Performance of a Deep Neural Network at Detecting North Atlantic Right Whale Upcalls

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Passive acoustics provides a powerful tool for monitoring the endangered North Atlantic right whale (NARW), but improved detection algorithms are needed to handle diverse and variable acoustic conditions and differences in recording techniques and equipment. Here, we investigate the potential of Deep Neural Networks for addressing this need. ResNet, an architecture commonly used for image recognition, is trained to recognize the time-frequency representation of the characteristic NARW upcall. The network is trained on several thousand examples recorded at various locations in the Gulf of St. Lawrence in 2018 and 2019, using different equipment and deployment techniques. Used as a detection algorithm on fifty 30-minute recordings from the years 2015–2017 containing over one thousand upcalls, the network achieves recalls up to 80%, while maintaining a precision of 90%. Importantly, the performance of the network improves as more variance is introduced into the training dataset, whereas the opposite trend is observed using a conventional linear discriminant analysis approach. Our work demonstrates that Deep Neural Networks can be trained to identify NARW upcalls under diverse and variable conditions with a performance that compares favorably to that of existing algorithms.

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[XYZ] Pages: 1–11

I. INTRODUCTION

The North Atlantic right whale (NARW) comprises a small cetacean population that counted ~ 400 individuals in 2017 (Hayes et al., 2018; Pace et al., 2017; Pettis et al., 2018). Listed as endangered in Canada (COSEWIC, 2013), this population has been declining since 2010 (Pettis et al., 2018). NARW used to be mainly distributed along the US continental shelf, up to the Bay of Fundy and the Western Scotian shelf in Canada. This distribution, however, has changed in the last decade (Davis et al., 2017). The occasional yearly occurrence of a few individuals in the Gulf of St. Lawrence in summer and fall markedly increased in 2015 and a high seasonal occurrence has continued since (Simard et al., 2019). This area is a site of intensive fishing with fixed gears. It is crossed by the main continental seaway that connects the Atlantic and the Great Lakes (Simard et al., 2014). In 2017, 12 individuals died in the Gulf of St. Lawrence. The mortalities involved collisions with ships and entanglement in fixed fishing gears. Protection measures, which include vessel speed reduction and fishing closure, were then put in place by the management authorities in an effort to prevent the recurrence of such events (DFO, 2018).

The key information required to trigger vessel speed reduction and fishing closure is the presence of the animals in the highest risk areas. This information can be acquired over large areas for short time windows from systematic or opportunistic sightings from aircrafts or vessels. However, to obtain continuous round-the-clock information over the season, NARW detection with passive acoustic monitoring (PAM) systems is needed, see e.g. (Simard et al., 2019). Various configurations of PAM systems are possible for small- to large-scale coverages (Gervaise et al., 2019b), including some supporting detection in quasi real-time such as Viking-WOW buoys (https://ogsl.ca/viking/), Slocum gliders and fixed buoys (Baumgartner et al., 2019; 2013).

Such PAM systems rely on NARW upcall detection and classification (DC) algorithms. Several algorithms, exploiting the time-frequency structure of the call, have been used so far (Baumgartner et al., 2011; Gillespie, 2004; Mellinger, 2004; Simard et al., 2019; Urazghildiiev and Clark, 2006; 2007; Urazghildiiev et al., 2008). Their performance is dependent of the signal to noise ratio (SNR), which varies with the range of the calling whale, the noise levels and the other biological and instrumenta-
tion factors (Gervaise et al., 2019b; Simard et al., 2019). The DC performance of these classical signal processing methods under actual in situ recording conditions tends to plateau around a detection probability of about 50% (i.e. recall index) when the false detection probability is kept below about 10% (DCLDE 2013; Simard et al., 2019). The objective of the present study is to test if modern machine-learning approaches can break this apparent DC performance ceiling.

Within the last decade, artificial neural networks have become the preferred machine-learning approach for solving a wide range of tasks, outperforming existing computational methods and achieving human-level accuracy in domains such as image analysis (He et al., 2015) and natural speech processing (Hinton et al., 2012). Originally inspired by the human brain, neural networks consist of a large number of interconnected “neurons”, each typically performing a simple linear operation on input data, specified by a set of weights and a bias, followed by an activation function. In a supervised training approach, the network is given examples of labeled data, and the weights and biases are adjusted to produce the desired output using an optimization algorithm. Modern neural networks exhibit multi-layer architectures, which enable them to build complex concepts out of simpler concepts and hence learn a non-linear representation of the data conducive to solving a given task. Therefore, modern neural networks are often referred to as Deep Neural Networks (DNNs), and the strategy of representing complex data as a nested hierarchy of concepts is referred to as Deep Learning. Two of the most commonly encountered basic architectures are Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which are particularly well adapted to the tasks of analyzing image data and sequential data, respectively. The availability of large labeled datasets, containing millions of labeled examples, has been a key factor in the success of DNNs in domains such as image analysis and natural speech processing. Therefore, much of the current research in Deep Learning focuses on how to train DNNs more efficiently on smaller datasets.

Shallow neural networks have been employed for the purpose of sound classification in marine bioacoustics since the 1990s, usually combined with a method of feature extraction, e.g. (Bahoura and Simard, 2010), but also acting directly on the spectrogram (Halkias et al., 2013). In the last few years, the first studies employing modern DNNs have been reported. Examples include classification of fish sounds (Malfante et al., 2018), detection and classification of orca vocalizations (Bergler et al., 2019), classification of multiple whale species (McQuay et al., 2017; Thomas et al., 2019), and detection and classification of sperm whale vocalizations (Bermant et al., 2019). In all cases, CNNs have been leveraged to analyze the information encoded in spectrograms, which is also the strategy adopted in the present work.

The paper is structured as follows. In Sec. II we first describe how the acoustic data was collected, then discuss the generation of training datasets, the neural network design and the training protocol. In Sec. III we present the results of the classification and detection tasks, which are then discussed in Sec. IV. Finally, in Sec. V we summarize and conclude.

II. MATERIALS AND METHODS

A. Acoustic Data

The PAM data were collected in 2018 and 2019 at 6 stations in the southern Gulf of St. Lawrence (Fig. 1). Two different deployment configurations were employed, producing two distinct datasets, A and B. In the first case (A), the PAM system was deployed from the surface, with the hydrophone tethered to a real-time ocean observing Viking buoy (Multi-Electronique Inc., Rimouski, Qc, Canada, http://www.multi-electronique.com/buoy.html) with a 60-m long cable floating at the surface for half of its length. The recording digital hydrophone, at a depth of ∼ 30 m, was an ic-Listen HF (Ocean Sonics, Truro Heights, N.S., Canada, https://oceansonics.com/product-types/iclisten-smart-hydrophones/). It sampled continuously the raw (0 gain) acoustic signal with 24-bit resolution. The receiving sensitivity of the hydrophone was −170 dB re 1 V µPa⁻¹. In the second case (B), the PAM system used short (< 10 m) “T”-type oceanographic moorings, with an anchor, an acoustic release, and streamlined underwater floats, for bottom deployment at depths varying from 75 m to 125 m, with the autonomous hydrophone ∼ 5 m above the seafloor. The recording equipment consisted of AURAL M2 (Multi-Electronique Inc., Rimouski, Qc, Canada, http://www.multi-electronique.com/aural.html) sampling the 16-dB pre-amplified acoustic signal with a 16-bit resolution for 25% or 50% of hourly periods. The receiving sensitivity of the HTI 96-MIN (High Tech Inc., Gulfport, MS) hydrophone equipping the AURAL is −164 ± 1 dB re 1 V µPa⁻¹ over the < 0.5-kHz bandwidth used here. Further details can be found in Simard et al., 2019).

Because of the different acoustic equipment and deployment types, the recordings from the two datasets significantly differed in terms of signal amplitude and noise background from different sources, including flow noise, strum, and knocks resulting from the effects of tidal currents and the surface motion due to waves on the hydrophone and deployment apparatus. Additional SNR variability of the recordings is introduced by the different locations and depths at which the hydrophones were deployed in the southern Gulf of St. Lawrence, providing different exposures to the above environmental conditions and to the shipping noise field from the main seaway (Aulanier et al., 2016; Simard et al., 2019). The datasets used here therefore represent a large range of conditions that can be encountered in realizing the DC task for the low-frequency NARW upcall from acoustic data collected using different PAM systems. To develop a Deep Learning model that is robust to such realistic
range of variability, no effort was made to enhance the SNR before feeding the data to the neural network.

B. Training and Test Datasets

The two datasets were first analyzed with a classical time-frequency based detector (TFBD) following (Mellinger, 2004) and (Mouy et al., 2009). This algorithm looks for a typical image of NARW upcall in the SNR-enhanced high-resolution (32 ms × 3.9 Hz) spectrogram of the recordings, and a detection is triggered by the degree of cross-coincidence. The NARW upcall template used is a 1-s, 100–200 Hz chirp with a ±10 Hz bandwidth. For further details see (Simard et al., 2019). The resulting detections are then manually validated by an expert and labelled as “true” or “false” using the longer call pattern context in a ∼1-min window. In NARW occurrence studies, the false detections are then eliminated. For the present work, however, both true and false detections were extracted from the recordings and used as “positives” and “negatives”, respectively, for building the training datasets (Table I). The extracted segments are 3 s long and are downsampled to 1,000 samples s⁻¹. To examine the accuracy of the validation protocol, a second expert was subsequently tasked with reviewing a subset of the 3-s segments; the results of this examination are discussed in Sec. IV.

In addition to the training datasets A and B, generated from the PAM data collected in the Gulf of St. Lawrence, we also consider a third training dataset, C, which is a subset of the DCLDE 2013 dataset generated from PAM data collected in the Gulf of Maine. For the purpose of testing the classification performance of the trained models, including their capacity for generalizing, we split datasets A and B by time with a 85:15 ratio, using samples obtained at earlier times for training and samples obtained at later times for testing (Fig. 2). This split implies temporal separations of 52 min and 33 min between the latest sample in the training dataset and the earliest sample in the test dataset for A and B, respectively.

From the bottom deployments we also extract fifty 30-min segments, which are used for testing the detection performance of the neural network on continuous data. These data cover several years (2015–17), all four seasons, and all times of the day, hence providing a representative picture of the acoustic conditions found in the Gulf of St. Lawrence (Fig. 3). Moreover, the data has no temporal overlap with the training datasets A and B, which originate from 2019 and 2018, respectively. The continuous
TABLE I. Datasets.

| Dataset | Training | Test |
|---------|----------|------|
|         | No. samples | Positives | Negatives | No. samples | Positives | Negatives |
| A       | 1,767         | 42%       | 58%    | 307         | 18%       | 82%       |
| B       | 3,309         | 61%       | 39%    | 579         | 59%       | 41%       |
| C       | 3,000         | 50%       | 50%    | –           | –         | –         |
| AB      | 5,076         | 55%       | 45%    | 886         | 45%       | 55%       |
| ABC     | 8,076         | 53%       | 47%    | –           | –         | –         |

FIG. 2. (Color online) Time-split used to produce training and test sets for Datasets A (a) and B (b).

Test data were manually validated in their entire length by a third expert and found to contain 1,157 upcalls.

FIG. 3. (Color online) Temporal distribution of the training data and the continuous test data.

C. Spectrogram and SNR Computation

We compute the spectrogram representation of each 3-s, 0–500 Hz acoustic segment using a window size of 0.256 s, a step size of 0.032 s (88% overlap), and a Hamming window. These parameters have been shown to be optimal for identifying NARW upcalls (Gervaise et al., 2019a) and produce an image with the (time, frequency) dimensions $94 \times 129$. We note that the spectrograms are fed to the network in their raw form. In particular, no effort is made to normalize the spectrograms to correct for systematic differences in signal amplitude in the three datasets. This approach was adopted to produce the most general model possible.

The SNR was computed for each sample as the difference between the mean spectrogram value (in dB) in a 1-s window centered on the upcall and the mean spectrogram value in the 1-s adjacent windows, for the frequency interval 80–200 Hz. For diagnosis purposes, the same computational procedure was adopted for samples without upcalls.

D. Neural Network Architecture

The problem is setup as a binary classification: A neural network is trained to classify the 3-s spectrograms according to the criterion, contains (positive class, 1) or does not contain (negative class, 0) a NARW upcall. We use a Residual Network (ResNet), which is a CNN architecture mainly built on residual blocks with skip connections (He et al., 2016). CNNs consist of a stack of convolutional layers followed by a few fully connected layers. During the training process, the convolutional layers learn to extract patterns from the input images, which are passed to the fully connected layers for classification (Goodfellow et al., 2016, Chapter 9). The residual blocks in a ResNet are composed of convolutional layers, but allow some connections between layers to be skipped, thereby avoiding “vanishing” and “exploding” gradients during training (He et al., 2016). We use blocks with batch normalization (Ioffe and Szegedy, 2015) and rectified linear units (ReLU) (Nair and Hinton, 2010). The architecture is composed of eight such blocks preceded by one convolutional layer and followed by a batch normalization layer, global average pooling (Lin et al., 2013), and a fully connected layer with a softmax function, which is responsible for the classification. Finally, the output layer gives a score in the range 0–1 for each of the two classes (positive and negative), which add up to 1.
E. Training Protocol

We trained the models on two NVIDIA RTX 2080 Ti GPUs with 11GB of memory. For each dataset listed in Table I, training and test sets were produced by splitting the data by time with a 85:15 ratio, as discussed in Sec. II B. The models were then trained using 5-fold cross-validation (with a 85:15 random split between the training and validation sets), allowing us to inspect if the models were overfitting. After inspection, the models were trained on the full training datasets and tested on the test datasets. The training was repeated nine times with different random number generator seeds to assess the sensitivity to the initial conditions. Training was performed with a batch size of 128 and terminated after 100 epochs, i.e., 128 samples were passed through the network between successive optimizations of the weights and biases, and every sample in the training dataset was passed through the network 100 times. Weights and biases were optimized with the ADAM optimizer (Kingma and Ba, 2014) using the recommended parameters: an initial learning rate of 0.001, decay of 0.01, β2 of 0.9, and β2 of 0.999. No effort was made to explore the dependence of model performance on these parameters. The network was trained to maximize the $F_1$ score, defined as the harmonic mean of precision and recall, $F_1 = 2PR/(P + R)$, where $R$ is the recall, i.e., the fraction of the upcalls that were detected, and $P$ is the precision, i.e., the fraction of the detected upcalls that were in fact upcalls. Thus, the $F_1$ score considers both recall and precision and attaches equal importance to the two.

F. Linear Discriminant Analysis

To establish a baseline against which to compare the performance of the neural network, we implemented a linear discriminant analysis (LDA) model following the approach of (Martinez and Kak, 2001), noting that such models have traditionally been adopted for solving sound detection and classification tasks in marine bioacoustics. First, the $94 \times 129$ spectrogram matrix is flattened to a vector of length 12,126. Second, the dimensionality is reduced by means of principal component analysis (PCA). Third, we train the LDA classifier using a least-squares solver combined with automatic shrinkage following the Ledoit-Wolf lemma (Ledoit and Wolf, 2004). The training is repeated for several choices of PCA dimensionality using a 85:15 random split between training and validation sets, and the dimensionality yielding the best performance on the validation set is selected.

G. NARW Upcall Detection Algorithm

In the following, we describe the implementation of a simple algorithm capable of detecting NARW upcalls in continuous acoustic data. We begin by segmenting the data using a 3-s window and a 0.5-s step size. Each 3-s segment is then fed to the DNN classifier, producing a sequence of classification scores between 0–1, which we interpret as a time-series of upcall occurrence probabilities. Empirically, we find it useful to smoothen the classification scores using a five-bin (2.5 s) wide averaging window. This greatly reduces the number of false positives (factor of ~ 5) at the cost of a modest increase in the number of false negatives (factor of ~ 2). Finally, we apply a constant detection threshold, setting the bin value to 1 (“positive”) when the score is greater than or equal to the threshold and 0 (“negative”) when it is below. (The procedure used for computing the number of true/false positives and negatives is described in detail in Sec. III B.)

III. RESULTS

A. Classification Performance

We test the DNN and LDA models on the datasets from the Gulf of St. Lawrence (A, B, and AB), which are the focus of the present study. The classification performance is summarized in terms of the average $F_1$ score, recall, and precision obtained in nine independent training sessions with different random number generator seeds (Fig. 4). The DNN model trained on the ABC dataset exhibits the best overall performance, achieving a recall of 87.5% and a precision of 90.2% on the AB test set (with standard deviations of 1.1% and 1.2%) and outperforming the baseline LDA model by a statistically significant margin (as evident from Fig. 5 below).

We have investigated the effect of increasing the size of dataset C by up to a factor of 10, but find only a negligible improvement in the performance of the DNN model. We have also investigated the effect of discarding samples with SNR below a certain minimum value, $SNR_{min}$, from the AB test set (Fig. 5). For the LDA model (trained on AB), we observe only small changes in recall across a wide range of SNR values (~2.0 to +5.0). In contrast, the recall of the DNN model (trained on ABC) is seen to worsen with increasing SNR. This non-intuitive behavior is caused by the presence of a large number of samples in the AB test set, all originating from the surface recordings (Dataset A), which have wrong SNR values due to contamination from transient noise events (cf. samples A1858 and A134 in Fig. 6).

In the following, we examine a small set of representative spectrogram samples, which have been either correctly classified or misclassified by the DNN model (Fig. 6). We divide the samples into true positives, true negatives, false positives, and false negatives, and for each category we give three examples reflecting different levels of certainty and difficulty as perceived by the second expert: (a) certain and easy, (b) certain, but difficult, and (c) uncertain. Here, it must be remembered that the experts have access to a larger temporal context of ~ 1 min to inform their decision. Notably, this may help the expert to correctly identify calls with low SNR in cases where the calls form part of a call series.
A few observations can be made: The model is able to correctly identify upcalls with very different SNR (B2225, B3121); the model is able to correctly classify negatives containing potentially confusing patterns (A12), but not always (A111); the model struggles in cases with low SNR (A134, A1858); the model can be confused by tonal noises and multipath echoes (B205). These deficiencies could potentially be resolved by enlarging the temporal window, thereby giving the model access to the same contextual information that is available to the human analyst, notably the appearance of an upcall series. This hypothesis will be explored in a forthcoming paper.

B. Detection Performance on Continuous Data

We test the detection algorithm on the continuous data, which consists of fifty 30-minute segments with a total of 1,157 validated upcalls. The number of calls per file exhibits significant variation, ranging from none to 100 with a median value of 15.

From Sec. II G we recall that the detection algorithm outputs an array of zeros (0) and ones (1), where the values 0 and 1 indicate the absence or presence, respectively, of an upcall in a 3-s window, according to a chosen threshold, and each bin in the array represents a time step of 0.5 s. The performance of the detection algorithm is summarized in terms of recall, precision, and false-positive rate (Fig. 7). For the computation of these metrics, we merge adjacent positive (1) bins into “detection events” (DE). The recall is then computed as the fraction of annotated upcalls that have (at least) one overlapping DE, while the precision is computed as the fraction of the DEs that overlap with an annotated upcall. Any DE that does not overlap with an annotated upcall is counted as one false positive for the computation of the false-positive rate. To allow for minor temporal misalignments between annotations and detections, we adopt a temporal buffer of 1.0 s.

The detection threshold is seen to provide a convenient tunable parameter to adjust the detection performance, depending on whether high precision or high recall is desired. One also notes that the nine independent training sessions produce detectors with very similar recall, but varying levels of precision. In particular, the best-performing detector achieves a recall of 80%, while maintaining a precision above 90% (corresponding to a false-positive rate of ~ 4 DEs per hour for this particular test set), while the “average” detector only achieves a recall of 60% for the same level of precision.

Finally, we consider the effect of discarding samples with SNR below a certain minimum value, SNR\text{min}, from the test dataset (Fig. 8). We find a substantial (5–10% depending on the chosen detection) and rather sudden increase in recall around \(SNR_{\text{min}}\sim 1\) and again around \(SNR_{\text{min}}\sim 6\), where the recall saturates at 100%. (Note that only 30 samples have SNR > 6.0.)
FIG. 5. (Color online) (a) Effect of discarding samples with SNR < SNR\textsubscript{min} from the AB test set on the recall of the DNN and LDA models. The lines show the average recall obtained in the nine training sessions, while the shaded bands show the 10% and 90% percentiles. (b) Number of upcalls in the AB test set with SNR ≥ SNR\textsubscript{min}.

IV. DISCUSSION

The DNN classifier outperforms the baseline LDA model, achieving recall and precision of 87.5% and 90.2% on the AB test dataset. Additionally, we found that the DNN models trained on the combined datasets generally performed better than the models trained on the individual datasets, also when tested on the individual datasets. For example, models trained on AB consistently outperformed models trained exclusively on A, even when tested solely on A. In contrast, the baseline LDA model achieved worse performance when trained on combined datasets. This is an important observation, because it suggests that DNNs have the capacity to handle larger variance in the data, and indeed benefit from being trained on data with greater variance, producing models that are more robust to inter-dataset variability.

On the other hand, we found that the DNN models generally performed poorly when trained on one dataset, but tested on another (e.g., trained on A, but tested on B). This behavior is not observed with the LDA models, whose less performant solution appear to be less sensitive to the training dataset.

The quality and accuracy of the training datasets built as part of this work is limited by both the use of a classical time-frequency based detector to select candidate upcalls for expert validation and by human subjectivity in the validation step. Any bias in the selection or validation step will be reflected in the training dataset and hence affect the learning of the DNN. To explore the bias in the validation step, a second expert was tasked with reviewing all the misclassifications and an equally large number of correctly classified segments randomly sampled from the AB test dataset. The review differed from the validation in several ways: the second expert had knowledge of both the labels assigned by the first expert and the classification proposed by the DNN. The second expert used raw spectrograms while the first expert used SNR-enhanced spectrograms and a larger temporal context, including considerations of occurrence probability over the seasons. Finally, the first expert was instructed to prefer false negatives over false positives, whereas no such instruction was given to the second expert. The second expert flagged about half of the misclassified segments as “borderline”, implying that the expert considered these classifications as being highly uncertain. In contrast, the second expert only flagged 9% of the correctly classified segments as borderline. Removing the borderline cases from the test data improves the recall and precision by 2% and 5%, respectively. However, the second expert also changed some of the labels not considered to be borderline. Adopting the second expert’s revised labels for the test data, the recall decreases by 6% while the precision increases by 2%. These changes in performance metrics testify to the difficulty of obtaining accurate annotations on PAM data. It would be interesting to investigate the inter-annotator variability in a more systematic and controlled manner than done here, but this is beyond the scope of the present study. (For example, it can be argued that the second expert may have been biased by prior knowledge of the labels proposed by the first expert and the DNN.)

Finally, we have tested the performance of our DNN model as a NARW upcall detector on continuous acoustic data representative of the actual conditions required for a NARW upcall PAM DC system. Here, the best-performing model achieved a recall of 80%, while maintaining a precision above 90% (corresponding to a false-positive rate of ∼4 events per hour for the chosen test set), while the “average” model achieved a recall of 60% for the same level of precision. Restricting our attention to upcalls with SNR ≥ 1, our best-performing detector achieved a recall of ∼90% for the same level of precision. Existing algorithms are capable of achieving similar levels of recall, but at the cost of a significantly higher false-positive rate (DCLDE 2013; Simard et al., 2019).

V. CONCLUSION

In summary, we have demonstrated that DNNs can be trained to recognize NARW upcalls in acoustic recordings which have been made with different acoustic equipment and deployment types, and hence differ significantly in terms of signal amplitude and noise background. By training a DNN on a dataset comprised of about 4,000 samples of NARW upcalls and an approximately equal number of negative samples, we achieved recall and precision of 90% on a test dataset containing about 700 up-
calls and a similar number of negatives. The DNN was observed to benefit from being trained on data with increased variance, suggesting that improved performance could be achieved by further expanding the variance of the training dataset. Using the DNN classifier, we implemented a simple detection algorithm, which exhibited good performance on continuous test data, achieving a recall of 80% while maintaining a precision above 90%. It would be interesting to explore still more sophisticated machine-learning approaches, most notably approaches that consider a wider temporal context, as done by the human experts, but this is beyond the scope of the present study and is left for future work. These results highlight the potential of DNNs for solving sound...
FIG. 7. (Color online) Detection performance on continuous data in terms of recall (R), precision (P), and false-positive rate (FPR). The lines show the average performance while the shaded bands show the 10% and 90% percentiles. (a) R and P versus the adopted detection threshold. (b) P-R and FPR-R curves.

FIG. 8. (Color online) Recall on continuous data as a function of minimum SNR, for three different choices of detection threshold. The lines show the average performance while the shaded bands show the 10% and 90% percentiles. The number of upcalls with SNR > SNR\textsubscript{min} is also shown.

APPENDIX: SUPPLEMENTARY MATERIAL

Upon manuscript acceptance we will provide the code necessary to reproduce the results presented in the paper including initialization and training of the neural network, prediction on test data, and computation of test metrics, along with all necessary training and test data. We will also provide more spectrogram samples (including expert annotation, model output, and SNR) and a complete diagram of the neural network architecture.

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1https://soi.st-andrews.ac.uk/static/soi/dclde2013/documents/WorkshopDataset2013.pdf
2SNR enhancement can have two effects: It may allow extracting signals deeply embedded in noise, which cannot be seen in the raw spectrograms, but it may also generate artifacts that are mimicking real signals.

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