Article

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From Captive to Wild Jaguars: Automated Behavioral Classification and Space Use Monitoring with Machine Learning

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Simple Summary

Animal welfare can be estimated by assessing the behavior of captive animals through the lens of a behavioral baseline from wild conspecifics. However, manual assessments of animal behavior can be time-consuming and prone to bias. In this study, a machine learning model was trained with LabGym on footage of three captive jaguars to automatically track activity and inactivity from footage of the same three captive jaguars (*Panthera onca* Linnaeus, 1758) and from footage of wild jaguars. Additionally, heatmaps for visualizing space use were created based on the automatic tracking of the three captive jaguars. The captive jaguars exhibited mostly inactive behavior, and they did not exhibit natural bimodal nocturnal or crepuscular hunter activity patterns. Furthermore, the captive jaguars showed clear patrolling behavior in their enclosure. Moreover, the machine learning models showed promising results when testing their accuracy. Therefore, machine learning methods appear to be a promising tool for examining behaviors and space use of captive jaguars, and for inferring behaviors of wild jaguars when trained on footage of captive conspecifics. This might be valuable for saving time and reducing bias, which can lead to enhanced animal welfare and conservation.

Abstract

Monitoring both captive animals and wild populations is necessary to ensure adequate animal welfare and conservation. This could be achieved via camera traps, yet it could prove time-consuming and labor-intensive if handled manually. In this regard, machine learning (ML) is an active topic of scientific development. Here, ML models were made with LabGym and trained on footage of three captive jaguars to detect individuals and assess active and inactive behavior for both wild and captive jaguars in Bigai, Ecuador, and Randers Regnskov, Tropical Zoo (Randers Regnskov), respectively. The space use of the captive jaguars was also assessed. Footage of wild jaguars was received from camera traps in Bigai, and 123.8 hours of video footage were recorded of the enclosure in Randers Regnskov with three captive jaguars over 6 consecutive days. The ML model for individual recognition analyzed all videos from Randers Regnskov containing jaguars on November 1st, 2025, and another ML model trained to detect wild jaguars analyzed 67 videos from Bigai. The ML model showed clear patrolling behavior for captive jaguars on heatmaps. Captive jaguars exhibited a large amount of inactive behavior. Captive jaguars did not exhibit natural bimodal nocturnal or crepuscular hunter activity patterns. The ML model also showed promise in inferring behaviors of wild jaguars when trained on footage of captive jaguars. The results demonstrate that ML methods can provide a valuable tool in detection, behavior classification, and monitoring of space use.

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1. Introduction

1.1. Ecology and Conservation

The jaguar (*Panthera onca* Linnaeus, 1758) is the largest predator in its home ranges [1,2]. The natural home ranges of this opportunistic apex predator include northern Mexico to northern Argentina, where it mostly lives in tropical or subtropical forests [1,3–6].

The jaguar is listed as near threatened on IUCN's Red List and with a general decreasing population [7], where local populations of jaguars are critically threatened [6]. Its historic range has been reduced by about 50%, mainly due to habitat loss and fragmentation caused by anthropogenic actions. In addition, high food requirements and wide-ranging behavior combined with prey depletion elicit conflicts with humans and livestock, which leads to persecution of the jaguar [6,8–11]. The loss of jaguars in an area may have significant consequences with cascading effects [9].

Conservation of jaguars is essential for maintaining ecosystem integrity and biodiversity within their habitats, thereby safeguarding numerous co-occurring species [2,9,12]. It is essential to understand the jaguars' behavior and way of life for the management of their populations [13,14], and to predict how disturbances, for example, habitat loss and fragmentation, might influence the jaguars [15–18]. Studying the behavior and welfare of wild felines may be a challenge due to difficulty in localizing them in dense forests, low population densities, or avoidance of humans [1,15,19]. Camera traps and GPS technology have shown to be valuable in assessing Neotropical felids, such as jaguars, for evaluating their population sizes, densities, and movement ecology [1,20–24].

1.2. Welfare of Jaguars in Captivity

Animal welfare is about the well-being of animals [25], and it is an important ethical aspect of keeping animals captive and monitoring wild animals for conservation purposes [19,25–29]. Animal welfare often depends on the naturalness of their living conditions, meaning that welfare is assessed using a wild conspecific behavioral baseline [19,25,26,28–30]. For example, studies on behaviors in wild jaguars concluded that jaguars are solitary and have large home ranges with sex-specific variation, with males having a tendency for larger ranges and a tendency to move larger distances per day than females [11,31–34]. To achieve high welfare in captive animals, it is not necessarily better to fully mimic wild conditions but instead provide positive natural aspects and withhold some natural stressors like violent fights, as they are not wanted in captive settings [25,28,29]. For example, conventionally solitary animals, and potentially also the jaguar, may benefit from being part of a group in captive conditions as it heightens social complexity, stimuli, allows positive social behaviors, and reduces the risk of stereotypies [26,28,29,35,36]. Collaborative behaviors through potentially long-lasting coalitions have been observed in the wild among male jaguars, as well as other social interactions between both sexes, indicating that social groups are more natural than previously thought [37,38].

If jaguars in captivity are unable to express basic wild behaviors, e.g., walk, climb, and swim, they can become stressed and frustrated, which can lead to aggression and stereotypic behaviors such as pacing [26,28–30,39]. Another negative aspect of captivity for jaguars is increased inactivity both day and night compared to their wild conspecifics, which, when excessive, might result from lethargy, disease, or a stressful situation with low animal welfare [25,30,40,41]. To increase animal welfare, the implementation of enrichment and increased enclosure size and complexity can be an effective way to reduce the amount of time spent on stereotypical behaviors and inactivity. Instead, more time is spent on positive and activity-related behaviors [26,28,29,42].

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1.3. Activity Budgets

Activity budgets are used for examining the behavioral patterns of both wild and captive animal species to determine if they spend an excessive, normal, or inadequate amount of time on each behavior [25,30,34,43–45]. Activity budgets are also used for examining daily behavioral activity patterns and amounts throughout the 24 hours of the day. Hence, activity budgets are also an opportunity to compare the behavioral pattern of captive animals with that of wild animals to determine their naturalness, which can be a part of suggesting the welfare state [25,30,43–46]. For example, wild jaguars have different movement activity patterns and levels throughout the 24 hours of a day depending on their age, sex, and reproductive status, with the average being 11.7 hours of activity per day [34]. Another study found that a wild female jaguar was active for two-thirds of the day [24]. Furthermore, jaguars are mostly nocturnal and crepuscular, but activity patterns vary between individuals [31,34,40,47]). Activity budgets can be used as a part of assessing welfare through a behavioral assessment by knowing when and how much time is spent on positive and negative behaviors. In this regard, it is important to know the amount of time spent on stereotypies and inactivity, and at what time of day these are expressed [25,30,43–46]. However, there is uncertainty in deciding whether an expressed behavior is positive or negative [30]. For example, inactivity can be because the animal is content and resting, or it can be due to boredom, or it might be indicative of lethargy if excessive and associated with low behavioral diversity [30,41,48]. Furthermore, some behaviors, such as aggressive interactions, may have very negative effects on welfare even if they are brief [30]. Although, aggressive behaviors can also be difficult to assess the negativity of, as they can be part of maintaining a social hierarchy or other social interactions [49,50]. However, it should be noted that animal welfare cannot be assessed only with a behavioral assessment, as it should be assessed with a holistic approach that includes the parameters of the Five Domains (nutrition, environment, health, behavior, and mental state) [51].

1.4. Machine Learning

Machine learning (ML) is an active topic of discussion that is undergoing rapid scientific development, and could be applicable for many different cases, such as monitoring a species, their behavior, or space use, both in captivity and in nature [52–57]. Camera traps enable non-invasive monitoring of wildlife, yet their application has the potential to generate millions of images [58]. The benefit of ML is its adaptability and trainability, enabling it to handle some of these intractable or labor-intensive tasks [52]. The goal of training a model or algorithm is to improve its performance, which is its predictive accuracy on novel data. This is achieved by giving the model experience through repetitive training on varied data [52]. A ML model can be trained to correctly identify, track, and assess an animal's behavior and therefore aid in the automation of behavioral analysis and assessments [53,55,59]. Typically, behavioral assessments could be done manually using videography with human observations and judgments [55]. This method can, however, be highly time-consuming and can potentially lead to unforeseen problems regarding bias, subjectivity, or an observer's inability to properly assess a behavior. Some of these logistical problems might be aided with the usage of ML, as it offers a more objective and standardized way to assess behaviors [55]. ML has seen extensive scientific usage and testing on a variety of captive or wild animals' behavioral and spatial assessments [52,54,55,57,60,61]. Machine learning has also been shown to infer wildlife behaviors from acceleration data of captive animals [53,54,62], thus indicating the potential usage of machine learning for inferring wildlife behavior from captive animals, which may also be possible with video footage instead of acceleration data.

LabGym [63] is a computational tool using ML with a deep neural network (DNN) and a holistic approach to assess both "pattern image" (an animal's motion pattern) and "animation" (an animal's spatiotemporal details of a behavior) from video footage [63]. These elements, coupled with quantitative measurements and thorough training, enable accurate recognition of behaviors across a wide range of species. LabGym possesses three main modules consisting of Preprocessing, Training, and Analysis [63]. The Preprocessing module allows for video enhancement, trimming, and other pre-processing steps. The Training module is used to teach LabGym to recognize an animal or object, using either background removal or a trained detector, as well as to recognize an animal's behaviors, using the categorizer [63]. Here, another software like Roboflow may be used beforehand for video annotation to make use of a detector, rather than background removal [64]. Finally, the Analysis module is used to track, identify, and quantify the behaviors as well as display any significant findings [63]. It is still, however, paramount that thorough and diverse training of both the detector and categorizer is done to assure accurate predictions even amidst changing environments, camera shifts, occlusions, etc., to maintain the model's precision [57,65].

1.5. Aim of This Paper

The aims of this study are to develop ML tools to assess the behavioral activity of captive and wild jaguars, and to assess the capability of ML in examining the space use of captive jaguars.

2. Materials and Methods

2.1. Data Collection, Animals, and Enclosure

Two types of footage were used in the creation of this study. Firstly, 2,257 videos of about 15-30 seconds of animals recorded with 51 camera traps were received from Bigai, which is a nature reserve in Ecuador that Randers Regnskovs Naturfond ("Randers Rainforest's Wildlife Foundation") has worked to preserve since 2012 [66]. The videos were captured from a variety of camera models (ALPHA, alphacamhunt.com, COOLIFE, coolifepro.com, BUSHNELL, bushnell.com, and USOGOOD, usogood.co). Out of these, 70 videos of wild jaguars caught in camera traps were used.

The other type of footage was acquired by filming the jaguar enclosure in Randers Regnskov, Tropical Zoo ("Randers Rainforest, Tropical Zoo") (Randers Regnskov) in Denmark. In this study, the behaviors and space use of three captive jaguars were analyzed. These were Chica, the melanistic mother, Bentor, the father, and Sibba, their cub (Table 1). Their diet consists of varied meats, for example, deer or goat. They are fed 17 kg in total outside every Tuesday at 13:30 and Saturday at 13:00. At feeding time, the male jaguar is separated from the female and the cub as a precaution to avoid potential fighting, as jaguars are naturally solitary and food dominant.

Table 1. Summary of information regarding the three captive jaguars (*Panthera onca*) in Randers Regnskov, Tropical Zoo (Randers Regnskov), Denmark.

Name	Sex	Age (years)	Phenotype (Coat)	Born	Time at Randers Regnskov (years)	Parents
Chica	Female	11	Melanistic	Skærup Zoo in Denmark in 2014	11	-
Bentor	Male	5	Wild-type	Loro Parque in Tenerife in 2019	4	-
Sibba	Female	1	Wild-type	Randers Regnskov Denmark in 2024	1	Chica and Bentor

The enclosure is separated into two inner and two outer areas. The two areas of the outdoor enclosure total about 769 m^2 (Appendix A.1) and are surrounded by netting that allows guests to view inside. The outdoor enclosure also includes varying amounts of foliage, a tin roof atop a hilltop for sunbathing, a brook, and a small pool that allows for swimming. A cabin and a small excavator have also been placed for added decorations. The inner stable enclosure totals 49.9 m^2 (Figure A2) and is made to look like the inside of a cabin with a table in the middle of the room, constructed of an open wooden crate, and a bunk bed, cabinet, chest, and a big glass window for the guests to look through. Lastly, there is also a backstage area not visible to the public. Unless there was a need to close off certain parts of their enclosure for management purposes, e.g., for feeding or cleaning, then the jaguars could move freely between all areas of the enclosure – both day and night.

The jaguars were video recorded continuously at 15 FPS and at a frame size of 1296x2304 pixels with three cameras (Hunters Choice LPV Live Panorama Vildtkamera, guntex.dk) for 6 days in 2025 from October 30th 11:25 to November 4th 15:18. The positions of the cameras were chosen in collaboration with the zookeeper to have them pointed at locations where the jaguars tended to spend a lot of time or used for moving around when patrolling their enclosure. This would ensure as little occlusion as possible for such a large enclosure with potentially many blind angles. However, large areas of the enclosure remained out of view. One camera was placed indoors in the jaguar stable, two cameras were outside, one pointing at a roof that the jaguars like to relax on and a flat grassy area that functions as a connection point between the two outside areas of the enclosure, and the other pointing into vegetation with a path and a small brook (Figure 1).

Figure 1. The three camera angles that were used to film the enclosure in Randers Regnskov, Tropical Zoo. The captive jaguars were annotated as ‘Bentor’ (turquoise), ‘Chica’ (purple), and ‘Sibba’ (pink) in Roboflow. The letters in the corners indicate the camera angles: (**a**) Angle from camera a) outdoors, pointing into vegetation with a path and a small brook; (**b**) Angle from camera b) outdoors, pointing at a roof and a flat grassy area that functions as a connection point; (**c**) Angle from camera c) indoors in the jaguar stable.

During the filming period, there was a mix of rainy, cloudy, and sunny weather, and the temperature ranged from 11-13 °C in the daytime and from 3-10 °C at nighttime. The video recordings of the captive jaguars resulted in 123.8 hours of video that were split into shorter videos of about 2-3

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minutes on average by the cameras themselves. The jaguars were only visible in around 24.2% of the videos recorded.

The ML model was trained in the behaviors described in the ethogram that was developed for this study (Table 2). Although, it must be noted that the ethogram more closely resembles categorizations than actual behaviors. The jaguars were initially observed manually and their behaviors were noted. However, as the ML model struggled with classifying more advanced behaviors, it was chosen to instead create two categorizations to examine active and inactive behaviors. These categorizations will henceforth be denoted as behaviors in an ethogram. The model was then used to analyze behaviors through continuous focal sampling and plot coordinates of the centers of the individuals for the creation of heatmaps. Both behaviors were treated as states [67].

Table 2. Behavioral ethogram used in this study for jaguars in captivity in Randers Regnskov, Tropical Zoo, and in the wild in Bigai.

Behavioral categories	Definition
Active	Jaguar has major movements of either the entire body or one or more individual body parts. Includes behaviors such as mating, running, jumping, walking, swimming, playing, and pacing.
Inactive	Jaguar can be lying, sitting, or standing with no major movements of individual body parts. Includes minor postural adjustments such as head tilting or weight shifts.

2.2. Development of Machine Learning Model

LabGym (Version 2.9.6) [63] was used to create the detectors and categorizer for behavioral and space use assessments (Figure 2). For the creation of the detectors and categorizer LabGym's Extended User Guide [68] was used for guidelines.

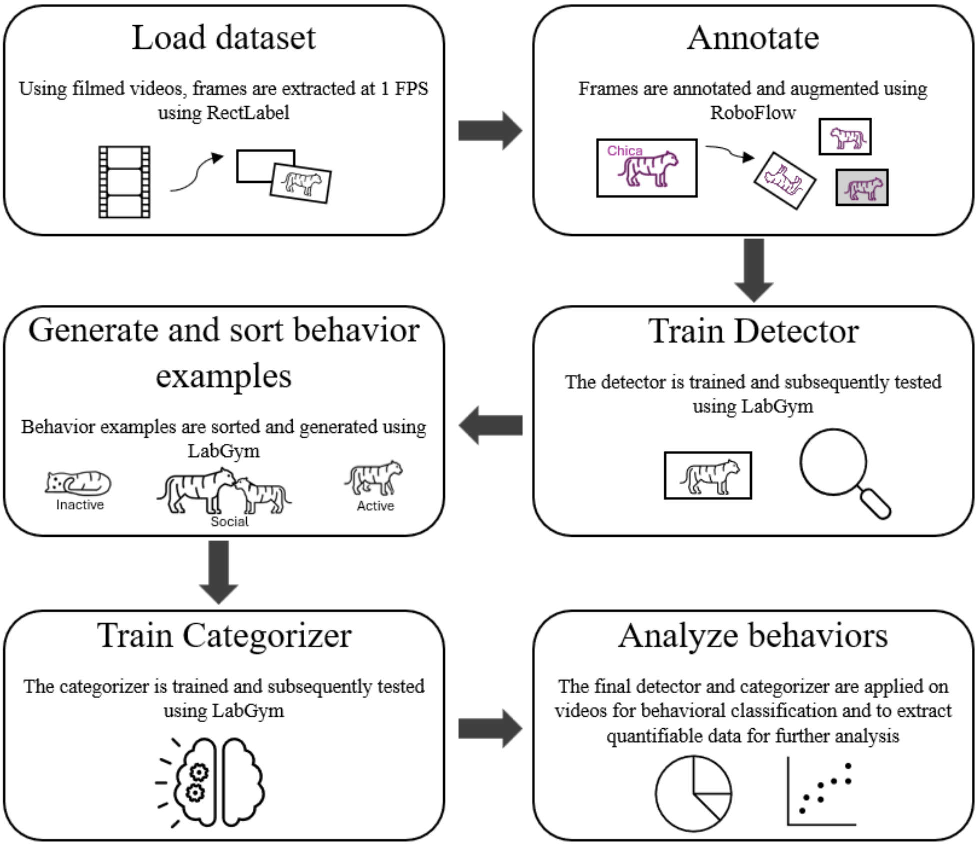

Figure 2. Illustrative pipeline used in this study for training machine learning models to both detect jaguars and assess their behaviors [69].

Initially, a dataset was created by extracting frames at 1 FPS from videos of both the wild and captive jaguars using the program RectLabel [70]. These frames were then manually annotated in Roboflow using "Instance segmentation" [71].

In this study two different detectors were trained, one for the captive jaguars and one for the wild jaguars in Bigai. To train the detector to perform individual recognition in the captive jaguars, annotated each individual jaguar present in a frame was annotated as either 'Bentor', 'Chica', or 'Sibba' (Figure 1). As jaguars have individually recognizable pelage patterns, individual recognition would be possible [20,72].

It was important that a sufficient number of individual and varied frames were included so that the detector would be able to spot and correctly identify jaguars in unseen videos. It was also important to show varied angles and frames that would include different behaviors. Frames without jaguars were also included in the training and testing images for the detector. The wild jaguar detector was instead annotated by either wild-type or melanistic coat color. This means that, whereas 'Bentor' and 'Sibba' would be annotated as 'Jaguar', 'Chica' would be annotated as 'Panther'. Frames containing a bisected silhouette of a jaguar were excluded from annotation for both detectors due to the outline consisting of multiple polygons, which may cause erroneous detections. Of the total annotated images, 3,091 images were used for training both the captive jaguar detector and the wild jaguar detector (80%), and the last 773 images (20%) were used for testing purposes (Table 3). Bentor was annotated 1,223 times, Chica 1,879 times, and Sibba 1,613 times. The training frames underwent additional augmentation using flip (horizontal and vertical), blur (up to 2.5 px), noise (up to 0.1% of pixels), and brightness (15% darker and 15% lighter), and the number of training frames was scaled up 5x to create a dataset version with 15,455 images. This dataset version was then used to train both detectors in LabGym with an inferencing frame size of 1296 pixels and 20,000 iterations, and resulted in the highest mean average precision (mAP) of 83.96% for the captive jaguar detector, when tested on the testing frames of the captive jaguars (Table 3) [63]. The wild jaguar detector achieved a mAP of 49.26% when tested on 321 annotated frames from videos from Bigai, with 210 instances of wild-type jaguars annotated as 'Jaguar' and 53 melanistic jaguars annotated as 'Panther' (Table 3). However, when looking through the testing results, the detector often correctly detects the wild-type jaguars as 'Jaguar' and the melanistic jaguars as 'Panther' with 100% confidence. The problem seemed to be that the detector had many false positives, as it detected vegetation as jaguars (Figure 3).

Table 3. Summary of the development and use of the detectors and categorizer, including precision parameters, such as mean average precision (mAP), of the detectors and categorizer used to assess either captive or wild jaguars. Furthermore, the number and proportion of training and testing frames for both detectors, number of training examples for the categorizer, and number of successfully analyzed videos are included.

Detector	Training frames	Testing frames	Final mAP	Number of training examples	Categorizer	Precision, recall, and F1-score	Number of successfully analyzed videos
Specific to captive jaguars	3,091 (80%) *	773 (20%)	83.96%	Active: 1,157, Inactive: 943 **	Active and inactive behavior **	Active: 0.92 Inactive: 0.90	326
Specific to wild jaguars	3,091 (80%) *	321 (100%)	49.26%	Active: 1,157, Inactive: 943 **	Active and inactive behavior **	-	67

* The same training frames of the captive jaguars were used for both detectors. ** The same categorizer was used for all analysis regardless of detector.

Figure 3. Examples of detections by the wild jaguar detector on the testing frames from Bigai. The following variants of detections are shown: (**a-c**) Correct detections with 100 % confidence; (**d-f**) False positive detections of vegetation or background; (**g**) A frame with several detections on the same jaguar; (**h**) A frame with missing detection; (**i**) An incorrect detection with 100 % confidence.

To train the categorizer to recognize behaviors in captive and wild jaguars, the videos were first pre-processed using LabGym to only contain footage with visible captive jaguars. Next, behavior examples and pattern images were generated for each individual as 1 second videos (15 frames) that were sorted based on the ethogram. Behavior examples where the detector had detected something that was not the specified individual were discarded and not used to train the categorizer. The resulting behavior examples and pattern images were reduced to a size of 512x512 pixels to generate 1,157 'active' and 943 'inactive' training examples for training the categorizer (Table 3).

Lastly, an "Interact advanced" type categorizer was created to recognize the sorted behaviors with the highest network complexity of 7 for both animation analyzer level and pattern recognizer level. The input shape was chosen to be 32 for both the animation analyzer and the pattern recognizer. 15 frames were used for an animation and pattern image. The background and body parts were included. An interaction distance of 0 and a standard deviation of 25 were chosen. Finally, the training examples and validation data were augmented by LabGym using the default settings. This categorizer was subsequently tested to assure its capabilities in predicting the correct behavior and achieved a sufficient precision, recall, and F1-score of 0.92 for active behavior and 0.90 for inactive behavior tested on 2,100 sorted behavior examples of the captive jaguars (Table 3).

2.3. Use of Machine Learning Model

Firstly, a day's worth of videos from the jaguar habitat in Randers Regnskov were analyzed from the day with the most evenly distributed number of videos across the cameras. For the analysis, the

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frame size was reduced to 288x512 pixels, and the batch size was set to 1 to prevent memory errors. For the categorizer, the uncertainty level was set to 10% and there was no minimum length for behaviors. Beforehand, the beginning time for analysis in each video's file name was specified to limit the amount of video without jaguars visible. For the captive jaguars, 326 videos out of 429 videos were successfully analyzed with jaguars visible from November 1st, 2025, using the detector that recognizes individuals and the categorizer for behavioral classification (Table 3). A NoneType area error message from LabGym was received on the remaining 103 videos, possibly because the detector did not detect the specified individuals and could therefore not calculate an individual's area. All quantitative measurements were analyzed with normalized distances [68] as well as the observed behaviors.

Secondly, 70 videos of wild jaguars in Bigai were analyzed, of which 63 included a wild-type jaguar and 7 included a melanistic jaguar using the wild jaguar detector and the categorizer for behavioral classification. The videos of wild-type jaguars were from 2024, and the videos of melanistic jaguars were from 2023. The same settings, as with the analysis of the captive jaguars, were chosen for this analysis. 67 videos were successfully analyzed with errors on three videos containing wild-type jaguars (Table 3).

Several files with data from LabGym were given for each successfully analyzed video. These would be consolidated into large datasheets using RStudio [73] to be used in the final data analysis. For behavioral assessments all behaviors with less than 80% probability were removed from the dataset when analyzing the behaviors. Contrariwise, all data from the analyzed videos were used for analysis of coordinate positionings. The duration of each instance of a behavior was calculated from the start time of the current behavior to the start time of the next behavior instance. The hour of day that the video took place was also noted in all datasets for the captive jaguars. Unfortunately, the videos of the wild jaguars could not yield reliable time stamps and an hour of day with the wild jaguars could therefore not be estimated. The coordinates, hour of day, and behavioral data were used for constructing plots for data analysis.

2.4. Data Analysis of Automated Behavioral Tracking and Space Use Monitoring

To assess behavior of the wild jaguars in Bigai and captive jaguars in Randers Regnskov, several plots were constructed using either Excel or RStudio based on the data from the analyzed videos. The following packages were used for data analysis within Rstudio, dplyr [74], ggplot2 [75], purrr [76], tidyverse [77], stringr [78], and writexl [79]. ChatGPT was occasionally utilized to aid in R code development [80]. Firstly, three heatmaps were constructed from the coordinates to show the space use from the point of view of each camera angle in Randers Regnskov (Figure 4). These were visualized using the 3D-map function in Excel [81]. Secondly, three summarized activity budgets were constructed as bar charts - one for each jaguar in Randers Regnskov (Figure 5). These show the amount of time in percentage that each jaguar spent on active and inactive behavior. Additionally, a similar summarized activity budget was constructed as a bar chart for the wild jaguars to show the amount of time in percentage that they spent on active and inactive behavior (Figure 5). Next, two activity budgets were constructed as cumulative activity curves (Figure 6) showing the expression of active and inactive behavior throughout the 24 hours to assess the combined circadian rhythm of the three captive jaguars in Randers Regnskov. The behaviors of the three jaguars were chosen to be combined, because there was not much behavioral data from each jaguar for every hour of day. The jaguars had their behavior determined for a total average of 9,020.2 seconds throughout the 24 hours of the day. The rest of the time the jaguars were either not visible or exhibited behavior with an inadequate probability to be used for further behavioral analysis. For comparison, the wild jaguars had their behavior determined for a total of 393.7 seconds.

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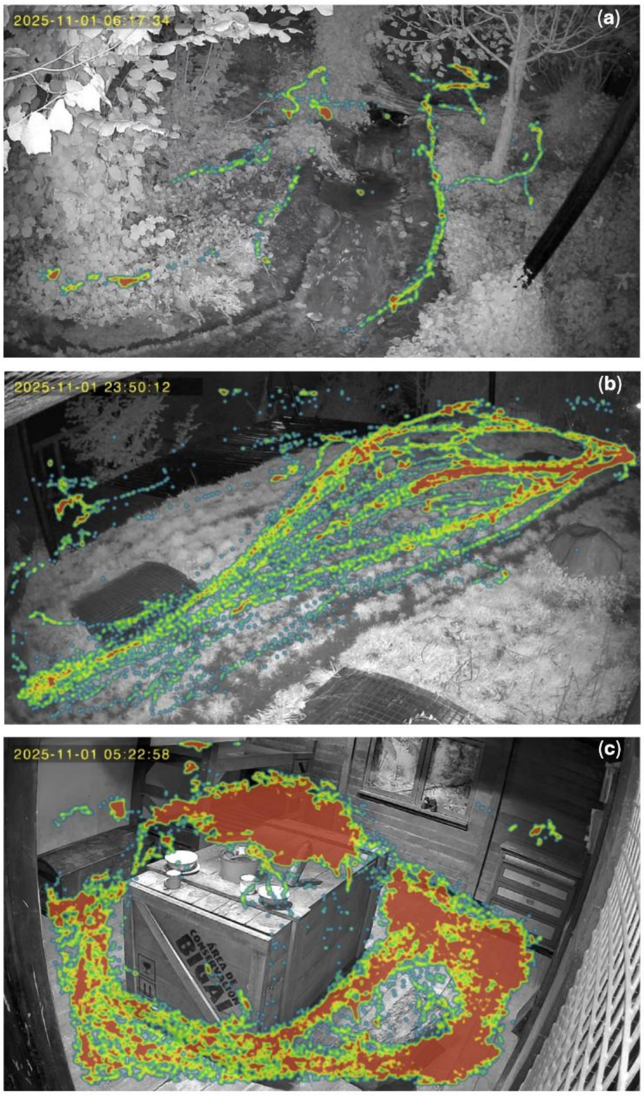

Figure 4. Coordinates of the centers of the captive jaguars, from Randers Regnskov, Tropical Zoo, combined from all analyzed videos from November 1st, 2025, and depicted on corresponding screenshots of the camera angles. The letters in the corners indicate the camera angles: (**a**) Angle from camera a) outdoors, pointing into vegetation with a path and a small brook; (**b**) Angle from camera b) outdoors, pointing at a roof and a flat grassy area that functions as a connection point; (**c**) Angle from camera c) indoors in the jaguar stable.

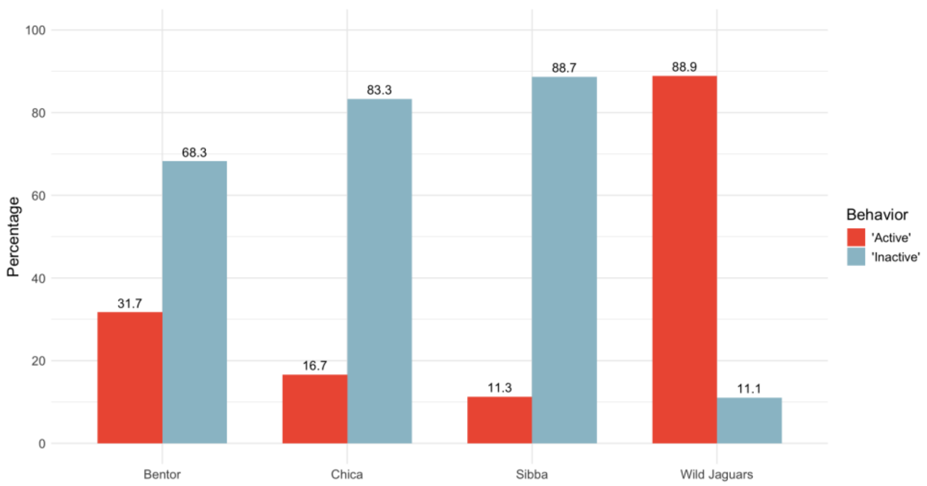

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Figure 5. Distributions of percentages of time spent on active (red) and inactive (blue) behavior for each captive jaguar, from Randers Regnskov, Tropical Zoo, and wild jaguars, from Bigai, with bars depicting the fraction of observed activity and inactivity. The x-axis shows the different jaguars: Bentor, the adult male, Chica, the adult female, Sibba, the female cub, and wild jaguars. The y-axis shows the percentage of time used on activity and inactivity. The number above each bar is the percentage of time used on activity and inactivity.

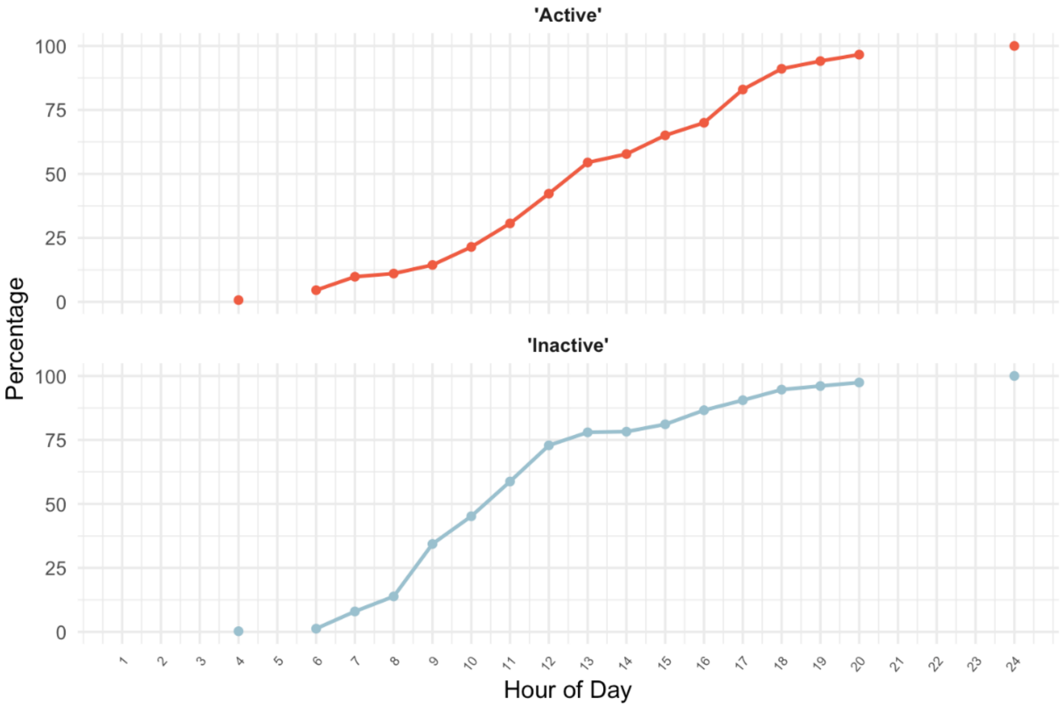

Figure 6. The cumulative activity curves of the two 24-hour behavioral activity patterns combined for three captive jaguars from Randers Regnskov, Tropical Zoo. The x-axis shows the hour of day. The y-axis shows the percentage of time spent on active (red) and inactive (blue) behavior. Missing areas of the curves indicate when there was no footage of jaguars within that hour of day.

3. Results

3.1. Space Use of Captive Jaguars

Heatmaps showed clear tracks, especially outside, and general space use preferences (Figure 4). Camera angle a) (Figure 4a) shows an area where the jaguars were thought to be patrolling. Here, clear tracks are seen alongside the brook and in the vegetation to the left and right. Camera angle b) (Figure 4b) shows a connection point between the outside areas of the enclosure. There are clear tracks on the hill from when the jaguars move between the outside area with the brook to the right and the other outside area that is out of sight to the left. Camera angle c) (Figure 4c) shows the indoor stable with space use focused on and around the box in the middle of the room, where the jaguars might rest.

3.2. Total Expression of Active and Inactive Behavior for Captive and Wild Jaguars

All three captive jaguars tended to spend most of the observable time on inactive behavior, with Sibba, the female cub, exhibiting the most, followed by Chica, the adult female, and Bentor, the male, respectively (Figure 5). The wild jaguars exhibited mostly active behavior (Figure 5).

3.3. Expression of Active and Inactive Behavior troughout the 24 Hours of the Day for Captive Jaguars

The jaguars were observed to have the most active behavior around noon (11th to 13th hour) and less in the morning and night (Figure 6). The jaguars showed most inactivity between the 9th and 12th hours with a more even distribution for the rest of the day. No behavior was observed from the 1st to 3rd hours or from the 21st to 23rd hours (Figure 6).

4.4. Discussion

4.1. Space Use of the Captive Jaguars

When constructing heatmaps to automatically examine space use for the jaguars in the three different camera angles, a clear pattern appeared (Figure 4). It was observed that, for the outdoor enclosure seen in camera angle a) and b) the jaguars' movement pattern appeared streaky and deliberate. Here, the use of ML highlights distinct tracks throughout their enclosure, potentially indicating patrolling behavior. Such behavior patterns of territory patrolling are often seen in wild conspecifics, where both genders of jaguars tend to patrol and guard their territory [34]. As it is important for animal welfare that a captive animal exhibits positive aspects of wild behaviors [25,28,29], similar camera setups could be established to examine long-term patrolling behaviors in captive jaguars or other species with a similar patrolling tendency.

Additionally, knowing an animal's space use in an enclosure may also aid in optimizing the animal's enclosure usage. For example, a study of pygmy hippopotamuses showed promise with using olfactory enrichment to alter and increase the captive pygmy hippopotamuses' space use [82]. Other studies have also demonstrated that computer vision technology can prove to be an asset in examining space use, position tracking, and behavioral assessment to help reduce labor-intensive manual observations [53–55,57].

4.2. Behavioral Assessment of Captive and Wild Jaguars

Daily activity budgets constitute another important aspect of behavioral welfare assessments and have been constructed for both captive and wild animals [25,30,34,43–45]. Here, a ML model trained to assess activity and inactivity may aid by giving notice when inactivity is excessively expressed, after which manual observations of more advanced behaviors to aid in a welfare assessment may be conducted. Of all the observed captive jaguars in this study, the male, Bentor, appeared to be the most active, while the reproductive female, Chica, and the cub, Sibba, appeared to spend less time on this behavior (Figure 5). This is partly in contrast to a study by Jędrzejewski et al. (2021) [34] on wild jaguars that observed reproductive female jaguars, which have to care for their cubs, mate, and defend territory, to have had the longest activity time. They also observed that males had the second-longest daily activity, and cubs had the least. A reason for the difference between our study and their study might be that the jaguars seen in our study were recorded in a captive environment and only for a single day. Therefore, if a different day or multiple days had been examined, the results, of which jaguar was the most and the least active, might have been different.

Inactivity is a common behavior seen in species of wild cats in zoos and has been found to be excessively expressed both day and night despite them being nocturnal animals [40,43]. An increase in inactivity was observed during the day, starting from the 9th to 12th hour (Figure 6). Observation of the captive jaguars briefly began with two videos in the start of the 4th hour of the day (about 03:00), with the adult female presumably waking up and leaving the box in the middle of the indoor enclosure, followed soon by the other two jaguars. The lack of observed inactivity or other behaviors seen by the ML model during the evening and nighttime hours could therefore be explained by the total or partial occlusion of the jaguars as they could be out of sight in the box or outside visible angles. The increased inactivity may be an expression of potential behavioral problems if alongside other behaviors such as stereotypic behavior, like pacing, caused by a lack of sufficient stimulation, or if it borders on lethargic behavior, which might indicate sickness or a welfare compromise if associated with low behavioral diversity [25,30,40,41,48]. However, inactivity might not in itself present a negative condition as the jaguar could simply be content and resting rather than bored because of a lack of stimuli [30]. The high amount of observed inactivity in captive jaguars may also be due to low enclosure complexity, small enclosure size, and readily available food that favors the occurrence of inactive behavior compared to conditions in wild jaguar habitats [29,40].

Another possible cause for the increased inactivity in the captive jaguars could be explained by the footage being recorded continuously in their size-limited enclosure throughout the 24 hours of the day, with one camera continuously filming their stable where they tend to rest. Therefore, there is much more footage of the captive jaguars relaxing and being inactive than there is footage of their wild conspecifics in Bigai being inactive. Additionally, the positionings of the camera traps in Bigai are typically meant for recording animal trails. This would likely increase the time spent on observed active behaviors like walking, as the jaguars would be seen more often as they travel throughout the area. Wild jaguars have wide-ranging behavior and travel long distances when patrolling their territory and searching for prey and mates [8,11]. This might also explain why the jaguars in the wild were observed to exhibit more active behavior than their captive conspecifics (Figure 5).

4.3. Performance of the Wild Jaguar Machine Learning Model

Despite the detector and categorizer having been trained on captive jaguars, it still indicated the potential of using a ML model when examining and inferring the behaviors of wild conspecifics. Although it must be noted that the wild jaguar detector did achieve a lower mAP of 49.26% when tested on images from videos from Bigai, probably because of false positive detections and a few misclassifications of 'Jaguar' and 'Panther' (Figure 3). In most annotated videos, created from analysis by the ML model, the model looks to be correctly detecting and annotating the jaguars, even when they might be very close to the camera, which is impressive, as the model has not been trained on images with jaguars this close. However, in some annotated videos, the model does occasionally struggle with close jaguars or may mistakenly detect some vegetation or other things as being the jaguar. The lower precision of the wild jaguar detector is likely due to the vastly different environments being filmed. Such differences in environments included not only the angles of the cameras but also the camera models, height from the ground, nearby foliage amount and type among other factors that might influence the ML model's capability to detect and differentiate a jaguar from the background. Such challenges with a ML model's ability to generalize to novel environments have been observed in other studies [58,83]. Here, a conclusion for the worsening of detection for novel settings could be due to overfitting, which might also be applicable when using the detector for wild jaguars in this study, and a possible reason for the lower mAP. Despite these occasional mistakes, using a ML model trained on videos of captive animals still shows promising results in being implemented to detect and infer behavioral data of wild animals. Increased accuracy might also be possible if the model can be trained on supplementary videos from similar camera traps or environments.

4.4. Daily Activity Patterns of the Captive Jaguars

Another usage of activity assessments may also be to assess the daily activity patterns [34,43]. For the jaguars in this study, it was observed that the expression of active behavior was relatively even throughout the day, with the most amount of active behavior being expressed around noon from the 11th to 13th hour (Figure 6). A study by Moreno et al. (2025) [84] measured the average movement speed across the 24 hours of the day for five wild jaguars. They found that one male and one female showed the typical bimodal predator activity pattern of being less active in the daytime and more active around dusk, dawn, and at night, while three females moved more in the daytime [84]. A similar study that estimated the activity level throughout the 24 hours of the day for wild jaguars found that the jaguars were mostly nocturnal and crepuscular, with variations between individuals [34]. When comparing these studies to the results of our study, it appears that none of the captive jaguars had a natural bimodal nocturnal or crepuscular hunter activity pattern, as they were mostly active during the daytime, with some exceptions of evening and nightly activity. For example, the mother, Chica, and the cub, Sibba, were seen walking around together outside in the 24th hour (Figure 6), which implies that the captive jaguars were nocturnal to some extent. In addition, the three captive jaguars were manually observed on the footage from all six recorded days to be patrolling or eating food outside at dusk and dawn on four different days and at night on three of those days. On two of the six recorded days, they were not outside to patrol at night, dusk, or dawn – only in the daytime. In future studies, it could therefore be interesting to examine how often and for how long captive jaguars exhibit crepuscular and nocturnal behavior across a bigger time scale than the one day that was analyzed in this study.

Similar patterns of captive animals being mostly active during the day have also been observed in captive jaguars in other studies [40,42] and partly in a study of captive ocelots (*L. pardalis*), which are also nocturnal hunters like jaguars [43]. Wild nocturnal hunters' activity peaks reflect the activity peaks of their main prey [43,85], but as captive jaguars in this study were fed around 13:00-13:30 in the daytime, they had no need to "hunt" at night. Thus, the usage of a ML model could aid in indicating a potential relationship between the feeding event around noon and the increased activity behavior during the daytime.

Additionally, there is only one day of analyzed footage which means that any prolonged occlusion of a jaguar will have a great effect on the daily behavior pattern. Furthermore, the jaguars' 24-hour activity patterns may vary for each day, which could be examined if more days were analyzed. Despite this small sample size, the ML model still showed promise in analysis of daily activity patterns, and a similar ML model could prove to be applicable in future studies.

4.5. Performance of the Individual Recognition of the Captive Jaguars

Occasional identity switching was observed, despite the model achieving a high detection mAP and high categorization F1-scores. The identity switch mostly occurred between the two wild-type coated jaguars, Bentor and Sibba. Specifically at times where they would be exhibiting similar body positions and therefore have similar body outlines. The identity switch could be because the detector had been trained on annotations of a specific body position on only one individual, and thereby it might confuse other individuals in this position as the one it had been trained on. Jaguars have pelage patterns that can be used for individual recognition [20,72], and it was observed that the ML model could observe such patterns. Although a ML model being trained mostly based on outline recognition might make a similar outline take precedence in a detector deciding which individual it detects. Here, other studies have found success with increasing accuracy by utilizing body-part-based individual recognition, for example, the ears of wild Asian elephants (*Elephas maximus*) [20], the side of the body of captive Amur tigers (*Panthera tigris altaica*), wild Amur leopards (*Panthera pardus orientalis*), and feral cats (*Felis catus*) [86,87]. This could be a possibility for optimizing a detector for individual recognition of the studied jaguars. However, the method may require that one initially tests if body-part-based individual recognition works with the studied species, since for some species such as the African wild dog (*Lycaon pictus*) the method can give worse results than when utilizing the full body outline of an animal [88].

4.6. Possibilities in Future Research

In a pilot experiment, we tried to categorize more advanced and complicated behaviors due to the possibility of researching these behaviors. Specifically, the captive jaguars were manually observed to be highly social. For example, allogrooming, playing, and cuddling were observed. However, with the amount of footage used for the training of the categorizer, the more advanced behaviors did not achieve a satisfying degree of precision, most likely because of their similar outlines. Here, supplementing an outline-based model with more body-part-based models might increase the accuracy of correct identity detections, but also more easily allow for future research and categorization of advanced behaviors. By training a ML model to classify more advanced behaviors,

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it may be used more directly as a part of a welfare assessment, instead of, for example, simply giving notice when inactivity is excessively expressed.

Overall, this study indicates the usage of ML for assessing behaviors, alongside a detector's individual recognition and space use monitoring. ML can therefore become a valuable tool in the conservation of jaguars when assessing their behaviors in footage from camera traps, since behavior is an important parameter for successful conservation results [13,14]. This study also highlights the possibility of inferring if captive jaguars exhibit behaviors akin to their wild conspecifics as an indicator of animal welfare [25,28,29].

5. Conclusions

Detection of jaguars with a ML model made with LabGym demonstrated the ability to accurately determine space use patterns of the patrolling captive jaguars in Randers Regnskov, and clear tracks were visible on the heatmaps. Additionally, it also showed promise with individual recognition, although it still struggled with occasional identity switching. Moreover, the implementation of this detector and categorizer trained from images of just three captive jaguars showed promise with recognition and activity tracking of wild jaguars. Furthermore, based on the activity tracked throughout the day, the captive jaguars did not exhibit natural bimodal nocturnal or crepuscular hunter activity patterns. Additionally, the captive jaguars showed a large amount of inactivity. Overall, integration of ML-based methods can be a promising tool for monitoring both captive and wild jaguars regarding individual recognition, spatiotemporal details, and activity tracking to enhance animal welfare and conservation.

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Institutional Review Board Statement: The Ethical Review Board was not consulted for the purposes of this study, as this study did not interfere with the daily routines of the subjects studied, and solely involved non-invasive observation through video footage.

Informed Consent Statement: We obtained approval from Randers Regnskov, Tropical Zoo, and the authors guarantee that all work was carried out within good animal welfare and ethical circumstances. There was no change in daily routines for the animals of concern.

Data Availability Statement: The data presented in this study is available on request from the corresponding author. The reason for this is that the data includes sensitive and private material, specifically video footage from a zoological institution and from camera traps in Bigai. Due to ethical considerations and agreements with Randers Regnskov, Tropical Zoo, the data cannot be shared publicly.

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Abbreviations

The following abbreviations are used in this manuscript:

ML	Machine learning
DNN	Deep neural network
Randers Regnskov	Randers Regnskov, Tropical Zoo
mAP	Mean average precision

Appendix A

Appendix A.1

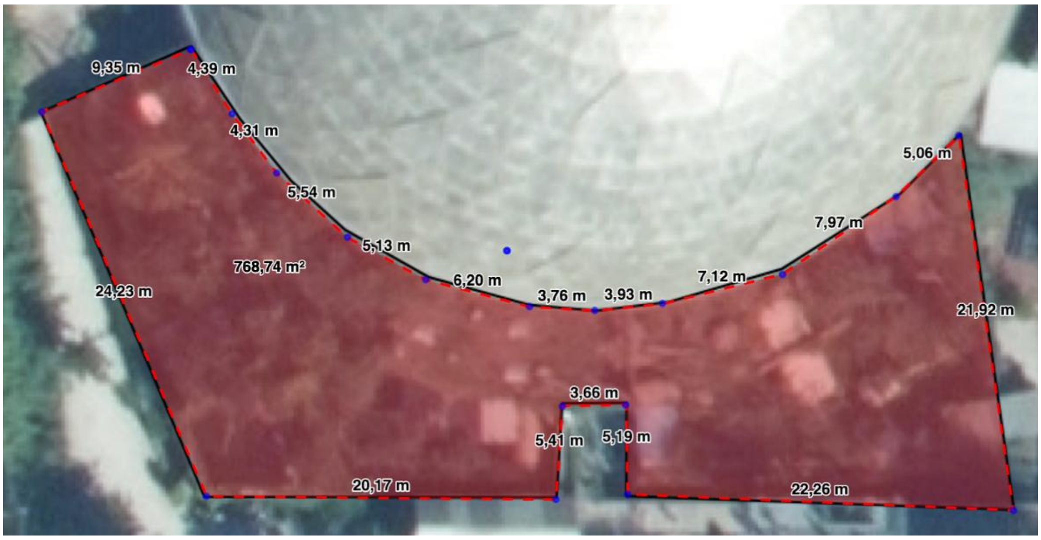

Figure A1. Aerial photo of the outdoor area of the jaguar enclosure in Randers Regnskov, Tropical Zoo (red area) with measurements of area (m²) and distances (m).

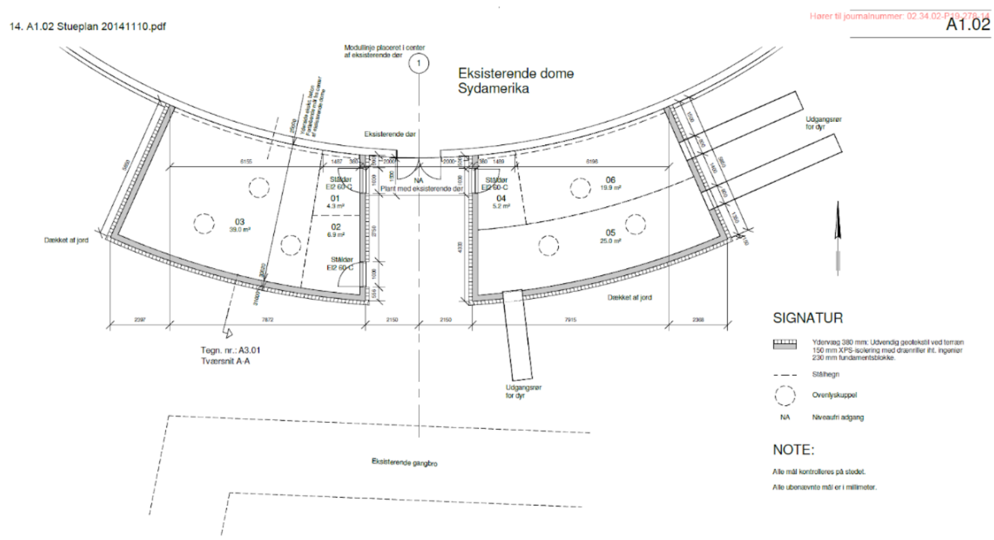

Figure A2. Floorplan of the indoor area of the jaguar enclosure in Randers Regnskov, Tropical Zoo to the right.

References

1. Blake, J.G.; Mosquera, D.; Guerra, J.; Loiselle, B.A.; Romo, D.; Swing, K. Yasuní – a Hotspot for Jaguars *Panthera onca* (Carnivora: Felidae)? Camera-Traps and Jaguar Activity at Tiputini Biodiversity Station, Ecuador. *Revista de Biología Tropical* **2014**, *62*, doi:10.15517/rbt.v62i2.11115.
2. Gaitán, C.A.; González-Castillo, V.R.; Guzmán-Flores, G.D.; Aguilera, A.L.; García, M.J. Visitation Patterns of Jaguars *Panthera onca* (Carnivora: Felidae) to Isolated Water Ponds in a Tropical Forest Landscape. *Therya* **2021**, *12*, 45–55, doi:10.12933/therya-21-915.
3. Weckel, M.; Giuliano, W.; Silver, S. Cockscomb Revisited: Jaguar Diet in the Cockscomb Basin Wildlife Sanctuary, Belize. *Biotropica* **2006**, *38*, 687–690, doi:10.1111/j.1744-7429.2006.00190.x.
4. Weckel, M.; Giuliano, W.; Silver, S. Jaguar (*Panthera onca*) Feeding Ecology: Distribution of Predator and Prey through Time and Space. *Journal of Zoology* **2006**, *270*, 25–30, doi:10.1111/j.1469-7998.2006.00106.x.
5. Hayward, M.W.; Kamler, J.F.; Montgomery, R.A.; Newlove, A.; Rostro-García, S.; Sales, L.P.; Van Valkenburgh, B. Prey Preferences of the Jaguar *Panthera onca* Reflect the Post-Pleistocene Demise of Large Prey. *Front. Ecol. Evol.* **2016**, *3*, doi:10.3389/fevo.2015.00148.
6. de la Torre, J.A.; González-Maya, J.F.; Zarza, H.; Ceballos, G.; Medellín, R.A. The Jaguar's Spots Are Darker than They Appear: Assessing the Global Conservation Status of the Jaguar *Panthera onca*. *Oryx* **2018**, *52*, 300–315, doi:10.1017/S0030605316001046.
7. Quigley, H.; Foster, R.; Petracca, L.; Payan, E.; Salom, R.; Harmsen, B. *Panthera onca* (Errata Version Published in 2018). The IUCN Red List of Threatened Species 2017: E.T15953A123791436. Available online: https://dx.doi.org/10.2305/IUCN.UK.2017-3.RLTS.T15953A50658693.en (accessed on 11 February 2026).
8. Rabinowitz, A.; Zeller, K.A. A Range-Wide Model of Landscape Connectivity and Conservation for the Jaguar, *Panthera onca*. *Biological Conservation* **2010**, *143*, 939–945, doi:10.1016/j.biocon.2010.01.002.
9. Ripple, W.J.; Estes, J.A.; Beschta, R.L.; Wilmers, C.C.; Ritchie, E.G.; Hebblewhite, M.; Berger, J.; Elmhagen, B.; Letnic, M.; Nelson, M.P.; et al. Status and Ecological Effects of the World's Largest Carnivores. *Science* **2014**, *343*, 1241484, doi:10.1126/science.1241484.
10. Mena, J.L.; Yagui, H.; Tejeda, V.; Cabrera, J.; Pacheco-Esquivel, J.; Rivero, J.; Pastor, P. Abundance of Jaguars and Occupancy of Medium- and Large-Sized Vertebrates in a Transboundary Conservation Landscape in the Northwestern Amazon. *Global Ecology and Conservation* **2020**, *23*, e01079, doi:10.1016/j.gecco.2020.e01079.
11. Thompson, J.J.; Morato, R.G.; Niebuhr, B.B.; Alegre, V.B.; Oshima, J.E.F.; de Barros, A.E.; Paviolo, A.; de la Torre, J.A.; Lima, F.; McBride, R.T.; et al. Environmental and Anthropogenic Factors Synergistically Affect Space Use of Jaguars. *Current Biology* **2021**, *31*, 3457-3466.e4, doi:10.1016/j.cub.2021.06.029.
12. Espinosa, S.; Celis, G.; Branch, L.C. When Roads Appear Jaguars Decline: Increased Access to an Amazonian Wilderness Area Reduces Potential for Jaguar Conservation. *PLoS One* **2018**, *13*, e0189740, doi:10.1371/journal.pone.0189740.
13. Festa-Bianchet, M.; Apollonio, M. *Animal Behavior and Wildlife Conservation*; 1st edition.; Washington, DC; Vol. 2003; ISBN 1-55963-959-8.
14. Macdonald, D.W. Animal Behaviour and Its Role in Carnivore Conservation: Examples of Seven Deadly Threats. *Animal Behaviour* **2016**, *120*, 197–209, doi:10.1016/j.anbehav.2016.06.013.
15. Archard, G.A.; Braithwaite, V.A. The Importance of Wild Populations in Studies of Animal Temperament. *Journal of Zoology* **2010**, *281*, 149–160, doi:10.1111/j.1469-7998.2010.00714.x.
16. Greggor, A.L.; Berger-Tal, O.; Blumstein, D.T.; Angeloni, L.; Bessa-Gomes, C.; Blackwell, B.F.; St Clair, C.C.; Crooks, K.; de Silva, S.; Fernández-Juricic, E.; et al. Research Priorities from Animal Behaviour for Maximising Conservation Progress. *Trends Ecol Evol* **2016**, *31*, 953–964, doi:10.1016/j.tree.2016.09.001.
17. Greggor, A.L.; Blumstein, D.T.; Wong, B.B.M.; Berger-Tal, O. Using Animal Behavior in Conservation Management: A Series of Systematic Reviews and Maps. *Environ Evid* **2019**, *8*, 23, doi:10.1186/s13750-019-0164-4.
18. Rahman, T.; Candolin, U. Linking Animal Behavior to Ecosystem Change in Disturbed Environments. *Front. Ecol. Evol.* **2022**, *10*, 893453, doi:10.3389/fevo.2022.893453.
19. Beaulieu, M. Capturing Wild Animal Welfare: A Physiological Perspective. *Biological Reviews* **2024**, *99*, 1–22, doi:10.1111/brv.13009.

20. Silver, S.C.; Ostro, L.E.T.; Marsh, L.K.; Maffei, L.; Noss, A.J.; Kelly, M.J.; Wallace, R.B.; Gómez, H.; Ayala, G. The Use of Camera Traps for Estimating Jaguar *Panthera onca* Abundance and Density Using Capture/Recapture Analysis. *Oryx* **2004**, *38*, 148–154, doi:10.1017/S0030605304000286.
21. Nakashima, Y.; Fukasawa, K.; Samejima, H. Estimating Animal Density without Individual Recognition Using Information Derivable Exclusively from Camera Traps. *Journal of Applied Ecology* **2018**, *55*, 735–744, doi:10.1111/1365-2664.13059.
22. Cerqueira, R.C.; de Rivera, O.R.; Jaeger, J.A.G.; Grilo, C. Direct and Indirect Effects of Roads on Space Use by Jaguars in Brazil. *Sci Rep* **2021**, *11*, 22617, doi:10.1038/s41598-021-01936-6.
23. Morato, R.G.; Thompson, J.J.; Paviolo, A.; de La Torre, J.A.; Lima, F.; McBride Jr, R.T.; Paula, R.C.; Cullen Jr, L.; Silveira, L.; Kantek, D.L.Z.; et al. Jaguar Movement Database: A GPS-Based Movement Dataset of an Apex Predator in the Neotropics. *Ecology* **2018**, *99*, 1691–1691, doi:10.1002/ecy.2379.
24. Schaller, G.B.; Crawshaw, P.G. Movement Patterns of Jaguar. *Biotropica* **1980**, *12*, 161–168, doi:10.2307/2387967.
25. Campbell-Ward, M. Quality-of-Life Assessments in Zoo Animals: Not Just for the Aged and Charismatic. *Animals (Basel)* **2023**, *13*, 3394, doi:10.3390/ani13213394.
26. Bacon, H. Behaviour-Based Husbandry—A Holistic Approach to the Management of Abnormal Repetitive Behaviors. *Animals (Basel)* **2018**, *8*, 103, doi:10.3390/ani8070103.
27. Sherwen, S.L.; Hemsworth, L.M.; Beausoleil, N.J.; Embury, A.; Mellor, D.J. An Animal Welfare Risk Assessment Process for Zoos. *Animals* **2018**, *8*, doi:10.3390/ani8080130.
28. Wolfensohn, S.; Shotton, J.; Bowley, H.; Davies, S.; Thompson, S.; Justice, W.S.M. Assessment of Welfare in Zoo Animals: Towards Optimum Quality of Life. *Animals* **2018**, *8*, doi:10.3390/ani8070110.
29. de Azevedo, C.S.; Cipreste, C.F.; Pizzutto, C.S.; Young, R.J. Review of the Effects of Enclosure Complexity and Design on the Behaviour and Physiology of Zoo Animals. *Animals (Basel)* **2023**, *13*, 1277, doi:10.3390/ani13081277.
30. Tallo-Parra, O.; Salas, M.; Manteca, X. Zoo Animal Welfare Assessment: Where Do We Stand? *Animals* **2023**, *13*, doi:10.3390/ani13121966.
31. Rabinowitz, A.R.; Jr, B.G. Nottingham Ecology and Behaviour of the Jaguar (*Panthers onca*) in Belize, Central America. *Journal of Zoology* **1986**, *210*, 149–159, doi:10.1111/j.1469-7998.1986.tb03627.x.
32. Sellinger, R.L.; Ha, J.C. The Effects of Visitor Density and Intensity on the Behavior of Two Captive Jaguars (*Panthera onca*). *J Appl Anim Welf Sci* **2005**, *8*, 233–244, doi:10.1207/s15327604jaws0804_1.
33. Morato, R.G.; Stabach, J.A.; Fleming, C.H.; Calabrese, J.M.; De Paula, R.C.; Ferraz, K.M.P.M.; Kantek, D.L.Z.; Miyazaki, S.S.; Pereira, T.D.C.; Araujo, G.R.; et al. Space Use and Movement of a Neotropical Top Predator: The Endangered Jaguar. *PLoS One* **2016**, *11*, e0168176, doi:10.1371/journal.pone.0168176.
34. Jędrzejewski, W.; Vivas, I.; Abarca, M.; Lampo, M.; Morales, L.G.; Gamarra, G.; Schmidt, K.; Hoogesteijn, R.; Carreño, R.; Puerto, M.F.; et al. Effect of Sex, Age, and Reproductive Status on Daily Activity Levels and Activity Patterns in Jaguars (*Panthera onca*). *Mamm Res* **2021**, *66*, 531–539, doi:10.1007/s13364-021-00589-0.
35. Price, E.E.; Stoinski, T.S. Group Size: Determinants in the Wild and Implications for the Captive Housing of Wild Mammals in Zoos. *Applied Animal Behaviour Science* **2007**, *103*, 255–264, doi:10.1016/j.applanim.2006.05.021.
36. DiVincenti, L.; McDowell, A.; Herrelko, E.S. Integrating Individual Animal and Population Welfare in Zoos and Aquariums. *Animals (Basel)* **2023**, *13*, 1577, doi:10.3390/ani13101577.
37. Cavalcanti, S.M.C.; Gese, E.M. Spatial Ecology and Social Interactions of Jaguars (*Panthera onca*) in the Southern Pantanal, Brazil. *Journal of Mammalogy* **2009**, *90*, 935–945, doi:10.1644/08-MAMM-A-188.1.
38. Jędrzejewski, W.; Hoogesteijn, R.; Devlin, A.L.; Tortato, F.; Concone, H.V.B.; Azevedo, F.; Eriksson, C.E.; Fragoso, C.E.; Abarca, M.; Morato, R.G.; et al. Collaborative Behaviour and Coalitions in Male Jaguars (*Panthera onca*)—Evidence and Comparison with Other Felids. *Behav Ecol Sociobiol* **2022**, *76*, 121, doi:10.1007/s00265-022-03232-3.
39. Mason, G.J. Stereotypies and Suffering. *Behavioural Processes* **1991**, *25*, 103–115, doi:10.1016/0376-6357(91)90013-P.

40. Boccacino, D.; Maia, C.M.; Dos Santos, E.F.; Santori, R.T. INACTIVITY AT NIGHT: A CASE STUDY OF THE NOCTURNAL BEHAVIORS OF TWO CAPTIVE *Panthera onca* (FELIDAE) SPECIMENS. *Acta biol. Colomb.* **2020**, *25*, 359–367, doi:10.15446/abc.v25n3.80892.
41. Hart, B.L. Biological Basis of the Behavior of Sick Animals. *Neuroscience & Biobehavioral Reviews* **1988**, *12*, 123–137, doi:10.1016/S0149-7634(88)80004-6.
42. Boccacino, D.; Maia, C.M.; Santos, E.F.D.; Santori, R.T. EFFECTS OF ENVIRONMENTAL ENRICHMENTS ON THE BEHAVIORS OF FOUR CAPTIVE JAGUARS: INDIVIDUALITY MATTERS. *Oecol. Aust.* **2018**, *22*, 63–73, doi:10.4257/oeco.2018.2201.06.
43. Weller, S.H.; Bennett, C.L. Twenty-Four Hour Activity Budgets and Patterns of Behavior in Captive Ocelots (*Leopardus pardalis*). *Applied Animal Behaviour Science* **2001**, *71*, 67–79, doi:10.1016/S0168-1591(00)00169-6.
44. Rees, P.A. Activity Budgets and the Relationship between Feeding and Stereotypic Behaviors in Asian Elephants (*Elephas maximus*) in a Zoo. *Zoo Biology* **2009**, *28*, 79–97, doi:10.1002/zoo.20200.
45. Auer, U.; Kelemen, Z.; Engl, V.; Jenner, F. Activity Time Budgets—A Potential Tool to Monitor Equine Welfare? *Animals (Basel)* **2021**, *11*, 850, doi:10.3390/ani11030850.
46. Yon, L.; Williams, E.; Harvey, N.D.; Asher, L. Development of a Behavioural Welfare Assessment Tool for Routine Use with Captive Elephants. *PLOS ONE* **2019**, *14*, e0210783, doi:10.1371/journal.pone.0210783.
47. Foster, V.C.; Sarmento, P.; Sollmann, R.; Tôrres, N.; Jácomo, A.T.A.; Negrões, N.; Fonseca, C.; Silveira, L. Jaguar and Puma Activity Patterns and Predator-Prey Interactions in Four Brazilian Biomes. *Biotropica* **2013**, *45*, 373–379, doi:10.1111/btp.12021.
48. Miller, L.J.; Vicino, G.A.; Sheftel, J.; Lauderdale, L.K. Behavioral Diversity as a Potential Indicator of Positive Animal Welfare. *Animals* **2020**, *10*, doi:10.3390/ani10071211.
49. Drea, C.M.; Hawk, J.E.; Glickman, S.E. Aggression Decreases as Play Emerges in Infant Spotted Hyaenas: Preparation for Joining the Clan. *Animal Behaviour* **1996**, *51*, 1323–1336, doi:10.1006/anbe.1996.0136.
50. Stagkourakis, S.; Williams, P.; Spigolon, G.; Khanal, S.; Ziegler, K.; Heikkinen, L.; Fisone, G.; Broberger, C. Maternal Aggression Driven by the Transient Mobilisation of a Dormant Hormone-Sensitive Circuit. *bioRxiv* **2024**, 2023.02.02.526862, doi:10.1101/2023.02.02.526862.
51. Mellor, D.J.; Beausoleil, N.J. Extending the 'Five Domains' Model for Animal Welfare Assessment to Incorporate Positive Welfare States. *Animal Welfare* **2015**, *24*, 241–253, doi:10.7120/09627286.24.3.241.
52. Valletta, J.J.; Torney, C.; Kings, M.; Thornton, A.; Madden, J. Applications of Machine Learning in Animal Behaviour Studies. *Animal Behaviour* **2017**, *124*, 203–220, doi:10.1016/j.anbehav.2016.12.005.
53. Rast, W.; Kimmig, S.E.; Giese, L.; Berger, A. Machine Learning Goes Wild: Using Data from Captive Individuals to Infer Wildlife Behaviours. *PLOS ONE* **2020**, *15*, e0227317, doi:10.1371/journal.pone.0227317.
54. Giese, L.; Melzheimer, J.; Bockmühl, D.; Wasiolka, B.; Rast, W.; Berger, A.; Wachter, B. Using Machine Learning for Remote Behaviour Classification—Verifying Acceleration Data to Infer Feeding Events in Free-Ranging Cheetahs. *Sensors* **2021**, *21*, doi:10.3390/s21165426.
55. Lund, S.M.; Nielsen, J.; Gammelgård, F.; Nielsen, M.G.; Jensen, T.H.; Pertoldi, C. Behavioral Coding of Captive African Elephants (*Loxodonta africana*): Utilizing DeepLabCut and Create ML for Nocturnal Activity Tracking. *Animals* **2024**, *14*, doi:10.3390/ani14192820.
56. Yang, X.; Bist, R.B.; Paneru, B.; Chai, L. Deep Learning Methods for Tracking the Locomotion of Individual Chickens. *Animals* **2024**, *14*, doi:10.3390/ani14060911.
57. Lund, S.M.; Gammelgård, F.; Nielsen, J.; Larsen, L.L.N.; Christensen, N.; Hansen, S.P.; Kristensen, T.; Rodkjær, H.H.Ø.; Sivagnanasundram, S.M.; Thomsen, B.Ø.; et al. Comparing Manual and Automated Spatial Tracking of Captive Spider Monkeys Using Heatmaps. *Animals* **2025**, *15*, doi:10.3390/ani15203056.
58. Gadot, T.; Istrate, Ștefan; Kim, H.; Morris, D.; Beery, S.; Birch, T.; Ahumada, J. To Crop or Not to Crop: Comparing Whole-Image and Cropped Classification on a Large Dataset of Camera Trap Images. *IET Computer Vision* **2024**, *18*, 1193–1208, doi:10.1049/cvi2.12318.
59. Hardin, A.; Schlupp, I. Using Machine Learning and DeepLabCut in Animal Behavior. *acta ethol* **2022**, *25*, 125–133, doi:10.1007/s10211-022-00397-y.
60. Schindler, F.; Steinhage, V. Identification of Animals and Recognition of Their Actions in Wildlife Videos Using Deep Learning Techniques. *Ecological Informatics* **2021**, *61*, 101215, doi:10.1016/j.ecoinf.2021.101215.

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61. Zamansky, A.; Sinitca, A.; Linden, D. van der; Kaplun, D. Automatic Animal Behavior Analysis: Opportunities for Combining Knowledge Representation with Machine Learning. *Procedia Computer Science* **2021**, *186*, 661–668, doi:10.1016/j.procs.2021.04.187.
62. Campbell, H.A.; Gao, L.; Bidder, O.R.; Hunter, J.; Franklin, C.E. Creating a Behavioural Classification Module for Acceleration Data: Using a Captive Surrogate for Difficult to Observe Species. *J Exp Biol* **2013**, *216*, 4501–4506, doi:10.1242/jeb.089805.
63. Hu, Y.; Ferrario, C.R.; Maitland, A.D.; Ionides, R.B.; Ghimire, A.; Watson, B.; Iwasaki, K.; White, H.; Xi, Y.; Zhou, J.; et al. *LabGym*: Quantification of User-Defined Animal Behaviors Using Learning-Based Holistic Assessment. *Cell Reports Methods* **2023**, *3*, 100415, doi:10.1016/j.crmeth.2023.100415.
64. Crates, R.; Stojanovic, D.; Heinsohn, R. The Phenotypic Costs of Captivity. *Biological Reviews* **2023**, *98*, 434–449, doi:10.1111/brv.12913.
65. Ardoin, T.; Sueur, C. Automatic Identification of Stone-Handling Behaviour in Japanese Macaques Using LabGym Artificial Intelligence. *Primates* **2024**, *65*, 159–172, doi:10.1007/s10329-024-01123-x.
66. Bigai: Randers Regnskov - Tropical Zoo. Available online: https://www.regnskoven.dk/laerbevar/naturbevarelse/bigai/ (accessed on 20 February 2026).
67. Altmann, J. Observational Study of Behavior: Sampling Methods. *Behaviour* **1974**, *49*, 227–267.
68. Hu, Y. The Extended User Guide for LabGym (v2.5.1). Available online: https://github.com/yujiahu415/LabGym/blob/master/LabGym_extended_user_guide.pdf (accessed on 11 February 2026).
69. Microsoft Corporation. Microsoft Word (Microsoft 365 Subscription). [Computer Software]. Microsoft Corporation. Available online: https://www.microsoft.com/en-us/microsoft-365/word (accessed on 11 February 2026).
70. RectLabel. Available online: https://rectlabel.com/ (accessed on 13 February 2026).
71. Roboflow (Version 1.0) [Software]. Available online: https://roboflow.com (accessed on 11 February 2026).
72. Nipko, R.B.; Holcombe, B.E.; Kelly, M.J. Identifying Individual Jaguars and Ocelots via Pattern-Recognition Software: Comparing HotSpotter and Wild-ID. *Wildlife Society Bulletin* **2020**, *44*, 424–433, doi:10.1002/wsb.1086.
73. Posit team RStudio: Integrated Development Environment for R. Posit Software, PBC, Boston, MA. Available online: https://posit.co/ (accessed on 11 February 2026).
74. Wickham, H.; François, R.; Henry, L.; Müller, K.; Vaughan, D.; Software, P.; PBC (2023). Dplyr: A Grammar of Data Manipulation. R Package Version 1.1.4, Https://CRAN.R-Project.Org/Package=dplyr 2026.
75. Wickham, H.; Chang, W.; Henry, L.; Pedersen, T.L.; Takahashi, K.; Wilke, C.; Woo, K.; Yutani, H.; Dunnington, D.; Brand, T. van den; et al. (2016). Ggplot2: Elegant Graphics for Data Analysis. Springer-Verlag New York. ISBN 978-3-319-24277-4, Https://Ggplot2.Tidyverse.Org 2026.
76. Wickham, H.; Henry, L.; Software, P.; PBC [cph; fnd (2023). Purrr: Functional Programming Tools. R Package Version 1.0.2, Https://CRAN.R-Project.Org/Package=purrr 2026.
77. Wickham, H.; Averick, M.; Bryan, J.; Chang, W.; McGowan, L.D.; François, R.; Grolemund, G.; Hayes, A.; Henry, L.; Hester, J.; et al. Welcome to the Tidyverse. *Journal of Open Source Software* **2019**, *4*, 1686, doi:10.21105/joss.01686.
78. Wickham, H.; Software, P.; PBC (2023). Stringr: Simple, Consistent Wrappers for Common String Operations. R Package Version 1.5.1, Https://CRAN.R-Project.Org/Package=stringr 2025.
79. Ooms, J.; cre; details, J.M. (Author of libxlsxwriter (see A. and C. files for details)) writexl author (2024). Writexl: Export Data Frames to Excel "xlsx" Format. R Package Version 1.5.1, Https://CRAN.R-Project.Org/Package=writexl 2025.
80. OpenAI (GPT-5, GPT-5 mini, GPT-5.1, GPT-5.1 mini). Available online: https://chatgpt.com/da-DK/ (accessed on 11 February 2026).
81. Microsoft Corporation. Microsoft Excel (Microsoft 365 Subscription). [Computer Software]. Microsoft Corporation. Available online: https://www.microsoft.com/en-us/microsoft-365/excel (accessed on 11 February 2026).

82. Nielsen, J.; Gammelgård, F.; Lund, S.M.; Præstekær, A.S.B.; Frandsen, A.V.; Strandqvist, C.; Nielsen, M.H.; Olsen, R.N.; Pagh, S.; Faddersbøll, T.L.; et al. Olfactory Enrichment of Captive Pygmy Hippopotamuses with Applied Machine Learning. *Animals* **2026**, *16*, doi:10.3390/ani16030385.
83. Schneider, S.; Greenberg, S.; Taylor, G.W.; Kremer, S.C. Three Critical Factors Affecting Automated Image Species Recognition Performance for Camera Traps. *Ecology and Evolution* **2020**, *10*, 3503–3517, doi:10.1002/ece3.6147.
84. Moreno, R.; de la Torre, J.A.; Ortega, J.; Young, N.; Puertes, A.; Kays, R. Jaguar Space Use in the Working Landscape of Darien, Panama. *Tropical Conservation Science* **2025**, *18*, 19400829251332163, doi:10.1177/19400829251332163.
85. Carrillo, E.; Fuller, T.K.; Saenz, J.C. Jaguar (*Panthera Onca*) Hunting Activity: Effects of Prey Distribution and Availability. *Journal of Tropical Ecology* **2009**, *25*, 563–567, doi:10.1017/S0266467409990137.
86. Shi, C.; Xu, J.; Roberts, N.J.; Liu, D.; Jiang, G. Individual Automatic Detection and Identification of Big Cats with the Combination of Different Body Parts. *Integrative Zoology* **2023**, *18*, 157–168, doi:10.1111/1749-4877.12641.
87. Akbar, R.R.S.; Rees, M.W.; Fleming, P.A.; Sohel, F. Body-Part-Based Individual Feral Cat Identification from Camera Trap Images Using Deep Learning. *Ecological Informatics* **2025**, *90*, 103258, doi:10.1016/j.ecoinf.2025.103258.
88. de Lorm, T.A.; Horswill, C.; Rabaiotti, D.; Ewers, R.M.; Groom, R.J.; Watermeyer, J.; Woodroffe, R. Optimizing the Automated Recognition of Individual Animals to Support Population Monitoring. *Ecology and Evolution* **2023**, *13*, e10260, doi:10.1002/ece3.10260.