

1 **Real-time alerts from AI-enabled camera traps using the Iridium satellite network:**
2 **a case-study in Gabon, Central Africa**

3

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25 **Abstract**

- 26 1. Efforts to preserve, protect, and restore ecosystems are hindered by long delays
27 between data collection and analysis. Threats to ecosystems can go undetected
28 for years or decades as a result. Real-time data can help solve this issue but
29 significant technical barriers exist. For example, automated camera traps are
30 widely used for ecosystem monitoring but it is challenging to transmit images for
31 real-time analysis where there is no reliable cellular or WiFi connectivity. Here,
32 we present our design for a camera trap with integrated artificial intelligence that
33 can send real-time information from anywhere in the world to end-users.
34
- 35 2. We modified an off-the-shelf camera trap (Bushnell™) and customised existing
36 open-source hardware to rapidly create a ‘smart’ camera trap system. Images
37 captured by the camera trap are instantly labelled by an artificial intelligence
38 model and an ‘alert’ containing the image label and other metadata is then
39 delivered to the end-user within minutes over the Iridium satellite network. We
40 present results from testing in the Netherlands, Europe, and from a pilot test in a
41 closed-canopy forest in Gabon, Central Africa.
42
- 43 3. Results show the system can operate for a minimum of three months without
44 intervention when capturing a median of 17.23 images per day. The median time-
45 difference between image capture and receiving an alert was 7.35 minutes. We
46 show that simple approaches such as excluding ‘uncertain’ labels and labelling
47 consecutive series of images with the most frequent class (vote counting) can be

48 used to improve accuracy and interpretation of alerts.

49

50 4. We anticipate significant developments in this field over the next five years and
51 hope that the solutions presented here, and the lessons learned, can be used to
52 inform future advances. New artificial intelligence models and the addition of
53 other sensors such as microphones will expand the system's potential for other,
54 real-time use cases. Potential applications include, but are not limited to, wildlife
55 tourism, real-time biodiversity monitoring, wild resource management and
56 detecting illegal human activities in protected areas.

57

58 **Introduction**

59 Goals towards biodiversity protection, the sustainable use of ecosystems, and mitigation
60 of climate change are now clearly defined for nearly every nation on earth (Convention
61 on Biological Diversity, 2021; UN General Assembly, 2015). However, efforts to protect
62 and preserve ecosystems are often hindered by long delays (months, years or more)
63 between the timing of data collection and data analysis. Ecosystem change and
64 ecosystem threats can therefore go undetected for extended periods. Affordable
65 technology for real-time ecosystem monitoring and threat detection could help address
66 this issue, but significant technological barriers exist. In particular, it has proven a
67 challenge to generate reliable, real-time data from some sensors such as automated
68 camera traps in the absence of wireless fidelity networks (WiFi) or broadband cellular
69 networks.

70

71 Automated camera traps (or ‘trail cameras’) are used to detect and survey wildlife and
72 by conservation managers to identify ecosystem threats (Bessone et al., 2020; Hobbs &
73 Brehme, 2017; Wearn & Glover-Kapfer, 2019). A typical camera trap comprises a
74 movement or heat sensor (e.g. a passive infra-red sensor), one or more digital image
75 sensors, a flash or night-vision capability, removable digital storage and a battery power
76 source. Many commercial models are available and cameras can also be easily
77 custom-built using off-the-shelf components (Droissart et al., 2021).

78

79 Network-enabled camera traps, which send captured images to users in real-time, are
80 now commercially available but typically need access to a reliable broadband cellular

81 network connection. In many countries, however, cellular network coverage is still
82 limited and is often unreliable, causing ‘data poverty’ (Leidig & Teeuw, 2015). Cellular
83 network coverage is also usually focused on human population centres, which might be
84 far from areas of ecological or conservation interest. As a result, camera traps with
85 network connectivity are rarely deployed at scale in these network-limited landscapes.

86
87 In network-limited landscapes, there have been some attempts to use WiFi or GSM
88 enabled camera traps by building dedicated infrastructure such as communication
89 towers and meshed networks. These systems transmit the images over the network for
90 later analysis. However, it can be prohibitively expensive to build the necessary
91 infrastructure and it is often logistically impossible in the most rugged landscapes. Legal
92 barriers also exist and commercial providers can own the exclusive rights to build and
93 install GSM towers and transmitters. Satellite networks have the best global coverage,
94 but high data transfer costs mean it is expensive to send images generated by camera
95 traps to end-users in real time.

96
97 Beyond network connectivity, another challenge limiting the usefulness of camera traps
98 for timely decision-making has been extracting relevant information from the image, or
99 “image labeling”. In ecology, images are typically labelled by identifying the species in
100 the image and counting the number of individuals seen. Camera trap projects collect
101 large volumes of data and it is not uncommon to generate millions of images or videos
102 that require terabytes of storage space. Solutions to labeling these large image
103 databases range from using dedicated software that speeds up manual image labeling,

104 to large-scale citizen science projects and the use of artificial intelligence algorithms
105 (Beery et al., 2019; Swanson et al., 2016). The precision and accuracy of the latest
106 artificial intelligence algorithms for image labelling now approach or match human
107 experts for some species but they typically require powerful computing resources either
108 based on ‘the cloud’ or locally using expensive hardware (Norouzzadeh et al., 2018;
109 Tabak et al., 2019; Whytock et al., 2021). However, recent developments in the field of
110 ‘edge computing’ allow artificial intelligence algorithms to be deployed on
111 microcomputers with relatively low computing and electrical power requirements. It is
112 therefore possible to integrate artificial intelligence with camera trap hardware for
113 deployment in the field. These advances mean that data-light image labels generated
114 by artificial intelligence algorithms can be inexpensively transmitted over wireless
115 networks (e.g. satellite) instead of the costly, data-heavy images.

116

117 Here, we present an overview of a ‘smart’ camera trap system that integrates artificial
118 intelligence with a popular off-the-shelf camera trap for real-time alerts over the Iridium
119 satellite network. The system also transmits information on power status, temperature
120 and humidity for the purposes of monitoring hardware integrity. Although the system is
121 based on existing (open source) hardware where possible, our aim is not to provide a
122 blueprint for a finished ‘tool’, such as the Audiomoth bioacoustic recorder (Hill et al.,
123 2018), but to provide insights into how we solved significant technical challenges.

124 Individual off-the-shelf components can also rapidly change or become unavailable (e.g.
125 components for a bioacoustic recorder (Whytock & Christie, 2017)), potentially making it
126 difficult for end-users to follow blue-print designs. As with all surveillance systems,

127 including existing camera trap technology, there are significant ethical and legal issues
128 to consider before using smart cameras in the field, particularly where human subjects
129 may be intentionally or unintentionally observed (Sandbrook et al., 2018). We therefore
130 caution that deployment of the technology presented here should be guided by robust
131 ethical review.

132

133 To evaluate the system's effectiveness, we present systematic results from testing in
134 the Netherlands and a field test in a high-canopy tropical forest in Gabon, Central Africa.
135 In Gabon, we deployed five systems for real-time detection of forest elephant *Loxodonta*
136 *cyclotis* with the long-term aim of using the system to help mitigate forest elephant crop
137 depredation incidents. These incidents are a pressing concern for the country's success
138 in aligning conservation objectives with rural development. Other uses for which the
139 system could also be used, such as real-time wildlife monitoring and detecting illegal
140 human activities such as poaching, are also discussed.

141

142 **Methods**

143 *General summary*

144 Our objective was to create a robust, field-ready system that could (1) provide real-time
145 alerts from camera traps at an affordable cost, (2) be deployed in the most rural
146 landscapes without existing GSM, Long Range radio (LoRa) or WiFi coverage, (3)
147 function without installing additional infrastructure such as communication towers, base
148 stations or meshed networks, (4) be easily deployed by users who do not have a
149 specialist background in using artificial intelligence-enabled technology and (5) avoid re-

150 inventing existing technology (e.g. camera traps), thus allowing us to solve the problem
151 within a relatively short time frame.

152

153 Our solution was to modify a standard Bushnell™ camera trap by adding additional
154 hardware allowing it to communicate wirelessly with separate, self-contained computing
155 resources installed nearby - which we named the 'smart bridge' (Figure 1). The smart
156 bridge is based on an earlier prototype designed to take photographs of wild penguins
157 (<https://github.com/IRNAS/arribada-pmp>), and provides an intelligent link, or 'bridge',
158 between the camera trap and the end user.

159

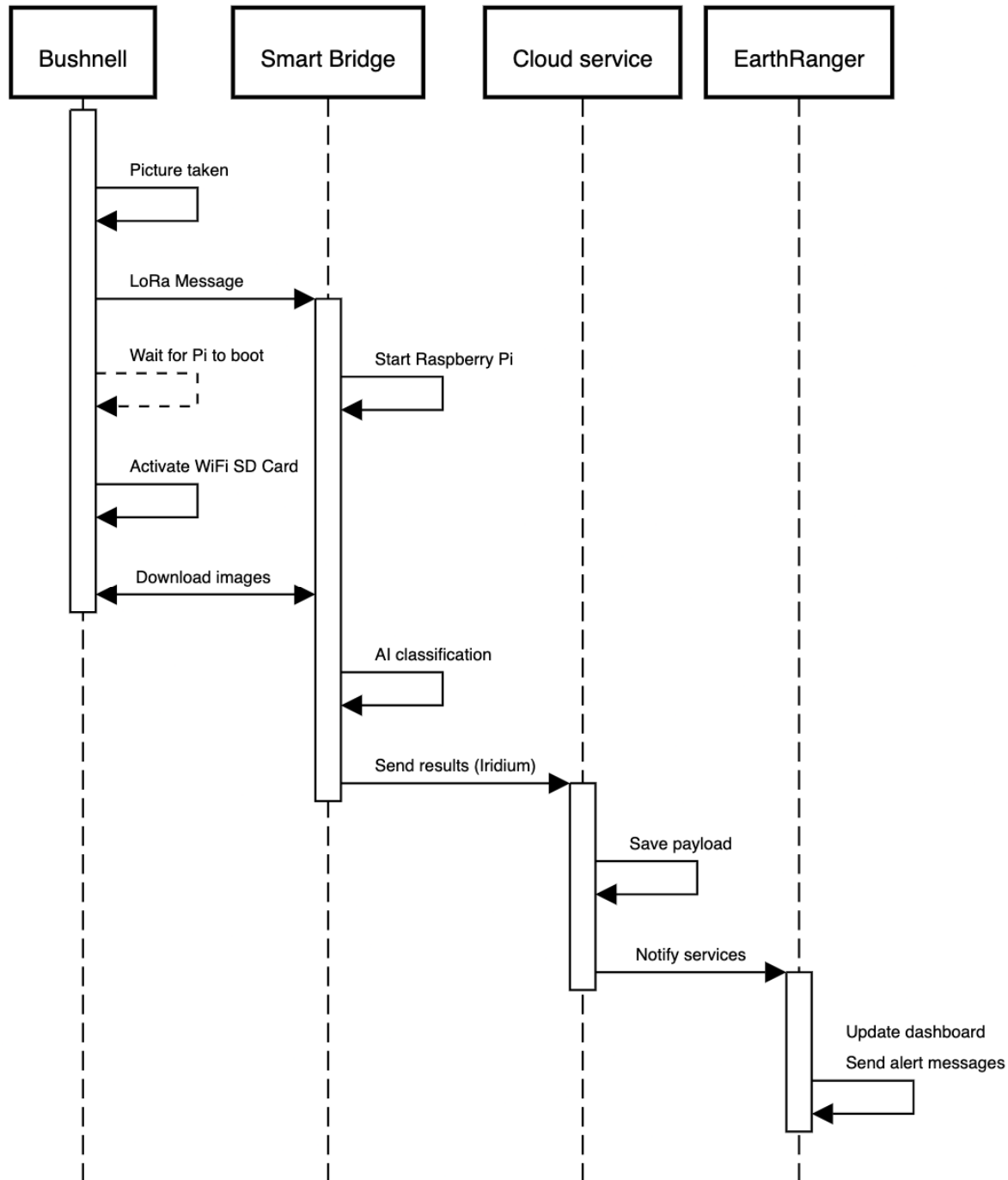


160

161 **Figure 1.** System deployed in the field showing the solar panel (a) and smart bridge (b)
162 attached to a tree approximately 6 m above ground level. The Bushnell™ camera trap
163 (c) is installed at ground level approximately 10 m away from the smart bridge.

164

165 We customised the camera trap by installing a microcontroller with LoRa capabilities
166 based on the OpenCollar Lion Tracker ([https://github.com/IRNAS/smartparks-lion-](https://github.com/IRNAS/smartparks-lion-tracker-hardware)
167 [tracker-hardware](https://github.com/IRNAS/smartparks-lion-tracker-hardware)). Instead of the standard secure digital (SD) card, we used a WiFi-
168 enabled SD card. When an image is captured by the camera trap, the LoRa board in the
169 camera alerts the smart bridge and activates the WiFi SD card, creating a local WiFi
170 network. The smart bridge boots a Raspberry Pi Compute Module 4 that joins the WiFi
171 network and retrieves the image or images from the camera. The species contained in
172 the image are then identified using an artificial intelligence algorithm for species
173 classification. The species and metadata associated with the image (time, date,
174 location) and smart bridge sensor data (internal temperature, humidity and power
175 status) are finally transmitted in an encoded message from the smart bridge to a web-
176 based application running in the cloud (Google's App Engine). The data are sent over
177 the Iridium satellite network, which provides global coverage within minutes. To save
178 power, the Raspberry Pi then shuts down and the smart bridge enters a low-power
179 sleeping mode. Pairing between the camera and smart bridge is automatic and requires
180 no user input or setup. A diagram of the system logic is shown in Figure 2.



181

182

183 **Figure 2.** Diagram showing the stepwise logic between the Bushnell™ camera trap

184 capturing an image and sending an alert via the smart bridge. Total duration of the

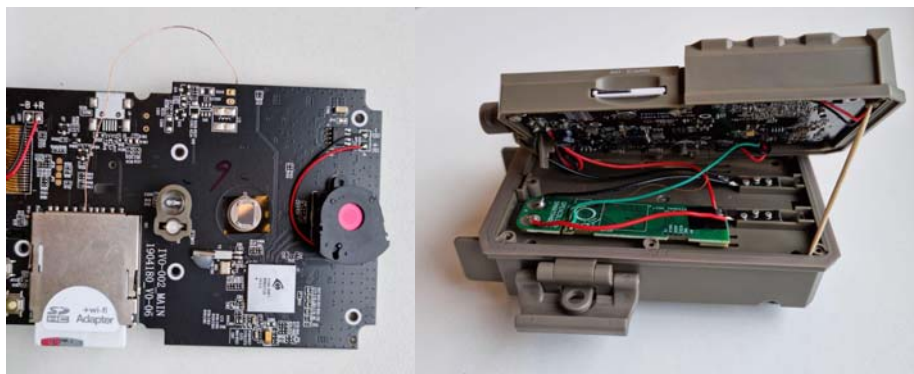
185 entire process is approximately five minutes under optimal conditions.

186 **Hardware stack**

187 *Camera*

188 We used a Bushnell™ Core 24MP Low Glow 119936C camera trap for development but
189 similar modifications can be made to other models and brands. The camera was set to
190 take single images (2304 x 1296 pixels, 72 dpi) at 10s intervals with sensitivity set to
191 auto, and the flash was set to low power mode. Normally, the Bushnell™ immediately
192 cuts power to the SD card once it has finished writing an image or images. This does
193 not allow sufficient time for images to be transmitted from the WiFi SD card to the smart
194 bridge using the WiFi network. To address this, the custom microcontroller keeps the
195 WiFi SD card powered on until the images have been transmitted to the smart bridge.
196 The WiFi SD card is secured permanently into the camera (to prevent the power
197 connection being damaged, Figure 3), but the images are also stored on a removable
198 micro SD for later download if required.

199



200

201

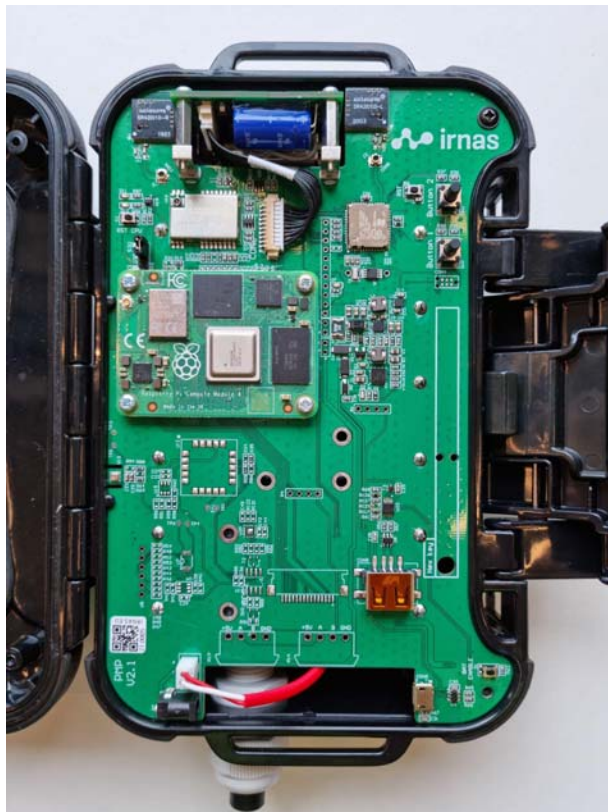
202 **Figure 3.** Modified bushnell™ camera trap showing the LoRA relay and printed circuit
203 board, the WiFi SD card and power supply (removed and installed).

204

205 *Smart-bridge*

206 The Smart-bridge (Figure 4) contains a custom printed circuit board (PCB) with a LoRa
207 STM32L0 ultra-low-power microcontroller, RockBLOCK satellite modem and
208 connections for a Raspberry Pi 4 Compute module. The hardware is stored in a
209 weatherproof NANUK NANO 330 case (L188 x W130 x H65 mm). By default, the
210 Raspberry Pi is turned off and thus the system consumes minimal power (less than 50
211 microampère; see *Power* later). When the smart bridge receives a LoRa message from
212 a nearby camera it turns on the Raspberry Pi, which then downloads and classifies the
213 images from the Bushnell™ using artificial intelligence. After sending the results over
214 the satellite network (see later), the system powers down.

215



216

217 **Figure 4.** Smart Bridge PCB

218 *Raspberry Pi*

219 The Raspberry Pi 4 compute module is integrated onto the Smart-bridge PCB with a
220 pair of 100-pin mezzanine connectors. Raspberry Pis provide an excellent platform for
221 development purposes and have been used widely in ecology (Jolles, 2021; Sethi et al.,
222 2018; Sturley & Matalonga, 2020). Furthermore, although the Raspberry Pi 4 is power
223 inefficient relative to other similar boards on the market (e.g. Arduino based systems),
224 the Pi 4 can run artificial intelligence models built on relatively large architectures. Our
225 approach of only briefly powering the Pi when needed allowed us to harness its
226 computational power in an energy-optimised way.

227

228 The Raspberry Pi 4 Compute module runs Raspbian lite and Python 3 scripts together
229 with the Tensorflow Lite runtime to fetch the images and run the artificial intelligence
230 model. A SQLite database is used to track image status (download status,
231 transmission status etc).

232

233 *Satellite modem*

234 There are many satellite networks available for civilian use. We chose the Iridium
235 satellite network because it has near global coverage, is relatively inexpensive, and has
236 widely available hardware including miniaturised, low-power modems. The Iridium
237 network is also well known in the ecology community where it is regularly used for
238 animal tracking using GPS collars. We used the RockBLOCK 9603 modem from Rock
239 Seven to connect to the Iridium network.

240

241 *Environmental data*

242 The smart bridge PCB is equipped with a temperature, humidity and barometric
243 pressure sensor. Since these are mounted directly on the PCB they are not currently
244 suitable for external environmental monitoring (other than barometric pressure) but they
245 are useful for evaluating if the smart bridge is intact. For example, the smart bridge
246 housing is completely sealed once closed and contains silica gel. In a humid
247 environment such as a tropical forest, the humidity should drop once the bridge is
248 installed and closed. A future rise in humidity could be used as an indicator of a possible
249 hardware problem. We do not present data from these sensors or discuss them further.

250

251 *Power*

252 For the smart bridge we used six NCR18650PF rechargeable batteries totalling 16,500
253 mAh power and a 6 volt 6 watt solar panel for charging. Initial testing in the Netherlands
254 showed an active smart bridge, processing and transmitting approximately 17 images
255 per day (see results), could be powered indefinitely by a solar panel without
256 intervention.

257

258 For the Bushnell™ camera trap, we used six Energizer® Ultimate Lithium™ AA
259 batteries (non-rechargeable). Normally the Bushnell™ has a battery life of
260 approximately one year using these batteries. The addition of the microcontroller and
261 the WiFi SD card draws additional power, however, which will reduce deployment times.
262 During testing in the Netherlands the camera achieved three months of battery life when
263 activated up to 17 times per day on average (see Results). We expect field deployment

264 times to be longer than this since the camera is likely to be triggered less frequently
265 when correctly installed and parameterized.

266

267 *Optimising alerts and minimizing data transmission costs*

268 The Iridium satellite network supports short burst data and a maximum of 340 bytes can
269 be sent in a single transmission. Satellite data is relatively expensive so we optimised
270 the alerts to maximise the amount of information transmitted per message. The
271 timestamp was reduced to 4 bytes by sending the number of elapsed seconds since
272 January 1st 2010. The image label from the artificial intelligence model (e.g. elephant)
273 was mapped to a 1 byte number and later converted back to a text label on the web
274 backend. All other data, like AI prediction 'confidence' for the top-scoring species label
275 (softmax algorithm probabilities), temperature and smart bridge voltage are mapped to 1
276 byte numbers. This allowed us to send up to 55 image classification results in a single
277 satellite message.

278

279 **Software stack**

280 *Artificial intelligence model*

281 Our aim was to provide reliable alerts of species detections without requiring images to
282 be transmitted to the end-user over a wireless network. Since our focus was on forest
283 elephants during the pilot, we initially tested the model from (Whytock et al., 2021),
284 which classifies 26 central African forest mammal and bird species, including forest
285 elephants. However, the model was built using a relatively large convolutional neural
286 network (CNN) architecture (ResNet50) and is 100 MB in size. This model took over 20

287 seconds to classify a single image using the Raspberry Pi 4 compute module, which
288 drew a substantial amount of power and made the model unsuitable for our purposes.
289
290 To find a suitable alternative architecture to ResNet50, we compared inference times
291 among a suite of 16 pre-trained computer vision models using their Fast.ai (Howard &
292 Guggen, 2020) implementations (see Figure S1 for results). We did not evaluate
293 classification accuracy using these models but only inference times. Then, we trained a
294 Tensorflow Lite model (using Google Cloud's AutoML service) and a Fast.ai model
295 (SqueezeNet 1.1, the second-fastest from our tests) using a dataset of 105,000 images
296 (a subset from Whytock et al. (2021)) with three, almost equally distributed classes
297 (elephant, human and other). For these two models, we compared model precision and
298 accuracy using a smaller, held out subset of 14,642 images, with almost equal
299 distribution among the classes. We found that the TensorFlow Lite model provided the
300 shortest inference time (~100 ms vs ~1200 ms for SqueezeNet) and precision and
301 accuracy was similar between the two architectures (Table S1). Therefore, the
302 Tensorflow Lite model trained using AutoML was chosen for deployment during the
303 pilot.

304

305 *Back-end*

306 An important element of receiving real-time alerts from camera traps is a centralised
307 platform that can be used to receive, interpret and display the incoming data. Following
308 our philosophy of using existing technology, we integrated the system with the
309 EarthRanger platform (www.earthranger.org). Incoming data is first stored on our own

310 Django-based back end. Once an alert is received the raw data is stored in a SQL
311 database. A task-queue based system is then used to send the data to integrated
312 platforms (e.g. EarthRanger or others). As well as offering a web-platform and mapping
313 capabilities for displaying alerts, EarthRanger can also be configured to send messages
314 in real-time using WhatsApp[™], short message service (SMS), e-mail and other
315 methods.

316

317 **Case study**

318 Real-time alerts from cameras have many potential applications but our interest was
319 testing if they could be used to help manage human-elephant interactions during crop
320 depredation, in Gabon, central Africa. Gabon is almost 270,000 km² with 88% of the
321 country covered in closed-canopy forest. The country is home to more than 50% of the
322 global population of the critically endangered forest elephant (Gobush et al., 2021).
323 Although Gabon's human population is relatively small (c. 2 million), with most people
324 living in urban areas, rural communities across the country can suffer significant
325 agricultural losses due to elephants (Walker, 2012). This affects the safety and
326 wellbeing of both humans and elephants (e.g. retaliatory killing of elephants, humans
327 injured or killed during interactions) and can have substantial economic consequences
328 for rural communities (Terada, 2021).

329

330 Many villages work with Gabon's National Park Agence (ANPN: the Agence Nationale
331 des Parcs Nationaux) to manage elephant crop depredation. We therefore partnered
332 with ANPN to test the camera's ability to detect elephants and send real-time alerts to

333 ANPN ecoguards (employees of the national park who lead fieldwork, tourism, and law
334 enforcement) over WhatsApp™ in two locations. The first location was the Station
335 d'Etudes des Gorilles et Chimpanzés (SEGC) in Lopé National Park, where elephants
336 are common in the surrounding area. The facilities at the research station allowed us to
337 test the system under controlled but realistic conditions (elephants regularly enter the
338 station grounds). The second location was Kazamabika village, in the northern edge of
339 Lopé National Park, where communities have established farms. Kazamabika received
340 an electric fence to protect crops from elephants in 2016, and the local community is
341 highly engaged in research to help understand and mitigate human-elephant conflict
342 (Rakotonarivo et al., 2021). Although the electric fence is functional and effective,
343 elephants still enter the village and surrounding forest to feed on domestic fruit trees
344 that are also harvested by people. Although rare, elephants also occasionally succeed
345 in entering the fence, potentially causing some damage to crops.

346
347 We tested whether alerts from the smart cameras could be used by ANPN ecoguards in
348 Lopé National Park to detect when elephants are approaching the electric fence or
349 village, allowing them to alert villagers to potential problems. There remains uncertainty
350 about the most effective action villagers can take when they receive an alert, but at
351 minimum they can have pre-warning and avoid the forest where elephants are detected
352 to not be endangered, or they can take action to scare the elephants (e.g. creating
353 noise, or smoke fires). In future, the system could potentially trigger auto-deterrents,
354 such as sounds or lights, assuming effective deterrents are developed (see Discussion).
355 Mitigating human-elephant conflict using sound, smoke, bees and plant species (e.g.

356 chilli pepper) is an active area of research across Africa and Asia (Dror et al., 2020;
357 Ndlovu et al., 2016; Pozo et al., 2019) and we did not explore the effectiveness of
358 particular deterrents during our trials.

359

360 *Field testing*

361 We constructed seven systems and tested five under different settings for a combined
362 total of 72 days (Table 1). Camera locations were chosen to test (a) how the position of
363 the smart bridge and vegetation structure (e.g. forest canopy cover) affected data
364 transmission and satellite connectivity, (b) how far the smart bridge could be installed
365 from the camera, (c) how well the solar panel functioned under different light levels, and
366 (d) how well the artificial intelligence algorithm performed with different camera
367 backgrounds (open areas, farmland and forest). We chose the testing locations based
368 on qualitative differences in vegetation structure, light availability and image background
369 (Table 1). In summary, the smart bridge and solar panel were installed together on a
370 tree 2 - 6 m above ground level at a distance of 5 - 20 m from the camera trap. Camera
371 traps were installed on a tree approximately 40 - 50 cm above ground level,
372 perpendicular to and approximately four metres from the centre of well-used elephant
373 paths.

374

375 We compared results from field testing with benchmark data from two systems operated
376 in the Netherlands for three months during the development stage. Both of these
377 systems were deployed in urban settings (a private garden and empty roof-top) with a
378 clear view of the sky. During field testing, all images were stored on the camera trap SD

379 card and retrieved at the end of the testing period for validating artificial intelligence
380 labels.

381
382 **Table 1.** Description of test locations and field conditions with qualitative descriptions of
383 light availability (Light: low, medium, high), distance between camera and smart bridge
384 (Bridge: near < 5 m, moderate 5 - 10 m, far 10 - 20 m), the positioning of the Smart
385 Bridge (Bridge position) and image background (considered important for artificial
386 intelligence performance).

387

Site name	General description	Days	Light	Bridge distance	Bridge position	Image background
SEGC	Research station with buildings and open short grassland. No forest cover.	7	High	Near	Approximately 2 m above ground level under the canopy of a small shrub.	Open grassland, buildings
Forest West	Closed canopy forest with vegetated understory. Moved a short distance to a new location due to false positives from the artificial intelligence algorithm (see Results).	15	Low	Moderate	Approximately 5 m above ground level on the trunk of a tree approximately 15 cm diameter at breast height (DBH)	Green vegetation in the background and a large tree crossing the left of the image.
Forest East	Closed canopy forest with open understory	18	Mode rate	Far	Approximately 5 m above ground level on a large tree trunk.	Background of large woody lianas, a fallen tree and little vegetation. Brown forest floor. Little green vegetation.
Kazamabika	Village edge. Closed canopy forest beside a	17	High	Far	Approximately 5 m above ground level on a large	Green vegetation with some brown forest floor

	small river,				tree trunk.	
Cayette	Forest fragment of secondary growth. With a rather open understory.	15	Low	Far	Approximately 2 m above ground level on a small tree.	Green vegetation with some brown forest floor.

388

389

390 *Data analysis*

391 To evaluate the speed at which alerts were transmitted and received, we calculated the
392 median time-difference in minutes between image capture and receipt of the alert by the
393 back end for each location individually, and for all stations. For each of the test locations
394 we also created time-series plots showing changes in smart bridge power during
395 deployment. Camera power was also monitored during tests in the Netherlands but not
396 during the field testing.

397

398 We assessed artificial intelligence model performance (precision, recall, accuracy and
399 F1 score (Kuhn, 2020)) on the newly captured images by comparing artificial
400 intelligence-generated image labels with ‘expert’ labels. Expert labels were created by
401 first labeling the captured images using the Mbaza AI software (Whytock et al., 2021)
402 and manually validating all results (co-author RW).

403

404 During field testing we observed that, within a given image sequence of elephants (i.e. a
405 number of images taken during the same presence event), the first and last images
406 could be mislabelled when only a small part of the elephant was visible. We therefore
407 tested if (a) a simple vote-counting approach (i.e. counting the most frequently predicted
408 top-one label in an image series) could improve predictions on an event, and (b) if

409 thresholding on the softmax values (i.e. excluding images below a softmax threshold
410 before vote counting) could improve event prediction accuracy. Events were defined as
411 a series of images taken within an independent 30-minute time window. Softmax
412 thresholds were from 0 to 0.9 in 0.1 intervals. In some instances, vote counting resulted
413 in a tie between the number of votes for each class. In these cases, we chose 'elephant'
414 if it was among the ties, or otherwise chose the label 'other'.

415

416 **Results**

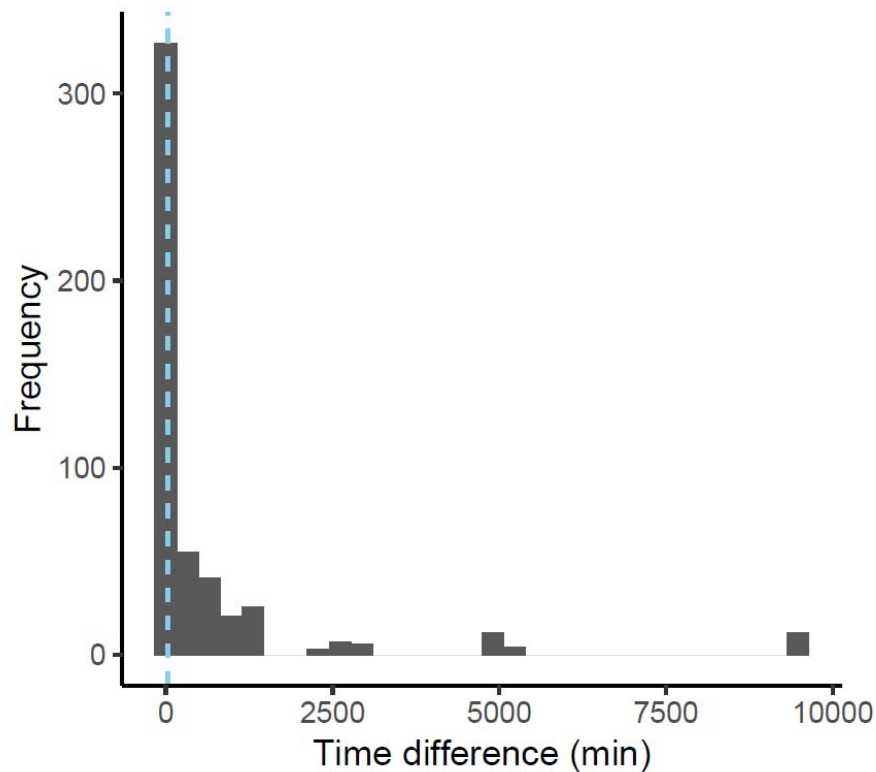
417 A total of 814 images were captured during the field test (Table S2) and alerts for 588
418 images were received by the backend. Of the 226 alerts not received, 72 were from
419 Cayette, which was not able to send any alerts due to the position of the smart bridge (2
420 m above ground level under a tall, closed canopy) and 154 were from Forest East
421 because the smart bridge unexpectedly ran out of battery after just six days. This was
422 caused by a problem with the charging circuit and was inconsistent with tests in the
423 Netherlands, which achieved > 3 months of battery life (see *Battery life* for further
424 details). We removed a further 17 images which had no timestamp (human error during
425 camera setup) and which could not be used to evaluate alert time delays, leaving $n =$
426 571 alerts from four systems for the analysis.

427

428 *Alert times*

429 There was a median 7.35 minutes time difference between capturing an image and
430 sending an alert ($n = 4$ camera stations). Median, minimum and maximum alert times
431 are given in Table S3 for each location. Of the four systems, Kazamabika had the

432 slowest median alert time (306.3 min). A total of 296 (52%) of alerts were received
433 within 15 minutes or less (Figure 5, Figure S2).
434



435
436 **Figure 5.** Histogram showing time difference between image capture and alert
437 transmission time. The dashed line shows the median alert time of 7.35 minutes.

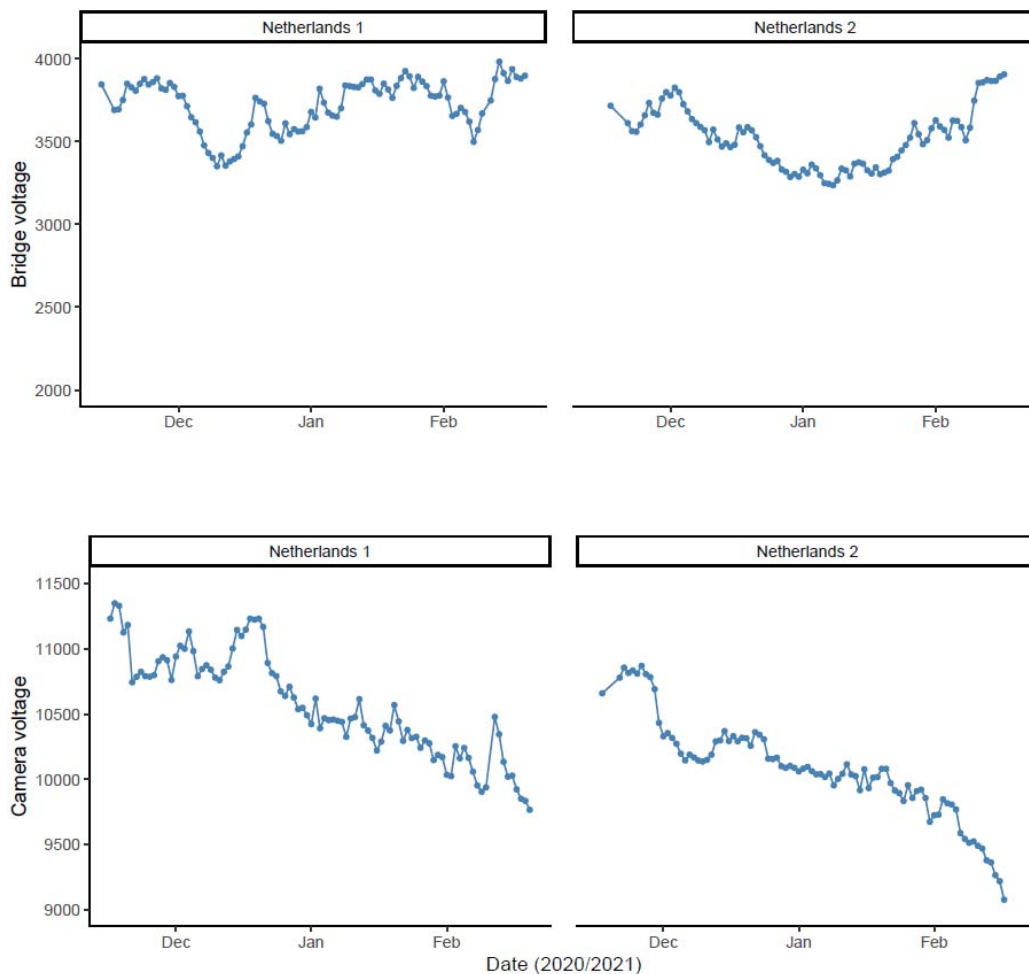
438
439 *Battery life*

440 Preliminary tests in the Netherlands showed that even with a median of 17.23 image
441 captures per day (range 0 - 40), the systems could operate continuously during the
442 winter under low sunlight for a minimum of three months (Figure 6). During field testing
443 in Gabon, we found mixed results (Figure 7) and one system discharged in six days
444 (Forest East). Forest West lasted the full 18 days but did not show signs of substantial

445 charging as was seen in the Netherlands. Kazamabika and SEGC both operated as
446 expected.

447

448 Initially it was thought that the forest canopy was preventing charging by the solar panel
449 in Forest East and Forest West, despite careful positioning. However, further tests
450 revealed the mechanism designed to prevent the charging circuit from overheating was
451 being triggered prematurely by the high ambient temperatures and high voltage output
452 from the solar panel in Gabon, in contrast to the Netherlands. This problem has been
453 solved by removing the overheating protection.

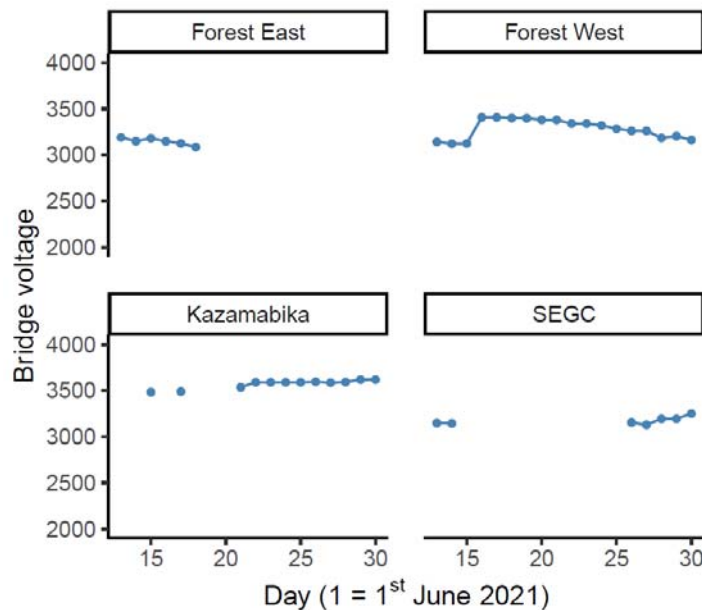


454

455 **Figure 6.** Smart bridge and camera voltage change over time during testing of two
456 systems in the Netherlands using a solar panel.

457

458



459

460 **Figure 7.** Smart bridge voltage changes over time during testing of four systems in
461 Gabon using a solar panel.

462

463 *Artificial intelligence model accuracy and interpreting alerts*

464 Overall model accuracy on new data collected during the field test ($n = 571$ images) was

465 84%, with a Kappa statistic of 0.74. For the elephant class, precision was 82% and

466 recall 86%, with a balanced accuracy of 86%. Test statistics for all classes and a

467 confusion matrix are given in Table 2 and Figure 8. Classification of events using vote

468 counting without any softmax thresholding (i.e. choosing the most frequently predicted

469 class in a 30 minute time window) gave an overall performance of 78% and a Kappa

470 statistic of 0.64 ($n = 142$ events) (Table 2). Excluding uncertain image labels using a
471 softmax threshold before vote counting improved overall accuracy for event
472 classification, as well as balanced accuracy for the elephant events ($n = 29$ true events,
473 $n = 30$ predicted), which reached 98% at a threshold where images were excluded with
474 a softmax value < 0.9 (Figure 9). This almost matched human accuracy with just one
475 false positive event and no false negatives.

476

477 One camera (Forest West) returned several false-positive elephant detections during
478 the first two days of deployment. Verification of the images in the field showed this was
479 likely to be caused by an unusual branch resembling an elephant trunk or limb, close to
480 the camera lens. Moving the camera to another location a short distance away solved
481 this issue.

482

483

484 **Table 2.** Model performance by class for $n = 571$ images and $n = 142$ events using vote
485 counting.

486

Test statistic	Elephant_African	Human	Other
<i>Images</i>			
Pos Pred Value	0.82	0.92	0.81
Neg Pred Value	0.89	0.95	0.91
Precision	0.82	0.92	0.81
Recall	0.86	0.80	0.82
F1	0.84	0.86	0.82
Prevalence	0.44	0.22	0.34
Detection Rate	0.38	0.18	0.28
Detection Prevalence	0.46	0.20	0.34
Balanced Accuracy	0.86	0.89	0.86
<i>Events</i>			
Pos Pred Value	0.62	0.72	0.94
Neg Pred Value	0.97	0.96	0.72
Precision	0.62	0.72	0.94
Recall	0.90	0.81	0.77
F1	0.73	0.76	0.85
Prevalence	0.20	0.18	0.61
Detection Rate	0.18	0.15	0.47
Detection Prevalence	0.30	0.20	0.50
Balanced Accuracy	0.88	0.87	0.85

487

488

489

490

491

A confusion matrix for image-based classification. The vertical axis is labeled 'Prediction' and the horizontal axis is labeled 'Truth'. Both axes have three categories: 'Elephant_African', 'Human', and 'Other'. The matrix cells contain the following counts:

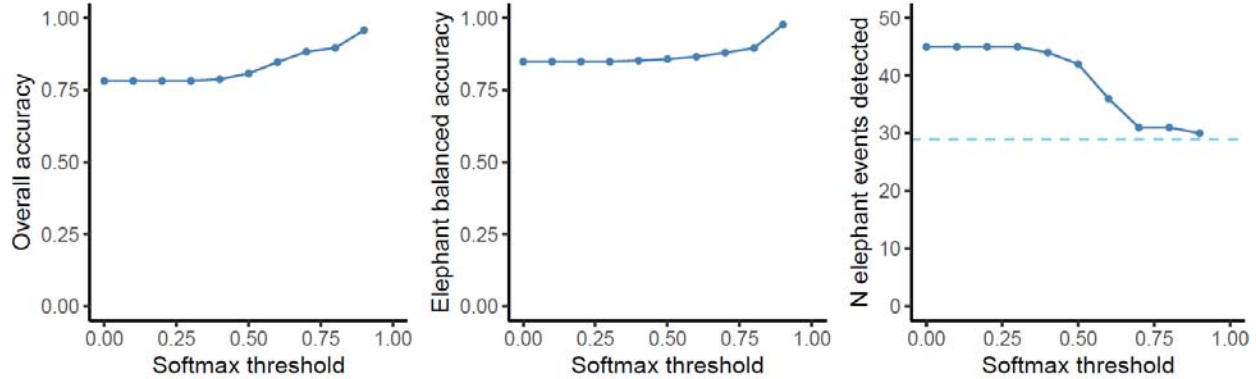
Prediction \ Truth	Elephant_African	Human	Other
Elephant_African	217	21	26
Human	1	103	8
Other	33	4	158

492

493

Figure 8. Confusion matrix for image-based classification

494



495

496 **Figure 9.** Effects of using a softmax threshold to exclude uncertain labels before vote
497 counting to classify an event on (a) overall accuracy, (b) balanced accuracy for events
498 labelled as elephant and (c) the number of elephant events detected (dashed horizontal
499 line shows $n = 29$ true events).

500

501 Discussion

502 Sending real-time alerts from ecological sensors such as camera traps in areas with
503 poor data connectivity is complex and involves fine tuning a large number of software
504 and hardware parameters. These include camera settings, camera positioning,
505 achieving reliable network connectivity, training and running artificial intelligence
506 models, interpreting and displaying artificial intelligence outputs and providing a reliable
507 source of power. Our results demonstrate that these parameters can be tuned to
508 achieve reliable, near real-time alerts from camera traps under challenging field
509 conditions. We also identified potential pitfalls and areas that should be prioritised for
510 future research and development.

511

512

513 *Problems and solutions*

514 Battery charging using the solar panel in Gabon did not function in forests as expected
515 given results from testing in the Netherlands. However, this was rapidly diagnosed as
516 an issue with the charging circuit and has now been rectified.

517

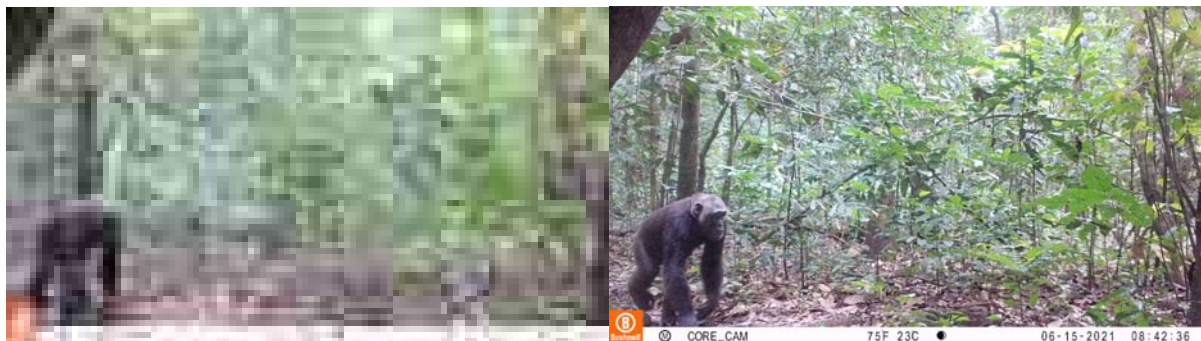
518 At one camera location, false positive elephant detections were quickly remedied by
519 moving the camera position. However, this could be difficult to detect during a real
520 deployment after cameras have been left in-situ by field teams. Improved models and
521 training data will likely reduce this issue in future (Beery et al., 2018). The problem can
522 also be mitigated by ensuring that cameras are positioned so that new images replicate
523 training data as closely as possible.

524

525 A total of 588 alerts were generated by our four systems during 18 days of testing, and
526 the final total could have been as high as 814 if all alerts had been received. This is a
527 substantial amount of data to interpret on a rolling basis with just four systems and three
528 label classes. In future, we recommend first implementing vote-counting combined with
529 softmax thresholding on the smart bridge to reduce the total number of alerts, which
530 would have been just 30 (with one false positive) if restricted only to elephants. Similar
531 vote counting approaches have also been successfully used to summarise camera trap
532 image labels made by citizen scientists using online platforms (Swanson et al., 2015).
533 Summarising alerts into temporally independent events using vote counting would not
534 only improve alert accuracy but also reduce data transmission costs. This approach will
535 be implemented into future versions of the smart camera system.

536 Our system does not currently send images but this would be possible using an on-
537 demand approach. For example, users could request certain images or an image series
538 by sending a message (relayed via satellite) to the smart bridge. The main limitations to
539 implementing this is achieving a reasonable trade-off between image quality and
540 transmission cost. For example, sending an extremely compressed thumbnail would
541 cost \$2 USD per image with a \$20 per month contract on the Iridium network (Figure
542 10). Scaling this up to hundreds of cameras could be financially unfeasible for many
543 use-cases.

544



545

546 **Figure 10.** Camera trap image of a chimpanzee, with example compressed thumbnail
547 (left) compared to the original image (right). The compressed thumbnail would require
548 three messages sent over the Iridium network using a RockBlock modem and cost
549 approximately 2 USD (on a 20 USD monthly contract). The thumbnail provides limited
550 information for interpretation by both human and artificial intelligence algorithms.

551

552 The next generation of camera traps will run artificial intelligence models on the camera
553 hardware directly (known as 'edge computing') instead of using a separate smart bridge.
554 However, if the goal is to transmit real-time data from cameras installed near the ground

555 for wildlife monitoring, then developers should be aware that it will be difficult to achieve
556 network connectivity under a dense forest canopy. We were not able to send any
557 images from Cayette forest patch, where the smart bridge was installed just 2 m above
558 ground level. The wireless smart bridge, which can be mounted in a tree, might
559 therefore be a useful design feature for future edge computing solutions.

560

561 A final problem that only became apparent during field testing was that users need to
562 know if the system is still functioning when no alerts are received. The latest version of
563 the system now sends a timed, daily 'keep-alive' message notifying the user that it is
564 functioning as expected.

565

566 *Potential applications beyond our case study*

567 Our results show that we have created a viable hardware solution for running powerful
568 artificial intelligence algorithms in the field and transmitting results over a satellite
569 network. The computing power of the Raspberry Pi 4 is currently underused and there is
570 scope for attaching other sensors, such as microphones for bioacoustic recording.
571 There are already a substantial number of open-source Raspberry Pi projects available
572 for ecological research, and many of these could be integrated with the smart bridge
573 with relatively minimal effort (Jolles, 2021). Likewise, there is scope for implementing
574 other artificial intelligence models, for example to count animals in images or to
575 recognise species from other ecoregions. The list of potential applications for the
576 hardware is limited only by imagination, but some examples relevant to ecology and
577 conservation are given in Table 3.

578 **Table 3.** Potential ecology and conservation applications for real-time, artificial
579 intelligence-enabled smart cameras

580

Application	Description	Considerations
Phenology	Monitoring the timing of biological events (e.g. tree flowering) in real-time across landscapes.	None
Detecting illegal activities (e.g. logging, hunting)	Detecting human hunters with guns, hunted animals or humans entering protected areas illegally.	At minimum must comply with local surveillance laws. Significant ethical concerns have been raised (Sandbrook et al., 2018).
Human-wildlife conflict	Detect and provide alerts of predators and crop pests or trigger sounds and lights to act as an automated deterrent.	There is a risk of harm to people and wildlife when acting upon an alert.
Non-timber forest product monitoring	Provide alerts of wild resource availability (e.g. seasonally available wild fruits or other non-timber forest products).	Increased efficiency of gathering wild resources could create or contribute to unsustainable levels of harvesting.
Wildlife tourism	It can be challenging to keep track of wildlife such as habituated apes. Alerts could help wildlife guides locate species of interest more easily.	The tourists could be satisfied by bringing them to a location where they can watch wildlife without searching around, but there is risk to disturb their environment to often

581

582

583 *Current limitations*

584 Using the system outside of our case study would require both technical expertise to
585 build or modify all of the necessary hardware components and sufficient training data to
586 create a new artificial intelligence model. The Audiomoth bioacoustic recorder (Hill et
587 al., 2018) project has overcome this challenge using a ‘group buy’ format, where the
588 design is completely open-source and customers order the units in advance. The units
589 are then only manufactured and shipped when a target number is reached. Currently,

590 the system presented here costs approximately 1000 euros per unit including the
591 camera, smart bridge and solar panel, but this does not include labour costs for building
592 the units, satellite contract costs or field deployments. This is more expensive than a
593 standard camera trap but like all technology these costs will reduce in future. We
594 anticipate that our approach will be superseded by new developments in the next five
595 years, but hope the lessons learned here can help drive and inform the development of
596 new technologies.

597

598 Other limitations include the sometimes low accuracy of the artificial intelligence model
599 at the image-level. However, our main focus was building a complete system that was
600 field-ready rather than attempting to achieve perfect artificial intelligence predictions,
601 and we found that the model was usable, particularly when applying a vote-counting
602 approach. Improved models can be built using new incoming data and new approaches
603 will give gains in precision and accuracy in future (Beery et al., 2019; Schneider et al.,
604 2019).

605

606 **Conclusion**

607 We have shown that it is possible to send reliable, real-time information from camera
608 traps over the Iridium satellite network by integrating artificial intelligence, off-the-shelf
609 and custom hardware. Our solution does not depend on installation of additional
610 network infrastructure in the landscape and can be operated by non-experts from
611 anywhere on earth. Real-time data gathering and interpretation will change how
612 ecologists and conservationists understand and manage ecosystems. We piloted the

613 system for detecting elephants, but new artificial intelligence algorithms will be created
614 in future to capture other species or objects in images, such as illegal human activities
615 in protected areas.

616

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635

636 **Author contribution statement**

637 RCW contributed to the system design, co-wrote the manuscript, collected the data and
638 analysed the data. TS designed the system, co-wrote the manuscript and collected
639 data. TvD co-designed the system and collected data. JS created the AI model. HM co-
640 designed the pilot. NM collected data. JAZ supplied data for the AI model. AFKP
641 supervised RCW and contributed to writing the manuscript. LB supplied data for the AI
642 model. SB supplied data for the AI model and contributed to writing the manuscript.
643 AWC supplied data for the AI model. PH supplied data for the AI model and contributed
644 to the system's design. DL contributed to the system's design and contributed to writing
645 the manuscript. BM supplied data for the AI model and collected data. LM collected
646 data. CO contributed to the system's design and supplied data for the AI model. LJTW
647 contributed to the system's design and co-designed the pilot study. DMI contributed to
648 manuscript writing and interpreting results. KAA contributed to the manuscript,
649 contributed to the system's design and co-designed the pilot.

650

651 **Ethics statement**

652 The work was approved by the University of Stirling General University Ethics Panel,
653 application number GUEP (2021) 1044.

654

655 **Research permissions**

656 The work was carried out in collaboration with the Tropical Ecology Research Institute in
657 Gabon as part of the GCRF-TRADE Hub partnership.

658

659 **Data availability statement**

660 *All data used in the analyses (excluding raw images) will be made publicly available on*
661 *acceptance of the manuscript.*

662

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777

778

779

780 **Supplementary Material**

781

782 **Table S1.** Comparison between model accuracy for the Fast.ai SqueezeNet model and
783 the TensorFlow Lite model trained using three classes.

Model	Class	Number correct	Percentage correct
SqueezeNet	Human	4529 / 5000	90.58%
TensorFlow Lite	Human	4631 / 5000	92.62%
SqueezeNet	Elephant_African	4516 / 5000	90.32%
Tensorflow Lite	Elephant_African	4507 / 5000	90.14%
SqueezeNet	Other	4358 / 5000	87.16%
Tensorflow Lite	Other	4586 / 5000	91.72%

784

785

786

787

788 **Table S2.** Images captured during each day of the field test for each location. NA
789 indicates the system was deactivated.

Day (June 2021)	Forest East	Forest West	Cayette	Kazamabika	SEGC
13	12	2	NA	NA	50
14	18	4	NA	24	5
15	13	14	NA	1	NA
16	13	29	5	5	NA
17	8	4	4	32	NA
18	17	5	0	0	NA
19	1	8	3	0	NA
20	10	12	1	0	NA
21	7	9	11	32	NA
22	1	8	7	13	NA
23	16	30	2	1	NA
24	7	2	7	2	NA
25	12	7	7	27	NA
26	8	40	2	2	8
27	38	18	7	18	4
28	12	34	2	1	4
29	25	1	3	6	4
30	4	27	13	3	5

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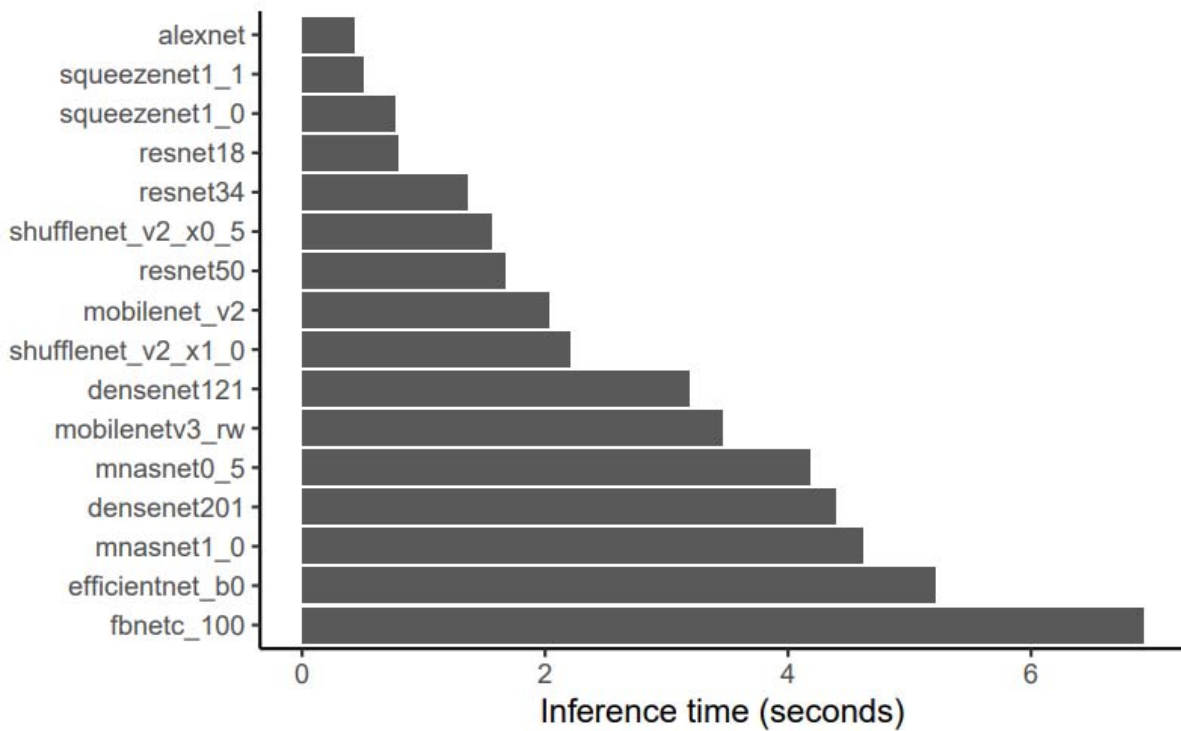
793 **Table S3.** Mean, minimum and maximum time difference between image creation time
794 and alert time for four sites.

Site	Minutes	Min.	Max.
Forest East	6.9	2.37	863.8
Forest West	6.5	1.28	1299.2
Kazamabika	306.3	1.68	9473.9
SEGC	< 1	< 1	1277.1

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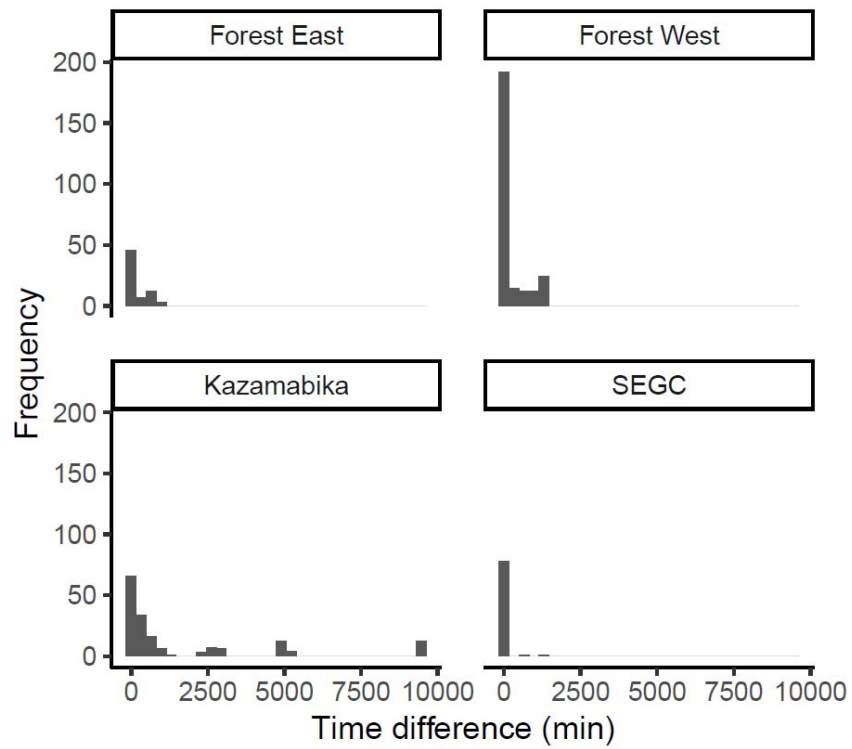
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Figure S1. Mean inference time in seconds ($n = 8$ images 224×224 pixels) for 16 pre-trained computer vision CNN architectures run on the Raspberry Pi 4 compute module using PyTorch.



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Figure S2. Alert times for each of $n = 4$ camera stations.