



Original software publication

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.

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If available, link to developer documentation/manual

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v4

<https://github.com/ElsevierSoftwareX/SOFTX-D-22-00141>

MIT License

Git

R, RStudio, conda, SoX

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https://github.com/zjruff/Shiny_PNW-Cnet/blob/main/Shiny_PNW-Cnet_installation_and_use.docx

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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.

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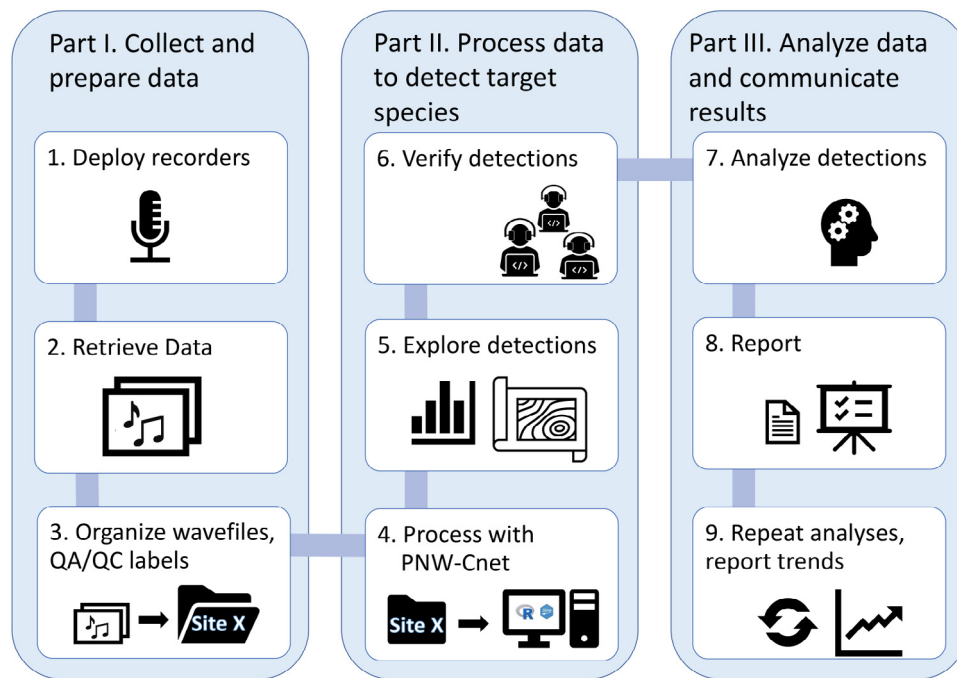


Fig. 1. General life cycle of passive acoustic monitoring data processed using PNW-Cnet. PNW-Cnet and the associated Shiny application are designed to facilitate steps in Part II of this cycle, while the steps in Part I and Part III are completed using external software or outside of the computing environment.

2021 [5]). Both species are highly vocal, with distinctive vocalizations (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 detected 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. The

software has high accuracy for most classes, but manual verification is generally advisable to minimize the impacts of false positive detections.

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 (Fig. 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 for this purpose, as it 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. PNW-Cnet v4 is a deep convolutional neural network that has been trained to recognize call signatures of 37 species of birds and mammals found in the Pacific Northwest, as well as several other miscellaneous sounds, in spectrogram images (Table 1). The trained model file can be used indepen-

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 assigned 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).

Species	Scientific name	Type	Class code	Sound	In training set	In test set	Apparent detections	Precision	Recall
Northern saw-whet owl	<i>Aegolius acadicus</i>	Owl	AEAC		15,395	5,287	4,892	0.979	0.906
Great horned owl	<i>Bubo virginianus</i>	Owl	BUVI		14,357	5,059	4,486	0.990	0.878
Northern pygmy-owl	<i>Glaucidium gnoma</i>	Owl	GLGN		14,354	8,972	7,708	0.986	0.847
Barred owl	<i>Strix varia</i>	Owl	INSP	Inspection call	16,558	3,239	1,951	0.924	0.557
Western screech-owl	<i>Megascops kennicottii</i>	Owl	MEKE		16,406	3,488	2,823	0.987	0.799
Flammulated owl	<i>Psiloscops flammeolus</i>	Owl	PSFL		18,685	4,591	4,594	0.849	0.850
Northern spotted owl	<i>Strix occidentalis caurina</i>	Owl	STOC	Location call	24,729	10,118	6,372	0.835	0.526
Northern spotted owl	<i>Strix occidentalis caurina</i>	Owl	STOC_IRREG	Series call	2,582	3,030	773	0.750	0.191
Barred owl	<i>Strix varia</i>	Owl	STVA	Two-phrase hoot	29,746	7,200	4,032	0.973	0.545
Barred owl	<i>Strix varia</i>	Owl	STVA_IRREG	Series call	12,452	1,214	527	0.981	0.426
Spotted or Barred owl	<i>Strix</i> spp.	Owl	WHIS	Contact whistle	1,763	807	433	0.820	0.440
Common raven	<i>Corvus corax</i>	Corvid	COCO		21,524	5,436	4,205	0.924	0.714
Steller's jay	<i>Cyanocitta stelleri</i>	Corvid	CYST		19,901	4,303	1,349	0.963	0.302
Clark's nutcracker	<i>Nucifraga columbiana</i>	Corvid	NUCO		911	0	1	NA	NA
Canada jay	<i>Perisoreus canadensis</i>	Corvid	PECA		9,584	1,313	1,069	0.920	0.749
Canada goose	<i>Branta canadensis</i>	Game bird	BRCA		4,104	1,009	773	0.984	0.754
Sooty grouse	<i>Dendragapus fuliginosus</i>	Game bird	DEFU		11,095	2,379	1,387	0.981	0.572
Mountain quail	<i>Oreortyx pictus</i>	Game bird	ORPI		3,703	787	215	0.726	0.198
Band-tailed pigeon	<i>Patagioenas fasciata</i>	Game bird	PAFA		10,197	3,735	3,122	0.989	0.827
Mourning dove	<i>Zenaidura macroura</i>	Game bird	ZEMA		4,048	2,550	2,476	0.742	0.720
Marbled murrelet	<i>Brachyramphus marmoratus</i>	Other bird	BRMA	Flight call	5,757	1,942	1,798	0.987	0.914
Common nighthawk	<i>Chordeiles minor</i>	Other bird	CHMI	Call	1,282	133	12	1.000	0.090
Common nighthawk	<i>Chordeiles minor</i>	Other bird	CHMI_IRREG	Boom	1,456	103	28	0.643	0.175
Common poorwill	<i>Phalaenoptilus nuttallii</i>	Other bird	PHNU		7,692	245	208	0.750	0.637
Gray wolf	<i>Canis lupus</i>	Mammal	CALU	Howl	11,855	0	2	NA	NA
American pika	<i>Ochotona princeps</i>	Mammal	OCPR		844	25	10	NA	NA
Douglas' squirrel	<i>Tamiasciurus douglasii</i>	Mammal	TADO1	Rattle	9,090	3,337	2,770	0.984	0.817
Douglas' squirrel	<i>Tamiasciurus douglasii</i>	Mammal	TADO2	Chirp	8,280	2,381	1,878	0.964	0.761
Chipmunk	<i>Neotamias</i> spp.	Mammal	TAMI	Chirp	9,714	5,288	4,942	0.942	0.880
Hermit thrush	<i>Catharus guttatus</i>	Songbird	CAGU		15,072	9,307	3,917	0.989	0.416
Swainson's thrush	<i>Catharus ustulatus</i>	Songbird	CAUS		9,419	5,402	3,663	0.916	0.621
Olive-sided flycatcher	<i>Contopus cooperi</i>	Songbird	CCOO		3,718	599	184	0.940	0.289
Wrentit	<i>Chamaea fasciata</i>	Songbird	CHFA		5,457	2,630	2,052	0.984	0.768
Varied thrush	<i>Ixoreus naevius</i>	Songbird	IXNA		15,327	11,135	3,202	0.995	0.286
Townsend's solitaire	<i>Myadestes townsendi</i>	Songbird	MYTO	Call	750	70	3	NA	NA
Spotted towhee	<i>Pipilo maculatus</i>	Songbird	PIMA	Call	637	147	76	0.895	0.463
Chickadee	<i>Poecile</i> spp.	Songbird	POEC	Song	2,305	112	7	NA	NA
Nuthatch	<i>Sitta</i> spp.	Songbird	SITT		11,463	5,914	2,561	0.990	0.429
American robin	<i>Turdus migratorius</i>	Songbird	TUMI	Whinny	5,549	262	33	0.424	0.053
Northern flicker	<i>Colaptes auratus</i>	Woodpecker	COAU	Series	12,258	4,337	4,102	0.935	0.884

(continued on next page)

dently 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, e.g., transfer learning or retraining for recognition of other species or sounds.

2.2. Software functionalities:

The user interface is simple and straightforward to use, consisting of a single window with a side panel containing input

Table 1 (continued).

Species	Scientific name	Type	Class code	Sound	In training set	In test set	Apparent detections	Precision	Recall
Northern flicker	<i>Colaptes auratus</i>	Woodpecker	COAU2	"Skew"	1,090	360	0	NA	NA
Downy woodpecker	<i>Dryobates pubescens</i>	Woodpecker	DRPU	Call	2,394	3	3	NA	NA
Woodpecker spp.		Woodpecker	DRUM	Drum, non-sapsucker	5,973	1,036	19	0.579	0.011
Pileated woodpecker	<i>Dryocopus pileatus</i>	Woodpecker	HYPI	Call	9,437	2,369	1,913	0.926	0.748
Sapsucker	<i>Sphyrapicus</i> spp.	Woodpecker	SPRU	Drum	2,257	266	2	NA	NA
Domestic dog		Nuisance	DOG	Bark	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

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 (Fig. 1). ARUs are deployed at these stations, allowed to record for several weeks, and retrieved along with the data (Fig. 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 (Fig. 1, Step 3).

The user launches the program through RStudio, inputs the target directory and clicks the *Check Directory* button. The program verifies that the target directory is valid and contains readable audio files. The user then clicks the *Process Files* button. 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 (Fig. 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 (Fig. 1, Step 5; Fig. 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 (Fig. 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 by clicking the *Extract Review Clips* button.

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 h 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 min on a desktop computer with an 8-core processor and 16 GB

of memory. This process is demonstrated in the Supplementary Video, and additional 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 users to apply different levels of review effort to 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 v4 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 call-back surveys (i.e., observers broadcasting recorded target species calls to elicit a territorial response) 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. PNW-Cnet v4 is an integral component of northern spotted owl monitoring (Lesmeister and Jenkins 2022 [21]) and, when followed by sex prediction modeling (Dale et al. 2022 [22]), can inform pair status

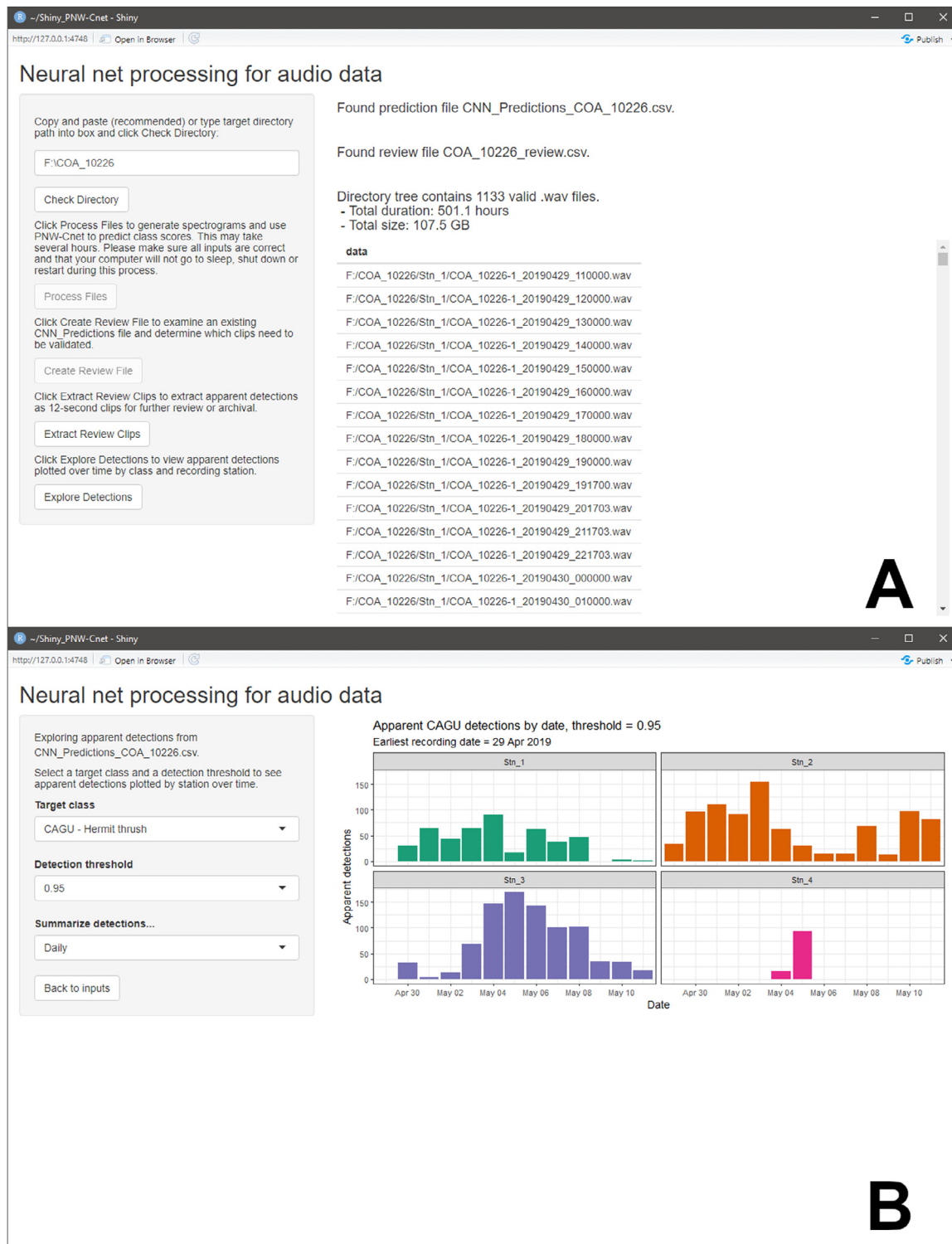


Fig. 2. The user interface of the PNW-Cnet v4 Shiny app in Input (A) and Explore (B) view.

and multi-state occupancy models (Appel et al. 2023 [23]; Weldy et al. 2023 [24]). 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 [25]). PAM is effective at detecting marbled murrelets and is a viable alternative

to traditional survey methods for monitoring populations (Borker et al. 2015 [26]).

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

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.

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	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	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

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. We stress that the intended workflow for the program includes verifying the neural network's apparent detections manually to remove false positive detections, which can potentially bias inferences drawn from the data. Some target species, such as the northern spotted owl, are targeted in call-back surveys and therefore warrant particular care because these surveys can contaminate PAM data with false positives of humans mimicking territorial spotted owls. Recorded northern spotted owl calls broadcasted and then recorded by PAM can be

difficult to distinguish from true northern spotted owl calls. As part of the regular workflow of a PAM program, we encourage manual verification of detections and soliciting information from call-back survey crews on the timing and location of their surveys. As an additional measure, call-back surveyors can play a standard artificial tone (in the same frequency range as northern spotted owls) at the conclusion of surveys that identifies those spotted owl calls as call-back surveys.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

We have made a subset of the data available as a sample and can provide the full dataset on request

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We thank the many technicians who assisted with validating model output and building the training dataset. The findings and conclusions in this publication are those of the authors and should not be construed to represent any official U.S. Department of Agriculture or U.S. Government determination or policy. The use of trade or firm names in this publication is for reader information and does not imply endorsement by the U.S. Government of any product or service.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.softx.2023.101473>.

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