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RESEARCH ARTICLE

Death detector: Using vultures as sentinels to detect carcasses by combining bio-logging and machine learning

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Abstract

1. Bio-logging technologies allow scientists to remotely monitor animal behaviour and the environment. In this study, we used the combination of natural abilities of African white-backed vultures *Gyps africanus* and state-of-the-art bio-logging technology for detecting and locating carcasses in a vast landscape.
2. We used data from two captive and 27 wild vultures to create a reference data set for the training of a support vector machine to distinguish between six behaviour classes based on acceleration data. Next, we combined the classified behaviour of the initial 27 and 7 additional vultures with GPS data and used the 'Density-Based Spatial Clustering of Applications with Noise' algorithm to cluster all GPS data to get a position of potential feeding locations. Finally, we used the clustered data set to train a Random Forest algorithm to distinguish between clusters with and without a carcass.
3. The behaviour classifier was trained on 14,682 samples for all behaviour classes, which were classified with a high performance (overall precision: 0.95, recall: 0.89). This enabled a ground team to examine 1900 clusters between May 2022 and March 2023 in the field, 580 linked to a carcass and 1320 without a carcass. The cluster classifier trained on this data set was able to correctly distinguish between carcass and no carcass clusters with high performance (overall precision: 0.92, recall: 0.89).
4. *Synthesis and applications*. We showed that a carcass detection system using vultures, loggers and artificial intelligence (AI) can be used to monitor the mortality of numerous species in a vast landscape. This method has broad applications, such as studying the feeding ecology of vultures, detecting and monitoring of disease outbreaks, environmental poisoning or illegal killing of wildlife. Similar to vultures and carcasses, our methodological framework can be applied to other species to locate their respective food resources. It could also be applied to other types of resources like temporary water sources, roosting sites and to other behaviours such as marking to locate marking sites.

KEYWORDS
accelerometry, behaviour classification, carcass detection, feeding sites, gyps africanus, machine learning, random forest, support vector machine

1 | INTRODUCTION

The use of wild animals as sentinels has valuable implications for combating global problems, including natural disasters, disease outbreaks, human–wildlife conflicts and illegal activities. Leveraging animals as mobile sensors can establish an effective system for detecting wildfires, crucial for early intervention and for preventing the natural disaster from spreading further (Sahin, 2007). Animal sentinels can be used to predict disease outbreaks or spread. For example, the death of primate sentinels can indicate outbreaks of Ebola, providing an early warning for health organizations to implement preventive measures to protect human health (Halliday et al., 2007; Rouquet et al., 2005). Poisoning wildlife can occur as a result of human–wildlife conflict (Mateo-Tomás et al., 2012). For example, eagles that are accidentally poisoned can serve as sentinels to detect intentional poisoning targeting coyotes (Wobeser et al., 2004). In the marine realm, albatrosses show major potential in detecting illegal fishing activities by shadowing fishing ships (Weimerskirch et al., 2020).

Bio-logging technologies enable us to monitor these animal sentinels remotely, which, contrary to traditional field observations, allows for continuous and large-scale monitoring, collecting data in inaccessible environments and reducing observer bias on animal behaviour (Nathan, 2008; Schneirla, 1950). GPS tracking in combination with powerful tools such as utilization distribution and step-selection function were designed to study animal space use and habitat preferences (Kranstauber et al., 2012; Thurfjell et al., 2014). In addition, by using GPS trajectories together with methods such as first passage time, Bayesian partitioning, change point analysis and multistate random walk, we can distinguish between behaviours such as resting, searching and moving that an animal exhibits in a certain habitat (Gurarie et al., 2016). However, with GPS data alone we cannot distinguish between behaviours with similar spatio-temporal pattern such as resting and feeding. Accelerometry (ACC) data became a valuable tool to infer behaviours with characteristic body motion patterns. A popular method to extract behaviour information is the use of supervised machine learning (Nathan et al., 2012). Such an approach first requires a reference data set with which a machine learning algorithm is trained. The data set can be collected on the same individuals that are studied (Grünewälder et al., 2012) or on captive individuals (Nathan et al., 2012; Rast et al., 2020). Using the same species is important since applying the trained algorithm on a different species might result in higher rates of incorrect classifications (Campbell et al., 2013). Where and when an animal exhibits certain behaviours can be studied by combining GPS data and behaviour information.

Although several studies used bio-logging data to investigate a wide range of ecological aspects (review in Cooke et al., 2004) with some focusing on feeding behaviour (Giese et al., 2021; Horie et al., 2017; Lok et al., 2023), few specifically looked at scavengers detecting carcasses. Two of scavenger studies focused on GPS data alone (Mateo-Tomás et al., 2023; Peters et al., 2023). Another scavenger study included behaviour classification from ACC data (Arkumarev et al., 2020). Mateo-Tomás et al. (2023) identified potential carcasses by evaluating GPS clusters with feeding behaviour (from ACC data) of single vultures, Arkumarev et al. (2020) considered only clusters with at least two vultures and Peters et al. (2023) considered only clusters visited by one or more vultures (GPS data only). Considering multiple vultures can be affected by the density of tagged vultures in the study area and give underestimated number of detected carcasses. To improve the methodology and make it more time-efficient, we propose a methodological framework that automatically analyses the GPS and ACC data of individual animals for carcass detection.

The African white-backed vulture (*Gyps africanus*), hereafter referred to as the vulture, is widespread across Sub-Saharan Africa and can be found in a variety of biomes, including savanna, semi-desert, grassland, shrubland and forested areas. It is an obligate scavenger that relies on carcasses as its main food source (Mundy et al., 1992). By soaring across open landscapes, vultures scan large areas for carcasses, which they can locate from kilometres away using their keen eyesight (Cortés-Avizanda et al., 2014). They are gregarious in their feeding habits and dozens of vultures can congregate at the same carcass (Cortés-Avizanda et al., 2014; Mundy et al., 1992). These features make the vulture a good model species for studying carcass detection.

In this study, we develop a method for detecting and locating carcasses by using a combination of natural abilities of vultures and bio-logging technology. Such a methodological framework does not only promote understanding of feeding ecology of the study animal but also enables us to use the study animal as a sentinel which helps us locate the food resource itself. Consequently, we can monitor mortality of land-based mammals and investigate reasons of death, including natural and anthropogenic causes. This will help with combating global problems such as detecting hotspots of wildlife diseases like anthrax (Ebedes, 1977), environmental toxins like the ones produced by cyanobacteria (Wang et al., 2021), poisoning of predators (Ogada et al., 2016), illegal carcass dumping (Mateo-Tomás et al., 2023) or wildlife poaching (Lavadinovi et al., 2021). This method has applicability beyond our study system and the broad potential to be used in other environments with different resources and wildlife species.

2 | MATERIALS AND METHODS

2.1 | Ethical statement

This research and animal treatment was permitted by the local authorities (National Commission on Research Science & Technology, certificate no.: RCIV 00032018, authorization no.: AN202101120 [for 2022] and authorization no.: AN20170811 [for 2023]).

2.2 | Data collection in captive vultures

2.2.1 | ACC data recording in captive vultures

Two captive vultures were situated in an enclosure (see Section S3 in the Supporting Information) in a zoo in Berlin, Germany (Tierpark Berlin-Friedrichsfelde GmbH). The enclosure housed 10 additional vultures of different species. We observed little to no interactions between study vultures and the others.

Both vultures were equipped with GPS/ACC bio-loggers (e-obs GmbH, Grünwald, Germany, hereafter referred to as loggers). These loggers were fitted and attached as backpacks with teflon using a neck loop (Figure 1, see also 'body harness' in Thaxter et al., 2014). The logger and attachment weight was 60 g which amounts to approx. 1.15% of a vulture's body mass (5.2 kg, SD = 1.07 kg, n = 27, five of the vultures were not weighed).

ACC data for three axes (x: left–right, y: front-back, z: up-down) was recorded continuously at 20 Hz within a range between −2G and 2G. The loggers recorded a UTC timestamp for each ACC measurement that we later used to sync ACC data and video observations. The internal clock of the logger is synced to the GPS time whenever GPS data are recorded. However, we did not collect GPS data in the zoo to save energy. The logger sampled a GPS position once a day to resync the internal clock regularly.

2.2.2 | Behaviour observation in captivity

We recorded six distinct behaviour classes: feeding, preening, lying, standing, walking and wing spreading (see Table S1 for the Ethogram). To annotate the videos with behaviour classes, we used BORIS (Version: 8.6.2) (Friard & Gamba, 2016). To sync the video recordings with the ACC data, we used a smartphone app (MasterCo 2012) for the camcorder. At the beginning of each recording session, we filmed the app to get the exact timestamp of the video's beginning. To sync the fixed camera with the ACC data, an NTP time server was connected to the recording PC. See more details on the behaviour observations and equipment used in Section S5 in the Supporting Information.

FIGURE 1 Logger position on the vulture—see Section S1 for detailed attachment description.

2.3 | Data collection in Etosha

2.3.1 | GPS and ACC data recording in free-ranging vultures

The study area for the free-ranging vultures was Etosha National Park, Namibia (hereafter referred to as Etosha), a large protected area with a size of 22,270 km^2 (18°51′0″ S, 15°54′0″ E) (see Section S4 for more information).

We equipped 34 (27 in May 2022 and seven more in October 2022 only for the cluster classification) free-ranging vultures with GPS/ACC bio-loggers (same model as in the zoo). The loggers had two different sampling modes. In the high sampling mode, GPS/ACC data were recorded in parallel every minute for 7 s; GPS data at 1 Hz and ACC data at 20 Hz. In the low sampling mode, GPS data were recorded once every 30 min and no ACC data were recorded. We used the ACC-informed protocol of the loggers to switch between the two sampling modes. We set the threshold to switch between the modes so that feeding behaviour would always be recorded in the high sampling mode. Standing and lying would most likely trigger the low sampling mode, while preening might trigger both modes depending on the intensity of the behaviour (see Section S6 for setting details). We restricted any data recording to UTC time between 04:00 and 18:00 as we expected no vulture activity during the night (Spiegel et al., 2013). Data were automatically downloaded via the GSM network twice a day and send to Movebank (Kays et al., 2022).

2.3.2 | Behaviour observation and deduction from free-ranging vultures

We deduced two distinct behaviour classes from 27 free-ranging vultures (tagged in May 2022): active flight (flapping wings) and passive flight (soaring) (Table S1). We visually analysed the ACC data in the software Firetail® (Berger et al., 2022) and annotated samples for both behaviours. We considered Sections with GPS speed higher than 5 m/s as flight behaviour. The minimum gliding speed was found to be 8.85 m/s for straight flight (Pennycuick, 1971). We set a lower threshold to also include the early flight phases after taking off. Secondly, we used the difference in GPS altitude between high speed Sections and Section with GPS speeds near 0 m/s where we assumed the vulture was stationary in a tree or on the ground to confirm that the vulture was airborne. We labelled all data in these Sections as passive flight. For all Sections, we excluded 1 min at beginning and the end from being labelled. To differentiate between active and passive flight, we used the video recordings of the release as references (see Section S2). The difference between active and passive flight was quite distinct (Figure S2). We labelled active flight within passive flight Sections accordingly.

2.4 | ACC data processing

We pooled all labelled data from captive and free-ranging vultures. We combined consecutive ACC measurements to reach a total sequence length of 2s (40 samples, hereafter referred to as burst). To obtain a data set that is as unambiguous as possible, we removed bursts with more than one label from the data set. This happened when the vulture changed behaviour within 2s. We collected a total of 45,631 labelled ACC bursts. The zoo vultures contributed a total of 16,111 bursts of feeding, preening, lying, standing, walking and wing spreading. The free-ranging a total of 29,520 bursts of active and passive flight (see Table S4). The number of bursts we were able to label varied among behaviour classes. We were able to label 180 and 127 bursts of walking and wing spreading respectively while the third lowest sample size for an identified class was 2447 for lying. Therefore, we removed walking and wing spreading from the data set and chose 2447 bursts from each behaviour class at random to achieve a balanced data set in which all behaviour classes were equally represented.

We rescaled all ACC values to reflect G-values by using the formula $g = (\mathrm{acc} - 2048)/1024$ as provided by the manufacturer of the loggers. To compile the training data set for the behaviour classifier, we calculated a total of 44 summary statistics (hereafter referred to as features, Table S2) and used a min–max scaler from the scikit-learn library to rescale all values to range between −1 and 1. All data processing was done in Python 3.8 (Van Rossum & Drake, 2009).

2.5 | Behaviour classifier

We compared a support vector machine (SVM) (Cortes & Vapnik, 1995) (Python implementation in scikit-learn as 'SVC'), a Random Forest (RF) (Breiman et al., 1984) (Python implementation in scikit-learn as 'RandomForestClassifier') and Extreme Gradient Boosting (XGB) (Chen & Guestrin, 2016) (Python implementation in xgboost) in their ability to classify vulture behaviour. For training and validation, we used the python library 'sklearn' (Pedregosa et al., 2011). We used the same algorithm for hyper-parameter optimization, feature selection and training data set for each classification algorithm. For the hyper-parameter optimization, we used 'GridSearchCV' from the scikit-learn library.

$$\mathrm{F1} = \frac{2 \times (\mathrm{precision} \times \mathrm{recall})}{\mathrm{precision} + \mathrm{recall}}, \tag{1}$$

$$\mathrm{recall} = \frac{\mathrm{true\ positives}}{\mathrm{true\ positives} + \mathrm{false\ negatives}}, \tag{2}$$

$$\mathrm{precision} = \frac{\mathrm{true\ positives}}{\mathrm{true\ positives} + \mathrm{false\ positives}}, \tag{3}$$

$$\mathrm{accuracy} = \frac{\sum \mathrm{true\ positives}_i}{N}. \tag{4}$$

All steps of hyper-parameter optimization and feature selection involved a fivefold cross-validation. The dataset is split into five equal parts. The model is trained on four parts and validated on the fifth. This is repeated until each part was used for validation once. As validation metric, we chose the macro F1-score (mean of all F1-scores; Formulas 1–3, which are all calculated per behaviour); we also calculate overall accuracy for better comparability with other publications, i (Formula 4) denotes the behaviour class and N is the total amount of samples (see Powers, 2020). We first used a grid search approach with the training data set including all features to find the best hyper-parameters (see supplementary code for details; Rast et al., 2024).

We used the best hyper-parameters found in the first step for a feature selection that works as follows: Training and validation of the classifier with only one of the features. This was repeated for all features. The best-performing feature was kept for the next round where training and validation were repeated for the remaining features in addition to the first retained feature. This was done for 10 rounds so the resulting feature set would include 10 features, adjusted from Yu and Klaassen (2021). We further reduced the feature set by removing any feature whose F1-score increased by less than 0.01 in two consecutive rounds. We then repeated the hyper-parameter optimization with the selected features only.

Finally, we ran a fivefold cross-validation to evaluate the performance of the behaviour classifiers. In this step, we also considered the classification probability that is reported by the classifier to set a minimum threshold below which we did not accept the classification and considered all classifications this applied to as 'unsure'. We tested thresholds between 20% and 90% in steps of 10. As precision increased, the recall decreased. We decided on a threshold (0.7) by balancing both value changes. The goal was to maximize precision while minimising the reduction in the recall.

2.6 | Cluster identification and data processing

We preprocessed the collected ACC data of free-ranging vultures the same way as we did with the reference data (see Section 2.4) to apply the behaviour classifier. The classifier calculates a class label with a corresponding probability for each burst. We considered all classifications below the threshold (0.7) as 'unsure'. Finally, we matched the behaviour information with the GPS data based on the timestamps as GPS and ACC data were recorded at the same time.

We used the clustering algorithm Density-Based Spatial Clustering of Applications with Noise (DBSCAN, implemented in 'scikit-learn'; Ester et al., 1996) on the longitude and latitude to identify clusters of GPS positions. In the algorithm, the ε parameter sets the maximum distance two samples can be from each other to still be considered neighbours. We set the ε value to $\frac{5}{6{,}371{,}008.8}$ with the metric set to 'haversine'. This way, the ε neighbourhood corresponded to a radius of 5m.

This ensured that GPS locations at a carcass and those at a close by tree, that was used for perching, were recognized as separate clusters. Clusters are only considered valid when they consisted of at least three points. As the tags' sampling frequency was dependent on the vulture activity (ACC-informed GPS), we considered clusters with a duration of more than 10 min. We filtered the data by date and separated for each vulture. Thus, every cluster corresponded to a single vulture on a specific date. When several vultures visited the same site, each vulture formed its own cluster, regardless of the vultures present there at the same time or on different dates. We also did not combine clusters if a vulture remained at the site on the following day or returned to the same site on a different date.

We calculated summary statistics containing 12 features from each GPS/ACC cluster (see Section S7 and Table S3) and used a min-max scaler from the 'scikit-learn' library to rescale all values to range between −1 and 1. We estimated the location of each cluster by calculating the mean of the longitude and latitude of all GPS locations of each cluster.

2.7 | Cluster classification

We investigated estimated cluster locations in person to determine whether a carcass is or was present at the location. The difference in time between the investigation and the first vulture at the cluster was 20 ± 14 (mean ± SD) days. We considered a cluster of type 'carcass' when we found a carcass, its remains (e.g. blood, a gut pile, bones or hair) or other evidence of feeding (e.g. disturbed ground with many vulture feathers, carnivore footprints and vegetation showing that a carcass was dragged). We treated a cluster as type 'no carcass' when we found a tree with evidence for roosting or perching (e.g. vulture droppings or regurgitated hair pellets found under the tree or on its leaves). We considered active nests as 'no carcass'. We cross-checked the GPS data of the specific vulture to identify regular returns and thus confirming an actively used nest.

We randomly sub-sampled data from both cluster types to get an equal sample size for both classes. To find the best hyper-parameters and features we used the same approach as for the behaviour classifier. Again, we compared the performance of the SVM, RF and XBG, evaluated the performance of each algorithm and tested thresholds (best for the cluster classifier was 0.6) as before (see Section 2.5).

3 | RESULTS

3.1 | Behaviour classification

We focused on the results of the SVM with a radial basis kernel as this algorithm performed slightly better than the RF and XGB (Tables 1 and 2; Tables S6–S9, S11, S12, S14–S17) (see complete RF and XGB results in Section S8).

We used the same grid for both rounds (before and after feature selection) of the hyper-parameter optimization (Table S10). After the first round of hyper-parameter optimization, we set C to 1000 and gamma to 0.01.

With the feature selection, we found five features out of 44 that reached an F1-score of 0.93 (Figure 2). These features were *inverse coefficient of variation of the z-axis*, the *minimum value of the y-axis*, the *mean of the y-axis*, *Pearson correlation coefficient between the y and z-axis* and the *maximum value of the z-axis*.

Overall, the SVM showed very good results for most behaviour classes (Table 2). We found the lowest F1-scores for preening and standing, showing some misclassification between these behaviours as well as between lying and standing. Preening was sometimes misclassified as feeding but feeding was a lot less often misclassified as preening (see Table 1). We tested different probability thresholds to accept the classifications and found that 0.7 is a good compromise between the increase in precision (reaching 0.95 at this threshold) and the decrease in recall (Figure S5).

3.2 | Cluster classification

We found a total of 38,879 clusters in the data from 11 May 2022 to 30 March 2023. We investigated the type of 1927 clusters (95% on foot, 5% with a light aircraft). We confirmed 580 clusters to be of type 'carcass' and 1320 as 'no carcass' (301 'tree' and 1019 'nest'). We found nothing at 27 clusters, which were removed from further analysis.

TABLE 1 Confusion matrix of the support vector machine—the diagonal shows all correctly classified bursts.

	Active flight	Feeding	Preening	Lying	Passive flight	Standing	Unsure	Total n
Active flight	**2417**	6	0	0	0	0	24	2447
Feeding	16	**2291**	29	0	1	2	108	2447
Preening	0	120	**1827**	2	2	167	329	2447
Lying	0	0	2	**2269**	0	117	59	2447
Passive flight	0	7	0	0	**2427**	0	13	2447
Standing	0	3	131	22	0	**1905**	386	2447

Note: The maximum value for each row is indicated in the last column. Numbers in the unsure column show the number of bursts that were labelled as unsure because the classification probability did not exceed the set threshold. Rows indicate observed behaviour; columns indicate classified behaviour.

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All three algorithms show very similar performances when classifying the cluster type. We focused on the RF as mean precision and recall were higher than for the other two algorithms (see Section S9; Table 4; Tables S19, S21, S23, S25, S27).

We used the same grid for both rounds (before and after feature selection) of the hyper-parameter optimization (Table S5). After the first round of hyper-parameter optimization, we set n_estimators to 200, min_samples_split to 3, min_samples_leaf to 1, max_depth to 7 and criterion to 'entropy'.

With the feature selection, we found two features out of six that reached an F1-score of 0.91 (Figure 3). These features were *proportion of feeding points* and the *proportion of unsure points*. After the second round of hyper-parameter optimization, we set n_estimators to 300, min_samples_split to 3, min_samples_leaf to 1, max_depth to 7 and criterion to 'gini' for the final classifier.

Overall, the RF showed very good results (Tables 3 and 4; Tables S18 and S19). We tested different probability thresholds to accept the classifications and found that 0.6 is a good compromise between the increase in precision and the decrease in recall (Figure S8).

TABLE 2 Classification metrics for the support vector machine with a threshold—see Formulas (1)–(3) for the calculations of Precision, Recall and F1 score.

Behaviour	Precision	Recall	F1	Total *N*
Active flight	0.99	0.99	0.99	2447.0
Feeding	0.94	0.94	0.94	2447.0
Preening	0.92	0.75	0.82	2447.0
Lying	0.99	0.93	0.96	2447.0
Passive flight	1.0	0.99	1.0	2447.0
Standing	0.87	0.78	0.82	2447.0
Unsure				919.0
Mean	0.95	0.89	0.92	
Overall accuracy	0.89			

Note: Total *N* denotes the total number of samples for the given behaviour and the total number of classifications that are considered 'unsure'. The mean is calculated for each metric across all behaviour classes.

4 | DISCUSSION

In this study, we evaluated a method to identify potential carcass locations that were found by vultures. This method relies on three consecutive steps: behaviour classification from acceleration data, clustering of GPS data and cluster-type classification based on the behaviour classification and time of the day. Our feature selection showed that using the proportion of feeding behaviour, which was derived from ACC data, was more relevant than any of the parameters that we derived from GPS data. This highlights the benefit of combining GPS data with behaviour classification of ACC data. This method could be applied to African white-backed vultures throughout their range as it is not sensitive to the population size or density of vultures in an area as carcasses can be detected with data from a single individual. With changes only to the last of the three steps, this methodological framework could also be used to locate nests during the breeding season. We showed that the behaviour classifier is able to classify lying behaviour which should match with the body posture of a vulture incubating an egg.

In general, a behaviour classifier is specific to the species it was trained on (Campbell et al., 2013). Given that a behaviour classifier for the target species is available, this methodological framework can be expanded to locating resources or sites of interest for any species.

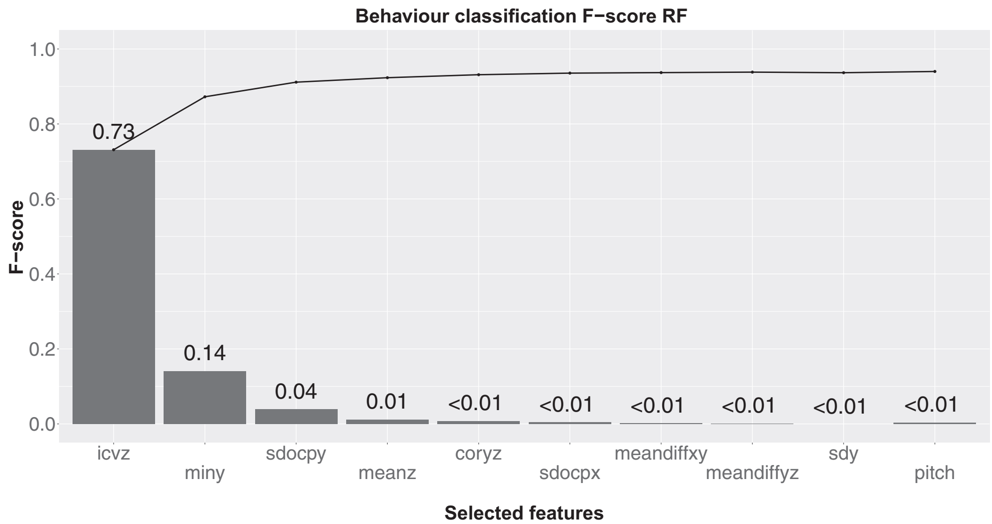

FIGURE 2 F1-score in relation to the used features for the support vector machine (SVM)—the *x*-axis displays the features that were sequentially added to the classifier (see Table S2 for abbreviations). The *y*-axis shows the F1-score of the classifier. The first bar displays the F1-score of the classifier only using the first feature. All further bars show the increase in the F1-score when adding the according feature. The above line displays the total F1 score of the classifier.

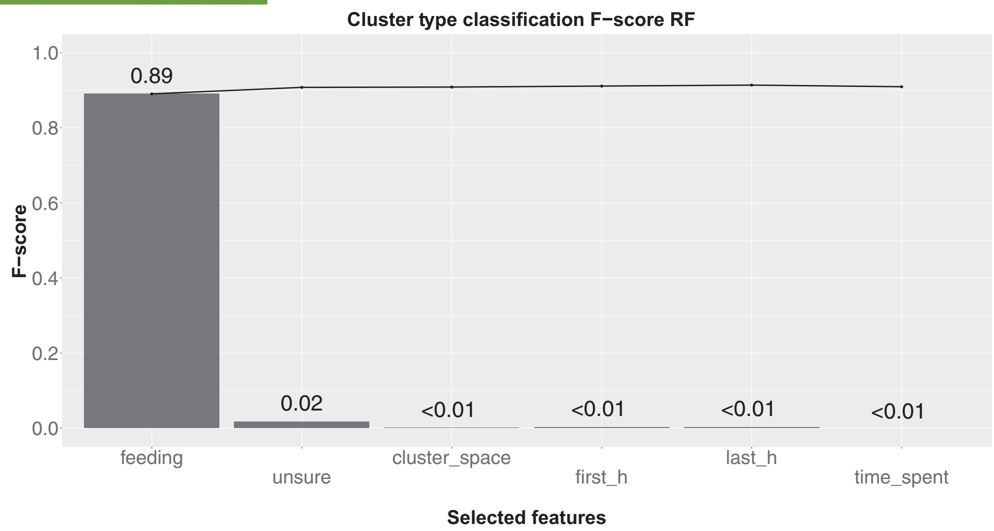

FIGURE 3 F1-score in relation to the used features for the Random Forest (RF)—the *x*-axis displays the features that were sequentially added to the classifier (see Table S3 for abbreviations). The *y*-axis shows the F1-score of the classifier. The first bar displays the F1-score of the classifier only using the first feature. All further bars show the increase in the F1-score when adding the according feature. The above line displays the total F1 score of the classifier.

TABLE 3 Confusion matrix of the Random Forest—the diagonal shows all correctly classified clusters.

	Carcass	No carcass	Unsure	Total *n*
Carcass	**507**	53	20	580
No carcass	37	**521**	22	580

Note: The maximum value for each row is indicated in the last column. Numbers in the unsure column show the number of clusters that were labelled as unsure because the classification probability did not exceed the set threshold. Rows indicate observed cluster type; columns indicate classified cluster type.

TABLE 4 Classification metrics for the Random Forest with threshold—see Formulas (1)–(3) for the calculations of Precision, Recall and F1 score.

Cluster type	Precision	Recall	F1	Total *N*
Carcass	0.93	0.87	0.90	580.0
No carcass	0.91	0.90	0.90	580.0
Unsure				42.0
Mean	0.92	0.89	0.90	
Overall accuracy	0.89			

Note: Total *N* denotes the total number of samples for the given cluster type and the total number of classifications considered 'unsure'. The mean is calculated for each metric across all cluster-type classes.

4.1 | Behaviour classification

Our classifiers work very well in distinguishing six different behaviour classes. A comparison between a SVM, RF and XGB showed that all three perform very similar to each other (Table 1; Tables S6, S8, S12, S14, S16). Our SVM slightly outperforms other models that classified behaviour of other vulture species (*Gyps fulvus*; Nathan et al., 2012; Resheff et al., 2014). We could also show that a long list of features is not necessary to get good results. Five features out of 44 were needed to train our SVM (Figure 2).

The metrics of our SVM look very good, but they reflect the performance of the classifier on the reference data set (Figure 2). To account for behaviours that occur in free-ranging vultures but were not observed in captivity or samples of mixed behaviours that were removed in the reference dataset but can occur during data recording, we applied a minimum probability threshold to all classifications. Our assumption is that behaviours that were not trained on will receive a low probability and thus, likely are behaviours that in our classification scheme, were labelled 'unsure'.

We collected four out of six behaviour classes for the reference data in captivity. This greatly increased our accessibility to the vultures during observation. While several authors also suggest this approach (see Giese et al., 2021; Graf et al., 2015; Nathan et al., 2012), we were not able to observe some behaviours (e.g. soaring [passive flight] and active flight) in this setting with a high enough sample size. However, we could use the movement data from the tagged free-ranging vultures to sample data for these behaviours.

Some other behaviours are completely missing from our reference data. We never observed fighting, hopping, jumping or running which are all closely connected to feeding, in the zoo. If the threshold works as intended, these four behaviours should be considered 'unsure' by the classifier. The unsure class is relevant for distinguishing carcass from non-carcass clusters (3), which indicates that some behaviours are grouped in the unsure class that are only displayed at one of the two cluster types. Since we lack the observations, we cannot confirm if this is true for the aforementioned behaviours.

To improve the applicability of this behaviour classifier, these behaviours should be targeted by observation in free-ranging vultures.

4.2 | Cluster classification

We trained our cluster classifier specifically to correctly classify a carcass with a single vulture present. Previous studies on carcass detection through vultures made it a prerequisite that at least two tagged vultures were present to consider the presence of a carcass (Arkumarev et al., 2020; Peters et al., 2023). Even though African white-backed vultures are known to assemble in big groups at carcasses (Houston, 1974; Spiegel et al., 2013), the number of tagged vultures present at the scene is unpredictable. Our classifier is insensitive to the number of vultures attending a carcass therefore reducing tagging effort and financial costs and could therefore be applied in many different circumstances.

Overall, we classified clusters as carcasses with high precision (0.93 with RF) (Table 4). Similar to the behaviour classifier, the comparison between the RF, SVM and XGB for cluster classification showed only very small differences between the three models (Table 4; Tables S21 and S25).

One limitation could be bathing behaviour at waterholes. We assume that bathing involves rapid movements of the whole body which is also true for feeding behaviour but we lack the data to verify this. However, this could lead to a confusion of bathing with feeding as the SVM was only trained on feeding. Ultimately, this could result in clusters at waterholes showing an increased proportion of feeding and therefore being falsely classified as carcasses. But since carcasses can also occur at waterholes, we could not treat all 'carcass' clusters at waterholes as misclassifications. Conversely, carcasses could be misclassified as no carcasses when the rate of false negatives for feeding is high; especially in cases where the total amount of feeding was low.

4.3 | Future applications

Our proposed methodological framework can be used to locate carcasses in a vast landscape. It can serve as a tool to get more insight into the feeding ecology of vultures. Scavengers including vultures could also function as sentinels to investigate the circumstances around a dead animal. Direct investigation would make it possible to test carcasses for potential diseases like anthrax and set up a monitoring system of seasonal trends or to detect local outbreaks (Ebedes, 1977; Lindeque & Turnbull, 1994). Similarly, an early warning system could be developed for environmental poisoning detection. In 2020, over 300 African elephants died in Botswana, most likely due to cyanobacteria toxins (Wang et al., 2021). Lastly, this methodological framework can be used to detect illegal activities involving animal carcasses such as leaving livestock in unauthorized areas (Mateo-Tomás et al., 2023), poaching, predator poisoning (Csermak Jr et al., 2023) or poisoning of the sentinel itself regardless of whether the sentinel was targeted or not (Ogada et al., 2016; Stoynov et al., 2019).

AUTHOR CONTRIBUTIONS

Wanja Rast designed the first draft of the framework, analysed the data, coordinated and participated in the behaviour observation of captive vultures, participated in the capture of free-ranging vultures and drafted the article. Rubén Portas collected carcass information in the field, drafted parts of the article and reviewed and improved the carcass detection framework. Gabriel Iita Shatumbu coordinated the capture of the free-ranging vultures and collected carcass information. Teja Curk drafted parts of the manuscript and reviewed and improved the carcass detection framework. Theresa Götz, Anne Berger and Claudine Cloete reviewed and improved the carcass detection framework. Ortwin Aschenborn collected carcass information in the field, participated in the capture of free-ranging vultures, and reviewed and improved the carcass detection framework. Jörg Melzheimer coordinated the behaviour observation of captive vultures, participated in the capture of free-ranging vultures and reviewed and improved the carcass detection framework. All authors gave final approval for the publication and contributed substantially to revisions.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The code to this manuscript and the raw ACC data with the respective behaviour labels are stored on figshare (Rast et al., 2024) (https://doi.org/10.6084/m9.figshare.25289212). The GPS tracks and the data set containing the carcass locations will be shared upon request with qualified researchers.

STATEMENT OF INCLUSION

Our study brings together authors from a number of different countries, including scientists based in the country where the study was carried out. All authors were engaged early on with the research and study design to ensure that the diverse sets of perspectives they represent were considered from the onset. Whenever relevant, literature published by scientists from the region was cited.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Data S1: Supplementary Material, Figures and Tables.

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