Data-Driven Collaborative Intelligent System for Automatic Activities Monitoring of Wild Animals

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***Abstract*— Activity profiling is key to understand individual behavior and group dynamics for a species. To date, individuals monitoring is directly performed by the ethologist, leading to several limitations in the quantity and quality of the results. In this work, we propose a data-driven collaborative system for automatic remote monitoring of wild animals, in a challenging environment, properly designed to satisfy the ethologist's needs. This smart system fuses sensors data to perform an intelligent behavior identification, allowing for automatic activity profiling. As a case study, a dataset collecting data acquired by tri-axial accelerometer and GPS applied to 26 baboons for 35 days, to identify running, walking, sitting, standing and feeding activities was used. The results obtained in terms of prediction accuracy and decision-making process interpretability show that the system can overcome the hostile environment's challenges, proving to be an effective support to perform smart remote automatic profiling.**

I. Introduction

Observing the behavior of a species, including the human one, allows to understand its needs and internal states and to infer group dynamics [1], [2]. For this to be possible, activity monitoring is necessary to collect a dataset representative enough to allow robust analysis and inference. Today, the ethologist directly observes the specimens and records their activities, choosing them from those reported in the ethogram to ensure standardizing and uniformity. An ethogram is defined as the set of behaviors proper to a given species and usually has a hierarchical structure [3]. Direct animal monitoring is expensive and time-consuming and susceptible to data tampering and human error. In fact, feeling observed, individuals behave differently than they usually do [4], [5], [6]. Besides, as the monitoring time increases, so does the possibility for the ethologist to be distracted or to delay the recording of the transitions between activities [7], [8]. Finally, as the number of individuals increases, more ethologists are required to perform the task.

With the advent of the Golden Age of bio-logging [9], more and more researchers are trying to adapt the intelligent data-driven systems widely used for the recognition of human activities, to allow automatic remote animal monitoring. These systems leverage tacking sensors data fusion to enable intelligent monitoring. The most employed sensors are tri-axial accelerometers, which already proved to be valid in human activities recognition [10]. Especially dealing with free-ranging species, also GPS data can be useful, to geolocate individuals. To date, more than 120 different species have been instrumented and monitored, e.g. [7]. Most works aim at distinguishing stationary from non-stationary behavior and are not considered in our research that aims at going more deeply into activity identification further dividing both classes. The works in literature that share this goal can be divided into cattle-related and wild-animals-related ones. The limited environment in which cattle lives can often be fully instrumented and allows to perform animal monitoring leveraging a single tri-axial accelerometer, achieving an average accuracy on a single activity of more than 94.0% [11]. Wild animals' automatic remote monitoring i much more challenging, since individuals are often free-ranging. In this context, a GPS is essential to geolocate the animal, as the area is too large to be instrumented and the sensors can not be replaced in case of damage or low battery. The maximum accuracy of predictions in this context ranges between 69.0% [12] and 77.8% [13].

The monitoring systems in the literature, especially considering wild animals-related are not yet ready to fully allow automatic functioning. We aim at demonstrating that the lack of accuracy that affects the machine-learning approaches presented in the literature is mostly due to having overlooked the preliminary processing of the acquired signals. Moreover, ethologist needs do not seem to have been taken care of in the available methods. Predictions alone, in fact, are not exhaustive without a series of additional information related to the decision-making process that overlays the predictions, which he/she would acquire directly monitoring the animals.

Therefore, we propose an accurate and interpretable collaborative intelligent system, based on sensors data fusion, time-series processing, and machine-learning models, that aims at enabling automatic remote wild animals' monitoring. This system outperforms the accuracy performances reported in literature thanks to a time-series pre-processing phase composed of:

- Equalization of the time-series' frequency resolution;
- Low-pass filtering of the high-frequency noise;
- Sensor bias removal;
- Event detection mechanism appropriately tuned to recognize inconsistent data. This technique is not used in any other work in the literature.

The main novelty we propose is to evaluate the performance of the system also with respect to its interpretability, aiming to explain the decision-making process behind the predic-

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tions. This goal is achieved through:

- The selection of features that are logically correlated with the activities to be recognized;
- A classification model in line with the ethogram's structure. This model hierarchically combines many classifiers, each of which corresponds to a split node in the ethogram;
- A features ranking scheme based on the importance they had in the decision-making process. This ranking is returned to the ethologist, to help him/her knowing the system's decision-making process.

As a case study, we considered a dataset that collects time-series measured on 26 Olive baboons instrumented with a collar equipped with a tri-axial accelerometer and GPS. The obtained results show that the system we developed outperforms the state of the art by an accuracy lift about 10%. Also, it is easily interpretable and user-friendly. Therefore, it represents a valid solution able to perform automatic remote animal monitoring, allowing the ethologist to devote himself to the phases of inference and analysis without renouncing to the information he/she would have acquired performing a direct observation.

This paper is organized as follows: Section II describes the dataset analyzed as a case study and the techniques leveraged to clean the raw time-series provided. Then, Section III describes the approach to perform features extraction and the criteria for their selection. Section IV show the architecture of the classification model produced. The obtained results and the evaluation metrics are exposed and discussed in V. The conclusions are reported in VI.

II. Dataset and Pre-Processing

This section shows the structure of the dataset used as a case study, highlighting its main peculiarities. Then, the techniques used to pre-process the data are presented.

A. Dataset Structure and Challenges

The dataset analyzed as a case study collects the time-series measured by instrumenting 26 olive baboons from August 1st to September 4th, 2012, at the Mpala Research Centre, in Laikipia County, Africa. Each baboon was equipped with a collar that embeds a tri-axial accelerometer and GPS, as reported in 1.

Fig. 1. Instrumented Baboon. Each monitored baboon was equipped with a collar that embeds a three-axial accelerometer and a GPS. This image has been retrieved from [14].

The first sensor operates at 12Hz and provides one time-series for each of the measured axes, the second at 1Hz and measures speed, heading, latitude, and longitude. Measurements were taken from 6 a.m. to 6 p.m., while night hours were used to download the collected data. In total, the dataset contains 220 hours of observation, of which only 4 are labeled. The labeling process was carried out by the ethologists using videos, then collecting their labels and performing a majority voting. The Crofoot Lab was responsible for both data collection and labeling process. The activities used as labels were chosen from those proposed by the reference ethograms, shown in Figure 2. For each activity instance, two labels were provided, one from each ethogram. The first is related to the individual positional states, divided into *stationary* and *non-stationary* and further in *sitting* and *standing at rest*, and *walking* and *running*. The second ethogram contains the individual activity states, divided into *feeding* and *non-feeding*. Both the dataset and the ethograms are retrievable from [15].

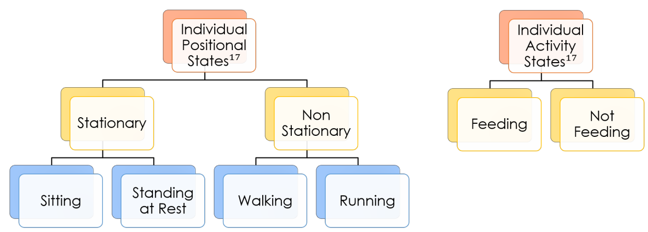

Fig. 2. Ethograms for Individual Positional States and Individual Activity States for Olive Baboons. This figure shows the ethogram for the individual positional state (left), and for the individual activity state (right).

The dataset is strongly unbalanced, as it often happens with wild animals' monitoring. The percentage for each class reflects the normal behavior of the species, which often tend to adopt behaviors aimed at minimizing energy expenditure [16]. Also, the dataset is affected by a decreasing trend of baboons recorded per day, starting from 26 on August 1st to 1 on September 4th. Considering the individual positional states observed overall, it turns out that the non-stationary states are 13.9% of the dataset and running is only 0.9% of the total observations. Considering individual activity states observed overall, feeding represents 51% and non-feeding 49%. However, Table I and Table II show that, analyzing the observations recorded for each baboon and on different days, both individual positional and activity states are strongly unbalanced among different individuals.

B. Pre-Processing

Each activity can in principle be reconstructed from 7 time-series. However, not all of them are informative for classification purposes. So that GPS latitude, longitude and heading are discarded. Then equalization of the time-series

TABLE I
BABOONS LABELS DISTRIBUTION FOR INDIVIDUAL POSITIONAL STATE LABEL.

Collar ID	Individual Positional State			
	Sitting	Standing at Rest	Walking	Running
2426	51.55%	29.15%	17.33%	1.97%
2427	77.09%	7.11%	14.46%	1.34%
2428	58.82%	✗	41.18%	✗
2436	95.75%	3.30%	0.95%	✗
2443	80.40%	6.46%	13.14%	✗
2447	100.00%	✗	✗	✗
2449	76.34%	2.23%	20.09%	1.34%
2451	60.07%	18.90%	20.41%	0.62%
2454	54.29%	10.00%	31.90%	3.81%
2457	86.64%	3.31%	9.11%	0.94%
Average	68.5%	13.0%	17.6%	0.9%

TABLE II
BABOONS LABELS DISTRIBUTION FOR INDIVIDUAL ACTIVITY STATE LABEL.

Collar ID	Individual Activity State	
	Feeding	Non-Feeding
2426	83.24%	16.76%
2427	66.47%	33.53%
2428	✗	100%
2436	2.83%	97.17
2443	71.05%	28.95
2447	✗	100%
2449	37.50%	62.50%
2451	30.82%	69.18%
2454	98.10%	1.90%
2457	45.38%	54.62%
Average	51.00%	49.00%

frequency resolution is performed. Since the individual positional and activity states labels are given at one second intervals, the frequency of the labeling process is 1Hz. As the accelerometer works at a sampling frequency of 12Hz, the three related time-series are down-sampled. Note that GPS speed is already sampled at 1Hz, so no downsampling is needed.

A spectral Analysis of the time-series is performed, revealing high frequency noisy harmonics superimposed to the signal. For this application, time-series filtering is performed leveraging two 2nd-order cascaded low-pass Chebyshev whose cutoff frequency was set to 0.6Hz. This filters family was chosen due to the zero transition band and reduced ripple amplitude. The zero frequency harmonic is removed, as it is mainly due to sensor bias. Filtering procedure and its effect on the time-series is reported respect with both time domain and frequency domain (Figure 3 and Figure 4).

The most relevant pre-processing stage deals with the classification of inconsistent labels/activity pairs. Since the individual positional states ethogram distinguishes stationary and non-stationary activities, we have chosen to base the algorithm on the analysis of the speed provided by GPS. To detect possible mislabeling, an event-based algorithm is used. More specifically, an upper and lower-bound on the speed are used to classify instances that cannot be physically associated to either stationary ($v > 1.75\frac{m}{s}$) or not stationary ($v < 0.2\frac{m}{s}$) state. As shown in Figure 5, the thresholds are extremely loose so as to highlight only the anomalous instances.

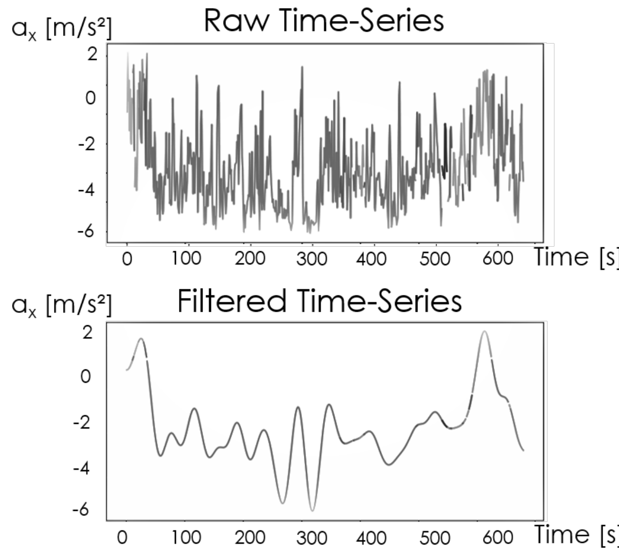

Fig. 3. Raw and Filtered Time-Series in Time Domain. This figure shows a window of a raw time-series (top), and the filtered version (bottom).

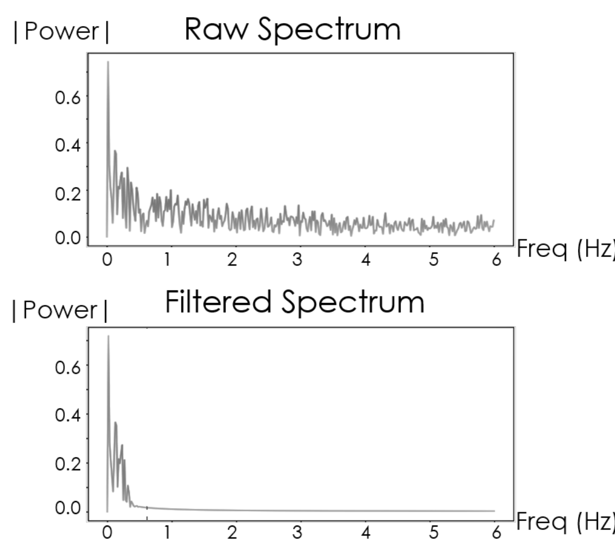

Fig. 4. Raw and Filtered Time-Series in Frequency Domain. This figure shows the spectra of a window of a raw time-series (top), and the filtered version (bottom) .

The output of this algorithm will then be used to train a binary classifier to recognize anomalous instances, preventing them from being attributed to an incorrect class. Note that the inconsistencies detection is performed only on the training set and to possibly correct the label for evaluating the classifier performances on the test set.

III. FEATURES EXTRACTION AND SELECTION

The four processed time-series, i.e., three axis from the accelerometer and the speed from the GPS, are used to extract new features. In particular, the system extracts:

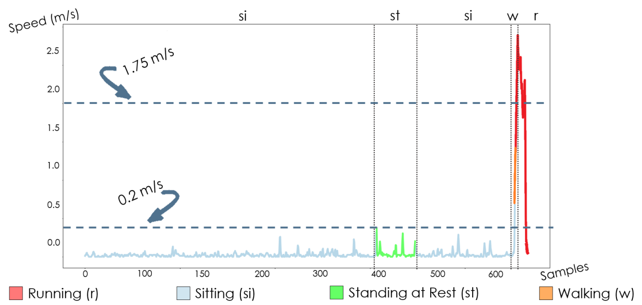

Fig. 5. Inconsistency Detection. The figure shows the two threshold set on the speed and the respective constraints used to enhance the presence of inconsistent samples.

- The acceleration norm

$$|a| = \sqrt{|a_x|^2 + |a_y|^2 + |a_z|^2}. \tag{1}$$

- The acceleration ratios

$$v = \left[\frac{a_x}{ay}, \frac{a_y}{az}, \frac{a_x}{az}\right]. \tag{2}$$

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Those features account for the overall energy of the movements, and for the relative influence of each direction involved, respectively. As reported in Figure 6, all the features were correlated to the labels, so none of them were discharged.

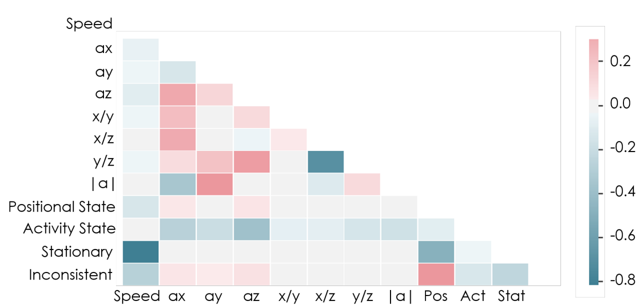

Fig. 6. Correlation Matrix Features vs Labels.

IV. Activity Classification

To ensure interpretability, we develop a hierarchical structure composed of several classifiers, one per split node of the reference ethogram for the considered species. The algorithm we choose to implement each of the classifiers that constitute the hierarchical model is XGBoost, state of the art for the boosted trees algorithms [17]. A boosted algorithm combines several weak learners, which together contribute in determining the prediction. In a boosted trees-based classifier, the function used to define the first tree is:

$$F_o(x) = \arg\min \gamma \sum_{i=1}^{n} L(y_i, \gamma) \tag{3}$$

where γ allows the model to generalize, preventing overfitting. The following trees are computed as:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x) \tag{4}$$

The function that defines each single tree is computed as the first derivative of the loss function r_{im}:

$$r_{im} = -\alpha\left[\frac{\partial(L(y_i, F(x_i)))}{\partial F(x_i)}\right] \tag{5}$$

Where y_i is the target variable and α is the learning rate. The result is a classifier composed of many interpretable and shallow trees, each trained to minimize the classification errors of the previous one.

Three classification models have been designed combining multiple boosted trees classifiers:

1) Inconsistencies detection. Composed of a single binary classifier, trained to recognize the inconsistent instances, based on the labels obtained as the output of the event detection algorithm. This model will replace the event detection algorithm in the final system.
2) Individual positional states autonomous classification. It consists of three binary classifiers. The first is trained to divide the instances between stationary and non-stationary ones; the second divides stationary behavior into sitting and standing at rest, while the last divides non-stationary behavior into walking and running.
3) Individual activity states classification. It is composed of a single classifier that defines whether the observations are related to feeding or non-feeding behavior.

In addition,for each classifier was extracted a ranking for the 8 proposed features, based on the importance they had in determining the predictions. This metric has been measured leveraging the F-Score, available from XGBoost library. It represents the ratio between the number of times a feature is used as a split criterion and the total number of splits in the classifier. This was essential in order to obtain a smart system with embedded intelligence that, unlike those in the literature, is easily interpretable, providing to to the ethologist not only the predictions, but also additional information on the decision-making process.

V. Experimental Results

This section reports the results achieved by applying the proposed system to the available labeled data.

Since the dataset is strongly unbalanced, we consider as reference metrics:

- Accuracy, i.e. the percentage of positive classifications that are correct

$$acc = \frac{tp + tn}{tp + fp + fn + tn}; \tag{6}$$

- Recall, i.e. the percentage of positive elements that have been classified as positive

$$rec = \frac{tp}{fp + tp}; \tag{7}$$

- Specificity, i.e. the percentage of negative elements that have been classified as negative

$$spe = \frac{tn}{tn + fp}. \tag{8}$$

The validation was carried out by 10-fold cross-validation, using 70% of the dataset for training and 30% for testing. Their compositions were randomly changed at each iteration. Classification models performance, in terms of accuracy, recall and specificity respect to 10-fold cross-validation are reported in Table III. Table IV compares our approach with the state of the art. It turns out that our automatic remote animals' monitoring system identifies all the activities in the ethograms more accurately than existing solutions. The highest improvement is recorded on the individual positional states, where our model gains 10% of accuracy with respect to existing ones.

TABLE III
QUANTITATIVE CLASSIFIER PERFORMANCE.

Behavior	**Metrics**		
	Accuracy (%)	Recall(%)	Specificity(%)
Stationary Non-Stationary	100 ± 0.02	100 ± 0.02 100 ± 0.03	100 ± 0.04 100 ± 0.03
Sitting Standing at Rest	90.0 ± 0.7	90.5 ± 0.5 84.8 ± 0.5	98.4 ± 0.1 45.8 ± 1.5
Walking Running	99.0 ± 1.0	98.9 ± 1.7 99.0 ± 1.7	90 ± 1.8 83.3 ± 1.2
Feeding Non-Feeding	87.9 ± 0.4	87.6 ± 1.1 88.6 ± 0.7	88.5 ± 2.1 $87.2 \pm .8$
Consistent Inconsistent	89.0 ± 0.9	90.7 ± 1.4 76.6 ± 2.6	96.7 ± 1.7 52.5 ± 3.1

The classifiers used to recognize individual stationary positional states and individual activity states are those whose accuracy performances are the lowest. We believe this is due to the positioning of the sensors. The patterns related to neck movement in these activities do not seem sufficient to allow for better accuracy in predictions. It would be useful to provide the model with additional information, such as time-series measured by an accelerometer placed on a front limb of the animal. The challenge introduced by the unbalance of the dataset has been optimally managed, thanks to the correct processing of the time-series. All the metrics concerning the correctness of predictions related to non-stationary behavior and in particular to running, the classes that are less represented in the dataset, show excellent results.

Considering the ranking of the features produced by each classifier, is it possible to assess that the provided collaborative data-driven intelligent system reports a series of additional information useful and supportive for prediction purposes. F-Score computed for each feature in the decision-making process of the different classification models is reported in Table V.

As can be seen, the inconsistencies classifier bases its predictions mainly on the speed, features used by the event detection algorithm, but also on accelerations. So, the pattern given by the provided features is enough to let the classifier understand if the speed is affected or not by a GPS failure. This makes the provided data-driven intelligent system robust to GPS failure by recognizing the inconsistency between speed values and accelerations, it identifies anomalies in new observations and informs the models aimed at identifying individual states that the value sampled by the GPS is not a reliable predictor. The classifier aimed to distinguish between stationary and non-stationary observations bases its predictions almost entirely on speed, exactly as the ethologist would do when directly performing animals' monitoring. The distinction between walking and running is strongly influenced by speed but also considers acceleration. Although they have a common speed range, in fact, the locomotive dynamics of the two behaviors, related to the acceleration pattern recorded at the neck level, are different. The decision-making process aimed at recognizing sitting and standing at rest, on the other hand, neglects speed. This is reasonable, considering that both activities are stationary. Feeding and non-feeding, instead, are identified considering both speed and acceleration. Dependence on speed reveals a well-known relationship, i.e., that the faster the individual is moving, the less likely it is to be eating. The dependence on the acceleration norm, instead, is due to the positioning of the sensors, embedded in the collar. In fact, as shown in Figure 7, the repetitive movement of the neck during the act of eating gives rise to characteristic patterns for that activity.

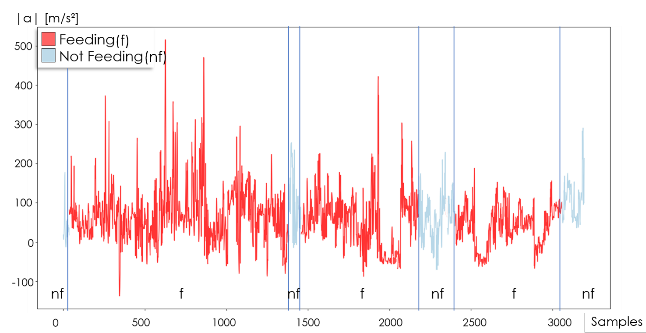

Fig. 7. Acceleration Norm and Labels: individual activity states.

Choosing features closely related to the activities to be identified and consistent with those used by the ethologist when directly performing animal monitoring, has allowed us to obtain a data-driven intelligent system that is easily interpreted. In this way, this automatic remote animals' monitoring system is able to meet its end-user needs. In fact, it provides to the ethologist the additional information related to the dynamics underlying the decision-making process, which would be lost using the data-driven systems currently in the literature, which return only the predicted labels.

VI. Concluding Remarks

This paper presented a data-driven intelligent system that allows automatic remote animals' monitoring with activity-classification capabilities. Its design proved that wearable sensors can indeed be used also to monitor the behaviour of wild animals with great accuracy. The proposed method was designed to support ethologists by offering an easily interpretable tools that stems from their description of the animals activity using ethograms. Current work is being devoted to apply the designed classifier to non-labeled measurements, taken over a longer time horizon, and extract from them a richer description both the individual and group behaviors

TABLE IV

COMPARISON OF THE CLASSIFIER PERFORMANCE WITH RESPECT TO THE STATE OF THE ART.

Recognized behavior	Accuracy		
	Our Approach	Wang et al. [12]	G.Muscioni [13]
Stationary vs Non-Stationary	100%	✗	85.75%
Sitting, Standing at Rest, Walking, Feeding	94.50%	69.00%	82.90%%
Feeding vs Non-Feeding	87.90%	63.70%	86.30%%

TABLE V

F-SCORE OF THE FEATURES USED BY THE OPTIMAL CLASSIFIER.

Considered Classifier	Features							
	$Speed$	$\|a\|$	a_x	a_y	a_z	$\frac{a_x}{a_y}$	$\frac{a_x}{a_z}$	$\frac{a_y}{a_z}$
Consistent vs Non-Consistent	97.0%	17.4%	17.0%	17.3%	17.4%	17.3%	17.5%	17.5%
Stationary vs Non-Stationary	98.4%	1.4%	1.2%	1.4%	1.4%	1.4%	1.2%	1.1%
Sitting vs Standing at Rest	33.3%	97.6%	52.0%	59.2%	59.5%	62.2%	92.5%	70.5%
Walking vs Running	98.1%	41.9%	36.2%	✗	19.4%	12.8%	✗	25.9%
Feeding vs Non-Feeding	98.2%	33.4%	29.5%	27.4%	45.1%	90.0%	31.0%	39.0%

of the animals, leveraging the classification accuracy and the more realistic nature of the data that are collected without the presence of humans, which may alter the animals natural behaviour.

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