INTRODUCTION

The continuous development and improvement of tracking devices has enabled researchers to study animal movement ecology, physiology and behaviours in ever-increasing detail (Williams et al., 2019; Wilson et al., 2019). In addition to positional data, various micro-sensors on-board of tracking devices enable the monitoring of different aspects of the wildlife tracked as well as their environment (Ropert-Coudert & Wilson, 2005). Accelerometer (ACC) data is one such feature measured with micro-sensors that is increasingly used to study animal behaviours and energetics (e.g. Williams et al., 2014).

Abstract

1. Over the past two decades, accelerometer (ACC) data have been increasingly used to study animal behaviours and energetics. However, the large amount of raw ACC data can be a burden to device storage and power consumption and in many cases may also require device retrieval for data collection. On-board data processing to reduce data volume and power consumption for data transmission may hold promise to alleviate these problems and allow for next-generation, smart trackers.

2. We developed a tracking system processing raw ACC data on-board of trackers into behaviours using an XGBoost machine learning model. We used this system on six free-ranging Pacific black ducks Anas superciliosa to study eight behaviours every 2 s.

3. The on-board XGBoost model for behaviour classification had 92.04% overall accuracy. One day of continuous behaviour records was compressed on-board to as little as 17.28 kB for routine transmission via the 3G network. We received behaviour data from the six ducks continuously for periods ranging between 56 days and 14 months.

4. On-board processing of raw ACC data and data transmission proofed highly energy efficient and came at a minimal weight cost to the trackers, providing great potential to open up new areas in ecological and behavioural research.

KEYWORDS
accelerometer, machine learning, time-activity budget, wildlife tracking, XGBoost
However, large amounts of ACC data are required to allow determination of an animal's behaviour (Roux et al., 2017), which can be a burden to device storage and transmission. Transmission of large amounts of raw sensor data through VHF/UHF and satellite or mobile networks is energy demanding (Nuijten et al., 2020) and sometimes also impossible due to data volume constraints. For example, due to bandwidth limits, satellite transmission does not allow for large amounts of raw ACC data transmission (Cox et al., 2017). One often used solution to this problem is to sample in bursts rather than continuously record ACC data (e.g. Gilbert et al., 2016; Weegman et al., 2017) with the other option for data collection being device retrieval (e.g. Hicks et al., 2017).

On-board data processing, to shrink raw data volume, is another way to resolve this bottleneck in remote behavioural data collection and transmission (Yu et al., 2021). Several studies have applied on-board processing of ACC data for animal behaviour research. For example, Nuijten et al. (2020) used 2 s ACC data recorded every 2 min when tracking Bewick’s swan Cygnus columbianus bewickii to calculate 20 ACC data summary statistics over a total of 120 days. These were subsequently transmitted using UHF after which supervised behaviour classification followed. Cox et al. (2017) used a simple rule-based method that relied on a predefined threshold value to extract prey-catch attempts from ACC data in free-ranging southern elephant seals Mirounga leonina, where the extracted prey-catch attempts were transmitted through the Argos satellite system. Roux et al. (2017) used specially designed biotelemetry tags to perform on-board behaviour classifications using a supervised machine learning method (linear discriminant analysis) to study five different behaviours (standing, walking, grazing, running and lying down) in sheep Dohne merino. They used the same method to study three behaviours (standing, walking and lying down) in two rhinoceros species Ceratotherium simum and Diceros bicornis, where the calculated behaviours were transmitted using UHF. Unfortunately, these tags still needed retrieval for data downloading and hardware reprogramming in the ‘training’ stage of the behaviour classification model, which may be problematic for animals that are difficult to recapture.

Here, we report on a novel tracking system allowing for continuous behaviour recording using ACC data overcoming some of the above-mentioned limitations in similar tracking devices to date. Aside from allowing for continuous, high-resolution behaviour classification using supervised machine learning and allowing for a multitude of behaviours to be distinguished with high precision, it allows for on-board storage of behavioural data for up to 7 months. Moreover, positional and behavioural data can be downloaded using the mobile phone network as well as long-range Bluetooth, the latter also allowing for the collection of raw ACC data important for the training of a behaviour classification model. The mobile network and Bluetooth can also be used to modify any tracker settings including updating the behaviour classification model. We tested this energy-efficient, solar-powered system on six free-ranging Pacific black ducks Anas superciliosa starting November 2020, continuously recording eight different behaviours complemented with hourly GPS positions.

2 | METHODS

2.1 | Tracking device

The Lego trackers used in this study were developed by Druid Technology Co., Ltd (Chengdu China), measuring 68 mm × 20 mm × 26 mm (length × width × total height) and weighing 25 g. The tracker had an elevated solar panel to reduce the risk of coverage by wing feathers when attached as a backpack. The solar panel measured 42 mm in length and 22 mm in width. The tracker was powered by a 200 mAh rechargeable lithium battery. It contained a nRF52840 SoC (system on a chip), with a 64 MHz microprocessor, 1 MB Flash and 256 kB RAM memory. The BLE (Bluetooth Low Energy) feature of this SoC enables data communication between tracker and personal cell phones up to a distance of 70 m. Other modules on-board of the tracker included a 3G module for data communications through the mobile network, a GPS module for positioning, a three-axial ACC sensor, and sensors to obtain temperature, air pressure, humidity and light intensity.

Using the ‘Utopia’ app (Druid Technology Co., Ltd) for android, the tracker’s continuous ACC data can be live streamed and stored on a mobile device using Bluetooth, while the app’s video function allows for simultaneous recording of the behaviour of the focal animal (Figure 1). The labelling function of this app allows users to choose behaviour labels from a set of user-defined behaviours and thus assign behaviour labels to ACC data. These labelled ACC data can next be used to train and validate a supervised machine learning model on a personal computer. This supervised machine learning model or behaviour classifier can next be uploaded to the tracker through either the 3G mobile network or via the mobile device’s Bluetooth connection (using the ‘nRF Toolbox’ app; Nordic Semiconductor). After uploading the behaviour classifier, the tracker can transform raw ACC data into behaviour continuously and regularly send this data through the 3G mobile network to the cloud storage.

2.2 | Fieldwork

The fieldwork associated with setting up the ACC data to behaviour conversion consisted of three phases: (i) only recording 10-min overall dynamic body acceleration (ODBA) through ACC data to identify broad-scale activity patterns and identify suitable sites and periods for ground truthing; (ii) collection of ground truthing data (i.e. raw ACC data + simultaneously recorded videos + behaviour labels); and (iii) uploading the behaviour classifiers to trackers for continuous on-board behaviour classification. The collection of GPS fixes and environmental data by trackers remained unchanged during these three phases.

We captured 18 (2 on 23/12/2019; 6 on 29/01/2020; 3 on 23/09/2020, 1 on 30/09/2020, 1 on 16/12/2020, 1 on 23/12/2020, 1 on 21/01/2021, 3 on 03/02/2021) Pacific black ducks A. superciliosa on a small water body in Wallington, Victoria, Australia (38.23°S, 144.53°E). Ducks were captured with tapered funnel traps (Mcnally...
& Falconer, 1953) baited with wheat. Before tagging, the captured duck’s eyes were covered with a baby sock to reduce the birds’ stress level and facilitate the tagging process. The straps of the backpack harness were made from Teflon ribbon (Telonics Inc.) with a weak-link where the four straps of the backpack met on the centre of the duck’s sternum (Cumming & Ndlovu, 2011). Tagging of a bird was typically completed within 8 min. Ducks were released immediately after tagging. Weight of harness and tracker was approximately 28 g and less than 3% of the body mass of the tracked ducks (body mass range upon capture 0.94–1.33 kg).

The trackers were set to record GPS fixes at 1-hr intervals. Together with the GPS fix, environmental data—temperature, air pressure, humidity and light intensity—were also recorded. The tracker recorded three-axial ACC data. Since the recording of this data consumes little battery power (Nuijten et al., 2020), the on-board ACC was set to ‘always-on’ mode with a 25 Hz sampling rate (sampling current \(31 \mu A\)). Every 10 min, ACC data were summarized into a single mean overall dynamic body acceleration value (mean-ODBA, which is the mean of 100 ODBA values measured every 6 s) following Wilson et al. (2006). Trackers were set to transmit records to the cloud server through the 3G mobile network at 1-day interval, if battery levels allowed for this relatively energy demanding process. Otherwise, data remained in the device’s storage until battery levels again allowed transmission.

The ODBAs and positional information indicated that the tracked ducks were mostly active around dawn and dusk and tended to be site faithful at these times of day. Therefore, field observations aiming at simultaneous collection of behavioural data and ACC recordings were concentrated around dusk. Raw ACC data were transmitted to the phone in real time. Using the ‘Utopia’ app on an android phone equipped with a 12× phone camera lens, ACC data, video and audio were simultaneously collected. The observer’s audio recordings were notably needed in addition to the video to provide details of the focal duck’s behaviour when among conspecifics. Recordings were exported from the Utopia app into Excel where 16 different behaviour labels (Table 1) were added to the recorded ACC data. In total, we thus collected raw ACC data with behaviour labels from 6 (i.e. d5099_1, d5230, d5232, d5238, d5239 and d5248) of the 18 ducks. The capture, tagging and observing protocols were approved by Deakin Animal Ethics Committee (approval B13-2019).

The behaviour-classification model training followed the process as outlined by Yu and Klaassen (2021) in their description of the R package, in which we reduced the initial 16 behavioural categories to 8, based on their functional similarities and their similarities in accelerometer recordings (Table 1). For detailed information on model training and on-board data compression, see Supporting Information. Between 20/11/2020 and 03/02/2021, we uploaded the behaviour classification model on six trackers (i.e. d5099_2, d5210, d5239, d5241, d5246, d5248; only d5239 was used in the previous ACC data collection with behaviour labels and model training) through 3G mobile network communication.

3 | RESULTS

In total, 9,343 segments were used in the model training (7 segments from d5099_1, 3020 from d5230, 3198 from d5232, 1865 from d5238, 784 from d5239 and 469 from d5248) and evaluation with eight behaviour types including: dabbling (2385 segments), feeding (1031), floating (365), flying (47), preening (1370), resting (3334), running (51) and walking (760). The recall rate of the XGBoost model through five-fold, cross-validation ranged from 78.95% to 96.44%, and the precision rates ranged from 81.41% to 97.78% (Figure 2). The overall accuracy across the eight behaviours was 92.04%. The overall accuracy across the initial 16 behaviours (Table 1) was 88.75% (see recall and precision rates in Figure S2). The on-board current tests showed that the add-on of the continuous behaviour classification calculations required little additional current. The default settings of the device are to sample ACC data continuously and summarize the data into one ODBA every 10 min, which consumed a mean current of \(62.71 \mu A\). Adding feature calculations and behaviour prediction through the XGBoost model for every 2 s of ACC data only increased this current by \(1.4 \mu A\). To illustrate the energy efficiency of the behaviour classification process, assuming the 200mAh tracker battery

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**Figure 1** Flow of data between tracker, mobile device in the field, 3G mobile network, cloud storage and computer for advanced data processing, collectively forming the system for continuous on-board behaviour classification in free-ranging animals.
is solely used for mean ODBA calculation without solar charging, the device can work 133 days. Adding behaviour prediction only decreases this value by 3 days (i.e. reducing the number of days the device can theoretically work without solar charging to 130 days). In comparison, transmitting raw ACC data to a phone through Bluetooth consumed a mean current of 602.4 μA. The storage requirement for the XGBoost model and tree parameters, as well as the code needed to do the calculations of the features was 55.428 kB, which is well below the limit of the 1 MB Flash memory.

A representative, detailed account of the continuous behaviour records obtained in the Pacific black ducks is presented for d5210, covering a total of 3 days (from 11:00 am 20/11/2020 to 11:00 am 23/11/2020). The recording demonstrates detailed daily activity routines across three different sites where it spends most of the day, dusk and night, respectively (Figure 3). At the diurnal site, d5210 mainly rested and preened with occasional dabbling bouts. Then, around dusk, d5210 flew 6.8 km to stop at a site close to the nocturnal site where it engaged in almost continuous feeding with little

| Initial behavioural category | Definition | Final behavioural category |
|-----------------------------|------------|---------------------------|
| Swimming                    | Swimming   | Dabbling                  |
| Dabbling                    | Feeding from the water surface | Dabbling                  |
| Dabbling deep               | Feeding with head under water | Feeding                  |
| Wader foraging              | Slow walk in shallow water and feeding with head under water | Feeding                  |
| Feeding                     | Terrestrial feeding, slow walk pecking food from ground | Feeding                  |
| Floating                    | Floating without locomotion | Floating                  |
| Flying                      | Flying     | Flying                    |
| Shaking                     | Shaking of the whole body | Preening                  |
| Preening                    | Preening feathers with beak | Preening                  |
| Foot scratching             | Head or body scratching with foot | Preening                  |
| Head shaking                | Head shaking | Preening                  |
| Tail shaking                | Tail shaking | Preening                  |
| Resting                     | Sitting on the ground | Resting                  |
| Standing                    | Standing   | Standing                  |
| Running                     | Running    | Running                   |
| Walking                     | Walking    | Walking                   |

FIGURE 2 Confusion matrix plot of duck behaviour classification. Green and pink dots indicate correct and incorrect classification results, respectively

### TABLE 1 Duck behaviours as recorded during field observations and their reclassification based on their UMAP clustering and their functional similarities
Methods in Ecology and Evolution

YU et al.

walking in between the feeding bouts. At the nocturnal site, d5210 first rested for around 2 hr after which it showed alternate feeding and walking behaviour. When it rained on the third day, d5210 increased preening behaviour and decreased the time in feeding at the nocturnal site compared to the previous 2 days.

We received continuous behaviour records from six ducks. D5099_2 (3/2/2021–30/3/2021) stopped working when its device dropped off. D5241 (4/1/2021–13/3/2021) stopped working with full battery for unknown reasons and we also have not seen the bird since. D5239 (23/12/2020–17/2/2021), d5246 (3/2/2021–18/4/2021) and d5248 (24/11/2020–9/6/2021) stopped working due to low battery levels, yet two of these individuals have been regularly seen since. D5210 (20/11/2020–21/1/2022) continued working up till at least the date of submission of this manuscript (see ethogram of d5210 in Figure 4).

4 | DISCUSSION

We used a recently developed solar-powered tracking system by Druid Technology to successfully study the behaviours of six free-ranging Pacific black ducks in continuous mode and in unprecedented detail. Following deployment and using a dedicated cell phone app, the trackers allowed us to collect raw ACC data and combine these with direct visual behavioural observations in six ducks. We next used XGBoost supervised machine learning to generate a model to translate ACC data collected on six ducks into eight different behaviour types with an overall accuracy of 92.04%. Because five out of six individuals (except d5239) at the on-board behaviour classification stage were not used for model training and evaluation, the actual model accuracy might be lower. After remotely uploading this model to the trackers of the six ducks, we were able to record the birds’ behaviour almost continuously due to the high energy and storage efficiency of the devices. During winter, when solar charging of the batteries was sub-optimal, 3G data transmission rate was poor in some birds. Moreover, most individuals appeared to prefer roosting under trees also limiting the solar charging of the batteries. However, downloading data using Bluetooth when birds were within 70 m range and the 7-month data storage capacity of the trackers helped overcoming this problem in some cases. When the tracker’s battery level is lower than 3.6 V (i.e. 5% of usable battery capacity), it will stop on-board behaviour classification through ACC data. In the extreme case where tracker storage reaches capacity (i.e. no data transmission has taken place in 7 months), the earliest recorded data will be discarded to make space for newly recorded data. The obtained continuous and accurate behavioural data when animals are out of sight provide interesting avenues for detailing animals’ environmental requirements and (health) status to facilitate and direct (e.g. through timely intervention) research and management.

The tracker also supports other types of ACC data calculation and behaviour classification models. In the tracker’s default settings, only ODBA is calculated (every 10 min) as an index of energy expenditure and transmitted back. Previously, we tested runtimes of 78 features (including ODBA) calculated from ACC data using the same SoC (Yu et al., 2021). A subset of these features (or other customized features) can also be calculated and transmitted back to the user. Other than the XGBoost model used in this study, we proved that artificial neural network and random forest were also suitable for on-board behaviour classification (Yu et al., 2021). Moreover, the sampling frequency can also be customized (i.e. 12.5, 25, 50, 100, 200, 400 Hz) for different research species adding to the versatility of the system.

A fascinating recent study by Korpela et al. (2020) used behaviour classification to control data sampling of an on-board
camera to capture prey types, illustrating how our on-board continuous behaviour classification could potentially be used to direct both data collection but possibly also other types of intervention for research and management. For instance, a sudden decrease in feeding time of an individual might indicate illness or injury and cause for intervention. In their study, Korpela et al used an on-board 32 kB program memory, while in our study we used a 1 MB Flash memory, nRF52840 SoC, providing ample space to load the code for feature calculation and the XGBoost model enabling detailed behaviour classification. In addition to its low energy consumption mentioned earlier, it is also worth noting that the use of nRF52840 SoC was not at the cost of tracker weight. The current lightest tracker of Druid Technology with this SoC and similar capabilities except 3G data communication, weighs 2.8 g.

Current applications of continuous behaviour recording in humans and livestock may provide inspiration for where wildlife tracking with the same continuous behavioural monitoring could take us. In the livestock industry, behaviour and activity count data are already being used to improve livestock welfare and to increase production. For example, anomaly detection in long-term activity counts was used for livestock disease detection, and long-term rumination behaviour records of dairy cows were used to detect oestrus (Chapa et al., 2020). Similarly, long-term behaviour records of wildlife can potentially be used for health and fitness estimation and the detection of key life stage events. In human activity monitoring, data from wearable devices have been applied in fall detection of elderly people, sleep monitoring, training load monitoring and biomechanical performance measurements of athletes, and population-level epidemics research (e.g. Haghi et al., 2017; Radin et al., 2020; Seshadri et al., 2019). Likewise, continuous behaviour records combined with other sensor data, which can potentially also be processed on-board, provide us the potential opportunities to study critical events in wildlife, such as death detection and death reason inference, in-depth monitoring of wildlife sleep, and biomechanical performance. Provided enough trackers can be deployed this could even result in population-level assessments including wildlife epidemiological monitoring.

**AUTHORS’ CONTRIBUTIONS**

H.Y., G.L. and M.K. conceived the ideas; H.Y., J.D. and M.K. designed the methodology; H.Y., T.L. and M.K. participated in the field work; H.Y. analysed the data with advice from M.K.; J.D. wrote the code installed on the tracking device and ran all on-board tests; H.Y. and M.K. led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.
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CONFLICT OF INTEREST
The authors declare that they have no competing interests.

PEER REVIEW
The peer review history for this article is available at https://publons.com/publon/10.1111/2041-210X.13878.

DATA AVAILABILITY STATEMENT
The raw accelerometer data from 6 Pacific black ducks with 16 behaviour labels and 8 behaviour labels are archived in Dyrad at https://doi.org/10.5061/dryad.rbnzs7hd5 (Yu et al., 2022).

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SUPPORTING INFORMATION
Additional supporting information may be found in the online version of the article at the publisher’s website.

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