

# gibbonNetR: an R Package for the Use of Convolutional Neural Networks and Transfer Learning on Acoustic Data

immediate

## Abstract

Automated detection of acoustic signals is crucial for effective monitoring of vocal animals and their habitats across large spatial and temporal scales. Recent advances in deep learning have made high performing automated detection approaches more accessible to more practitioners. However, there are few deep learning approaches that can be implemented natively in R. The ‘torch for R’ ecosystem has made the use of transfer learning with convolutional neural networks possible for R users. Here we provide an R package and workflow to use transfer learning for the automated detection of acoustic signals from passive acoustic monitoring (PAM) data collected in Sabah, Malaysia. The package provides functions to create spectrogram images from PAM data, compare the performance of different pre-trained CNN architectures, and deploy trained models over directories of sound files.

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## Introduction

### *Passive acoustic monitoring*

We are in a biodiversity crisis, and there is a great need for the ability to rapidly assess biodiversity in order to understand and mitigate anthropogenic impacts. One approach that can be especially effective for monitoring of vocal yet cryptic animals is the use of passive acoustic monitoring (Gibb et al. 2018), a technique that relies on autonomous acoustic recording units. PAM allows researchers to monitor vocal animals and their habitats, at temporal and spatial scales that are impossible to achieve using only human observers. Interest in use of PAM in terrestrial environments has increased substantially in recent years (Sugai et al. 2019), due to reduced price of the recording units and improved battery life and data storage capabilities. However, the use of PAM often leads to the collection of terabytes of data that is time- and cost-prohibitive to analyze manually.

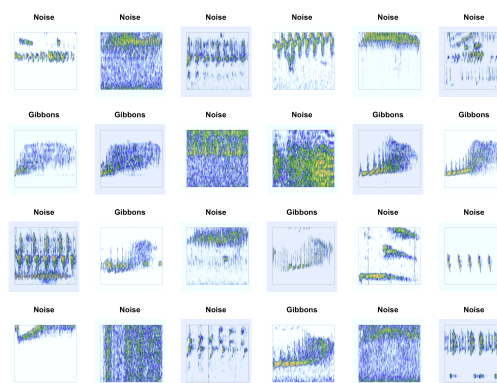
### *Automated detection*

Some commonly used non-deep learning approaches for the automated detection of acoustic signals in terrestrial PAM data include binary point matching (Katz, Hafner, and Donovan 2016), spectrogram cross-correlation (Balantic and Donovan 2020), or the use of a band-limited energy detector and subsequent classifier, such as support vector machine (Clink et al. 2023; Kalan et al. 2015). Recent advances in deep learning have revolutionized image and speech recognition (LeCun, Bengio, and Hinton 2015), with important cross-over for the analysis of PAM data.

## ***‘torch for R ecosystem’***

The two most popular open-source programming languages are R and Python (Scavetta and Angelov 2021 ). Python has surpassed R in terms of overall popularity, but R remains an important language for the life sciences (Lawlor et al. 2022). ‘Keras’ (Chollet and others 2015), ‘PyTorch’ (Paszke et al. 2019) and ‘Tensorflow’ (Martín Abadi et al. 2015) are some of the more popular neural network libraries; these libraries were all initially developed for the Python programming language. Until recently, deep learning implementations in R relied on the ‘reticulate’ package which served as an interface to Python (Ushey, Allaire, and Tang 2022). However, the recent release of the ‘torch for R’ ecosystem provides a framework based on ‘PyTorch’ that runs natively in R and has no dependency on Python (Falbel 2023). Running natively in R means more straightforward installation, and higher accessibility for users of the R programming environment.

## **Materials and methods**



**Figure 1:** Spectrograms of training clips for CNNs

## **Results**

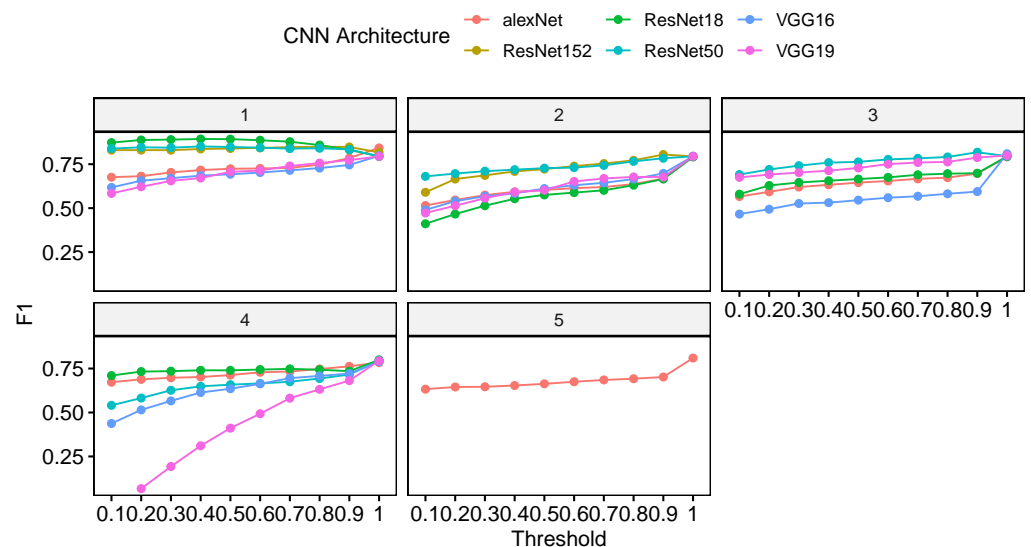
## **Discussion**

## **Acknowledgments**

So long and thanks for all the fish.

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**Figure 2:** Evaluating performance of pretrained CNNs

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