Classification of animal sounds in a hyperdiverse rainforest using Convolutional Neural Networks

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Abstract

To protect tropical forest biodiversity, we need to be able to detect it reliably, cheaply, and at scale. Automated species detection from passively recorded soundscapes via machine-learning approaches is a promising technique towards this goal, but it is constrained by the necessity of large training data sets. Using soundscapes from a tropical forest in Borneo and a Convolutional Neural Network model (CNN) created with transfer learning, we investigate i) the minimum viable training data set size for accurate prediction of call types ('sonotypes'), and ii) the extent to which data augmentation can overcome the issue of small training data sets. We found that even relatively high sample sizes (> 80 per call type) lead to mediocre accuracy, which however improves significantly with data augmentation, including at extremely small sample sizes, regardless of taxonomic group or call characteristics. Our results suggest that transfer learning and data augmentation can make the use of CNNs to classify species' vocalizations feasible even for small soundscape-based projects with many rare species. Our open-source method has the potential to enable conservation initiatives become more evidence-based by using soundscape data in the adaptive management of biodiversity.

Keywords: Sound Classification, Conservation, Convolutional Neural Network, Data Augmentation, Tropical forest, Soundscapes, Transfer Learning, Bioacoustics

1 Introduction

The extinction of species is an irreversible loss to humanity, and preventing biodiversity loss is one of the biggest challenges our society faces (Ceballos et al., 2010). Tropical forests represent some of the most species-rich terrestrial ecosystems, yet they are highly threatened by human activities, such as deforestation, hunting, mining, and selective logging (Betts et al., 2017). An increasing number of conservation projects strive to be evidence-based, which in the case of biodiversity conservation often requires being able to effectively monitor the presence, absence, or density of

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individual species (Burivalova et al., 2019a). However, in tropical forests, the monitoring of animal biodiversity at an appropriate scale and level of replication is notoriously difficult through direct observational studies (Hillebrand et al., 2018), as well as by using remote sensing: the dense tropical forest canopy does not allow for most fauna species to be seen on satellite images (Burivalova et al., 2019b).

Biodiversity monitoring is undergoing a transformation through the synergy of new data streams, better data storage, and novel analytical techniques that can turn 'big biodiversity data' into insights. Soundscapes, defined as the collections of all sounds in a given landscape (Sueur and Farina, 2015), are a particularly important new data stream in tropical forests. This is because many species, across several taxonomic groups (birds, invertebrates, mammals, amphibians) vocalize or make sounds to communicate (Fletcher, 2014). Soundscapes can be used either to gain insights about the totality of vocalizing species, by calculating various soundscape indices or acoustic features (Buxton et al., 2018; Sethi et al., 2020; Bradfer-Lawrence et al., 2019), or by identifying individual species through template matching or Convolutional Neural Networks (CNN) (Zhong et al., 2020; Wood et al., 2019).

CNNs are becoming increasingly popular in the detection and classification of biodiversity based on sound (Zhong et al., 2020; LeBien et al., 2020; Stowell et al., 2019). Existing studies typically focus on a few, common species, such as a pre-trained CNN to classify among 24 bird species in Puerto Rico, based on a training data set of 100,000 positive (presence of a call of the species of interest) and 243,000 negative (absence of species) data points (Zhong et al., 2020; LeBien et al., 2020). Other studies focus on the arguably best-known animal group on Earth - North American and European birds - with thousands of data points even for less common species (Kahl et al., 2021). These highly successful CNN applications present unprecedented advances for biodiversity monitoring. Yet, these methods may not be directly applicable in cases where all vocalizing species are of interest, such as in rapid biodiversity surveys, inventories, or prioritization projects. In such cases, rare species, naturally occurring at low densities or in limited areas, might be especially important to detect.

There are challenges to sound-based recognition of individual species in any natural soundscape, such as due to a variable distance of the sound source (the animal) to the sensor (microphone); interspecies and inter-individual variation in vocalizations; multiple unique vocalizations (sonotypes) per species, including mimicry; or biases due to equipment (Towsey et al., 2012; Darras et al., 2020). Additional factors make such species recognition exponentially harder in tropical forests, which are often extremely diverse in terms of vocalizing species, some of which are as yet unknown. This hyper-diversity can result in partial overlap in individual species' vocalizations, such as between continuous cicada choruses and bird vocalizations. Dense vegetation results in signals that attenuate quickly and in a non-uniform way (Rappaport et al., 2020; Darras et al., 2016). An important hurdle in tropical forests is the heavily skewed distribution of species: whereas there are a few common species, there is typically a large number of rare species, making it challenging to create balanced training data sets.

Every level of variation in a species' vocalization, be it due to the species' behaviour or the physical environment, requires additional training data for a machine learning model to be successful. Indeed, generating sufficient training data sets is a bottleneck in uptake of this technology in conservation, especially for small to medium-size conservation projects (Lamba et al., 2019). We set out to address this limitation by investigating the minimum necessary training data size, and by testing approaches that can boost performance at small sample size.

Specifically, we investigate the feasibility of using transfer learning to create CNN models to classify amongst *all* audible sounds emitted by birds, mammals, amphibians and invertebrates. We test our models on a set of exhaustively, manually labeled soundscapes from a hyperdiverse

rainforest in Indonesian Borneo. Our aim is to i) identify the minimum viable size of a training data set that would allow a reasonable classification accuracy; and ii) test whether we can achieve an improved classification performance with data augmentation. Our overarching goal is to create a robust, open-source model to classify rare as well as common sound types from rainforest soundscapes, that could be easily adapted and reused by individual conservation projects in need of fauna monitoring.

2 Materials and Methods

2.1 Study Site and Soundscape Data

The data set that we used is publicly available on the bioacoustic workbench ecosounds.org. It consists of a selection of soundscape recordings collected at 15 sites in the tropical rainforests of Berau and East Kutai Regencies in East Kalimantan, Indonesia, from June 2018 to June 2019, within a selective logging concession (Burivalova et al., 2019b). The soundscapes were recorded with autonomous, mono Bioacoustic Recorders (Frontiers Lab), at 2 m above ground, pre-programmed to record continuously in 30-min segments, at 40 dB gain, and at a 44.1 kHz sampling rate. The devices were programmed at variable schedules throughout the year, and at sites that were at least 600 m away from each other; at least 200 m distant from the nearest active or inactive logging roads, ridgeline foot trails, or rivers; and at altitudes ranging from 387 to 517 m. For our experiment, we selected minutes for manual annotation as follows. First, at two sites, we selected one minute at random within a 1 hour period in the morning (dawn ± 30 min) and evening (dusk ± 30 min), and sampled the same minute once a month for 12 months. Then, we selected also the same dawn and dusk minute from all 15 sites, but only during one day. This resulted in a total of 63 sample minutes, encompassing the period of the highest acoustic diversity, across both time and space. Each soundscape captures a mix of geophony (rain, thunder, wind), anthrophony (airplanes, machinery), and biophony (all animal vocalizations) (Sueur and Farina, 2015).

Using Scipy (Virtanen et al., 2020) with Tukey window and shape parameter equal to 0.25, we processed each soundscape sample to obtain its spectrogram, encoded in a $129 \times 353,389$ image depicting the frequency components of the soundscape in the 0 to 22,050 Hz range. Simultaneously, using recordings and spectrograms in Raven Pro 1.5 (Center for Conservation Bioacoustics, 2019), an expert sound analyst manually identified 3629 animal vocalizations $V_1, V_2, \ldots, V_{3629}$ for 448 sonotypes. Each vocalization V_i was encoded in a gray-scale image, enclosing the portion of the spectrogram from the initial to the final times of the vocalization, and from the lowest to the highest dominant frequencies of the vocalization (see Box 2.1). The analyst also assigned a label to each vocalization, classifying it into (a) one of four higher taxonomic groups: birds, invertebrates, mammals, and amphibians, and (b) its sonotype, defined as "a note or series of notes that constitute a unique acoustic signal "(Aide et al., 2017). It is important to highlight that one sonotype does not necessarily correspond to one species, since a species can have multiple vocalizations, such as a song and call in the case of birds. All data was examined by the same analyst (TMM), who had previous experience with acoustic fauna identification. When the analyst was uncertain about a sonotype's taxonomic group, three other specialists were consulted. Sonotypes that could not be assigned to a category even after specialist consultation were classified as unknown. Vocalizations spaced by more than 2 s were labeled as separate, even if they were of the same sonotype.

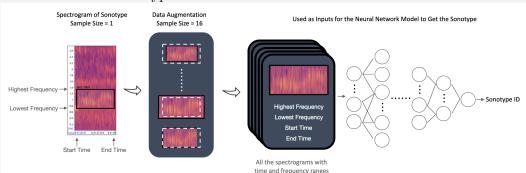
Given a new vocalization V, our goal is to automatically determine (a) its higher taxonomic group, and (b) its sonotype. To this end, we propose the deep neural network architecture detailed below.

Transfer learning and data augmentation in acoustic classification

Deep learning classifiers generally rely on the availability of a large number of samples for each class (i.e. sonotype). Successful data sets range in the order of thousands to millions of samples per class. Due to the high level of expertise and time required to identify and classify vocalizations into sonotypes, our data set is orders of magnitude smaller (Fig. 3). Yet, it is representative of what a small to mid-size conservation project may be able to achieve. Deep learning models tend to overfit small data sets, producing a large generalization error. To address this issue, the machine learning community has developed transfer learning and data augmentation.

Transfer learning is the process of importing insights learnt in related tasks. This is done by initializing a neural network's parameters with those obtained after training another network on a similar task. For example, one can initialize a neural network that aims to learn Spanish with the parameters of a network that already knows French. Transfer learning has been shown to improve learning speed and accuracy with fewer data, reduce generalization error and improve the overall network performance (Yosinski et al., 2014). Recent years have produced highly successful image classification architectures, such as the VGG-19 (Chollet et al., 2015) and ResNet-50 (He et al., 2016), and well-organized image databases that can be used to pre-train models, such as the Image-Net (Russakovsky et al., 2015).

Illustration of the sonotype classification work flow:



Box 1 Figure 1: Each sound is delimited with a box and labeled as a sonotype by an expert analyst. Then, it is augmented to 16 samples by means of several data augmentation techniques (Fig. 1). The augmented samples, along with their time and frequency ranges, become input for the neural network model (Fig. 2). The model has the goal to assign the sonotype ID to a new sound sample, reserved from the original data as a testing data set.

Data augmentation aims to artificially increase the sample size. Common augmentation methods involve image flipping, shifting, zooming in or out, rotating, and distorting. For instance, a study on image classification with such augmentation methods found an increase in accuracy by 7 percentage points when classifying cats and dogs and by 4 percentage points when classifying dogs and goldfish (Wang et al., 2017). A study of bird call classification found that data augmentation increased the classification accuracy by 9 percentage points, whereby the largest improvements were generated by adding background noise (Lasseck, 2018). Other studies have augmented data sets by transposing, squeezing, or stretching the images (Nanni et al., 2020). Data augmentation of spectrograms requires special care, as certain transformations (e.g., flipping) could result in spectrograms corresponding to entirely different sound patterns (Nanni et al., 2020).

2.2 Transfer Learning and Pre-processing

Our work aims to take advantage of these existing models via transfer learning (Box 2.1). We transferred the parameters of the Keras VGG-19 model (Chollet et al., 2015) after being trained on the Image-Net data set (Russakovsky et al., 2015). The first step towards this endeavor is to pre-process our data to match the Keras VGG-19 format, which is 8-bit per RGB (red, green, blue) channel, 224×224 colored images. To this end, we first adjusted all vocalizations to a common scale, using Numpy's linear normalization (Harris et al., 2020). More precisely, we identified the highest and lowest frequency intensities F_i , f_i of each vocalization image V_i , and performed the following transformation, to obtain the normalized vocalization V_i :

$$V_i' = \frac{V_i - f_i}{F_i - f_i} \cdot 255 \tag{1}$$

After this procedure, each pixel in the normalized vocalization image V_i' will take a value between 0 and 255, corresponding to the standard 8-bits format used to store single-channel gray-scale images. To transform V_i' to the required colored image, we simply replicated each V_i' into the three RGB channels, and resized each image to 224×224 pixels with Open-cv (Bradski, 2000). All data (including vocalization images, time and frequency ranges, and classification labels) were stored in hdf5 format using h5py (Koranne, 2011), as is standard practice for large data sets.

2.3 Data Augmentation

We used the following data augmentation techniques (Box 2.1), tailored to simultaneously produce variation in our spectrograms, while maintaining a realistic vocalization pattern:

- Cropping of the spectrogram's time range (X axis of the spectrogram), frequency range (Y axis), or both.
- Adding the sound of light, medium or heavy rain, thunder, aircraft, chainsaw, and car/truck to the spectrogram.
- Translating the whole spectrogram up or down in terms of frequency.
- Widening the spectrogram in the time or frequency range.
- Sharpening the spectrogram by squeezing it in time and frequency range.

We implemented the augmentation methods with Numpy (Harris et al., 2020) and open-cv (Bradski, 2000). When applying data augmentation with cropping, squeezing, widening, and translating, we modified the spectrogram by a random number between 5% and 10% of the size of the original spectrogram, as this reflects the approximate range of variation in nature. When adding noise, we first normalized the noise in the same way as the original spectrogram (see eq. (1)). Then, we added 1/3 of the noise, including the sound of rain, thunder, aircraft, chainsaw, and car to the original spectrogram, to reflect a typical amount of background noise and normalized the new spectrogram again.

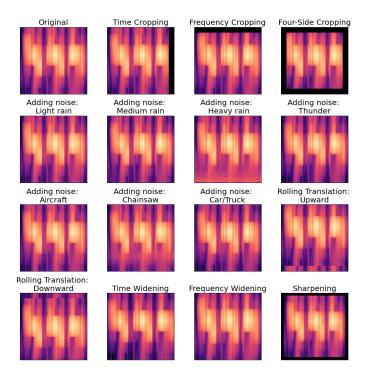


Figure 1: Illustration of the different data augmentation techniques that we used to augment our data set of labeled rainforest sounds.

2.4 The Deep Learning Model

Our proposed neural network architecture passes the vocalization images V_i through the architecture of the Keras VGG-19 model (Chollet et al., 2015) without the 4 top layers (see Figure 2). The output (image) of the Keras VGG-19 model is then flattened into a vector and concatenated with the four values corresponding to the starting time, ending time, lowest frequency, and highest frequency of the vocalization (depicted as Auxiliary Input in Figure 2). This vector is then passed through two couples of dense-dropout layers and a softmax dense output layer to obtain the final output.

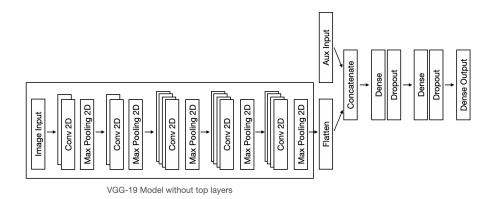


Figure 2: Architecture of our Deep Learning model. The Image Input are the spectrograms, and the Aux Input are the highest and lowest frequencies as well as the starting and ending times.

2.5 Experiments

In each trial of all our experiments, we first split our available data (before augmentation) into training, validating, and testing sets. We used the training set to train the model and update its parameters; the validation set to evaluate whether we will continue or stop the training process; and the testing set to evaluate the model after training. To avoid contaminating our results with peeking bias, we discarded all sonotypes with fewer than 3 samples. This guaranteed that each sonotype (class) had at least one independent sample for each purpose (training, validating, and testing). All sonotypes with 3 or more samples were respectively split to 80%, 10% and 10% for training, validation, and testing, or in the closest possible proportion, so long as at least one independent sample was available for each purpose.

We measured the performance of our model with accuracy, area under the Receiver Operating Characteristic Curve (AUC), precision, recall, specificity, and f1 scores. The accuracy of our learning model is the fraction of correctly classified previously unseen vocalizations from the testing data set. We also measured multi-class AUC as the average of AUCs for each sonotype. Precision is measured as TP/(TP+FP), recall as TP/(TP+FN), and specificity as TN/(TN+FP), where TP is true positive, TN true negative, FP false positive, and FN false negative. F1 score is measured as 2*(precision*recall)/(precision+recall). We average recall, specificity, and f1 score across sonotypes in each run and then average them across all the replicated runs, respectively. For precision, we calculate mean average precision (mAP), and class-wise mean average precision (cmAP). cmAP is calculated by first computing the average precision, AP, for each sonotype, and then computing the mean of the APs across sonotypes without weighting on sample sizes. mAP is calculated in a similar way as cmAP, except we weight on sample sizes when computing the mean of the APs across sonotypes.

In our first experiment, we investigated the effects of sample size and data augmentation on a balanced data set. In 40 independent sets of trials, we fixed the sample size s for each sonotype and varied s from 3 to 80, selecting K=6 different sonotypes uniformly at random among the ones that have at least s samples. Then we selected s samples from each of K=6 different sonotypes uniformly at random and evaluated the performance of our model after training it with and without data augmentation. For the former, we augmented data such that the 80-10-10 proportions of training, validating, and testing data were maintained, selecting randomly from the transformations described above, yielding a total of 200-25-25 samples per sonotype. As the largest sample size across all sonotypes is 231, augmenting the samples to a total of 250 samples per sonotype ensured an appropriate level of augmentation. We set the maximum sample size s to 80 as there are only 6 sonotypes with at least 80 samples. The results are summarized in Fig. 4.

In our second experiment, we investigated the effects of sample size and data augmentation on an imbalanced data set. In each of the 3114 independent trials, we selected K=6 different sonotypes uniformly at random and and performed the same experiment as before. The results are summarized in Table 1 and Fig. 7.

In our third experiment, we studied the effect of the number of sonotypes and data augmentation. In each of the 95 independent sets of trials, we fixed the number of sonotypes, K, and varied K from 2 to 6. Then we selected K different sonotypes uniformly at random (among those that have $s \geq 49$ samples), selected s = 49 samples uniformly at random for each sonotype, and evaluated the performance of our model after training it with and without data augmentation. We fixed the sample size of each sonotype to 49 because there are only 11 sonotypes with at least 49 samples in our data set to achieve enough replicates. For data augmentation, we augmented each sample to 16 samples using all of the transformations described above and illustrated in Fig.1. The results are summarized in Fig. 5.

Finally, we analyzed whether classification performance is influenced by the taxonomic group, or other sonotype properties, such as minimum and maximum frequency, frequency range, and the duration of the sound. The results are summarized in Fig. 6.

2.6 The Training Process

The training is processed using TensorFlow (Abadi et al., 2016) and Keras (Chollet et al., 2015). To apply transfer learning, we initialized the layers of the Keras VGG-19 model with weights trained on the Image-Net and froze these layers during training. Overfitting and generalization errors would appear if we trained the model for too many epochs (iterations of the whole training data set). To avoid this issue, we applied early stopping to terminate the model appropriately. We decided whether to stop training based on validation loss, which represents how far the predicted outputs deviate from the expected output and whether the model is able to generalize well on data. The loss is computed with Keras categorical cross-entropy loss function for each epoch. If the model keeps generalizing to the data instead of overfitting, the validation loss will keep decreasing. Therefore, we applied early stopping with a patience of 15 epochs. In other words, we terminated the training process when the validation loss did not decrease for 15 continuous epochs. We also applied checking points to the model that saved the model with the lowest validation loss, which represents the highest possibility to generalize well on the data, and used the model with the lowest validation loss as the final model for testing.

3 Results

From the 63 sample minutes that we exhaustively labeled for all biophony, we obtained 3629 sounds emitted by fauna, falling under 448 sonotypes, within four broad taxonomic groups: birds, amphibians, invertebrates, mammals. Eight sounds were labeled as unknown, and additional 154 sounds were labeled as anthrophony or geophony, and used in data augmentation. Beyond a few common sonotypes, the vast majority were rare (Fig. 3). For example, there were only ten sonotypes with sample size > 50; 76 sonotypes with sample size > 10; and 142 sonotypes with sample size > 5. To produce a classification system for this highly imbalanced sonotype collection, we created an open-source CNN model (https://github.com/solislemuslab/tropical-stethoscope), pre-trained on ImageNet (Russakovsky et al., 2015), with the Keras VGG-19 neural network architecture (Chollet et al., 2015).

3.1 Impact of data augmentation and sample size

Data augmentation increased the classification accuracy, defined as the fraction of correctly classified vocalizations from the testing data set, by 39.0 percentage points (from $51.4\% \pm 18.2\%$ to $90.4\% \pm 9.7\%$) (Fig. 4). It also reduced the variability in accuracy by 8.5 percentage points, signifying a more stable classification performance. Similarly, data augmentation increased the AUC by 15.0 percentage points, from $82.9\% \pm 12.7\%$ to $97.9\% \pm 4.0\%$ (Table 1). The relative increase in accuracy due to sample size was larger without data augmentation than with data augmentation (linear regression without augmentation: p < 0.01, slope = 0.46, 95% CI 0.41-0.50; with augmentation: p < 0.01, slope = 0.05, 95% CI 0.03-0.08).

To investigate the influence of an imbalanced data set - a principal challenge in training neural networks with a small data set - we conducted a similar experiment but without fixing the sample size of sonotypes. Instead, we selected 6 sonotypes at random, and trained and tested the model with and without data augmentation. For each selection of 6 sonotypes, we calculated the average and

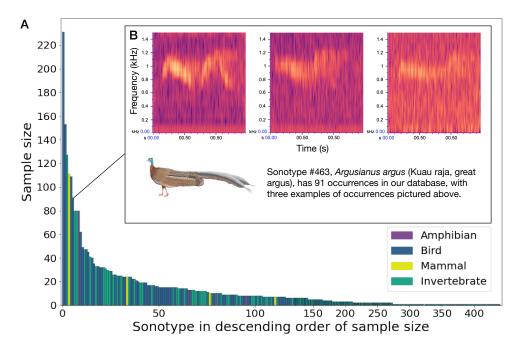


Figure 3: A - Sonotypes (unique animal sound types) from 63 exhaustively labeled minutes of rainforest soundscape, classified into 4 taxonomic groups, and ordered in descending sample size (number of occurrences of each sonotype). B - Spectrograms of three example occurrences of one sonotype, call of the Kuau raja (*Argusianus argus*, illustration from (Del Hoyo et al., 1992)).

minimum sample size. In this experiment, data augmentation increased classification accuracy from $70.4\% \pm 17.7\%$ to $93.2\% \pm 7.2\%$, and the impact of data augmentation was even more pronounced on recall and f1 scores (Table 1). Accuracy also increased with *mean* and *minimum* sample size per sonotype (Fig. S7).

3.2 Impact of data augmentation and the number of sonotypes

We found a decrease in classification accuracy with the increasing number of sonotypes both without and with data augmentation (Fig. 5), but this decrease was lower with data augmentation. Data augmentation increased the average accuracy by 8.7 percentage points when classifying 2 sonotypes and by 33.6 percentage points when classifying 6 sonotypes. Augmentation also reduced the variation in classification accuracy by 12.4 percentage points. We note that for this experiment, we randomly selected sonotypes with sample size \geq 49. As a result, for model runs with smaller numbers of sonotypes, there are more possible combinations.

3.3 Factors influencing accuracy

The taxonomic group which a particular sonotype belongs to did not influence the model performance, regardless of data augmentation (Fig. 6). The classification accuracy was not influenced by the average or minimum frequency, or by the frequency range, indicating similar performance regardless of the sound-producing organism.

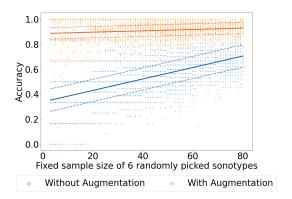


Figure 4: Classification accuracy without (blue) and with (orange) data augmentation among 6 sonotypes. Each point represents one run of training, testing, and validation. In each run, the sample size per sonotype is balanced, i.e., all six sonotypes that we are classifying amongst are represented by exactly n samples. Lines represent the fits of linear regression, with 95% CI. Random sonotypes are chosen every time.

Table 1: Accuracy measures for balanced and imbalanced data set without and with data augmentation. mAP = mean average precision; cmAP = class-wide mean average precision; AUC = area under Receiver-Operator curve.

	Balan	ced	Imbalaı	nced
Augmentation	Without	With	Without	With
Accuracy	51.4	90.4	70.4	93.2
mAP	57.5	90.4	75.2	93.2
cmAP	57.4	90.4	73.4	93.2
AUC	82.9	97.9	86.3	98.7
Recall	51.4	90.4	60.4	93.2
Specificity	81.6	97.0	84.7	98.1
F1 score	42.8	89.2	55.3	92.6

4 Discussion

Using a pre-trained CNN and a fairly limited training data set (n = 3629) of high diversity (448 sonotypes emitted by rainforest fauna), we were able to create a machine learning model that successfully classified among combinations of any six sonotypes at a time, of variable sample sizes. With the novel technique of data augmentation, we were able to increase the mean accuracy of our model from 51.4% to 90.4%, even at extremely small sample sizes (Fig. 4). Our work advances the field by enabling the classification of *all* sound types, including rare ones, those emitted by birds, mammals, amphibians, and insects. With our open-source model, even relatively small projects may be able to use CNNs to classify calls within acoustic biodiversity surveys, focusing on all vocalizing organisms. Such capabilities are important in a number of conservation uses, from prioritization surveys when designating protected forest areas (Williams et al., 2002), monitoring the effectiveness of biodiversity conservation projects (Burivalova et al., 2019a), or understanding the impact of land use change on biodiversity (Powers and Jetz, 2019).

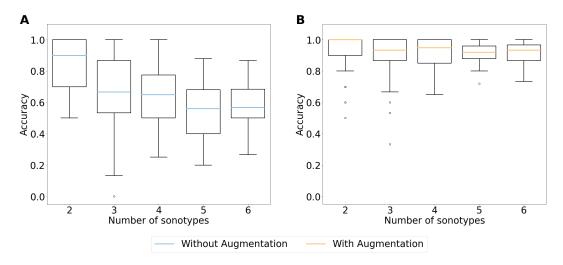


Figure 5: Classification accuracy without (A) and with (B) data augmentation among 2 - 6 sonotypes.

From our results, we conclude that when data augmentation is not used, a training data set that contains ~ 80 labelled occurrences of each sound class (sonotype) is insufficient, yielding only modest accuracy of 75.1% (Fig. 7A). Yet, even a sample size of 80 can be challenging to achieve for rare species, which might vocalize unpredictably, only a few times a day, or for highly mobile species, which might only rarely pass through the recording site.

In cases where obtaining several hundreds or thousands labeled occurrences of each sonotype is not feasible, our results suggest that augmenting the training data by artificially cropping, squeezing, and stretching the sounds, as well as by adding noise, can vastly increase the classification accuracy (Fig. 4, 7, and 5). Even at extremely small sample sizes, such as only a handful of examples per sonotype, our model with data augmentation reached high and consistent average accuracy of $\geq 90\%$. Data augmentation was beneficial regardless of the original training data set being balanced or not, and regardless of the taxonomic group (Fig. 6, Table 1).

Whereas there is as yet no standardized reporting for the performance of bioacoustic CNN models, our results compare favourably with existing literature (Table 2 and S 3). Most CNN studies classify sounds from active, directional recordings, such as those available throught the Xeno-Canto database (https://www.xeno-canto.org/). When translated to passive soundscapes, the performance typically drops. Despite using exclusively passive soundscapes, both for training and testing, our study reaches high levels of accuracy.

There are several limitations to our experiments. First, our training, validation, and testing data sets were all from the same set of recordings, obtained at the same set of rainforest sites during dawn and dusk. Future studies should test our method in other forest types across different biogeographic regions, as well as for organisms that vocalize during different parts of the day. Second, vocalizing species are in some cases able to adapt their vocalizations to changing environmental conditions and competing species, including in terms of frequency and the precise nature of the song (Derryberry et al., 2020; Grant and Grant, 2010). Tentatively, we suggest that accuracy would not decrease with shifts in frequency, as such changes are simulated through data augmentation. However, empirical testing to see whether our model is robust under such changes are necessary. Importantly, we only classified amongst six sonotypes during each model run, so as to achieve enough replicates that would allow a reliable measure of accuracy. Classifying amongst larger number of sonotypes with our model should be further tested with extensive data sets.

Table 2: Accuracy achieved by related studies on animal call classification using neural networks. See supporting Table S3 for model parameters. mAP = mean average precision; cmAP = class-wide mean average precision; AUC = area under Receiver-Operator curve; Rec. = recall (or sensitivity); Spec. = specificity; F1. = F1 Score

Author	Accura	c y mAP	cmAP	AUC	Rec.	Spec.	F1.
Our model ¹	93.0	94.5	94.5	98.8	93.0	98.2	92.5
	94.5	94.5	94.5	98.9	94.5	99.3	94.1
Kahl et al.	77.7	79.1	69.4	97.4	-	-	-
2021							
LeBien et al.	-	97.5	89.3	-	-	-	-
2020							
Zhong et al.	-	-	-	97.5	82.1	96.9	-
2020^2				97.9	84.1	97.7	
				99.5	97.7	96.4	
Tabak et al.	90	-	-	-	-	-	91
2020^{3}							
Goeau et al.	83	-	19.3	-	-	-	-
2019^4							
Kahl et al.	-	74.5	35.6	-	-	-	-
2020^4							
Ruff et al. 2021	99.5	-	-	-	-	-	-
Ruff et al. 2019	-	-	-	-	-	-	-
Khalighifar et	90	-	-	-	-	-	-
al. 2021							
Hidayat et al.	97.1	95.2	97.6	-	96.4	-	-
2021							
Chen et al.	90.2	-	-	94	90.9	85.3	-
2020							
Xie et al. 2019	86.3	92.1	-	-	99.5	91.6	93.3
Xie and Zhu	-	-	-	-	-	-	95.95
2019							
Xu et al. 2020^5	94.7	93.1	-	-	94.3	-	92.9
	86.4	86.9			85.1		86.1

¹Sets of 2 numbers represent values for classification with fixed sample sizes (40 samples) per sonotype and with varying sample sizes (averaging 40 to 41 samples, inclusive) per sonotype. ²Sets of 3 numbers represent values before pseudo-labeling, pre-trained with ResNet50, and with pseudo-labeling.

³Pre-print.

⁴Working paper.

⁵Sets of 2 numbers represent values for frogs and crickets, respectively.

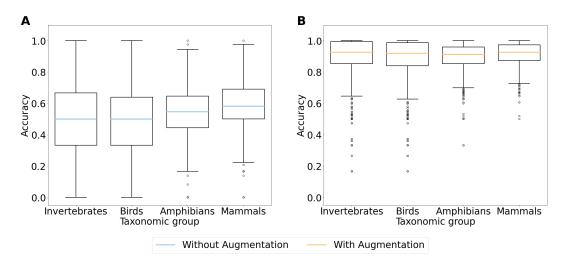


Figure 6: Classification accuracy and taxonomic groups without (A) and with (B) data augmentation

A potential source of uncertainty is introduced during the manual labeling of soundscapes. Two separately labeled sounds could be classified as one or two sonotypes, depending on the analyst, quality of the recording, and a random error. In our case, we tried to minimize this error by consulting experts in uncertain cases, and revisiting our classification multiple times. This is a time-consuming process and further research should quantify the level of uncertainty due to different analysts. Importantly, the number of sonotypes does not translate to number of species, as some species may produce more than one call type.

Ultimately, for a fully automated classification of biodiversity from soundscapes, two steps are needed: first, the soundscape needs to be segmented in terms of time and frequency, so that individual sounds are isolated. Existing approaches use a e.g. threshold in amplitude or nonnegative matrix factorization to detect the beginning and end of a sound in time, alternatively they cut the soundscape into equal segments of a few seconds each (Araya-Salas and Smith-Vidaurre, 2017; Stowell et al., 2019; Lin et al., 2017; Lin and Tsao, 2020). These approaches work well in cases where there is little overlap between individual sounds, but not yet under substantial temporal or frequency overlap, such as is the case in a hyper-diverse rainforest soundscape. Second, the isolated sounds need to be classified as belonging to one of the predefined classes, and our work addresses this. A final step, which should be addressed by future studies, is to design a model that is able to distinguish previously not encountered sonotypes, and incorporate them into the model.

5 Conclusions

We have developed an open-source Convolutional Neural Network that can classify amongst common and rare vocalizing mammals, birds, amphibians and invertebrates from Borneo's rainforest. Using transfer learning and data augmentation, our models achieve > 90% accuracy even at extremely small training data sample size. Our model is designed to help small to mid-size conservation projects with limited budgets to deploy the automated classification of rainforest soundscapes in biodiversity surveys and evidence-based conservation.

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7 Conflict of Interest

The authors have no conflict of interest.

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8 Appendix

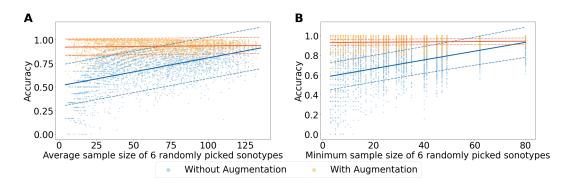


Figure 7: Classification accuracy without (blue) and with (orange) data augmentation among 6 sonotypes. Each point represents one run of training, testing, and validation. In each run, the sample size per sonotype is not set to be balanced. Accuracy is plotted by the average sample size (A) and minimum sample size (B). Lines represent the fits of linear regression, with 95% CI. Random sonotypes are chosen every time.

Table 3: Related studies on animal call classification using neural networks. See table 1 for accuracy measures.

Author	Base model	Augment.	Augment. Input data	Sample size	Classes	Taxonomic groups
Our model	VGG19	Yes	soundscapes	3629	448 (6 at a time)	Birds, invertebrates, mammals,
Kahl et al. 2021	ResNet	Yes	Xeno-canto, Cornell, sound-	226,078 recordings, max. 500 per class	984	Birds
LeBien et al. 2020	ResNet	$_{ m O}$	Soundscapes	86,652 t.p.; 188,908 f.p.	24	Birds, frogs
Zhong et al. 2020	VGG16, ResNet50	Pseudo- labeling	Soundscapes	100,000 p.; 243,000 n.	24	Birds, frogs
Tabak et al. 2020 Goeau et al. 2019	ResNets Inception-V3	m No	Call library Xeno-canto	11,514 $36,496$	10 1500	Bats Birds
Kahl et al. 2020 Ruff et al. 2021	Inception, ResNet 6 trainable layers, 4 convolu-	Yes Yes	Xeno-canto	50,153 $53,292$	659 17	Birds Birds
	tional layers, 2 fully connected layers					
Ruff et al. 2019	4 convolutional layers, 2 fully connected layers	No	Field recordings	3000-4000 per class	9	Birds
Khalighifar et al. 2021	ResNet-18	m No	Bat echolocation calls	11,514 for bats	10	Bats
Hidayat et al. 2021	Adapted from Sprengel et al. 2016	Yes	Xeno-canto	752		Birds
Chen et al. 2020	BatNet, 22 convolutional layers	$_{ m O}$	Field recordings	130,858	36	Bats
Xie et al. 2019	VGG, SubSpectralNet	No	Field recordings	5428	43	Birds
Xie and Zhu 2019 Xu et al. 2020	3 convolutional layers multi-view CNN, 3 views each with 3 convolutional layers	No No	Xeno-canto		14 14; 20	Birds Frogs, crickets