Automatic Identification of Animal Breeds and Species Using Bioacoustics and Artificial Neural Networks

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Abstract

In this research endeavor, it was hypothesized that the sound produced by animals during their vocalizations can be used as identifiers of the animal breed or species even if they sound the same to unaided human ear. To test this hypothesis, three artificial neural networks (ANNs) were developed using bioacoustics properties as inputs for the respective automatic identification of 13 bird species, eight dog breeds, and 11 frog species. Recorded vocalizations of these animals were collected and processed using several known signal processing techniques to convert the respective sounds into computable bioacoustics values. The converted values of the vocalizations, together with the breed or species identifications, were used to train the ANNs following a ten-fold cross validation technique. Tests show that the respective ANNs can correctly identify 71.43% of the birds, 94.44% of the dogs, and 90.91% of the frogs. This result show that bioacoustics and ANN can be used to automatically determine animal breeds and species, which together could be a promising automated tool for animal identification, biodiversity determination, animal conservation, and other animal welfare efforts.

1. Introduction

Identification of animal breeds or species\(^1\) is an important method in animal conservation, biodiversity determination, animal welfare efforts, animal breeding, and other human programs that are geared towards production, improvement, protection and conservation. The usual method to identifying animal species is by visual inspection of the animal’s anatomical features vis-à-vis a published set of standards [Coile, 2005; Ford and Cannatella, 1993].

\(^1\)For brevity, the term “species” is used henceforth throughout the text to mean either “breeds” or “species” depending on the context without loss of specificity.
Examples of anatomical features inspected are body dimensions, types and colors of coats, and skin covering. This method is usually done by experts in the field, particularly the breeders and the systematists. Identifying the species of birds that migrate to a certain place, for example, requires a tedious bird-watching procedure that is often conducted over several days. To identify the visiting bird species, the observers need to actually see and capture with a high-resolution camera the images of the animals. Obtaining an unobstructed line of sight between the observer and the observed requires proper positioning of the observer at some safe-enough distance, with some observers going to the extent of wearing camouflage so as not to distract the observed. This procedure becomes much more complicated to conduct if the animals to be observed are nocturnals, are perched atop high canopy trees, or are underwater.

The problems with the current method result from its inherent requirement that the observer must have an unobstructed line of sight with the observed, and with ample enough lighting. This is because light travels along a straight line and can only be detected by human eyes at a certain range of intensities (Marriott et al., 1959). Because humans are predominantly visual in nature (Thorpe et al., 1996), most of its activities rely much on the sense of seeing, using only the other senses for verifying what was seen (Ernst and Banks, 2002). Identifying an animal, for example, starts from obtaining an image of its anatomical features, either by the naked eye or as captured by a camera system. The physical process of obtaining an image is by facing the sensor (e.g., eye, camera, or other image capturing devices) towards the direction of the light rays that incidentally reflected on the surface of the animal. The identification is optionally verified when the observed animal produces an identifiable vocalization and is heard by the observer. However, when the animal was not seen (i.e., reflected light did not reach the sensor) or was partially occluded (i.e., reflected light was blocked by another object), no image can be obtained and thus, no identification can be performed even if the vocalization was heard by the observer.

In recent years, researchers have directed their efforts towards utilizing animal vocalizations to detect and identify animals (Agranat, 2009; Aide et al., 2013; Clemins, 2005; Clemins and Johnson, 2002; Shapiro, 2009). This gives rise to the importance of bioacoustics, the study of animal vocalization. Detecting and identifying animals through their vocalizations do not have the problematic inherent requirements that identifying through visual means have. Sound waves are propagated by their sources to all directions in space and do not require an unobstructed line of sight as the waves can bounce back from object to object. Additionally, the observer do not have to find where the animals being observed are located to orient its sensor because the ear, or any other listening devices, can sense the sound waves from any direction and position. Because of this, most of biodiversity recording efforts started from what was heard first in the field, rather than what was first seen.

Animals vocalize to communicate information to other animals, whether within the same species or with another species (Witzany, 2014). The reasons for communicating, among many others, include (1) to impress and attract the opposite sex for reproduction purposes, (2) to declare territorial boundaries, (3) to identify family members, (4) to warn others of the presence of a predator, and (5) to inform others on the location of food source. For
example, birds sing and frogs croak to attract potential mates, while dogs bark to warn their human master of the presence of strangers.

Without the aid of hearing devices, the vocalizations of most animals within the same species appear the same to humans. This is because researchers found that human ears are sensitive to low-frequency sound while most animals are sensitive to high-frequency ones (Masterton et al., 1969). Other researchers have found out that through evolution, the superhearing, mimicking, and jamming capabilities of animals evolved as a result of survival pressure from their predators (Barber and Conner, 2007; Barber and Kawahara, 2013; Conner and Corcoran, 2012; Ige et al., 2015). However, because humans are the ultimate predator, human hearing has evolved to best detect sounds created by other human beings only (Nelken et al., 2005). As a result, the respective sounds produced by two animals from within the same genus but of different species do not appear distinctive from each other with regards to human ear. This is the reason why for the longest time, vocalization was not considered by researchers as a primary identifier of species. However, because of the recent advances in sound technology coupled with the development of complex signal processing methods, it has been found that communication for the purpose of individual identification within the same animal species is possible (Janik et al., 2006; Moore et al., 2006; Shapiro, 2009; Slabbekoorn and Smith, 2002; Witzany, 2014).

The use of vocalization as identifier of species is based on the framework that acoustic properties of sound are used by animals to encode their identities. The spectral features of sound waves, including the fundamental ones such as frequency and harmonics, differ between two different sources. Because of this, Cortopassi and Bradbury (2000) were able to differentiate pairs of orange-fronted parakeets (Aratinga canicularis) using the spectral features of bird calls. Similarly, the mother-pup pairs of South American fur seals (Arctocephalus australis), Galapagos fur seals (Arctocephalus galapagoensis), and Galapagos sea lions (Zalophus californianus wollebaeki) were also differentiated via their calls’ spectral features (Phillips and Stirling, 2000; Trillmich, 1981). It is based on this framework that the following null ($H_0$) and alternate ($H_1$) hypotheses are stated for this effort:

$H_0$: There does not exist any combination of the spectral properties of the vocalizations of animals that can differentiate breeds or species with at least 70% accuracy.

$H_1$: There does exist a combination of the spectral properties of the vocalizations of animals that can differentiate breeds or species with at least 70% accuracy.

The minimum accuracy level on the above stated hypotheses was chosen as 20% more than a randomized toss of coin, i.e., an unbiased coin toss is 50% while the additional 20% is attributed to the confidence that the system will provide. The choice of 70% is arbitrary because the standard for an acceptable accuracy level has not been set by the discipline nor by the industry.

In the past, the process of differentiating objects based on a complex combination of their visual features was automated by a machine vision system (MVS) that uses an artificial neural network (ANN) for efficient classification. ANNs are abstract models of
the human brain that is capable of supervised learning and then forming a generalization from a set of experiences (McCulloch and Pitts, 1943; Rosenblatt, 1958). ANNs, for example, have been used by local researchers to automate the error-prone object classification capabilities of humans such as grading the ripeness of tomatoes (Lycopersicon esculentum) (de Grano and Pabico, 2007a,b), and differentiating cracks, bloodstains and dirt in eggs (Zarsuela and Pabico, 2007). All of these automated systems used simple cameras as artificial eyes to extend the seeing capabilities of the human eyes beyond their normal working time and way above their normal working rate. As a result, the object classification process was made faster, almost error-free, and used less resources. This improves the classification efficiency significantly over the manual ones (Pabico et al., 2008, 2009, 2012).

In this effort, the spectral properties of vocalization of three animals were automatically identified using ANNs. The properties were extracted following the various techniques developed in the bioacoustic and the signal processing disciplines. Some of these properties are Spectral Centroid (SC), Spectral Flux (SF), Spectral Roll-off Frequency (SRF), Zero Crossing Rate (ZCR), Mel-Frequency Cepstral Coefficients (MFCC), and Linear Predictive Coding (LPC) (McEnnis et al., 2005). Combinations of these properties were used to train three independent ANNs to identify 13 bird species, eight dog breeds, and 11 frog species, respectively. These animals were chosen not only because they are the most common animals in the Philippines, but the Philippine mountains and forests play hosts to most known migratory species of birds, and are home to vast and various groups of amphibians and reptiles. In fact, the country ranks fourth in the world in terms of bird endemicism and first in terms of amphibians and reptiles (Ong et al., 2002). Dogs, on the other hand, were included because Filipinos in general are dog lovers (Gosling et al., 2010). To avoid the Type III errors in classification, each ANN was trained using a 10-fold cross validation technique (Kohavi, 1995; Mosteller, 1948).

An ANN that uses a combination of all known 28 spectral properties as its input yielded the highest accuracy rate of 71.43% for identifying bird species. On the other hand, the ANN that was trained to identify frog species also uses the 28 spectral properties and yielded a 90.91% accuracy rate. The ANN for identifying dog breeds only required a combination of 4 spectral properties to yield a high accuracy rate of 94.44%. These results show that there does exist a combination of the spectral properties of the vocalizations of animals that can differentiate breeds or species with high accuracy rate. One implication of this result is that a smartphone technology-enabled “crowdsourcing” solution to automatically and transparently collect information on fauna biodiversity by the common people may become a possibility in the near future. This could significantly enhance data collection, not only for biodiversity inventory efforts, but for other animal conservation and welfare endeavors.
Table 1: The bird species used in vocalization identification showing the common name, scientific name, and place of origin.

| Common Name            | Scientific Name              | Place of Origin     |
|------------------------|------------------------------|---------------------|
| 1. Bananquit           | *Coereba flaveola*           | South America       |
| 2. Black Crake         | *Amaurornis avirostra*       | Africa              |
| 3. Black Hornbill       | *Anthracoceros malayanus*    | Southeast Asia      |
| 4. Eurasian Skylark    | *Alauda arvensis*            | Europe, Asia, Africa|
| 5. European Goldfinch  | *Carduelis carduelis*        | Europe              |
| 6. Philippine Bulbul    | *Hypsipetes philippinus*     | Mindanao            |
| 7. Philippine Bush Warbler | *Cettia seebohmi*          | Luzon               |
| 8. Philippine Drongo Cuckoo | *Surniculus velutinus*    | Mindanao            |
| 9. Water Pipit         | *Anthus spinola*             | Europe, Asia        |
| 10. Rufous-tailed Hummingbird | *Amazilia tzacatl*  | America             |
| 11. Rusty Breasted Cuckoo | *Cacomantis sepulcralis*    | Southeast Asia      |
| 12. Spotted Kingsher    | *Actenoides lindsayi*       | Luzon               |
| 13. White Rumped Shama  | *Copsychus malabaricus*     | Southeast Asia      |

2. Materials and Methods

2.1. Collecting audio clips of animal vocalizations

2.1.1. Vocalization from birds

Vocalization data from 13 bird species was used in this study. The basic information on these bird species are shown in Table 1. Each bird species had 25 different audio clips, all came from the database of Michigan State University’s Avian Vocalizations Center (AVoCet, 2008). The total number of audio clips used was 325.

2.1.2. Vocalization from frogs

Sound data from 11 frog species were collected from different Internet databases (AmphibiaWeb, 2000). The species are *Boophis luteus*, *Bufo marinus*, *Fejervarya limnocharis*, *Hylarana glandulosa*, *Kaloula balana*, *Kaloula pulchra*, *Microhyla butleri*, *Odorrana hossii*, *Phrynoidis aspera*, *Polypedates leucomystax* and *Rana catesbeiana*. There were a total of 110 audio samples equally distributed to the 11 species.

2.1.3. Vocalization from dogs

Bark recordings of beagle, chihuahua, chowchow, shih tzu, and poodle were manually obtained from reputable pet shops. Bark recordings of labrador retriever and
syberian husky came from various contributed audio repositories from previous experiments (Jones and Gosling, 2005; Riede and Fitch, 1999). Ten samples of dog barks audio segments were used for each breed for a total of 90 samples.

2.1.4. Recordings of negative examples

Negative examples are sound clips that were neither produced by birds, dogs, nor frogs. These clips are important part of the dataset so that the ANN will be able to differentiate, not only between species, but sound from other sources as well (Aha et al., 1991; Dietterich and Michalski, 1983). In this research effort, pseudo “species” or “breed” was added to each dataset. That is, a “pseudo species” was added for the bird dataset, a “pseudo breed” for the dog dataset, and a “pseudo species” for the frog dataset. Thus, the bird, dog and frog datasets have 14 species, 9 breeds, and 12 species, respectively.

2.1.5. Training, test, and evaluation datasets

The dataset (Σ) collected was divided into three sets namely, training (Σ_{train}), test (Σ_{test}), and evaluation (Σ_{eval}) sets. If there are a total of N samples in Σ, then N is as defined in Equation 1 where N_{train} is the total number of samples in the training set, N_{test} is the total number of samples in the test set, and N_{eval} is the total number of samples in the evaluation set. Note that Σ is as defined in Equation 2 and that the sets are pairwise disjoint such that the expressions in Equations 3, 4 and 5 hold. The fraction of the datasets are N_{train} = 0.7N, N_{test} = 0.1N, and N_{eval} = 0.2N, with all the species equally distributed for each fraction.

\[
N = N_{\text{train}} + N_{\text{test}} + N_{\text{eval}} \quad (1)
\]

\[
\Sigma = \Sigma_{\text{train}} \bigcup \Sigma_{\text{test}} \bigcup \Sigma_{\text{eval}} \quad (2)
\]

\[
\{} = \Sigma_{\text{train}} \bigcap \Sigma_{\text{test}} \quad (3)
\]

\[
\{} = \Sigma_{\text{train}} \bigcap \Sigma_{\text{eval}} \quad (4)
\]

\[
\{} = \Sigma_{\text{test}} \bigcap \Sigma_{\text{eval}} \quad (5)
\]

2.2. Extraction of spectral properties of sound waves

The spectral properties of the respective audio clips were automatically extracted using a software system called jAudio (McEnnis et al., 2005). These spectral properties, including their respective physical principles, mathematical derivations, and proofs, were discussed in detail elsewhere (Bogert et al., 1963; Proakis and Manolakis, 2007) and are not presented
here. However, for the benefit of the lay readers as well as for completeness, a brief description of each property is provided as follows:

1. Mel-Frequency Cepstral Coefficients (MFCC) - Represents the short-term power spectrum of a sound and is primarily used in speech recognition.

2. Zero Crossing (ZC) - The number of times that the time domain signal crosses zero within a given window.

3. Root Mean Square (RMS) - Calculated per window in order to get the amplitude of the sound signal.

4. Fraction of Low Energy Window Frames (FLWEF) - Indicates the variability of the amplitude of windows.

5. Spectral Flux (SF): Signifies the degree of change of the spectrum between windows and is the spectral correlation between adjacent windows.

6. Spectral Rolloff (SR): Indicates the skew of the frequencies present in a window. Eighty-five percent of the energy in the spectrum is below this frequency.

7. Compactness (C): Indicates the noisiness of the signal by getting the summation of frequency bins of Fast Fourier Transform (FFT).

8. Method of Moments (MoM): Composed of the first five statistical models that make up the shape of the spectrograph of a given window. The components are area (zeroth order), mean (first order), Power Spectrum Density (second order), Spectral Skew (third order), and Spectral Kurtosis (fourth order).

9. Linear Predictive Coding (LPC): Calculates the linear predictive coefficients of a signal in which a particular value is estimated by a linear function of the previous values.

10. Spectral Centroid (SC): Indicates where the “center of mass” of the spectrum is and measures the brightness of the sound. This is used as an automatic measure of timbre.

11. Beat Sum (BS): Indicates the sum of the beats in a sound and pertains to the alternating constructive and destructive interference caused by sound waves of different frequency.

12. Strongest Beat (SB): The value of the beat with the strongest frequency.

13. Strength of Strongest Beat (SSB): The intensity of the strongest beat.

14. Spectral Variability (SV): Measures how the ranges of the elements of the sound differ from each other.

The overall average and standard deviation of each of these properties were used as quantified inputs to the ANN. This results to a total of 28 quantified properties as identifiers for species.
2.3. Structuring, Training and Evaluating ANNs

2.3.1. Structuring ANNs

ANN is an abstract mathematical model of the biological (specifically human) brain composed of a directed network of simple functions and coefficients. Here, the functions are nodes of the network and the coefficients are weights on the edges of the network. A function $f_1$ is connected to another function $f_2$ via a weighted edge represented by the coefficient $\alpha_{1 \rightarrow 2}$. Here, the output of $f_1$ is multiplied by coefficient $\alpha_{1 \rightarrow 2}$ and their product becomes an input to $f_2$. The direction of the network in this study goes from the quantified spectral properties as inputs to the final species identity as output. The identity is encoded as a computable value represented by an $n$-bit binary system for an $n$-species identification problem.

The general structure of the ANN is that the nodes are generally structured into $m + 2$ layers, where the layers are classified into three major classifications: one input layer $L_0$, $m \geq 1$ hidden layers $L_1, L_2, \ldots, L_m$, and one output layer $L_{m+1}$. Nodes within a layer are not connected to each other. Here, $L_0$ is composed of at most 28 nodes representing the 28 quantified spectral properties. The output layer is composed of $n$ nodes, where $n - 1$ is the number of species to identify. The extra node is for identifying the negative examples, i.e., the “pseudo species” or “pseudo breed.” Each of the $m$ hidden layers is composed of the same number of nodes $k$. Nodes in $L_i$ are connected to nodes in $L_{i+1}$, where the sub-graph induced by the nodes in $L_i$ and $L_{i+1}$ form a fully-connected weighted bipartite network with $\alpha_{(i) \rightarrow (i+1)}, \forall i$ as weights. The functions in the nodes are sigmoidal ones $f_{i+1} : \{O_i\} \times \{\alpha_{(i) \rightarrow (i+1)}\} \rightarrow \{0, 1\}$, where $f_{i+1}$ are the functions in $L_{i+1}$, and $O_i \in \{0, 1\}$ are the outputs of $f_i$ in $L_i$.

The ANNs in this work are denoted as $\text{ANN}(j, [k, m], n)$, where $j$ is the number of nodes in $L_0$, $k$ is the number of nodes in $L_m$’s, and $n$ is the number of nodes in $L_{m+1}$. The ANN for birds, dogs, and frogs are structured as $\text{ANN}_{\text{bird}}(j, [14, 1], 14)$, $\text{ANN}_{\log}(j, [9, 1], 9)$, and $\text{ANN}_{\text{frog}}(j, [12, 1], 12)$, respectively. The optimal values of $j$ for each ANN was obtained using a stepwise forward substitution method following the minimum description length criterion for model selection [Hansen and Yu (2001)].

2.3.2. Training ANNs

Each of the ANNs were trained using a feed-forward, back-propagation training algorithm over the samples in $\Sigma_{\text{train}}$. The errors generated by the initial random assignment for the set of coefficients $\{\alpha\}$ are minimized by back-propagating the identification differences, i.e., ANN classifies an audio clip as having vocalized by species $A$ but was actually vocalized by species $B$. The ANN error used for training was the mean square error (MSE). The process was iteratively conducted until one of the following stopping criteria was met:

1. When the ANN MSE over the samples in $\Sigma_{\text{test}}$ has already worsen over several iterations.
2. When the ANN MSE over the samples in $\Sigma_{\text{train}}$ has not been improved over 100 iterations.

3. When the ANN MSE over the samples in $\Sigma_{\text{train}}$ has already reached below 0.01.

The whole process described above was repeated nine more times in a 10-fold cross-validation manner (Kohavi, 1995; Mosteller, 1948), where at each fold, the samples in each of the sets were changed. For example, $\sigma_i \neq \sigma_{i+1}$, where $\sigma_i \in \Sigma_{\text{eval},i}$, $\sigma_{i+1} \in \Sigma_{\text{eval},i+1}$, $\forall i$ and $\Sigma_{\text{eval},i}$ is the evaluation set at the $i$th fold.

2.3.3. Evaluating the ANNs

The respective accuracies of the ANNs were evaluated over the samples in eval. Accuracy is simply computed as the percentage of correctly identified species. An additional secondary evaluation metric called error rate was computed following a multi-class confusion matrix (Bavaud et al., 2006; Kohavi, 1995; Manning et al., 2008). It is possible for each of the ANNs to have an accuracy of 100% and a non-zero error rate.

3. Results and Discussion

3.1. Collection of audio clips

The total file sizes of the audio clips collected are 1,100.0 MB, 88.3 MB, and 494.1 MB for birds, frogs, and dogs, respectively. All audio clips were encoded using the Waveform audio file format. This format was used because the spectral properties of soundwave are preserved when the audio stream is stored as raw and uncompressed bitstream.

3.2. Spectral properties of vocalizations

Figure 1 shows the SV box-and-whisker plot of each bird species. The plot shows that the respective SV distributions of the Philippine Bulbul and the Philippine Bush Warbler are extremely skewed to the right, while that of the Water Pipit and the Rusty Breasted Cuckoo are extremely skewed to the left. The plot also indicates that SV alone can be a good identifier between Philippine Bulbul and Philippine Bush Warbler, between Philippine Bulbul and Water Pipit, and between Philippine Bulbul and the Pseudo species. The reason for this is that the minimum SV of Philippine Bulbul is greater than the respective maximum SVs of Philippine Bush Warbler, Water Pipit, and Pseudo species. SV alone, however, can not be used to differentiate among Philippine Bush Warbler, Water Pipit, and Pseudo species. In fact, any other pairwise bird species will not be identified by SV alone. Although SV can not differentiate all other bird species, it is just but one dimension in the 28-dimensional spectral properties, the right combination of which may differentiate all pairwise combination of bird species considered in this study. Because of space limitation, the remaining 27 spectral
properties for birds, as well as the spectral properties of both dogs and frogs will not be described in this paper.

Figure 1: Box-and-whisker plot of the spectral variability (SV) of bird species. The yellow plot can be visually differentiated from the green plot.

3.3. ANN structure

The respective stepwise forward substitution methods applied to determine the optimal combination of the 28 spectral properties to structure the ANN\textsubscript{bird}, ANN\textsubscript{dog}, and ANN\textsubscript{frog} resulted into:

\[
\begin{align*}
\text{ANN}_{\text{bird}} &= \text{ANN}(28, [14, 1], 14) \\
\text{ANN}_{\text{dog}} &= \text{ANN}(4, [9, 1], 9) \\
\text{ANN}_{\text{frog}} &= \text{ANN}(28, [12, 1], 12)
\end{align*}
\]

This means that it will take a combination of all the 28 quantified spectral properties to differentiate with high accuracy the bird species and frog species, respectively. For dogs, however, only a combination of four spectral properties suffices to differentiate breed barks with high accuracy. These spectral properties are: (1) Average MFCC, (2) average MoM, (3) MoM standard deviation, and (4) average LPC.
3.4. Accuracy of ANNs

Tables 2, 3, and 4 show the confusion matrices for ANN\textsubscript{bird}, ANN\textsubscript{dog}, and ANN\textsubscript{frog}, respectively.

Table 2: Confusion matrix for the identification of 13 bird species. Blank entries mean zero.

| Bird Species | Bird species as determined by ANN\textsubscript{bird} | Total Correct |
|--------------|----------------------------------------------------|---------------|
| a. Bananaquit | 5 | 5 |
| b. Black Crake | 3 1 | 1 3 |
| c. Black Hornbill | 2 1 | 1 1 2 |
| d. Eurasian Skylark | 5 | 5 |
| e. E. Goldfinch | 4 1 | 4 |
| f. Phil. Bulbul | 4 1 | 4 |
| g. Phil. Bush Warbler | 1 1 1 1 1 1 | 1 |
| h. Phil. D. Cuckoo | 1 4 | 4 |
| i. Water Pipit | 5 | 5 |
| j. R.-t. Hummingbird | 1 1 3 | 3 |
| k. R. B. Cuckoo | 2 3 | 3 |
| l. S. Kingsher | 1 4 | 4 |
| m. W. R. Shama | 2 1 | 2 |
| n. Pseudo | 5 5 | 5 |
| Total Error | 1 2 1 0 1 2 2 2 3 1 1 1 2 | 50 |

Overall error rate (%) 28.57
Overall accuracy (%) 71.43

The ANN\textsubscript{bird} was able to identify 100% of the Eurasian Skylark, without additionally identifying other species as Eurasian Skylark (i.e., its error rate for Eurasian Skylark is 0%). Bananaquit was also identified 100% but mistaken one of the Philippine Drongo Cuckoo as a Bananaquit (i.e., error rate of 1.82%). All of Water Pipits were identified 100% as well, but mistakenly identified one black crake, one European Goldfinch, and one Rufous-tailed Hummingbird as Water Pipits. Thus, the ANN\textsubscript{bird} has an error rate of 5.45% for identifying Water Pipit. The Pseudo species was also correctly identified 100%, but also identified Black Crake and Black Hornbill as Pseudo species (i.e., error rate of 3.64%). Only one of the samples was identified by ANN\textsubscript{bird} as Philippine Bush Warbler (i.e., accuracy of 20%). It also identified one Philippine Bulbul and one Rufous-tailed Hummingbird as Philippine Bush Warbler (i.e., error rate of 3.64%). The overall accuracy of ANN\textsubscript{bird} is 71.43% while its overall error rate is 28.57%. With regards to identifying bird species, the null hypothesis $H_0$ is rejected and the alternate hypothesis $H_1$ is accepted in its stead.

The ANN\textsubscript{dog} was able to identify all dog breeds correctly (i.e., 100% accuracy, Table 3). It correctly identified the Pseudo breed 50% of the time. The other half of the Pseudo breed was identified erroneously as Chow Chow (i.e., error rate of identifying Chow Chow is 5.56%).
The error rate for identifying all the other breeds, including the Pseudo breed is 0%. The overall accuracy of \( \text{ANN}_{\text{dog}} \) is 94.44% and its overall error rate is 5.56%. With these results, the alternate hypothesis \( H_1 \) is accepted instead of the null hypothesis \( H_0 \).

Table 3: Confusion matrix for the identification of eight dog breeds. Blank entries mean zero.

| Dog Breed | Breed according to \( \text{ANN}_{\text{dog}} \) | Total Correct |
|-----------|-------------------------------------------|---------------|
| a. Beagle | 2 | 2 |
| b. Chihuahua | 2 | 2 |
| c. Chow Chow | 2 | 2 |
| d. Labrador Retriever | 2 | 2 |
| e. Pomeranian | 2 | 2 |
| f. Poodle | 2 | 2 |
| g. Shih Tzu | 2 | 2 |
| h. Siberian Husky | 2 | 2 |
| i. Pseudo | 1 | 1 |
| Total Error | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 17 |

Overall error rate (%) 5.56
Overall accuracy (%) 94.44

All frog species (Table 4), except for the Pseudo species were identified by \( \text{ANN}_{\text{frog}} \) correctly (i.e., 100% accuracy for each species and 0% accuracy for the Pseudo species). \( \text{ANN}_{\text{frog}} \) also identified all Pseudo species as \( B. luteus \). Thus, \( \text{ANN}_{\text{frog}} \) has an error rate of 9.09% for identifying \( B. luteus \). \( \text{ANN}_{\text{frog}} \) has an overall accuracy of 90.91% and an overall error rate of 9.09%. The accuracy of \( \text{ANN}_{\text{frog}} \) proves that the alternate hypothesis \( H_1 \) must be accepted and the null hypothesis \( H_0 \) rejected.

### 4. Summary and Conclusion

Three ANNs for respectively identifying 12 bird species, eight dog breeds, and 11 frog species were structurally optimized, trained, and evaluated. The animals were identified through the 28 quantifiable spectral properties of their respective vocalizations. Identifying bird and frog species requires all 28 properties while identifying dog breeds only requires four, namely average MFCC, average and standard deviation of MoM, and average LPC. The respective accuracies of identifying bird species, dog breeds, and frog species are 71.43%, 94.44%, and 90.91%. The respective alternate hypotheses that there exists combinations of the spectral properties of the vocalizations of these three animals that can differentiate among their respective breeds or species with at least 70% accuracy are accepted. Thus, by using bioacoustics methods, the sound produced by animals during their vocalizations can be used as identifiers of species, and that the process can be automated by ANNs.
Table 4: Confusion matrix for the identification of 11 frog breeds. Blank entries mean zero.

| Frog Species | Frog species as determined by ANN<sub>frog</sub> | Correct |
|--------------|-----------------------------------------------|---------|
| a. B. luteus | 2                                             | 2       |
| b. B. marinus| 2                                             | 2       |
| c. F. limnocharis | 2                                  | 2       |
| d. H. glandulosa | 2                             | 2       |
| e. K. baleata | 2                                             | 2       |
| f. K. pulchra | 2                                             | 2       |
| g. M. butleri | 2                                             | 2       |
| h. O. hossi  | 2                                             | 2       |
| i. P. aspera | 2                                             | 2       |
| j. P. leucomystax | 2                           | 2       |
| k. R. catesbeina | 2                          | 2       |
| l. Pseudo    | 2                                             | 0       |
| Total Error  | 2                                             | 0       |

| Overall error rate (%) | 9.09 |
| Overall accuracy (%)   | 90.91 |

One of the implications of this result is that species inventory procedures for biodiversity recording purposes maybe augmented and enhanced through a technique called “crowdsourcing” (Estellés-Arolas and González-Ladrón-de-Guevara, 2012). This technique is similar to the Christmas Day Bird Census that was started in 1900 and has become an annual tradition by the members of the National Audubon Society (Robbins, 2015). In crowdsourcing, however, the participants are not only bird enthusiasts but common people equipped with a modern-day smartphones whose applications can automatically record animal vocalizations, identify the animals, and send the dated and geo-located information to a central database. This automated process maybe transparently done by the application without user intervention, which is a much better system than what Huetz and Aubin (2012) proposed.

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References

I. Agranat. Automatically identifying animal species from their vocalizations, 2009. Technical White Paper, Wildlife Acoustics, Inc., Concord, MS, USA, 22 pp.

D.W. Aha, D. Kibler, and M.K. Albert. Instance-based learning algorithms. *Machine Learning*, 6(1):37–66, 1991. doi: 10.1007/BF00153759.

T.M. Aide, C. Corrada-Bravo, M. Campos-Cequeira, C. Milan, G. Vega, and R. Alvarez. Real-time bioacoustics monitoring and automated species identification. *PeerJ*, 1:e103, 2013. doi: 10.7717/peerj.103.

AmphibiaWeb. Information on amphibian biology and conservation, 2000. Berkeley, California, http://amphibiaweb.org.

AVoCet. Avian vocalizations center database, 2008. Michigan State University, http://avocet.zoology.msu.edu/.

J.R. Barber and W.E. Conner. Acoustic mimicry in a predator-prey interaction. *Proceedings of the National Academy of Sciences*, 104:9331–9334, 2007. doi: 10.1073/pnas.0703627104.

J.R. Barber and A.Y. Kawahara. Hawkmoths produce anti-bat ultrasound. *Biology Letters*, 9(4), 2013. doi: 10.1098/rsbl.2013.0161.

F. Bavaud, D. Picca, and B. Curdy. Non-linear correspondence analysis in text retrieval: A kernel view. In *Proceedings of Journées Internationales d’Analyse Statistique des Données Textuelles*, Besançon, 2006.

B.P. Bogert, M.J.R. Healy, and J.W. Tukey. The frequency analysis of time series for echoes: Cepstrum, pseudo autocovariance, cross-cepstrum and saphe cracking. In M. Rosenblatt, editor, *Proceedings of the Symposium on Time Series Analysis*, volume 15, pages 209–243, New York, 1963. Wiley.

P.J. Clemins. *Automatic Classification of Animal Vocalizations*. PhD thesis, Marquette University, Milwaukee, WI, USA, 2005.

P.J. Clemins and M.T. Johnson. Automatic speech recognition and speaker identification of animal vocalizations. In *Proceedings of the 4th International Conference on Methods and Techniques in Behavioral Research*, Amsterdam, The Netherlands, 2002.

D.C. Coile. *Encyclopedia of Dog Breeds*. Barron’s Educational Series, 2005. ISBN: 0764157000.

W.E. Conner and A.J. Corcoran. The 65-million-year-old battle between bats and insects. *Annual Review of Entomology*, 57:21–39, 2012. doi: 10.1146/annurev-ento-121510-133537.

K.A. Cortopassi and J.W. Bradbury. The comparison of harmonically rich sounds using spectrographic cross-correlation and principal coordinates analysis. *Bioacoustics*, 11(2): 89–127, 2000. doi: 10.1080/09524622.2000.9753454.
A.V. de Grano and J.P. Pabico. Automating the classification of tomato (lycopersicon esculentum) maturity using image analysis and neural networks. *Transactions of the National Academy of Science and Technology, Philippines*, 29(1):131–132, 2007a.

A.V. de Grano and J.P. Pabico. A neural network-based computer color vision for grading tomatoes (lycopersicon esculentum). *Philippine Journal of Crop Science*, 31(1):130, 2007b.

T.G. Dietterich and R.S. Michalski. A comparative review of selected methods for learning from examples. In R.S. Michalski RS, J.G. Carbonell, and T.M. Mitchell, editors, *Machine Learning: An Artificial Intelligence Approach*, pages 41–81. Morgan Kaufmann, San Mateo, CA, 1983. doi: 10.1007/978-3-662-12405-5_3.

M.O. Ernst and M.S. Banks. Humans integrate visual and haptic information in a statistically optimal fashion. *Nature*, 415(6870):429–433, 2002. doi: 10.1038/415429a.

E. Estellés-Arolas and F. González-Ladrón-de-Guevara. Towards an integrated crowdsourcing definition. *Journal of Information Science*, 38(2):189–200, 2012. doi:10.1177/0165551512437638.

L.S. Ford and D.C. Cannatella. The major clades of frogs. *Herpetological Monographs*, 7:94–117, 1993. doi: 10.2307/1466954.

S.D. Gosling, C.J. Sandy, and J. Potter. Personalities of self-identified “dog people” and “cat people”. *Anthrozoos*, 23(3):213–222, 2010. doi: 10.2752/175303710X12750451258850.

M. Hansen and B. Yu. Model selection and the principle of minimum description length. *Journal of the American Statistical Association*, 96(454):746–774, 2001. doi: 10.1198/016214501753168398.

C. Huetz and T. Aubin. Bioacoustics approaches to locate and identify animals in terrestrial environments. In J.-F. Le Galliard, J.-M. Guarini, and F. Gaill, editors, *Sensors for Ecology: Towards Integrated Knowledge of Ecosystems*, page 342. INEE, CNRS, Paris, 2012. ISBN: 2954168307.

B. Igic, J. McLachlan, I. Lehtinen, and R.D. Magrath. Crying wolf to a predator: Deceptive vocal mimicry by a bird protecting young. *The Royal Society Proceedings B: Biological Sciences*, 282(1809), 2015. doi: 10.1098/rspb.2015.0798.

V.M. Janik, L.S. Sayigh, and R.S. Wells. Signature whistle shape conveys identity information to bottlenose dolphins. *Proceedings of the National Academy of Sciences*, 103(21):8293–8297, 2006. doi: 10.1073/pnas.0509918103.

A.C. Jones and S.D. Gosling. Temperament and personality in dogs (canis familiaris): A review and evaluation of past research. *Applied Animal Behaviour Science*, 95(1,2):1–53, 2005. doi: 10.1016/j.applanim.2005.04.008.

R. Kohavi. A study of cross-validation and bootstrap for accuracy estimation and model selection. In *Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence*, volume 2, pages 1137–1143, San Mateo, CA, 1995. Morgan Kaufmann.
C.D. Manning, P. Raghavan, and H. Schütze. *Introduction to Information Retrieval*. Cambridge University Press, Cambridge, MA, 2008. ISBN: 0521865719.

F.H.C. Marriott, V.B. Morris, and M.H. Pirenne. The minimum flux of energy detectable by the human eye. *The Journal of Physiology*, 145(2):369–373, 1959. doi: 10.1113/jphysiol.1959.sp006147.

B. Masterton, H. Heffner, and R. Ravizza. The evolution of human hearing. *Journal of Acoustical Society of America*, 45(4):966–985, 1969. doi: 10.1121/1.1911574.

W. McCulloch and W. Pitts. A logical calculus of ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics*, 5(4):115–133, 1943. doi: 10.1007/BF02478259.

D. McEnnis, C. McKay, I. Fujinaga, and P. Depalle. jAudio: A feature extraction library. In *Proceedings of the 6th International Conference on Music Information Retrieval*, pages 600–603, London, UK, 2005.

S.E. Moore, K.M Stafford, D.K. Mellinger, and J.A. Hildebrand. Listening for large whales in the offshore waters of Alaska. *BioScience*, 56(1):49–55, 2006. doi: 10.1641/0006-3568(2006)056.

F. Mosteller. A k-sample slippage test for an extreme population. *Annals of Mathematical Statistics*, 19(1):58–65, 1948. doi: 10.1214/aoms/1177730290.

I. Nelken, Y. Bitterman, R. Mukamel, R. Malach, and I. Fried. Frequency selectivity and context sensitivity of single neurons in human auditory cortex. In *Tucker-Davis Symposium on Advances and Perspectives in Auditory Neurophysiology (APAN III)*, Washington Convention Center, 2005.

P.S. Ong, L.E. Afuang, and R.G. Rosell Ambal, editors. *Philippine Biodiversity Conservation Priorities: A Second Iteration of the National Biodiversity Strategy and Action Plan*. Department of Environment and Natural Resources-Protected Areas and Wildlife Bureau, Conservation International Philippines, Biodiversity Conservation Program-University of the Philippines Center for Integrative and Development Studies, and Foundation for the Philippine Environment, Quezon City, Philippines, 2002.

J.P. Pabico, A.V. de Grano, and A.L. Zarsuela. Accuracy of neural models as classifiers in machine vision systems for automating the grading processes of tomatoes and eggs. In *Proceedings of the 4th Network of CALABARZON Educational Institutions, Inc. (NOCEI) Research Forum*, Batangas State University, Batangas City, 2008.

J.P. Pabico, J.R.L. Micor, and E.R.E. Mojica. A neural prototype for a virtual chemical spectrophotometer. *Philippine Computing Journal*, 4(2):39–42, 2009.

J.P. Pabico, A.V. de Grano, and A.L. Zarsuela. Neural network classifiers for natural food products. In H.N. Adorna, R.E.O. Roxas, and A.L. Sioson, editors, *Proceedings of the 12th Philippine Computing Science Congress (PCSC 2012)*, De La Salle Canlubang, Biñan, Laguna, Philippines, 2012. arXiv:1507.02346 [cs.CV].
A.V. Phillips and I. Stirling. Vocal individuality in mother and pup South American fur seals, *Arctocephalus australis*. Marine Mammal Science, 16(3):592–616, 2000. doi: 10.1111/j.1748-7692.2000.tb00954.x.

J.G. Proakis and D.M. Manolakis. Digital Signal Processing. *Pearson Prentice Hall*, 2007. ISBN: 978-0-13-187374-2.

T. Riede and T. Fitch. Vocal tract length and acoustics of vocalization in the domestic dog (Canis familiaris). *The Journal of Experimental Biology*, 202(20):2859–2867, 1999.

C. Robbins. Audubon’s Christmas Bird Count, 2015. Audubon Science (a multimedia presentation available at http://www.audubon.org).

F. Rosenblatt. The perceptron: A probabilistic model for information storage and organization in the brain. *Psychological Review*, 65(6):386–408, 1958. doi: 10.1037/h0042519.

A.D. Shapiro. Recognition of individuals within the social group: Signature vocalizations. In S.M. Brudzynski, editor, *Handbook of Mammalian Vocalization*, pages 495–504. Academic Press, Oxford, 2009. ISBN 9780123745934.

H. Slabbekoorn and T.B. Smith. Bird song, ecology and speciation. *Philosophical Transactions: Biology Sciences*, 357(1420):493–503, 2002. doi: 10.1098/rstb.2001.1056.

P.R. Stettenhelm. The integumentary morphology of modern birds – An overview. *Integrative and Comparative Biology*, 40(4):461–477, 2000. doi: 10.1093/icb/40.4.461.

S. Thorpe, D. Fize, and C. Marlot. Speed of processing in the human visual system. *Nature*, 381(6582):520–522, 1996. doi: 10.1038/381520a0.

F. Trillmich. Mutual motherpup recognition in Galapagos fur seals and sea lions: Cues used and functional significance. *Behaviour*, 78(1):21–42, 1981.

G. Witzany, editor. *Biocommunication of Animals*. Springer, Dortrech, 2014. ISBN 978-94-007-7413-1.

A.L. Zarsuela and J.P. Pabico. A neural network model for classifying duck eggs using computer vision. In *Proceedings of the 7th ISSAAS (International Society for Southeast Asian Agricultural Sciences) Philippine National Convention and Annual Meeting*, page 55, SEARCA, College, Laguna, 2007.