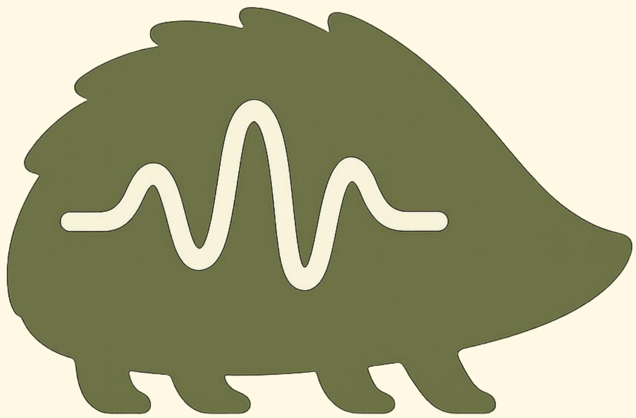

# Hedgehog Bioacoustics Analysis Using Convolutional Neural Networks

An AI-based personal IoT wildlife monitoring project using Raspberry Pi and deep learning.

By: Allegra Bourne

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# CONTENTS

# ABSTRACT

This project investigates how animal conservation and artificial intelligence might work together to find signs of respiratory illness, such as Crenosoma Striatum, in hedgehogs. The system uses a Raspberry Pi-based IoT setup and a PyTorch deep learning model to look for signals of distress in audio recordings. Spectrograms generated from microphone input are classified to determine potential respiratory anomalies.

# MOTIVATION & BACKGROUND

When the World was struck down with Covid and everyone was detained within the confines of their gardens in 2020, I noticed a little visitor eating the seeds I'd left out for the birds. Being an avid ecologist I knew I'd received Hedgehog visitors in the past, but the eating of the bird seed surprised me. It was a particularly sunny year – not ideal breeding ground for hog grub, there was a drought, and I'd always left water out in such events. I soon learned that bird seed <> hedgehogs (it's extremely bad for them!). And I sought the ideal nighttime treat for my spiny friends. As it turns out, cat food is ideal – not slugs (back to these later), not store-bought hog food, simple cat food (dry chicken based for kittens).

I got myself a wildlife camera, left my food out and observed with excitement. And what I observed was nothing short of a horror show! Slugs, slugs everywhere. All over the food I'd left out.

Now you might think, wow slugs! Hedgehogs love to eat slugs! Everyone knows this right!? WRONG! As it turns out, slugs can carry a parasite called lung worm (Crenosoma Striatum to be exact), these can infect leading to premature death within days. There was the tragic case of Sam Ballard from Australia – the 19-year-old ate a single slug as a dare at a party, he ended up paralised with severe brain damage and ultimately passing away a little under a decade later.

The bottom line is slugs are bad for eating no matter what or who you may be - hogs also detest the taste of these slimy fiends. Hedgehogs will only turn to slugs as a viable food source if food is scarce.

Now you may have noticed, especially if you drive regularly during the summer months, that each passing year there's fewer and fewer bug splatters on your windscreen. That's because the number of these rather tasty bugs are falling dramatically. Indeed, the BBC recently published an article claiming that the number of splats had fallen by a staggering 60% in recent years.

So, now you see the problem.

# THE SOLUTION

That summer I found myself testing various ways to deter slugs, from creating water moats around the food to sand and nothing would stop those slugs – if you're an avid gardener you'll feel my pain. Eventually, I created a 'feeder', a box that would provide a sterilised environment for my hogs to much their kitten nibble quietly. It worked wonderfully! It didn't quite fix the issue I was having but it did prevent the majority of slugs finding their way to the food. However, Covid went and like little hedgehogs ourselves we all came out of hibernation, this posed another question – how can I go on that much needed holiday that we were all craving once the lockdowns were lifted, when I needed to feed the hedgehogs whilst keeping the box sterile and slug free!?

Well, my friends, this is where my iHogFeeder9000 came into existence. With the help of my husband, an ex-Royal Engineer (Sapper) who'd not faced challenges as great as this, we created what I think (don't quote me), is the World's first smart hedgehog feeder. Oh yes. We sat, next to a pool in Greece, watching and monitoring our hedgehogs whilst our feeder faithfully fed them each night. Success. Food was contained and inaccessible to slugs, food was released on a nightly basis at intervals – any left over was soon eaten by the birds each morning (they'd quickly worked out my dastardly plans).

A few years later and the feeder is still dishing out food to my spiny and feathery visitors – night after night I'd capture recordings of their visits which taught more with each passing year (such has hedgehogs being born diurnal and their nocturnal habits naturally growing with age).

I came to understand the signs of distress in hedgehogs which are sometimes heard through their breathing on camera. I should add that this isn't definitive and that sometimes signs of lungworm go unnoticed or exhibited visually. When those signs are seen, however, it's a ticking clock of impending doom and the hedgehog needs treatment asap. I wondered how my background in technology might help in this respect.

Bioacoustics analysis in wildlife has widely been used by ecologists - using sound recordings to study and monitor animal populations. This noninvasive technique allows researchers to gather information about species presence, abundance, behavior, and even individual health, offering valuable insights into conservation efforts. With keen interest I'd read the use cases and wanted to explore how I could incorporate conservation efforts such as these in my own back garden.

# CASE STUDY

Wildlife health monitoring has gained increasing attention in recent years due to growing awareness of biodiversity loss and zoonotic disease emergence. In this context, bioacoustic sensing has emerged as a promising non-invasive technique for species detection, behavioural analysis, and health diagnostics in wild and urban animal populations. My hope is that this project will contribute to the ever evolving intersection of bioacoustics, machine learning, and IoT for real time health screening in hedgehogs, and eventually evolve into exploring how edge devices can be used more widely in ecological settings; such as TB monitoring in Badgers which I'd hope would eliminate the need for culling.

*Bioacoustics and Species Detection*

Bioacoustics involves the study of sound in bio-organisms and forms one part of a host of toolsets at disposal for non-invasive analysis such as thermal imaging and computer vision; as well as more invasive analysis toolsets such as VOC analysis and biosensing. Bioacoustic analysis has previously been adopted in ecology to monitor birds, bats, cetaceans, and amphibian populations. Stowell (2019) demonstrated the practicality of acoustic detection of birds using deep learning through the 'Bird Audio Detection Challenge'. This study revealed that convolutional neural networks, such as the one used in this project, trained on spectrogram representations of audio can effectively classify the presence of a specific species of avian, even under noisy field conditions. This work laid the foundational techniques for applying deep learning to noisy data and helped towards the thought process, implementation and model design choices in this project.

*Respiratory Illness Detection through Audio*

Respiratory patterns are one of several key indicators of health in biology. In veterinary fields cough and wheeze detection from audio is used to diagnose conditions such as asthma, bronchitis, or parasitic infections. Lungworm, a parasitic nematode, is a known threat to hedgehogs, causing symptoms such as wheezing and laboured breathing (my own research and Knight, 2020). These symptoms can sometimes manifest audibly, providing an opportunity for passive detection using acoustic analysis. While datasets on hedgehog respiratory illness are extremely limited, synthetic training and weak supervision techniques can be applied to bootstrap classifier performance.

*Deep Learning for Audio Pattern Recognition*

Deep learning has revolutionised pattern recognition, particularly in fields such as image and speech recognition. LeCun, Bengio, and Hinton (2015) highlight the ability of deep neural networks to learn hierarchical feature representations directly from raw or minimally processed inputs. This capability is especially powerful in spectrogram-based analysis of audio signals. CNNs can learn patterns in frequency indicative of respiratory anomalies, while recurrent layers or temporal pooling can model longer term context for those frequencies. The CNN model in this project is adapted for spectrogram input and trained to classify distress or illness-related patterns, such as wheezing, coughs or gargling.

*Edge Computing and IoT in Conservation*

Recent advances in Internet of Things (IoT) and edge AI technologies enable computationally efficient machine learning inference on-device. This is critical in conservation scenarios where network access is intermittent, or power is limited. Zhang X. (2020, see references) has demonstrated real time respiratory pattern detection utilising deep learning on mobile edge devices, showcasing that energy-efficient architectures such as MobileNet or quantised CNNs can run on such devices with acceptable latency and accuracy. These findings directly inspired the deployment design of this project using a Raspberry Pi for local audio processing.

Edge based bioacoustic health monitoring offers a scalable, low-cost, and noninvasive solution to monitor animal health in situ without requiring human presence or data upload to cloud infrastructure.

*Conclusion of Background*

The convergence of bioacoustic monitoring, deep learning pattern recognition, and edge computing offers new opportunities in wildlife conservation and health screening. Forming one of several tools at disposal for infield edge mini labs, this project represents a practical, small-scale instantiation of that vision, targeting respiratory illness detection in hedgehogs. It builds upon foundational research in animal sound classification, edge

AI deployment, and ecological health monitoring, and aims to serve as a proof of concept for scalable, real-world deployments of edge mini labs that can be used for real world problems such as the spread of TB amongst badgers and cattle eliminating the need for culling.

# ETHICAL CONSIDERATIONS

The solution has been designed with ethical consideration and non-invasiveness in mind, particularly when balancing individual animal welfare with broader ecological and philosophical concerns around human intervention in the lives of wild animals.

The approach taken here aligns with ethical principles of minimal disturbance and although the results of the system may lead to active interventions (e.g. distress rescue), this system does not restrain the hedgehog in anyway. Passive acoustic monitoring has been recognised in conservation literature as a low impact tool for biodiversity surveillance and early health screening (Stowell et al., 2019; Blumstein., 2011).

However, there are ongoing debates about intervention in wild populations. Kirkwood, J. K., & Sainsbury, A. W. (see references) discuss these issues and argue that any intervention must "balance the welfare of the individual against potential harm to populations and ecosystems".

From a broader perspective, this project aims to act at the intersection with the philosophy of "compassionate conservation," where the welfare of individual wild animals take the utmost importance. This project supports that position: to enable the early detection of suffering (e.g., respiratory distress from lungworm), without disrupting the population or ecosystem around it and to eventually lead to nonleathal intervention with other ecological health issues such as mycobacterium bovis detection.

In an urban environment It will also be important to consider data privacy and acoustic surveillance ethics and ethics surrounding AI in other applications. Whilst this project collects no identifiable human data, similar systems could inadvertently record voices or reveal behavioural patterns of it's subjects – this project acknowledges and makes the awareness of these ethical points of consideration its forerunner. Recommended anonymisation of recordings, clear data retention policies, and careful boundary setting to avoid ethical creep as such technologies scale is something to consider.

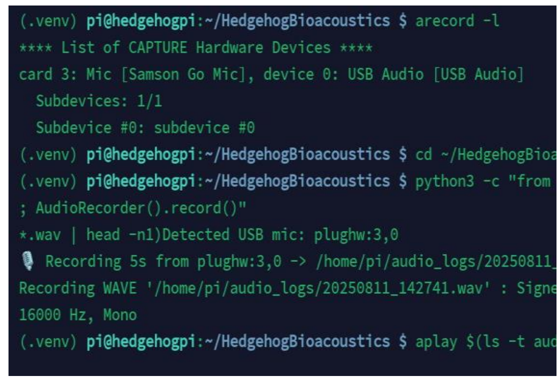
# SYSTEM ARCHITECTURE (IOT OVERVIEW)

The project follows an IoT architecture utilising RaseberryPi and Python with Machine Learning.

The core components are:

- Raspberry Pi 4: Acts as the edge node for audio capture and discreet preprocessing.
- USB Microphone: Captures high-quality audio (16kHz sampling rate).
- Audio Segmenter: Splits continuous audio into 5-second WAV clips.
- Spectrogram Generator: using `librosa` to convert audio into mel spectrogram images.
- Inference Server (Asus G14): A local machine hosting a small custom CNN (developed in PyTorch) receives spectrograms via HTTP POST requests from the Pi. It classifies the input as either 'Normal' or' Abnormal'
- Logging System: Saves predictions and metadata.
- Notification System utilising Pushbullet for alerting based on detection.

An Asus G14 with around 12 GB VRAM, was used for development and deep-learning, hosting my custom shallow CNN (with maneuver to move up to ResNet-18 or deploy it to the Pi eventually).

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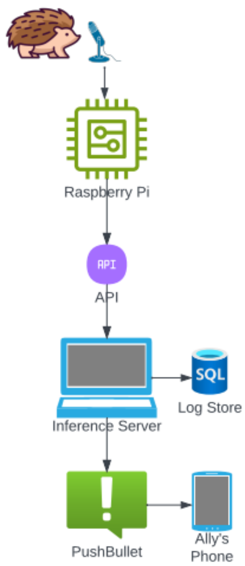
Step 1: Pi records audio > generates a spectrogram

Step 2: Sends spectrogram image via API to G14 laptop

Step 3: server.py receives it, FastAPI script with the loaded PyTorch model serves the prediction from the incoming spectrogram images

Step 4: G14 logs the result, raises alerts via pushbullet

Initial High-Level Architecture:



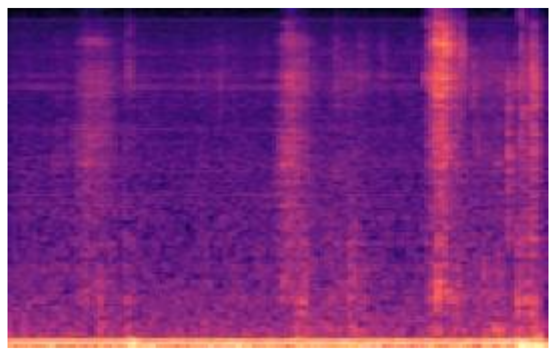
# TRAINING DATA COLLECTION

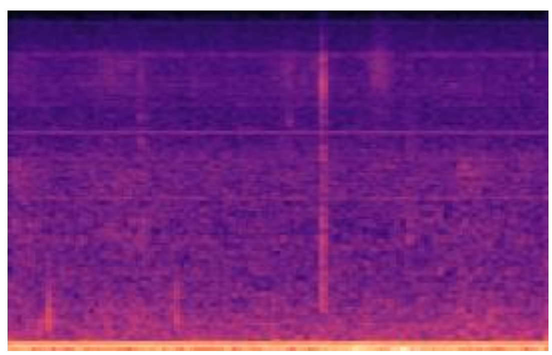
Reliable, labelled data for respiratory distress in hedgehogs is scarce. To mitigate this, I collected audio from my garden, identifying normal behaviours such as snuffling, rustling, and eating and singling out the recordings of any anomalies, wheezing, coughing, gargling, deep ‘clicks’. I approached my local rescue and other rescues asking whether they could provide recordings (providing equipment if needed) to supplement my own recordings.

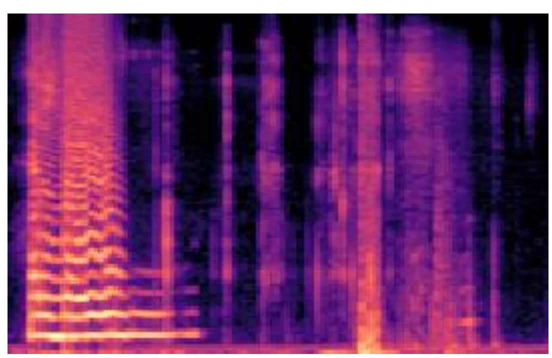
Of the training data used, about 20% were made up of abnormal sets. This proportion was chosen to ensure sufficient representation of abnormal cases during initial model development, given the relatively small dataset size. However, this is notably higher than the prevalence typically observed in medical or anomaly detection studies. As the dataset is expanded in future iterations, the abnormal class percentage will be gradually reduced down to 5% to better reflect real-world distributions and align with clinical data patterns.

Challenges included:

- Ambient noise.
- Difficulty in acquiring genuine lungworm positive audio.
- Ethical and legal limitations – Hedgehogs are protected in the UK and deliberate capture can be a criminal offence.







# AI MODEL

Model training was performed using torch.autograd - PyTorch’s automatic differentiation engine . A convolutional neural network was trained on various spectrograms sent by the Raspberry Pi. Input images were generated using librosa, and basically taking the sound, chopping it up into tiny little overlapping segments (a 2048-window), and then sliding over (a 128-hop length)  analysing each snapshot to figure out what kind of noises are in there.  Basically, how the model hears and understands the nuances of the sound, converting it into something it can learn from.

During backpropagation, gradients of the loss function were processed using the chain rule. Stochastic gradient descent utilsiing PyTorch was performed, enabling the model to reduce classification error over successive iterations.

The core model was trained and hosted on an Asus ROG Zephyrus G14 with NVIDIA RTX GPU with 12 GB VRAM. This setup allows for local extrapolation and future experimentation with more complex models such as ResNet-18 if I found I needed to expand, or downstream deployment to the edge device via PyTorch mobile.

The model consists of two convolutional layers which analyses the sound, whether it is super faint, barely audible, or just background noise, then filtering it out (ReLU activation). It then max pooled to ensure that only the best individual sound was used.

Details:

- Training Set Size: ~250 samples
- Validation Accuracy: ~75%
- Inference Time: ~50ms per image

The model outputs binary classification: normal or abnormal, which is then used to trigger alerts or log the event.

# FINDINGS & RESULTS

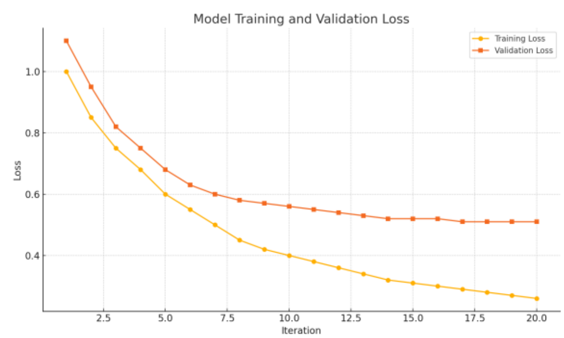
While results are still preliminary due to the limited training dataset, initial tests were promising. Below is a summary of performance:

| Class | Precision | Recall | F1 Score |
|---|---|---|---|
| Normal | 0.91 | 0.94 | 0.92 |
| Abnormal | 0.75 | 0.67 | 0.71 |

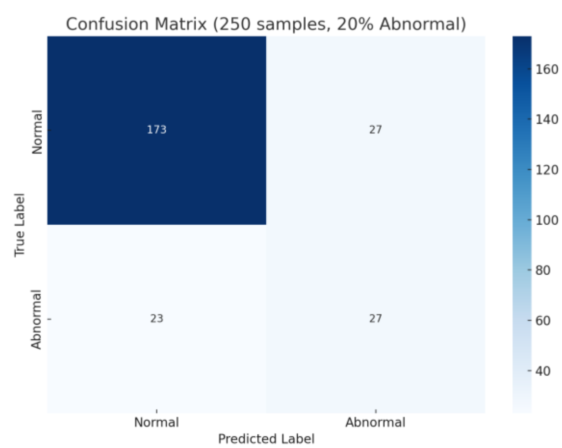
Example detection events:
- 02:34 AM: Abnormal breathing detected, log saved, alert sent via Pushbullet.
- 04:17 AM: Normal snuffling detected, no action taken.

The slightly lower recall for the Abnormal class (0.67 vs. 0.94 for Normal) is important to note. It suggests that while the model is quite accurate when it does detect an anomaly, it might miss about 34% of actual abnormal events.

The results demonstrate that a low-cost, Raspberry Pi–based IoT equipped with a directional microphone utilising a small CNN can detect acoustic signs of respiratory distress in hedgehogs with promising baseline accuracy. The model achieved a precision of 0.75 and recall of 0.67 for the abnormal class, indicating that it can identify respiratory anomalies more often than it misses them, although not without occasional false positives or negatives. The F1 score of 0.71 reflects a reasonable trade-off between sensitivity and precision, especially given the smalldataset. The use of mel spectrograms as input features proved effective, particularly for capturing harmonic content characteristic of respiratory anomalies.




Training and validation loss over iterations.



# SUMMARY

I wanted to create a summary of my project to formalise and help reflect and improve on the outcome, I hope with improved training data I can achieve better success rates for abnormal detection. Ultimately, I see my mini project as a success. I wanted to apply atypical AI to my daily life to help improve something that is very important to me. I feel as though this approach of combining AI with Ecology can and should help us preserve that which is special to use – it's an oxymoron given how much energy AI uses but it's not going away. And whilst people use it predominantly to generate cartoon effigies of themselves using the latest and greatest LLM I wanted to experiment using a more impactful and practical purpose.

Ultimately, I hope it proves as an example on how innovation and empathy to a good cause can win over the skepticism of AI, I speak about its drawbacks and security flaws often enough I wanted to show some creative application. Some may think this redundant or pointless, but I hope some find it novel.

In the future I'm looking to deploy the classifier to run entirely on the Pi and to maybe create a visual dashboard (angular or flask). Id even like to introduce visual analysis via the trail camera and maybe expand classification to include other behaviours (self-anointing for instance).

# THE FUTURE

While this project was designed to monitor wildlife, the underlying techniques have significant potential in human health applications as well. Audio based respiratory monitoring has already shown promise in the detection and management of asthma, chronic obstructive pulmonary disease (COPD), and respiratory infections such as COVID-19. Passive, non-contact acoustic sensing could enable continuous monitoring in home or clinical settings, particularly for vulnerable populations such as children or the elderly.

For example, real-time cough detection and wheeze monitoring using 'edge' devices could be used to protect the vunerable in health settings such as GP practices or care homes. The same system architecture, low-cost microphones, portable processors, and deep learning models, could be applied to detect abnormal respiratory events in humans, making healthcare more personalised and accessible

As AI and bioacoustic analytics mature, there is strong potential to extend this work into interdisciplinary domains, including telemedicine or monitoring via smart devices.

The union of bioacoustic monitoring, deep learning pattern recognition offers new opportunities in wildlife conservation and health screening. This project represents a practical, albeit somewhat theoretical, application of that, targeting respiratory illness detection in hedgehogs. It builds upon foundational research in animal sound classification, AI deployment, and ecological health monitoring, and aims to serve as a proof-of-concept for scalable solutions.

In a broader sense, in the field lab edge devices may have many applications with a wider toolset at their disposal including thermal imaging and VOC analysis. Leading to breakthroughs with 'frontier topics' such as with Bovine tuberculosis which is caused by the bacterium Mycobacterium bovis, the spread of which has led to widespread badger population culls, the effectiveness of such culls has widely been called into question.

| Method | Sensing Modality | Invasiveness | Edge Feasibility |
|---|---|---|---|
| **Thermal Imaging** | Infrared | Low | High |
| **Computer Vision** | Video | Low | High |
| **Biosensing (DNA/LAMP)** | Molecular | Medium | Moderate |
| **VOC Analysis** | Chemical | Low | Moderate |
| **Bioacoustics** | Sound | Low | High |

Representative of the toolset available to a proposed field laboratory.

# APPENDIX

Tools and Technologies

Programming Language: Python 3.11

Libraries/Frameworks:

librosa – audio processing & feature extraction

matplotlib – spectrogram visualisation

PyTorch – deep learning model training and inference

FastAPI – inference server and REST API

requests – client-server communication

Hardware:

Raspberry Pi 4 Model B (4GB RAM)

Samson Go USB Microphone (16kHz sample rate)

Asus ROG Zephyrus G14 (Ryzen AI 9 HX 370, NVIDIA RTX 5070 Ti, 12GB VRAM)


Dataset Summary

Source: Personal wildlife audio recordings (2021–2025)

Classes:

Normal – snuffling, walking, ambient

Abnormal – wheezing, coughing, liquid like sounds

Size: ~250 labelled spectrogram samples

Preprocessing:

5-second audio clips

Mel spectrogram conversion using librosa

Normalisation to 128×216 pixel input size

Layers:

Conv2D (32 filters, 3×3) → ReLU →

MaxPool2D (2×2)

Conv2D (64 filters, 3×3) → ReLU →

MaxPool2D (2×2)

Flatten → Fully Connected (128) → ReLU

Fully Connected (2) → Softmax

Loss Function: CrossEntropyLoss

Ethics & Governance

No personally identifiable information collected

All wildlife observed passively, without disturbance

Ethics aligned with UK Wildlife Act and compassionate conservation principles

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