Optimisation of a Raspberry Pi-based Bioacoustic Sensor for Data Collection

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Abstract

This paper details the optimisation of a Raspberry Pi-based bioacoustic sensing system designed for data collection for acoustic classification of birds. Optimised sensors are desirable when collecting data off-the-grid. The acoustic sensor's power consumption was studied under various conditions, such as using a full and Lite Raspberry Pi OS to guide the sensor's optimisation. The power management board used to power the sensor was also redesigned to improve efficiency. A machine learning model to classify 3 bird species and other sounds with an accuracy of 93% and loss of 30% on the test set was developed. An 80%-10%-10% train, test and validation split ratio was used to train and evaluate the model which was then quantized to tensorflowlite to run directly on the raspberry pi hardware in a miniaturized format. The optimised sensor was then deployed at a Wildlife Conservancy in Africa, Kenya to continously collect data and perform inference at the edge.

Keywords: Bioacoustics, Raspberry Pi, Sensor Optimisation, Off-grid Data Collection, Power Management, machine learning, quantization, miniaturized.

1. Introduction

Data collection for ecological monitoring often involves deploying sensors in environments not connected to the grid. Batteries are the most effective source of energy for these sensors. A custom battery and solar-powered Raspberry Pi-based acoustic sensor was designed for the purpose of eco-systems monitoring for use in wildlife conservancy gazetted areas for the monitoring of bird species (Whytock and Christie, 2017). A power management board was also designed to power the system autonomously. This study aims to optimise the acoustic sensor for deployment in the field. One of the main challenges encountered in designing sensors for off-grid deployment is power optimisation (Fanariotis et al., 2024). An ideal battery-powered sensor should be deployed for long periods without replacing the battery (Mazunga and Nechibvute, 2021). To reduce the power consumption of the acoustic sensors, some measures have been undertaken. They include comparing the power consumption of different Raspberry Pi versions and Raspberry Pis running on full Raspberry Pi OS and Lite OS, and developing a power-efficient power management board (Bathre and Das, 2023).Furthermore, a machine learning model was implemented and quantized in order to predict bird species and categorize the sound recordings of birds through a USB microphone attached to the raspberry PI, directly on the edge efficiently (Oliveira et al., 2024).

2. Methodology

2.1. Power Consumption Quantification

In order to quantify the power consumption of different Raspberry Pi versions running on both full and Lite Raspberry Pi OS, the Otii Arc Pro power logging tool was used (Rana et al., 2024). The measurement was done on both the Raspberry Pi 3 B+ and Pi Zero 2W, both running the 64-bit Raspberry Pi OS (Bullseye). The average current and power were logged during the continuous recording phase of the sensor when activity was detected by the microphone.

2.2. Development of an Efficient Power Management Board

A battery, a solar panel, and a power management board power the bio-acoustics sensor. The power management board enables safe powering of the Raspberry Pi using batteries. It provides autonomous mechanisms for shutting down the Raspberry Pi when the battery gets drained and rebooting it after the battery gets charged. The initial design, the power management board, uses a mechanical relay and a MOSFET-based latching circuit. A new design of the power management board, the PiWild, that uses a MOSFET-only latching circuit, was developed to improve the stability and efficiency of the system (Nguyen et al., 2021). The current drawn by the two boards was measured for comparison.

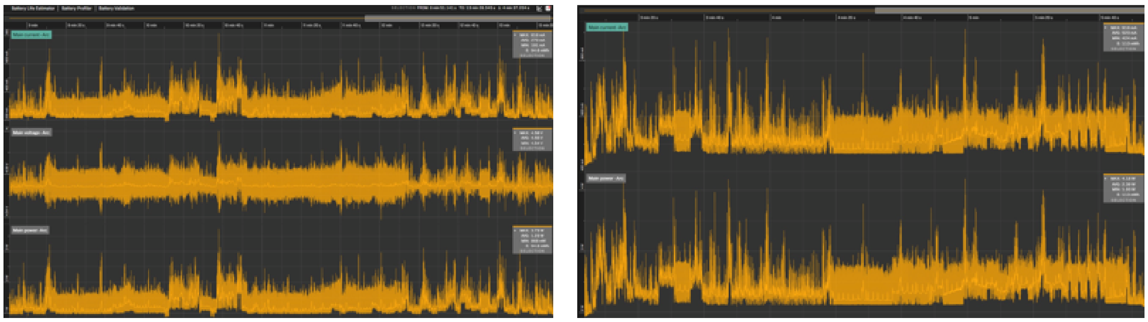
2.3. Development and Quantization of a Machine Learning Model

A machine learning model was implemented using YAMNet (Lachenani et al., 2024) to predict bird species. A locally collected dataset from the Wildlife Conservancy in Kenya and data sourced from Xeno-Canto was used to train the model for *Greybacked camaroptera , Tropical boubou, Hartlaub's turaco* and the others class for other species and sounds. This dataset contained a total of 1,415 audio samples of variable length and format either .MP3 or .WAV files which were pre-processed to standardize all files as .WAV files with a frequency of 16kHz and 16 bit audio depth as it is the audio YAMNet expects to provide audio embeddings(Purwins et al., 2019) as features for training.The model was trained for 50 epochs with an 80%, 10% and 10% split for the training, test and validation sets respectively after doing a shuffle on the dataset to have samples sparsely distributed across the 3 sets. The model was then quantized using the inbuilt TensorFlowLite Converter(Verma et al., 2021) with a float32 bit architecture into a tensorflowlite(Warden and Situnayake, 2019) of 3.8 MB in size to run lightweight on the Raspberry Pi. TensorFlow 2.6 for 32 bit OS was installed on the Raspberry Pi and the corresponding dependencies as well as the tflite runtime interpreter to be able to run the quantized model directly on the raspberry pi.

3. Results

3.1. Power Consumption Comparison

Figure 1 shows a comparison between power being drawn by the Raspberry Pi Zero 2W and the Raspberry Pi 3B+.



(a) (b)

Figure 1: Plots of Current and Power drawn by (a) Raspberry Pi Zero 2W (b) Raspberry Pi 3B+ during recording.

Table 1: Average current and power drawn by the Raspberry Pi Zero 2W and 3B+ during sound recording.

Device	Avg Current (mA)	Avg Power (W)
Pi Zero 2W	270	1.23
Pi 3B+	523	2.39

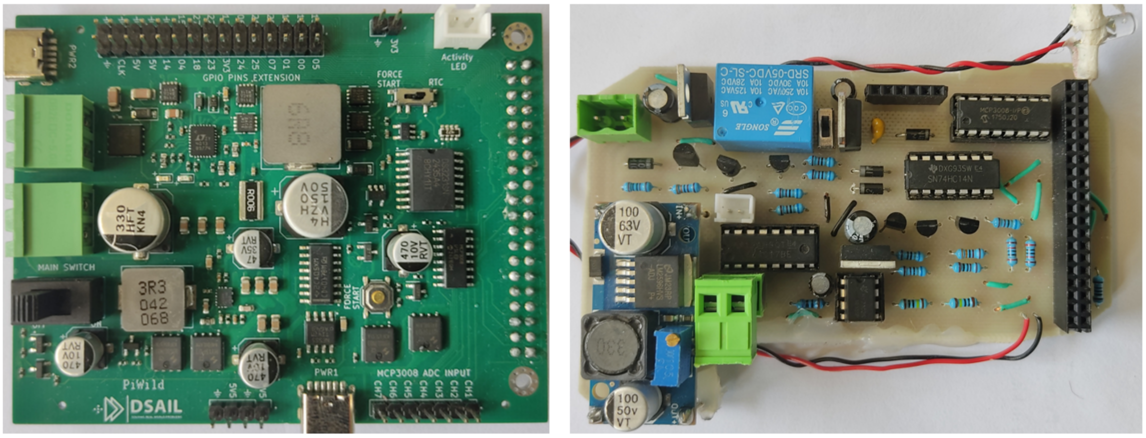
Based on Table 1, it can be observed that the Raspberry Pi Zero 2W draws less than half the power drawn by the Raspberry Pi 3B+. This makes the former more suitable for developing the acoustic sensor.

3.2. Development of an Efficient Power Management Board

The power management board draws 0.12 A from a 3.7 V source (0.444 W) while PiWild draws negligible current, as shown in Figure 3. The mechanical relay used in the power management board draws the current for its operation, hence, loading the source. This reduces the system's efficiency. PiWild will thus optimise the power consumption of the acoustic sensor, improving the system's efficiency.

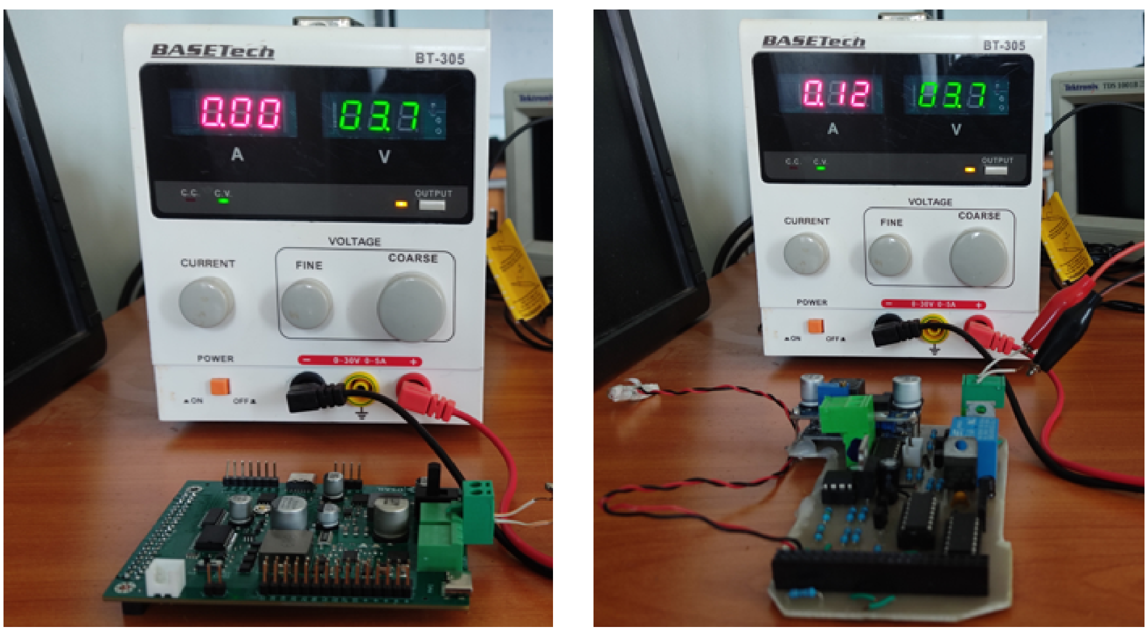
3.3. Model Development

The following section illustrates results from the dataset structure, training of the model and the prediction across the different classes on the dataset. The figure 4 shows the structure of the dataset with the class distribution. Figure 5 illustrates the training and validation



(a) (b)

Figure 2: (a) PiWild (b) Power Management Board



(a) (b)

Figure 3: Current drawn by (a) PiWild, (b) power management board.

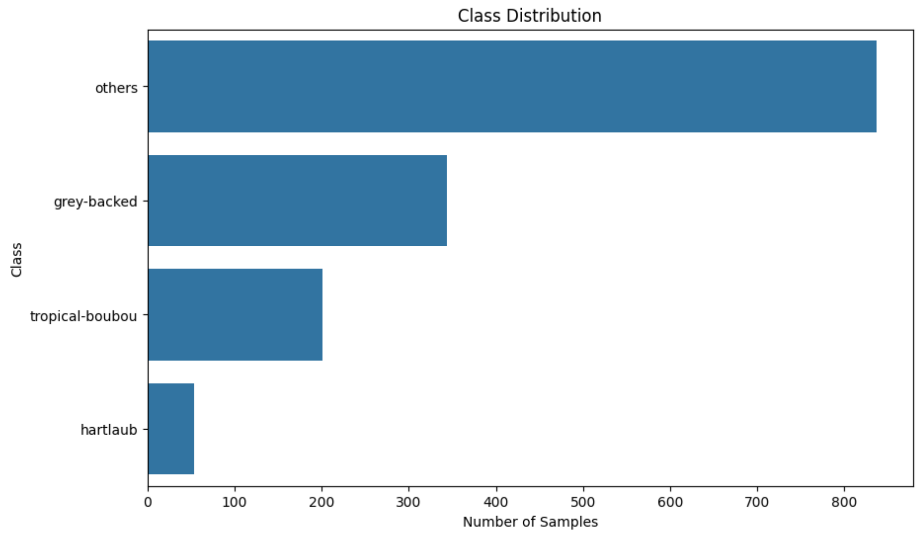


Figure 4: Dataset Split across the 4 classes

accuracy, as well as the training and validation loss. The table 2 showcases a classification

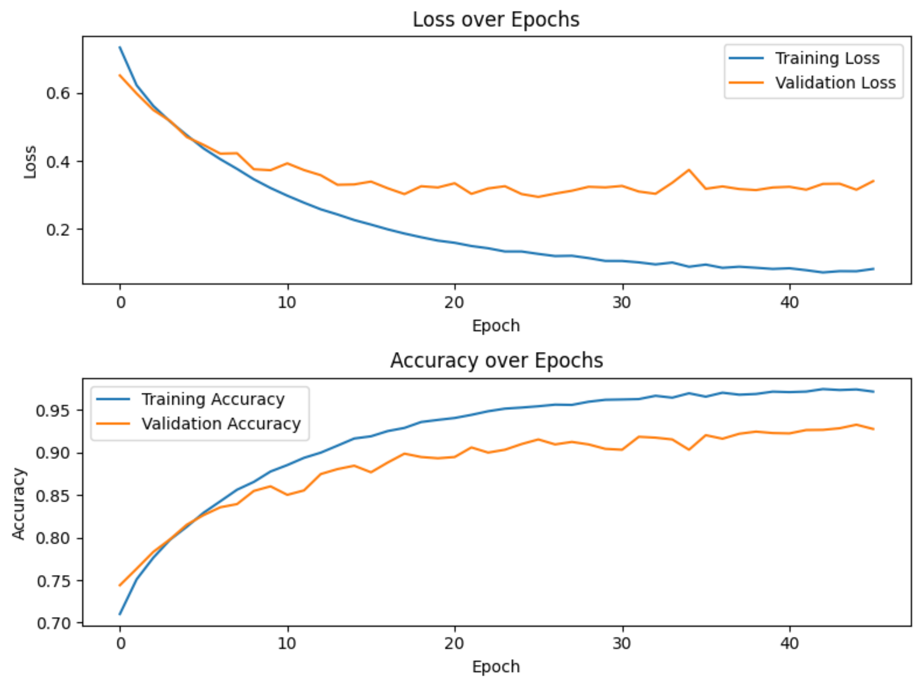


Figure 5: Training Accuracy & Loss, Validation Accuracy & Loss

report derived from training the model to predict the 4 classes for the bird species predictor model. Figure 6 represents a confusion matrix illustrating the true positives and false

Table 2: Classification report showing precision, recall, f1-score, and support per class.

Class	**Precision**	**Recall**	**F1-score**	**Support**
grey-backed	0.93	0.97	0.95	2369
hartlaub	0.91	0.74	0.82	381
others	0.93	0.94	0.94	556
tropical-boubou	0.92	0.89	0.91	1481
Accuracy			0.93	4787
Macro avg	0.92	0.89	0.90	4787
Weighted avg	0.93	0.93	0.93	4787

positives as well as the true negatives and false negatives of the model when performing prediction.

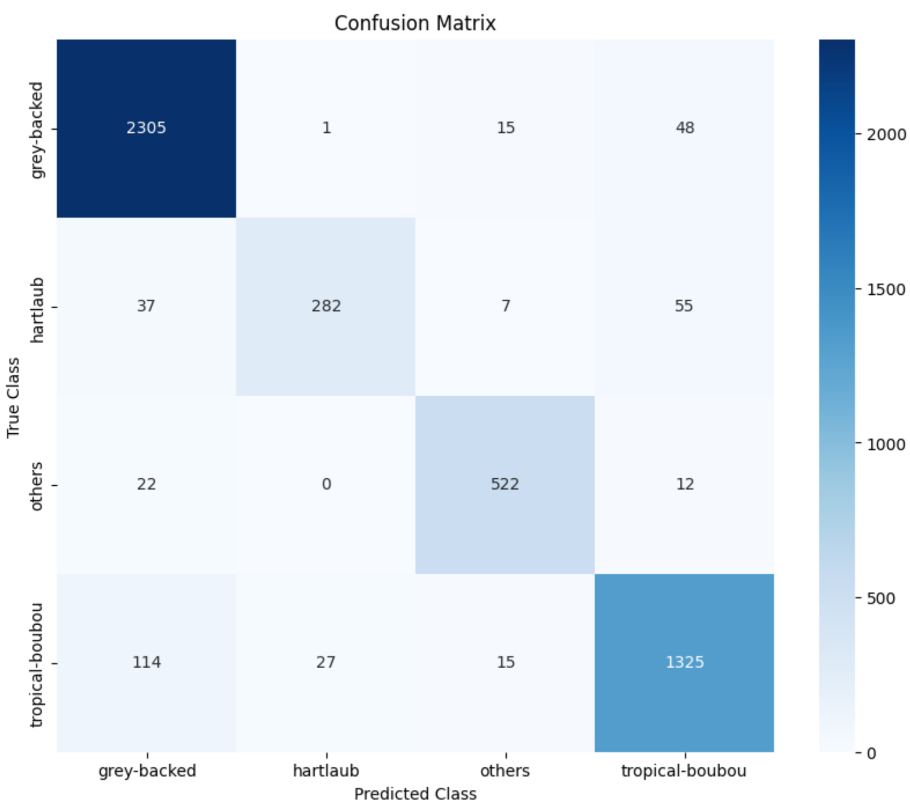
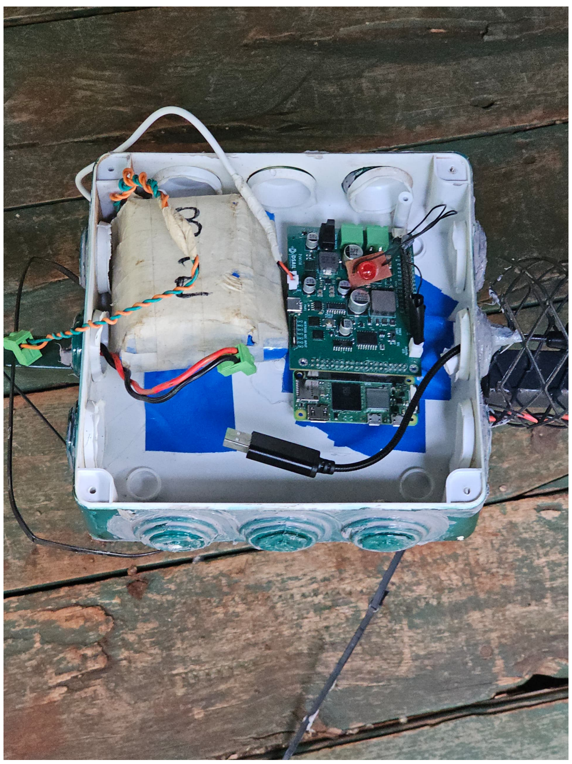


Figure 6: Confusion matrix for bird species prediction

4. Conclusion

Data plays a central role in machine learning (Jakubik et al., 2024). Environmental data collection requires the deployment of sensors off the grid that are battery-powered. Battery-powered sensors need to be optimised for longevity in the field. The power consumption of different Raspberry Pi versions was analysed to guide the choice of the board to use for the acoustic sensor. It was observed that the Raspberry Pi Zero 2W consumed less power. The power management board used to power the Raspberry Pi was also optimised by replacing a mechanical relay-based latching circuit with a MOSFETs-only latching circuit. The quantized model was also used to do sample predictions when a sound was recorded for the target bird classes, which maintained close prediction with the pre-quantized model making it ideal for collecting bird sounds according to classes in the field. The figure 7 shows the sensor assembly (a) as well as the deployment in the field (b).



(a) Sensor assembly

(b) Deployed sensor

Figure 7: Sensor setup. (a) Sensor assembly with PiWild board and Raspberry Pi Zero 2W. (b) Deployed sensor performing edge inference in a wildlife conservancy.

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