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# PNW-Cnet v4: Automated species identification for passive acoustic monitoring

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# PNW-Cnet v4: Automated species identification for passive acoustic monitoring

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## Abstract

We present PNW-Cnet v4, a deep neural net with an associated Shiny-based application designed to facilitate efficient data processing to detect terrestrial wildlife species through passive acoustic monitoring. PNW-Cnet v4 is a deep convolutional neural network that detects audio signatures of 37 focal species of birds and mammals that inhabit forests of the Pacific Northwest, USA, along with other commonly occurring forest sounds. The primary objective of developing PNW-Cnet v4 was to support a long-term northern spotted owl (*Strix occidentalis caurina*) monitoring program. By incorporating additional species classes, PNW-Cnet v4 expands applicability of the program to broadscale biodiversity research and monitoring. Using the Shiny app with PNW-Cnet v4, users can process audio data using a graphical user interface, summarize apparent detections visually, and export results in tabular format.

## Keywords

Bioacoustics, machine learning, automated detection, wildlife monitoring, ecology, biodiversity

## Metadata

| Nr | Code metadata description | *Please fill in this column* |
|---|---|---|
| C1 | Current code version | v4 |
| C2 | Permanent link to code/repository used for this code version | |
| C3 | Permanent link to reproducible capsule | |
| C4 | Legal code license | MIT License |
| C5 | Code versioning system used | Git |
| C6 | Software code languages, tools and services used | R, Rstudio, conda, SoX |
| C7 | Compilation requirements, operating environments and dependencies | Windows 64-bit |
| C8 | If available, link to developer documentation/manual | https://github.com/zjruff/Shiny_PNW-Cnet/blob/main/Shiny_PNW-Cnet_installation_and_use.docx |
| C9 | Support email for questions | zjruff@gmail.com |

## 1. Motivation and significance

Passive acoustic monitoring (PAM) is an emerging approach in wildlife research that has seen wide adoption in recent years, largely due to the availability of high-quality autonomous recording units

(ARUs). ARUs are typically small, rugged, battery-powered audio recorders that can operate unattended for long periods in the field. PAM has the advantage of being largely non-disruptive to wildlife, capturing unprompted vocalizations and other audible behaviors over long periods, and ARUs can be deployed in large numbers to achieve large spatial coverage as well. This has enabled researchers to collect very large audio datasets, potentially comprising millions of hours of recordings.

PAM is used as part of a long-term population monitoring program for northern spotted owls (*Strix occidentalis caurina*) in the Pacific Northwest, USA (Lesmeister et al. 2021 [1], Kantor et al. 2022 [2]). Northern spotted owls were listed as Threatened under the Endangered Species Act in 1990 and have undergone widespread population declines due to persistent loss of old-growth forest habitat and competition from barred owls (*Strix varia*), which are closely related but invasive in the region (Lesmeister et al. 2018 [3], Franklin et al. 2021 [4], Wiens et al. 2021 [5]). Both species are highly vocal, with distinctive vocalizations that may be audible at distances > 1 km (Forsman et al. 1984 [6], Odom and Mennill 2010 [7]), making PAM an effective tool for detecting their presence (Duchac et al. 2020 [8]). The PAM program designed for northern spotted owls has also been effective for studying a wide range of other vocal wildlife species in Pacific Northwest forests (Duchac et al. 2021 [9], Lesmeister et al. 2022 [10]).

PAM generates large volumes of data, making manual review of the data impractical and necessitating automated detection to locate signals of interest. The first version of the neural network (PNW-Cnet v1) was effective in detecting vocalizations of six owl species (Ruff et al. 2020 [11]). Successive versions have shown improved performance through the inclusion of additional target classes and larger training datasets. PNW-Cnet v1 was trained using 94,589 spectrogram images from vocalizations detected using a semi-manual process (Ruff et al. 2020 [11]). Ruff et al. (2021 [12]) expanded to 14 species identified with PNW-Cnet v2 (173,964 training images) and described an efficient workflow for data processing. PNW-Cnet v3 was trained on 194,524 images and detected 25 different species (Lesmeister et al. 2022 [10]).

The Shiny application was developed to support data processing by non-expert users using the same automated detection tools used by the northern spotted owl PAM program, running on standard personal computers through familiar, widely available free software such as Rstudio. An earlier version of this application has been published (Ruff et al. 2021 [12]), but we have made substantial improvements for ease of use and interpretation and have incorporated advancements in neural network performance with PNW-Cnet v4, which was trained on 426,605 images and detects 37 species (Table 1).

The typical end user envisioned for this software is a wildlife biologist using ARUs to survey for owls and other forest wildlife listed in Table 1. ARUs are deployed for several weeks or months at a time, recording for several hours per day on a programmed schedule. Once the data have been retrieved from the field, the user then uses the software to process these audio recordings, generating a set of potential detections of the target species. These detections are then verified by knowledgeable human reviewers or used directly as input for ecological analyses.

Various free and commercial programs exist for automated or semi-automated detection of animal vocalizations, e.g. Kaleidoscope (Wildlife Acoustics, Inc [13]), Raven (Cornell Lab 2022 [14]), and the R package warbleR (Araya-Salas and Smith-Vidaurre 2017 [15]). PNW-Cnet v4, and the associated Shiny app, fills a useful niche in that it fits neatly into a practical workflow developed specifically to facilitate long-term monitoring of target species at large scales, including efficient processing of audio data and the extraction and verification of apparent target species detections (Figure 1).

## 2. Software description

### 2.1. Software architecture:

The software is provided as a Shiny app (Chang et al. 2021 [16]), a graphical user interface that can be launched from Rstudio (RStudio Team 2021 [17]). Initial setup includes the installation of R (R Core Team 2021 [18]) and Rstudio, several R packages, and the program Sound eXchange (Bagwell et al. 2015 [19]). The source code is written entirely in R. Some of the required R packages depend on Python, so it is also necessary to create a conda environment (Anaconda 2016 [20]) through which Python code can be executed. We recommend using Miniconda, which can be installed through Rstudio for ease of setup. The app uses SoX to generate spectrograms and extract short audio clips.

The trained PNW-Cnet v4 neural network model is provided as an HDF5 file called PNW-Cnet_v4_TF.h5, which is included with the Shiny application. This file can be used independently of the Shiny application; the neural net can therefore be loaded and used by other scripts or applications and is freely adaptable for other purposes.

### 2.2. Software functionalities:

The user interface is simple and straightforward to use, consisting of a single window with a side panel containing input controls and a main panel for displaying information and results. Most controls are disabled on launch and become active during the processing workflow as required inputs become available, implicitly guiding users through the correct procedure.

A typical usage of this software would be processing the data from a single field site with one or more recording stations (Figure 1). ARUs are deployed at these stations, allowed to record for several weeks, and retrieved along with the data (Figure 1, Steps 1 and 2). After retrieval, the files are organized into a directory structure that reflects the field sampling scheme, and filenames are standardized to indicate where and when each recording was made (Figure 1, Step 3).

The user launches the program through Rstudio and inputs the target directory. The program verifies that the target directory is valid and contains readable audio files. The user then clicks Process Files. The program generates spectrograms representing non-overlapping, 12-s segments of audio in the frequency range 0 – 4000 Hz. The program then uses the PNW-Cnet v4 model to generate class scores for each image and writes the scores to a file (Figure 1, Step 4). The program also creates a file summarizing apparent detections, i.e., the number of clips with scores exceeding a detection threshold (generally 0.95) for each class. Optionally, users can use the Explore Detections button to view counts of apparent detections plotted graphically by recording station over time (Figure 1, Step 5, Figure 2).

Users can then use the Create Review File button to write the apparent detections to file. Audio segments included in the review files are those to which PNW-Cnet v4 assigned a score ≥ 0.25 for the northern spotted owl classes or ≥ 0.95 for any other class. Two review files are created. One is simply a filtered version of the PNW-Cnet prediction file with additional columns for the predicted class, station, and recording week. The other is formatted to be opened in Kaleidoscope, which can be used to review apparent detections and apply identification tags (Figure 1, Step 6).

Once the review files are generated, the user can choose to extract apparent detections as short audio clips for archival or other purposes.

## 3. Illustrative examples

To illustrate the processing workflow, we used the Shiny app to process two weeks' worth of data from a typical Northern Spotted Owl monitoring site in the Oregon Coast Range. The app processed 1,133 files totaling 501.1 hours of audio, generating 150,390 spectrogram images, classifying the images with the PNW-Cnet v4 model, and writing the output to file, in four hours and 21 minutes on a desktop computer with an 8-core processor and 16 GB of memory. This process is demonstrated in the Supplementary Video, and full details are provided in Supplementary Material.

The review files included 14,151 apparent detections covering 36 of the 51 target classes. This represents a non-trivial portion of the full dataset, and reviewing all of these detections in detail would take several days. However, most users are not equally interested in all classes. In this case, most of the apparent detections were of classes representing ubiquitous, highly vocal songbirds or "nuisance" sounds like buzzing insects (Table 2); such classes typically would not be reviewed in detail. Conversely, detections of rare species of conservation concern might be reviewed fully. The review file is structured to allow for different levels of review effort for each class as needed.

In this case, we found it was only necessary to review 633 clips from the review file (representing 4.5% of the review file and 0.4% of the full dataset) to construct weekly encounter histories for all 36 classes. This review process took one of the authors (ZR) approximately one hour to complete. We confirmed that 28 of the 36 classes were present in all combinations of station and week in which they were predicted to be present, and 31 of the 36 classes were confirmed present at all the stations where they were predicted to be present (Table 2). Only three of the 36 classes, representing just 85 apparent detections, were not confirmed present at the site.

## 4. Impact

The potential impact of PNW-Cnet and the associated Shiny application is significant for users conducting bioacoustic research, particularly in the Pacific Northwest, and the potential user base is large. Every year, federal agencies including the US Forest Service, US Fish and Wildlife Service, National Park Service, and US Bureau of Land Management conduct thousands of surveys for northern spotted owls for timber harvest clearance and population monitoring. Many more project clearance surveys are conducted by state and provincial governments in California, Oregon, Washington, and British Columbia. Additionally, private companies in the region are required to survey for northern spotted owls prior to beginning timber harvest, construction, and other projects with potential impacts on local wildlife. Transitioning from traditional playback surveys to PAM decreases risks to sensitive northern spotted owl populations and increases the potential for efficient, large-scale surveys in remote areas, improving our ability to monitor the species throughout the Pacific Northwest. Marbled murrelets (*Brachyramphus marmoratus*), another target class, are also an imperiled species and of significant timber management concern due to association with old-growth forest for nesting (Spies et al. 2019 [21]). PAM is effective at detecting marbled murrelets and is a viable alternative to traditional survey methods for monitoring populations (Borker et al. 2015 [22]).

As it becomes more feasible to deploy high-quality ARUs in large numbers, these tools have seen increasing use in wildlife monitoring and pre-project forest surveys, resulting in audio data collection on vast scales. However, audio data processing remains a significant bottleneck between data collection and ecological analysis. Robust, efficient, and accessible tools are needed to bridge this gap and allow biologists to realize the benefits of PAM. Tools that run well on consumer-grade desktop computers are especially needed, as these will allow project planners to tailor their available processing power to the scale of the planned surveys by simply purchasing additional computers that can be dedicated to processing the data collected.

## 5. Conclusions

We have presented a simple and easy-to-use tool that enables wildlife biologists and other non-expert users to process their own data collected for PAM focused on imperiled wildlife species in Pacific Northwest forests. The Shiny app with PNW-Cnet v4 runs well on consumer-grade hardware, facilitating the efficient processing of large quantities of acoustic data. The program is designed to fit within a practical and efficient workflow, allowing the user to convert raw data to meaningful ecological results in a reasonable timeframe, generating useful information that can inform timely management decisions, drive research, and decrease potential harm to sensitive species.

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**Table 1**

| Species | Scientific name | Type | Class Code | Sound | In training set | In test set | Apparent detections | Precision | Recall |
|---|---|---|---|---|---|---|---|---|---|
| Northern saw-whet owl | *Aegolius acadicus* | Owl | AEAC | | 15,395 | 5,287 | 4,892 | 0.979 | 0.906 |
| Great horned owl | *Bubo virginianus* | Owl | BUVI | | 14,357 | 5,059 | 4,486 | 0.990 | 0.878 |
| Northern pygmy-owl | *Glaucidium gnoma* | Owl | GLGN | | 14,354 | 8,972 | 7,708 | 0.986 | 0.847 |
| Barred owl | *Strix varia* | Owl | INSP | Inspection call | 16,558 | 3,239 | 1,951 | 0.924 | 0.557 |
| Western screech-owl | *Megascops kennicottii* | Owl | MEKE | | 16,406 | 3,488 | 2,823 | 0.987 | 0.799 |
| Flammulated owl | *Psiloscops flammeolus* | Owl | PSFL | | 18,685 | 4,591 | 4,594 | 0.849 | 0.850 |
| Northern spotted owl | *Strix occidentalis caurina* | Owl | STOC | Location call | 24,729 | 10,118 | 6,372 | 0.835 | 0.526 |
| Northern spotted owl | *Strix occidentalis caurina* | Owl | STOC_IRREG | Series call | 2,582 | 3,030 | 773 | 0.750 | 0.191 |
| Barred owl | *Strix varia* | Owl | STVA | Two-phrase hoot | 29,746 | 7,200 | 4,032 | 0.973 | 0.545 |
| Barred owl | *Strix varia* | Owl | STVA_IRREG | Series call | 12,452 | 1,214 | 527 | 0.981 | 0.426 |
| Strix spp. | *Strix spp.* | Owl | WHIS | Contact whistle | 1,763 | 807 | 433 | 0.820 | 0.440 |
| Common raven | *Corvus corax* | Corvid | COCO | | 21,524 | 5,436 | 4,205 | 0.924 | 0.714 |
| Steller's jay | *Cyanocitta stelleri* | Corvid | CYST | | 19,901 | 4,303 | 1,349 | 0.963 | 0.302 |
| Clark's nutcracker | *Nucifraga columbiana* | Corvid | NUCO | | 911 | 0 | 1 | NA | NA |

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|---|---|---|---|---|---|---|---|---|---|
| Canada jay | *Perisoreus canadensis* | Corvid | PECA | | 9,584 | 1,313 | 1,069 | 0.920 | 0.749 |
| Canada goose | *Branta canadensis* | Game bird | BRCA | | 4,104 | 1,009 | 773 | 0.984 | 0.754 |
| Sooty grouse | *Dendragapus fuliginosus* | Game bird | DEFU | | 11,095 | 2,379 | 1,387 | 0.981 | 0.572 |
| Mountain quail | *Oreortyx pictus* | Game bird | ORPI | | 3,703 | 787 | 215 | 0.726 | 0.198 |
| Band-tailed pigeon | *Patagioenas fasciata* | Game bird | PAFA | | 10,197 | 3,735 | 3,122 | 0.989 | 0.827 |
| Mourning dove | *Zenaida macroura* | Game bird | ZEMA | | 4,048 | 2,550 | 2,476 | 0.742 | 0.720 |
| Marbled murrelet | *Brachyramphus marmoratus* | Other bird | BRMA | Flight call | 5,757 | 1,942 | 1,798 | 0.987 | 0.914 |
| Common nighthawk | *Chordeiles minor* | Other bird | CHMI | Call | 1,282 | 133 | 12 | 1.000 | 0.090 |
| Common nighthawk | *Chordeiles minor* | Other bird | CHMI_IRREG | Boom | 1,456 | 103 | 28 | 0.643 | 0.175 |
| Common poorwill | *Phalaenoptilus nuttallii* | Other bird | PHNU | | 7,692 | 245 | 208 | 0.750 | 0.637 |
| Wolf howl | *Canis lupus* | Mammal | CALU | | 11,855 | 0 | 2 | NA | NA |
| American pika | *Ochotona princeps* | Mammal | OCPR | | 844 | 25 | 10 | NA | NA |
| Douglas' squirrel | *Tamasciurus douglasii* | Mammal | TADO1 | Rattle | 9,090 | 3,337 | 2,770 | 0.984 | 0.817 |
| Douglas' squirrel | *Tamasciurus douglasii* | Mammal | TADO2 | Chirp | 8,280 | 2,381 | 1,878 | 0.964 | 0.761 |
| Chipmunk chirp | *Neotamias sp.* | Mammal | TAMI | | 9,714 | 5,288 | 4,942 | 0.942 | 0.880 |
| Hermit thrush | *Catharus guttatus* | Songbird | CAGU | | 15,072 | 9,307 | 3,917 | 0.989 | 0.416 |
| Swainson's thrush | *Catharus ustulatus* | Songbird | CAUS | | 9,419 | 5,402 | 3,663 | 0.916 | 0.621 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Olive-sided flycatcher | *Contopus cooperi* | Songbird | CCOO | | 3,718 | 599 | 184 | 0.940 | 0.289 |
| Wrentit | *Chamaea fasciata* | Songbird | CHFA | | 5,457 | 2,630 | 2,052 | 0.984 | 0.768 |
| Varied thrush | *Ixoreus naevius* | Songbird | IXNA | | 15,327 | 11,135 | 3,202 | 0.995 | 0.286 |
| Townsend's solitaire | *Myadestes townsendi* | Songbird | MYTO | Call | 750 | 70 | 3 | NA | NA |
| Spotted towhee | *Pipilo maculatus* | Songbird | PIMA | Call | 637 | 147 | 76 | 0.895 | 0.463 |
| Chickadee song | *Poecile sp.* | Songbird | POEC | | 2,305 | 112 | 7 | NA | NA |
| Nuthatch | *Sitta sp.* | Songbird | SITT | | 11,463 | 5,914 | 2,561 | 0.990 | 0.429 |
| American robin | *Turdus migratorius* | Songbird | TUMI | Whinny | 5,549 | 262 | 33 | 0.424 | 0.053 |
| Northern flicker | *Colaptes auratus* | Woodpecker | COAU | Series | 12,258 | 4,337 | 4,102 | 0.935 | 0.884 |
| Northern flicker | *Colaptes auratus* | Woodpecker | COAU2 | "Skew" | 1,090 | 360 | 0 | NA | NA |
| Downy woodpecker call | *Dryobates pubescens* | Woodpecker | DRPU | | 2,394 | 3 | 3 | NA | NA |
| Woodpecker spp. | | Woodpecker | DRUM | Drum, non-sapsucker | 5,973 | 1,036 | 19 | 0.579 | 0.011 |
| Pileated woodpecker call | *Dryocopus pileatus* | Woodpecker | HYPI | | 9,437 | 2,369 | 1,913 | 0.926 | 0.748 |
| Sapsucker sp. | *Sphyrapicus sp.* | Woodpecker | SPRU | | 2,257 | 266 | 2 | NA | NA |
| Dog barks | | Nuisance | DOG | | 16,209 | 4,016 | 625 | 0.934 | 0.145 |
| Insect buzz | | Nuisance | FLY | | 23,926 | 6,400 | 764 | 0.987 | 0.118 |
| Frog chorus | | Nuisance | FROG | | 10,194 | 9,480 | 8,038 | 0.992 | 0.841 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Human speech | | Nuisance | HOSA | | 5,947 | 2,188 | 1,155 | 0.896 | 0.473 |
| Gunshot | | Nuisance | SHOT | | 1,247 | 62 | 79 | 0.190 | 0.242 |
| Yarder (machine) | | Nuisance | YARD | | 6,288 | 2,194 | 1,826 | 0.906 | 0.754 |

Table 1. Target classes detected by PNW-Cnet v4 and associated performance metrics. Except where otherwise noted, the vocalization or sound type described by each class is the typical territorial call for each species. "In training set" and "In test set" indicate the number of images containing call signatures of each class that were used to train and test the model, respectively. "Apparent detections" indicates the number of images to which PNW-Cnet v4 assinged a score >= 0.95 for each class. Precision is defined as the proportion of apparent detections that were confirmed to be positive examples, i.e. true positives / apparent detections. Recall is defined as the proportion of positive examples in the test set that were assigned a score >= 0.95 by PNW-Cnet v4, i.e. true positives / available positive examples. The full training set included 426,605 images, some of which contained multiple target classes. In some cases the test set did not contain enough positive examples of a particular class to accurately estimate performance metrics; metrics for these classes are marked "NA". For details on the composition of the training and test datasets and performance metrics, see Lesmeister et al. (2022). For details on target classes, especially those included in previous versions of PNW-Cnet, see Ruff et al. (2021) and Lesmeister et al. (2022).

**Table 2**

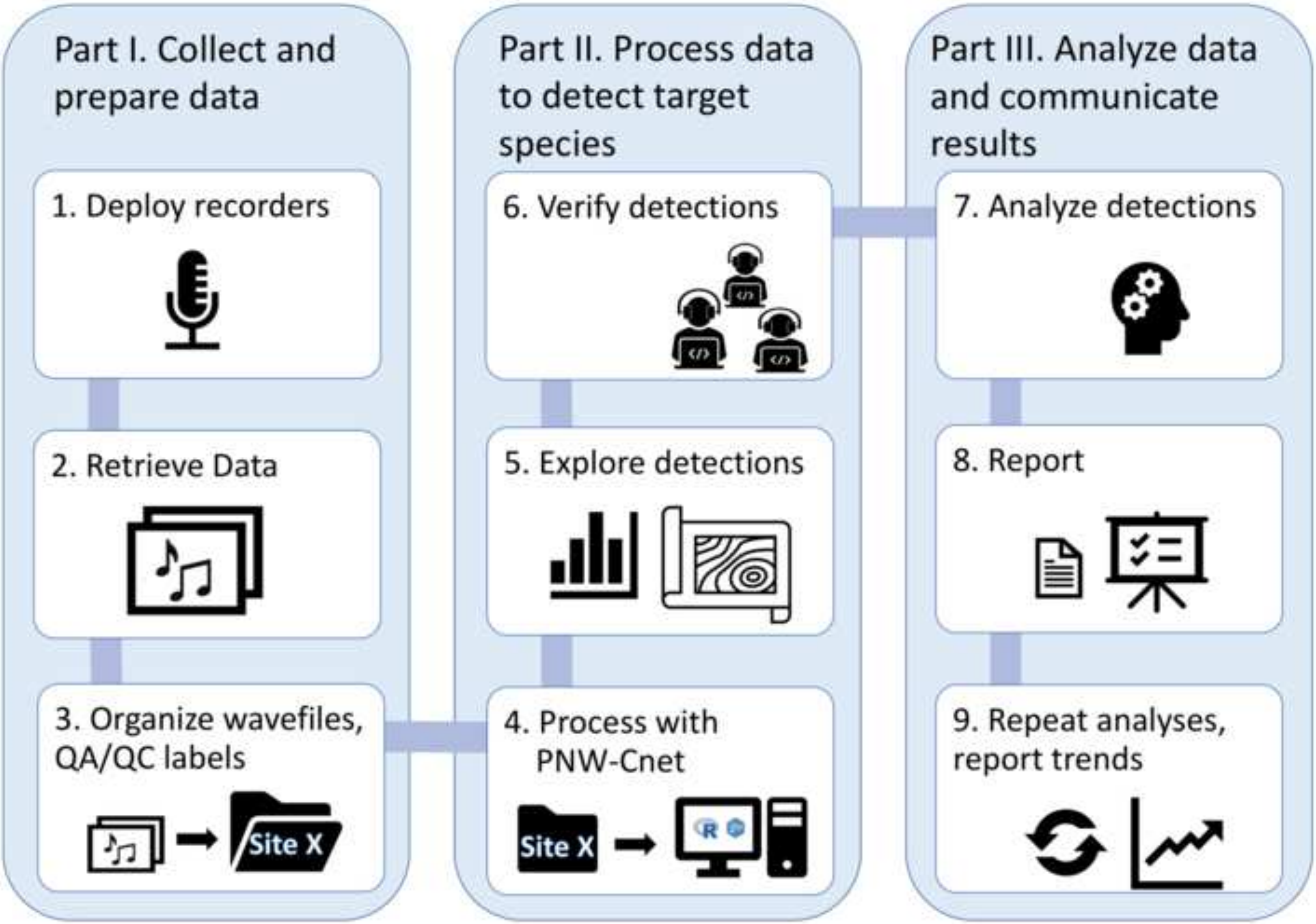
| Class Code | Sound | Apparent detections | Station-week presence predicted | Station presence predicted | Clips reviewed | Detections confirmed | Station-week presence confirmed | Station presence confirmed |
|---|---|---|---|---|---|---|---|---|
| AEAC | Northern saw-whet owl | 46 | 5 | 3 | 15 | 15 | 5 | 3 |
| BUVI | Great horned owl | 9 | 3 | 3 | 5 | 3 | 1 | 1 |
| CAGU | Hermit thrush | 2304 | 7 | 4 | 21 | 21 | 7 | 4 |
| CAUS | Swainson's thrush | 13 | 4 | 3 | 11 | 10 | 3 | 3 |
| CCOO | Olive-sided flycatcher | 12 | 1 | 1 | 3 | 3 | 1 | 1 |
| CHFA | Wrentit | 92 | 4 | 2 | 12 | 12 | 4 | 2 |
| COAU | Northern flicker | 83 | 7 | 4 | 27 | 12 | 3 | 2 |
| COCO | Common raven | 258 | 8 | 4 | 25 | 25 | 8 | 4 |
| CYST | Steller's jay | 1507 | 8 | 4 | 24 | 24 | 8 | 4 |
| DRUM | Woodpecker spp. | 159 | 2 | 1 | 6 | 6 | 2 | 1 |
| FLY | Insect buzz | 2775 | 8 | 4 | 24 | 24 | 8 | 4 |
| FROG | Frog chorus | 4 | 1 | 1 | 4 | 3 | 1 | 1 |
| GLGN | Northern pygmy-owl | 460 | 6 | 4 | 18 | 17 | 6 | 4 |
| HYPI | Pileated woodpecker call | 57 | 8 | 4 | 18 | 17 | 8 | 4 |
| INSP | Barred owl inspection call | 246 | 8 | 4 | 24 | 24 | 8 | 4 |
| IXNA | Varied thrush | 85 | 5 | 3 | 14 | 14 | 5 | 3 |
| MEKE | Western screech-owl | 203 | 8 | 4 | 20 | 16 | 6 | 4 |
| MYTO | Townsend's solitaire | 102 | 7 | 4 | 19 | 19 | 7 | 4 |
| NUCO | Clark's nutcracker | 2 | 1 | 1 | 2 | 0 | 0 | 0 |
| OCPR | American pika | 9 | 2 | 1 | 9 | 0 | 0 | 0 |
| ORPI | Mountain quail | 1631 | 8 | 4 | 24 | 24 | 8 | 4 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| PAFA | Band-tailed pigeon | 726 | 8 | 4 | 24 | 24 | 8 | 4 |
| PECA | Canada jay | 14 | 7 | 4 | 14 | 13 | 7 | 4 |
| PIMA | Spotted towhee | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| SHOT | Gunshot | 2 | 1 | 1 | 2 | 2 | 1 | 1 |
| SITT | Nuthatch | 1906 | 8 | 4 | 24 | 24 | 8 | 4 |
| SPRU | Sapsucker sp. | 2 | 1 | 1 | 2 | 2 | 1 | 1 |
| STOC | Northern spotted owl | 74 | 7 | 4 | 74 | 0 | 0 | 0 |
| STVA | Barred owl | 130 | 8 | 4 | 23 | 22 | 8 | 4 |
| STVA_IRREG | Barred owl | 133 | 7 | 4 | 19 | 19 | 7 | 4 |
| TADO1 | Douglas' squirrel | 78 | 8 | 4 | 24 | 24 | 8 | 4 |
| TADO2 | Douglas' squirrel | 307 | 8 | 4 | 23 | 22 | 7 | 4 |
| TAMI | Chipmunk chirp | 289 | 6 | 3 | 38 | 20 | 6 | 3 |
| TUMI | American robin | 8 | 4 | 2 | 8 | 8 | 4 | 2 |
| YARD | Yarder (machine) | 396 | 8 | 4 | 25 | 24 | 8 | 4 |
| ZEMA | Mourning dove | 28 | 2 | 2 | 7 | 7 | 2 | 2 |

Table 2. Results of processing ca. 500 hours of audio with the PNW-Cnet v4 Shiny app. The Review file contained 14,151 clips with a score >= 0.25 for a northern spotted owl class (n = 74) or >= 0.95 for any other class. We reviewed enough of these apparent detections to confirm the presence of each class at each combination of station and week in which they were predicted to be present. See Table 1 for more information on each class.

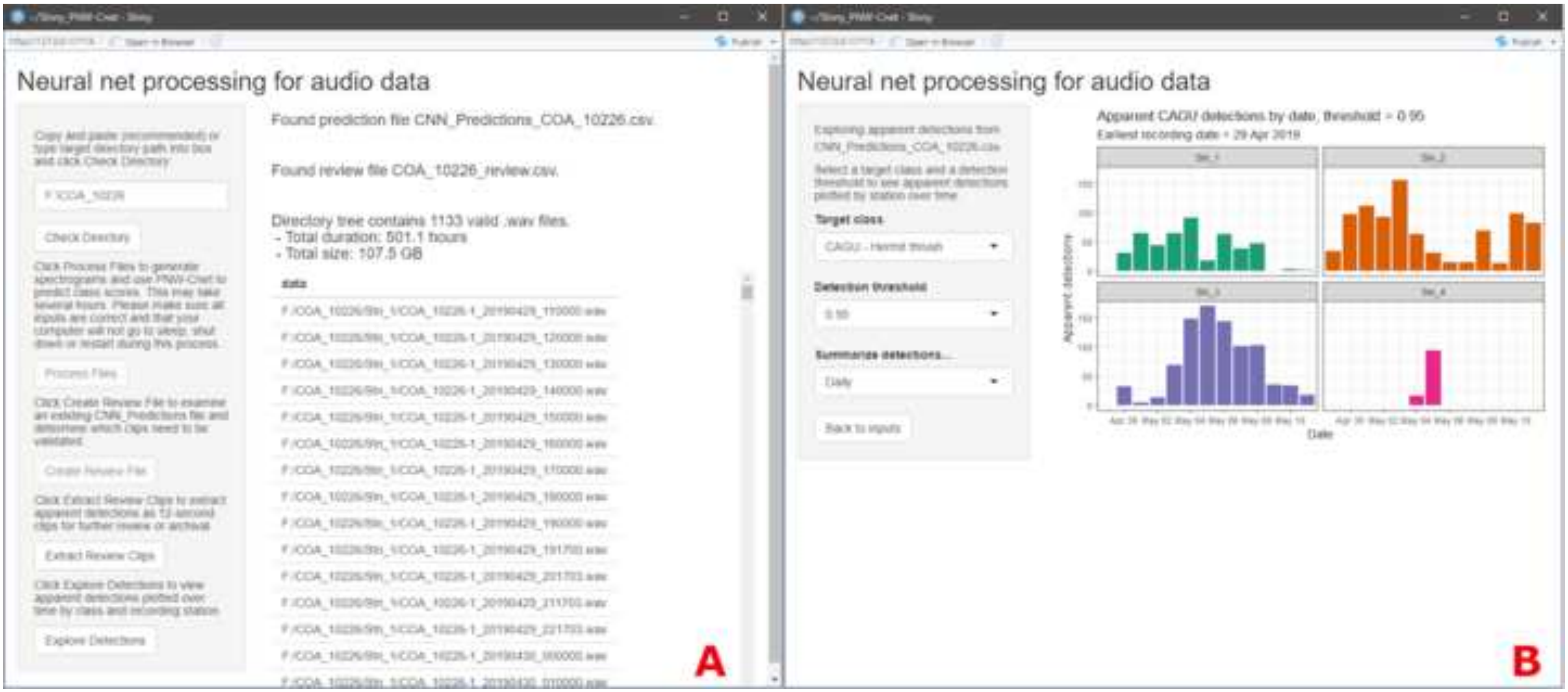
Figure 1. General life cycle of passive acoustic monitoring data processed using PNW-Cnet. PNW-Cnet and the associated Shiny application are designed to facilitate steps in Part II of this cycle, while the steps in Part I and Part III are completed using external software or outside of the computing environment.

Figure 2. The user interface of the PNW-Cnet v4 Shiny app in Input (A) and Explore (B) view.


Part I. Collect and prepare data
1. Deploy recorders
2. Retrieve Data
3. Organize wavefiles, QA/QC labels
Site X
Part II. Process data to detect target species
6. Verify detections
5. Explore detections
4. Process with PNW-Cnet
Site X
Part III. Analyze data and communicate results
7. Analyze detections
8. Report
9. Repeat analyses, report trends

Figure

Click here to download Figure Figure 2.png



**Supplementary information – Testing the PNW-Cnet Shiny app on real data**

As a test of the PNW-Cnet Shiny app, we compiled a dataset consisting of 1,133 WAV audio files with a total size of 107.5 gigabytes and a total duration of 501.1 hours. This dataset was a subset of the data collected during our 2019 field season from a typical field site in the Oregon Coast Range historic northern spotted owl demographic study area. The field site contained four recording stations, each consisting of one Wildlife Acoustics Song Meter SM4 automated recording unit. The test set contained approximately 125 hours of recordings from each of the four stations, all collected over the same period from 29 April to 12 May 2019.

We have not uploaded this test dataset to a public repository due to its large size; however, we can provide it upon request.

The processing was completed on a desktop computer running Windows 10 with an AMD Ryzen 7 2700X 8-core, 16-thread CPU and 16 GB of DDR4 memory with a 2933 MHz clock. The version of TensorFlow used by the app is the CPU-only variant, so the GPU was not significantly involved in the processing.

We organized the data as is usual for the northern spotted owl passive acoustic monitoring program, with a folder for the field site (COA_10226) broken into folders by recording station (Stn_1, Stn_2, Stn_3, and Stn_4). The filenames were standardized to also reflect this sampling scheme; each filename included an identifier for the field site and recording station, followed by date and time information marking the beginning of the recording, e.g. COA_10226-2_20190429_221502.wav.

In the Shiny app, we entered the path to the COA_10226 folder in the text box and clicked the Check Directory button. Using the information in the app user interface, we confirmed that the app had successfully located the audio files and clicked the Process Files button. The app took approximately two hours and 40 minutes to generate spectrograms (n = 150,390) representing all non-overlapping 12-s segments of the audio data in the frequency range 0 to 4000 Hz. It then loaded the PNW-Cnet v4 neural network model and generated class scores for our 51 target classes for each of the spectrogram images and wrote these to the file CNN_Predictions_COA_10226.csv. Based on the CNN_Predictions file, it generated a summary table giving the number of rows with a score exceeding a detection threshold for each of our target classes at each recording station on each date, for a range of detection thresholds from 0.05 to 0.99. This table was written to the file COA_10226_detection_summary.csv. The classification and output steps took an additional one hour and 41 minutes to complete.

Once the output files had been written successfully, we clicked the Create Review File button, at which point the app generated the COA_10226_review_kscope.csv file. This took roughly 30 s. This file contained 14,151 lines and included apparent detections of 36 of the 51 classes detectable by PNW-Cnet v4. We opened the review_kscope file in Kaleidoscope Pro to begin the process of reviewing the apparent detections.

In Kaleidoscope, we sorted the review_kscope file by the SORT column in ascending order (i.e., alphabetically) and the TOP1DIST column in descending order (i.e., highest to lowest). This ordered the clips by predicted class, recording station, week, and maximum class score, with clips that had the highest score for each class listed first.

To confirm the presence of each target class at each recording station in each week, we applied species tags in the MANUAL ID column through the Kaleidoscope interface. For each combination of predicted class, station, and week, we reviewed clips starting with those with the highest score for the class in question, until we had found at least one, and preferably three or more, clips containing unambiguous positive examples of that class. This is the procedure generally followed when reviewing apparent detections for the northern spotted owl monitoring program. We primarily reviewed clips visually, by examining the spectrogram, and listened to the audio only when the spectrogram alone was insufficient to confidently identify a sound, which was uncommon. The tags applied to each clip included the codes of all target classes that were detectable in that clip, not just the predicted class.

Ultimately we reviewed 633 clips, representing 4.5 percent of the review file and 0.4 percent of the full dataset. The review procedure took one of the authors approximately one hour to complete. A summary of the results is presented in Table 2 in the main text of the paper. 33 of the 36 classes that were apparently present at the field site were confirmed to be present, and 28 of the 36 classes were confirmed present in all weeks and at all stations where they were predicted to be present.

There were only 85 total apparent detections of the three remaining classes in the review file; 74 of these apparent detections were from the spotted owl class. Detailed examination of apparent detections for the spotted owl class indicated that most of these appeared to have actually been a spotted owl survey consisting of imitated spotted owl calls produced with a "hoot flute." Although these are superficially similar to actual spotted owl calls, we did not consider these to be confirmed detections.

Overall, using PNW-Cnet v4 through the Shiny app, it took approximately five hours and 20 minutes to process 501 hours of audio and to review apparent detections of 36 sound classes in sufficient detail to generate weekly encounter histories for these classes at four recording stations.

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target_classes.csv

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**Video**

Shiny_App_Demo.mp4