] indicate a promising new direction for the field requiring less manual annotation. Not requiring annotations, self-supervised learning mod-

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els can be trained on far larger datasets, however there is no control of what is being learned. The model might learn to differentiate between sounds based on very different characteristics than the species that produces them.

To evaluate bioacoustic deep learning models, a comparison of only the classifier performance obscures the fine-grained differences between models and how they analyze input sounds. Bioacoustic deep learning models consist of artificial neural networks which can be subdivided into feature extractors and classifiers. The feature extractor creates an embedding (vector representation) of an input sound and the classifier (which corresponds to the final dense layer of the model) maps the embedding onto classes. Commonly, in bioacoustics, a suite of established benchmarks is used to compare the classifier performance of state-of-the-art models [13]. This requires the models to have been trained on the classes present in the benchmarking datasets. However, there is an alternative: using the embeddings created by the feature extractors, the generated embedding spaces can be analyzed in regard to their structural characteristics, irrespective of what the classifiers were trained on.

Output dimensions of feature extractors vary greatly, but it is uncertain if their dimensionality correlates to the downstream classifier performance. Dimensionality reduction algorithms are useful to standardize the dimensionality of different feature extractors, as well as help visualize the high dimensional embedding spaces. However, there is little investigation of how reducing the embedding space affects performance. We therefore compare performance in both original and reduced embedding spaces.

Due to their size, datasets that are used to train bioacoustic models for bird detection are often based on citizen science data (e.g. xeno-canto [14]). The majority of these recordings are focal recordings of individuals which are weakly labeled with little polyphony. When models get applied to large PAM datasets, especially outside of North America (where the majority of the training data originates), the difference in recording conditions causes performance drops [15]. To accurately evaluate the models in this study, we use a PAM bird vocalization dataset from Colombia and Costa Rica [16], as well as a dataset of frog vocalizations from Brazil [17]. Both datasets are comprised of PAM recordings in noisy environments and can therefore be considered as challenging datasets. With this, we hope to on the one hand emphasize the performance differences between the models and on the other hand produce results that will reflect in real world applications.

This study aims to showcase the potential for evaluating and especially comparing bioacoustic deep learning models in regard to their training paradigm and training data. This evaluation is based on the structuring capabilities of their respective feature extractors analyzed through clustering and classification performance. Classification in this case refers to recognition of novel classes, as none of the models have been pretrained on the classes selected here. This way single classification layers are attached to each feature extractor, all of which are trained on the same evaluation sets (bird and frog vocalizations), i.e. same classes and same data, allowing us to compare their performance. Classification is done both in a linear and a k-nearest neighbor (kNN) approach. We perform our analysis in both the original embedding space and a reduced dimensional embedding space. That way we ensure the dimension is standardized for the second evaluation, whilst we can investigate performance differences between the original embedding space and the reduced space. This method of analysis opens up the possibilities for a fair comparison of deep learning feature extractors guiding the field to a better understanding how training configurations affect downstream performance.

2. METHODS

To incorporate a variety of training setups, covering popular models as well as models targeted to various species groups, we compare a total of 15 pre-trained bioacoustic different feature extractors. Table 1 shows the different feature extractors along with their model specific training setup. As can be seen both self-supervised and supervised learning feature extractors are represented. Furthermore, large variations in input length, embedding dimension and training data provide a landscape of feature extractors, allowing us to analyze performance of differently structured embedding spaces.

2.1 Dataset

The evaluation datasets that were used for this study are

1. a bird vocalization dataset (from hereon referred to as bird dataset) recorded in coffee farms in Colombia and Costa Rica [16] and
2. a frog vocalization dataset (from hereon referred to as frog dataset) recorded in Brazil [17].

The recordings in these datasets feature challenging soundscape recordings with overlapping vocalizers and





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noisy environments. Both datasets have been reduced from their original size to only include sound events corresponding to classes with more than 150 annotations. Due to the high amount of polyphony, the frog dataset has furthermore been reduced to only contain sound events with non-overlapping annotations, i.e. turning it into a single-label dataset. It is worth mentioning, that by excluding overlapping annotations, only polyphony of anuran species is removed, overlapping sounds created by insects and birds in the recordings remains.

For the bird dataset this results in 11 classes, while for the frog dataset 18 classes are included in the final dataset. We intentionally selected soundscape recordings with gradual changes of background noise and overlapping species vocalizations to amplify the differences between the feature extractors' capabilities to structure the data.

2.2 Data pipeline

For each of the feature extractors, the respective model code base was cloned, and the model was stripped of its classifier. For both animal2vec feature extractors, outputs from the attention heads and input lengths are averaged, resulting in one embedding per input segment (as is the case with all other feature extractors). Data is imported from the sound files, resampled to the model specific sample rate and padded to fit the model specific input length. All the necessary code to reproduce the computations can be found in the repository **bacpipe**¹ (bioacoustic collection **pipeline**).

2.3 Methods of evaluating embedding spaces

Embedding spaces are evaluated using clustering and classification. Our primary focus is the comparison of the two paradigms: supervised learning and self-supervised learning. Furthermore, we are looking into how the data chosen for training affects the clustering capabilities of different feature extractors.

The clustering is computed using KMeans with the same number of clusters as classes in the ground truth. Clustering performance will be evaluated using Adjusted Mutual Information (AMI) [22] to compare the KMeans clustering with the ground truth. Adjusted Rand Index is not included in this study, as it focuses on how well data points are grouped in a clustering, whereas we are primarily interested how well the KMeans clustering agrees

with the ground truth labels. Silhouette Score is also not included in this comparison as the challenging dataset yielded very low performance and variance, making a meaningful comparison impossible.

Performance is also evaluated by training a single-layer classifier on each of the embedding spaces. Classification is performed using a linear and a kNN approach. The linear classifier is trained on the 11 and 18 classes for the bird and frog datasets respectively for 10 epochs with a batch size of 64 and a learning rate of 0.001. For the kNN classifier a nearest neighbor parameter of 15 is chosen. Data is split into train, validation and test set in the ratio 0.65:0.15:0.2. Performance is evaluated using a balanced macro accuracy score [23] to handle the imbalance in class sizes.

Evaluations computed in both the original embedding spaces and an embedding space reduced to 300 dimensions. This way the embedding dimension is standardized and performance can be compared while controlling for this factor. It also allows us to compare the performance of each model in their high dimensional original embedding space, as well as in a reduced dimension. For the linear classifier, to preserve relative distances between data points, Principal Component Analysis (PCA), a linear dimensionality reduction is selected. For the kNN classifier uniform manifold approximation projection (UMAP) [24] is selected. UMAP is also used to visualize the embeddings in two dimensions in Fig. 1.

3. RESULTS

Two-dimensional UMAP embeddings are shown in Fig. 1. The worst performing feature extractors, produce large unstructured clouds of mixed color, indicating that no significant clustering is achieved. In the first and second row, feature extractors can be seen to separate the embeddings into meaningful clusters. It is noticeable that some feature extractors such as AvesEcho.PaSST and ProtoCLR seem to generate more subclusters than most other feature extractors. The seven best performing feature extractors are all trained using supervised learning and the top three additionally trained on bird vocalizations. All three of the AVES models (BirdAVES, AVES and NonBioAVES) reach similar performances in spite of big differences in their fine-tuning datasets [8].

Performance is evaluated by macro accuracy of kNN classification on the x-axis and AMI of clustering on the y-axis.

When focussing on the y-axis, all self-supervised

¹ github.com/bioacoustic-ai/bacpipe



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Table 1. List of feature extractors compared in this study. Columns "abbrev." shows the an abbreviated name used in Figures ?? and 2. "training" shows the training setup chosen during training, i.e. ssl for self-supervised learning, sup l for supervised learning and ft for fine-tuning. The "architecture" column more specifically describes the model architecture used. "dimension" shows the output dimension of the feature extractor. "trained on" summarizes the species group that was used to train the model. "ref." provides the respective publication for a given model.

name	abbrev.	training	architecture	dimension	trained on	ref.
Animal2vec_XC	brdnet	ssl	d2v2.0	768	birds	[12]
Animal2vec_MK	a2v_xc	ssl + ft	d2v2.0	1024	meerkats	[12]
AudioMAE	a2v_mk	ssl + ft	ViT	768	general	[10]
AVES_ESpecies	aud_mae	ssl + ft	HuBERT	768	general + animals	[8]
AvesEcho_PaSST	aves	sup l	PaSST	768	birds	[18]
BioLingual	bioling	mm sup l	CLAP	512	animals + birds	[19]
BirdAVES_ESpecies	birdaves	ssl + ft	HuBERT	1024	general + birds	[8]
BirdNET	aecho	sup l	EffNetB0	1024	birds	[11]
Google_Whale	i66	sup l	EffNetB0	1280	whales	-
Insect459NET	i459	sup l	EffNetv2s	1280	insects	-
Insect66NET	perch	sup l	EffNetv2s	1280	insects	-
NonBioAVES_ESpecies	p_clr	ssl + ft	HuBERT	1024	general + non-bio	[8]
Perch_Bird	s_perch	sup l	EffNetB0	1280	birds	-
ProtoCLR	g_whale	sup l	CvT-13	384	birds	[20]
SurfPerch	nonbioaves	sup l	EffNetB0	1280	coral reefs + birds	[21]

learning feature extractors (in red) reach clustering performances under 0.31. Performance by kNN classification is more equally distributed, however, again supervised learning feature extractors reach the six highest values. Furthermore, Animal2vec_XC, the only self-supervised learning feature extractor that was not fine-tuned, performs poorly by both clustering and kNN classification. Google_Whale represents the only supervised learning feature extractor performing very poorly by clustering and kNN classification.

Comparing by training data, feature extractors trained on only or including bird datasets outperform the other feature extractors by kNN classification and even more so by clustering. Aside from ProtoCLR the supervised learning models that are also trained on birds vastly outperform all other models in the combination of clustering and kNN classification. Perch and BirdNET lead in both clustering and kNN classification by a large margin. Animal2vec_XC is the only two feature extractor trained on birds that performs poorly. Biolingual, which was trained on large bird databases using a multi-modal approach per-

forms well by clustering, but comparably poorly by kNN classification.

When referring back to Table 1 embedding dimension does not correlate with clustering or kNN classification performance. Furthermore, the only two feature extractors trained on marine sounds, Google_Whale and SurfPerch (trained on birds and marine sounds) reach very different performances.

To highlight performance changes once the feature extractors are applied to a dataset different from their training domain, Fig. 2 shows the performance on the bird dataset (black) and the frog dataset (red and blue) connected by an arrow. Aside from Perch, BirdNET and Biolingual all feature extractors increase in clustering performance when applied to the frog dataset. All self-supervised feature extractors improve in clustering performance and aside from Animal2vec_MK also in kNN classification. The self-supervised AVES feature extractors (BirdAVES, AVES and NonBioAVES) drastically improve in both clustering and kNN classification on the frog dataset. So much so, that all three outperform all



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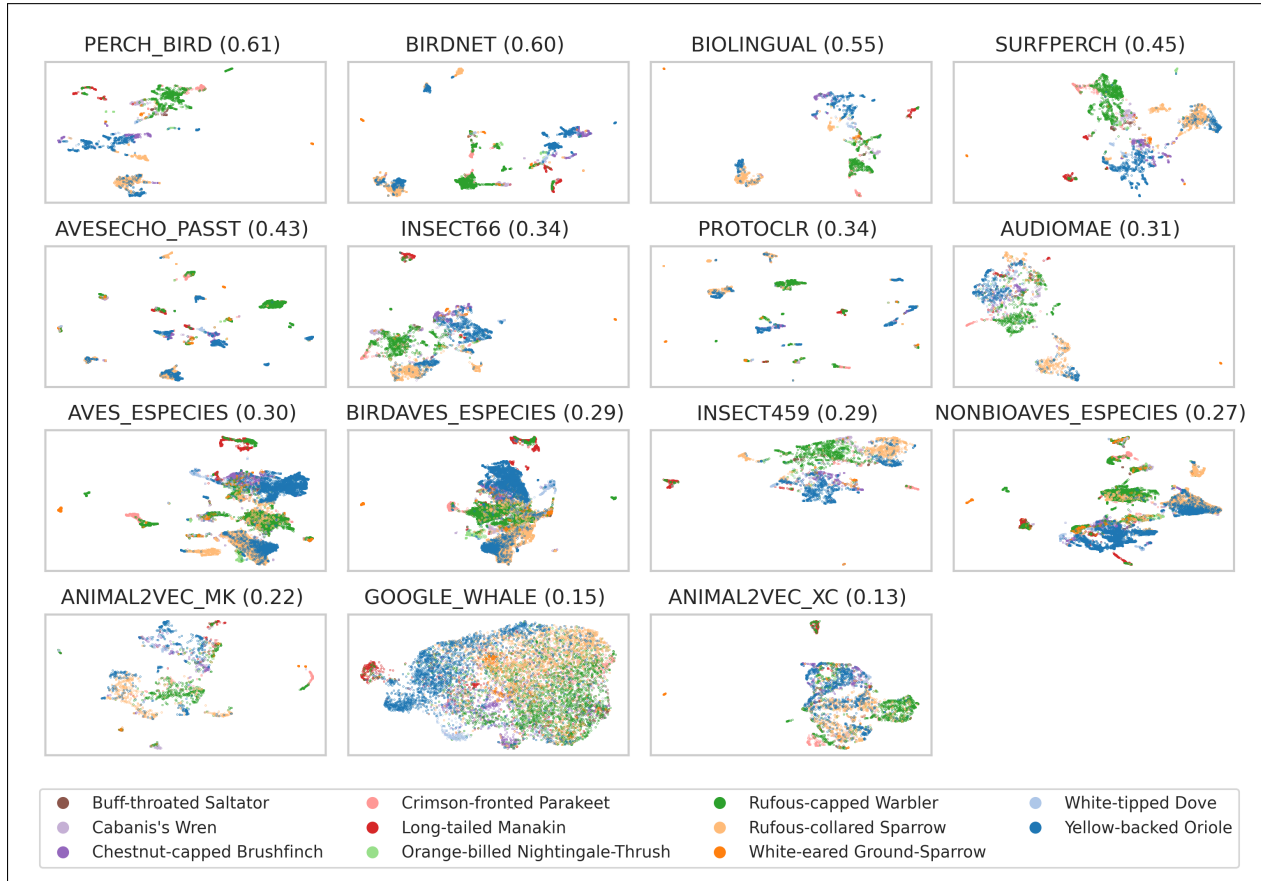


Figure 1. Two-dimensional embedding spaces of all feature extractors, sorted descending by their clustering performance of AMI values (indicated next to their name) from top left to bottom right. Given the different input lengths of the feature extractors, the number of embeddings vary significantly. Colors correspond to the class labels, which are 11 different tropical bird species.

other feature extractors by kNN classification. Among supervised learning feature extractors, kNN classification performance changes are more varied. All non-bird trained feature extractors improve in clustering. From the supervised bird trained feature extractors, only AvesEcho improves in both clustering and kNN classification. Again, all bird trained feature extractors except for Animal2vec_XC outperform the rest by clustering on the frog dataset. The top 6 models by clustering are again the supervised learning bird trained feature extractors. However, by kNN classification, results are more mixed by both training paradigm and training domain.

4. DISCUSSION

Although the self-supervised feature extractors represented in this study are trained on very large datasets, their combined performance is inferior to most of the supervised learning feature extractors including those trained on non-bird categories. Perch and BirdNET [11], both of which are trained on thousands of classes of bird vocalizations vastly outperform the other feature extractors. Similarly, SurfPerch [21] and AvesEcho_PaSST [18], both of which have largely benefited from Perch or BirdNET pretraining, perform well by both clustering and linear classification. More generally, the embedding spaces of feature extractors trained on very large annotated bird song datasets seem to yield good separation between clus-



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Table 2. List of feature extractors compared in this study.

bird data		classification (macro accuracy)		
category		original	umap	pca
ssl		0.617	0.619	0.587
supl		0.695	0.711	0.66
bird		0.712	0.723	0.607
non-bird		0.609	0.618	0.658
		clustering (AMI)		
ssl		0.256	0.405	0.25
supl		0.418	0.476	0.414
bird		0.426	0.479	0.411
non-bird		0.271	0.413	0.276
frog data		classification (macro accuracy)		
category		original	umap	pca
ssl		0.682	0.679	0.601
supl		0.668	0.655	0.673
bird		0.705	0.698	0.629
non-bird		0.638	0.627	0.662
		clustering (AMI)		
ssl		0.414	0.508	0.418
supl		0.488	0.546	0.49
bird		0.5	0.558	0.503
non-bird		0.411	0.5	0.414

ters. Interestingly, Insect66 and Insect459 both of which were trained on solely insect sounds and far fewer classes than the bird-trained biolingual, vastly outperform it in linear classification. As stated in the introduction, self-supervised learning models lack supervision and might therefore learn classes not meaningful to differentiate between species vocalizations. When comparing Figures 1 and ?? we observe poor clustering both in terms of AMI performance and by qualitative visual analysis of the embedding separation, which could be resulting from non-meaningful classes. However, for the three AVES feature extractors, the linear classifier is nonetheless able to learn a meaningful differentiation between the classes. This could be attributed to the fact, that while they are self-supervised, the training data consisted of curated and non-sparse sound events, thereby increasing the likelihood that meaningful classes are learned.

For the self-supervised learning feature extractors, fine-tuning seems to only marginally improve perfor-

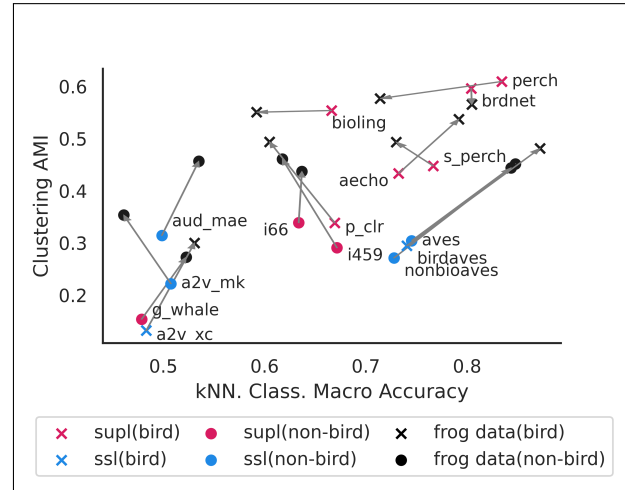


Figure 2. Comparison of feature extractor performance for bird and frog datasets. Axes, symbols and colors points correspond to the same as in Fig. ???. Here, black points show the performance of each feature extractor on the bird dataset. Red and blue points show the performance on the frog dataset. The grey arrow shows the performance change from the bird to the frog dataset.

mance. The three feature extractors based on the AVES models all share the same general audio pretraining and architecture but differ largely in fine-tuning. The similarity in performance indicates that the dominant influence on the structuring of embeddings is defined by either the pretraining or the architecture. Animal2vec_XC and Animal2vec_MK, the latter of which is fine-tuned, largely share the same architecture but were trained on very different datasets. Yet, both models reach similarly bad performance, this is especially surprising for the fine-tuned Animal2vec_MK. For the supervised learning feature extractor SurfPerch, which was developed for marine data in coral reefs, bird training data from Perch was mixed with coral reef sounds during pretraining. While the target domain is very different from the bird sound dataset used in this evaluation study, SurfPerch still reaches very high performance. Again, this indicates that including data of the target domain is more effective during pretraining than fine-tuning.

While the dimensions of the feature extractors vary greatly, performance does not correlate with dimension. Nonetheless, in Fig. 2 we demonstrated that using a stan-



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standardized embedding space only marginally impacts performance and does not change the hierarchy of performance among most of the models. The performance differences that can be observed are predominantly in linear classification, indicating that the graph structure, which KMeans builds for the clustering, does not change much through a linear dimensionality reduction.

This analysis underlines the high quality of embeddings created by large supervised learning feature extractors like BirdNET and Perch. While their training domain aligned with the domain of the evaluation dataset, so did that of biolingual, Animal2vec_XC and BirdAVES_ESpecies, none of which reached performance metrics similar to BirdNET and Perch. Nonetheless, reproducing this comparison with an evaluation set different from the training domains of these models would be very interesting. This study is meant to present a workflow for a more in-depth analysis of embedding spaces, which can be reproduced with the provided repository `bacpipe`². By establishing a default analyses of feature extractors alongside the common classification benchmarks, bioacoustic research can accelerate towards a better understanding of what training characteristics are beneficial in this domain.

5. CONCLUSION

In this study we have compared a variety of different state-of-the-art bioacoustic deep learning models, representing different training paradigms and training domains. To compare the models, we have isolated their feature extractors and used them to generate embeddings of a curated evaluation dataset consisting of annotated bird sounds from recordings in Costa Rica and Colombia. The aim of this study was to firstly present a large comparison of very different bioacoustic deep learning feature extractors and to evaluate how training paradigms and training domains affect performance. Performance was evaluated through clustering using an AMI score and through linear classification using a macro accuracy score.

We have shown that in spite of recent improvements in bioacoustic self-supervised learning, performance is still inferior to that of supervised learning models. This performance difference is visible in both linear classification and even more in clustering. Furthermore, we have shown that alignment of training domain and target domain during pretraining impacts performance more, than during fine-tuning. This study presents a roadmap for a

more in-depth performance evaluation of bioacoustic deep learning models, allowing for a better understanding of how training setup impacts downstream performance.

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² github.com/bioacoustic-ai/bacpipe



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