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PRACTICAL TOOLS

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

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Abstract

1. Efforts to preserve, protect and restore ecosystems are hindered by long delays between data collection and analysis. Threats to ecosystems can go undetected for years or decades as a result. Real-time data can help solve this issue but significant technical barriers exist. For example, automated camera traps are widely used for ecosystem monitoring but it is challenging to transmit images for real-time analysis where there is no reliable cellular or WiFi connectivity.
2. We modified an off-the-shelf camera trap (Bushnell™) and customised existing open-source hardware to create a 'smart' camera trap system. Images captured by the camera trap are instantly labelled by an artificial intelligence model and an 'alert' containing the image label and other metadata is then delivered to the end-user within minutes over the Iridium satellite network. We present results from testing in the Netherlands, Europe, and from a pilot test in a closed-canopy forest in Gabon, Central Africa. All reference materials required to build the system are provided in open-source repositories.
3. Results show the system can operate for a minimum of 3 months without intervention when capturing a median of 17.23 images per day. The median time-difference between image capture and receiving an alert was 7.35 min, though some outliers showed delays of 5-days or more when the system was incorrectly positioned and unable to connect to the Iridium network.

Robin C. Whytock and Thijs Suijten contributed equally to the manuscript.

4. We anticipate significant developments in this field and hope that the solutions presented here, and the lessons learned, can be used to inform future advances. New artificial intelligence models and the addition of other sensors such as microphones will expand the system's potential for other, real-time use cases including real-time biodiversity monitoring, wild resource management and detecting illegal human activities in protected areas.

1 | INTRODUCTION

Automated camera traps (or 'trail cameras') are used in wildlife surveys and to detect ecosystem threats (Bessone et al., 2020; Hobbs & Brehme, 2017; Wearn & Glover-Kapfer, 2019). Many commercial models are available and camera traps can also be custom-built using off-the-shelf components (Droissart et al., 2021).

Network-enabled camera traps, which send captured images to users in real-time, are commercially available but typically need access to a reliable broadband cellular network connection. Broadband network coverage is concentrated on human population centres, often far from areas of ecological or conservation interest. In 'data poor' countries, network coverage can also be limited or unreliable (Leidig & Teeuw, 2015). Several satellite networks have global coverage but data bandwidths are extremely limited or expensive, and they cannot be used to cost-effectively transmit images and audio. As a result, there are many landscapes where existing network-enabled camera traps cannot reliably be deployed at scale.

Using camera trap data for timely decision-making can be limited by the time required to label images generated by camera traps, which can number millions or more. Many attempts have been made to streamline the image labelling process, ranging from using dedicated software that optimises the labelling workflow, to large-scale community science projects and dedicated artificial intelligence algorithms (Beery et al., 2019; Swanson et al., 2016). However, the time needed to analyse data can still be in the order of months or years.

The precision and accuracy of the latest artificial intelligence algorithms for camera trap image labelling now approach or match human experts for some species. However, these algorithms typically require powerful computing resources either based online (i.e. in 'the cloud') or locally on a PC using expensive hardware (Norouzzadeh et al., 2018; Tabak et al., 2019; Whytock et al., 2021). Recent developments in the field of 'edge computing' allow artificial intelligence algorithms to be deployed on low-cost, energy-efficient microcomputers, opening the door to integration of artificial intelligence with camera trap hardware for deployment in the field. Image metadata from artificial intelligence classifiers, such as species labels and timestamps, is substantially smaller in size and therefore easier to transmit over satellite networks that have global coverage.

Here, we present a design for a 'smart' camera trap system that integrates artificial intelligence with a popular off-the-shelf camera trap to generate real-time alerts transmitted over a satellite network. Our goal was to create a system that could provide real time insights to help rangers protect wildlife. The system was designed to work in remote areas without existing internet or cellular connections and it therefore transmits data using the Iridium satellite network, which provides global coverage. We present results from systematic testing in the Netherlands and a field-pilot in Gabon, Central Africa in a landscape with no existing cellular or other terrestrial network connectivity. Our aim is to provide broad insights into how we solved the technical challenges posed by integrating artificial intelligence with existing camera trap models to achieve reliable alerts in challenging environments.

2 | METHODS

2.1 | System overview

Our objective was to create a robust, field-ready system within 1 year that could (1) provide real-time alerts from camera traps, (2) be deployed in the most rural landscapes without existing cellular, long range radio (LoRa) or wireless fidelity network (WiFi) coverage, (3) function without infrastructure such as communication towers, permanent base stations or meshed networks, (4) once configured, be easily installed in the field by users who do not have a technical background and (5) take advantage of existing technology (i.e. camera traps), thus allowing us to solve the problem within a relatively short time frame. The approximate cost for the hardware components is 1185 euros plus a monthly running cost of approximately 22.5 euros.

Our solution was to modify a nonnetwork enabled Bushnell™ camera trap so that it could communicate with a nearby microcomputer (Figure 1; Figure S1). The microcomputer, which we named the 'smart bridge' (Figure 1; Figure S2) is powered by 6 × 18,650 rechargeable lithium-ion batteries that are trickle charged by a small solar panel (Figure 1). The smart bridge is based on an earlier prototype designed to take photographs of wild penguins (see Data Availability Statement) and provides an intelligent link, or 'bridge', between the camera trap and the end user.

We customised the camera trap by installing a microcontroller into the camera housing with LoRa capabilities based on the OpenCollar Lion Tracker (see Data Availability Statement) (Figure S1) and by installing a WiFi-enabled SD card. When an image is captured by the camera trap, the LoRa board in the camera alerts the smart bridge, and the camera activates the WiFi SD card, creating a local WiFi network. The smart bridge boots a Raspberry Pi Compute Module 4

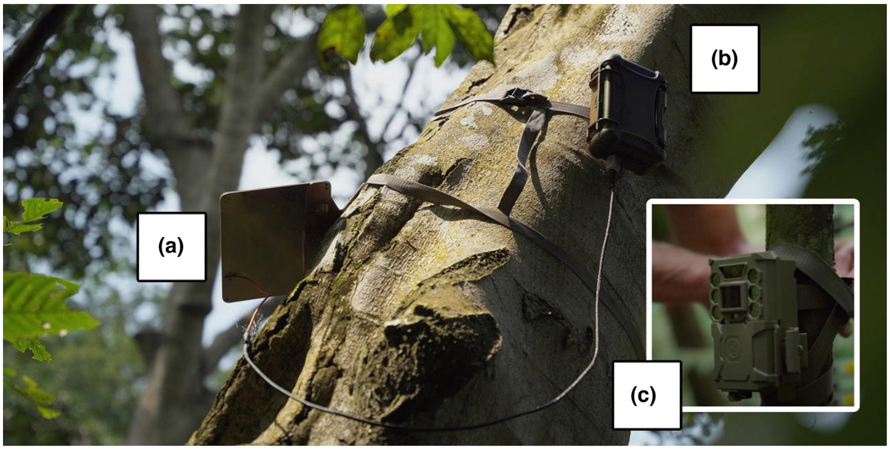

FIGURE 1 System deployed in the field showing (a) the solar panel and (b) smart bridge attached to a tree approximately 6 m above ground level. The Bushnell™ camera trap (c) is installed approximately 40–50 cm above the ground level and approximately 10 m away from the smart bridge.

microcontroller (Raspberry Pi Foundation, Cambridge, UK; hereafter Raspberry Pi) that joins the WiFi network and retrieves the image or images from the camera. The species captured in the image are then identified using an artificial intelligence algorithm for species classification (a TensorFlow Lite model, trained using Google's AutoML platform, Supplementary Material). The model was trained to identify three classes, 'elephant', 'human' and 'other'. Once an image is labelled, the species and metadata (time, date, location) and smart bridge sensor data (internal temperature and humidity sensors, and power status) are finally transmitted via a RockBlock modem (Ground Control, Billericay, UK; hereafter RockBlock) connected to the Iridium satellite network. The message is encoded and transferred to a web-based application running in the cloud (Google's App Engine). These data were then instantly provided to the end user as WhatsApp™ messages and web-based alerts by pushing the data to the EarthRanger software platform (www.earthranger.com). To save power, the Raspberry Pi then shuts down and the smart bridge enters a low-power sleeping mode. Pairing between the camera and smart bridge is automatic and requires no user input or setup. A diagram of the system logic is shown in Figure 2. A technical overview of the system design, components used and the artificial intelligence algorithm are given in the Supplementary Material and permanent Digital Object Identifiers for all open source code and hardware design files are given in the Data Availability Statement.

3 | CASE STUDY AND FIELD TEST

Real-time alerts from cameras have many potential applications but our interest was testing if they could be used to help manage human-elephant interactions during crop depredation, in Gabon, Central Africa. We therefore partnered with Gabon's Agence Nationale des Parcs Nationaux (ANPN) to test the camera's ability to detect elephants and send real-time alerts to ecoguards working for ANPN over WhatsApp™ in two locations. The first location was the Station d'Etudes des Gorilles et Chimpanzés (SEGC) in Lopé National Park, where elephants are common in the surrounding area. The facilities at the research station allowed us to test the system under controlled but realistic conditions (elephants regularly enter the station grounds). The second location was Kazamabika village, in the northern edge of Lopé National Park, where communities have established farms and work closely with ANPN to find solutions to human-elephant conflict.

3.1 | Field testing

We tested five systems under different conditions for a combined total of 72 days (Table 1). The artificial intelligence model was trained on three classes relevant to the pilot tests, which were elephant, human or 'other' (Supplementary Material). Camera locations were chosen to test (a) how the position of the smart bridge and vegetation structure (e.g. forest canopy cover) affected data transmission and satellite connectivity, (b) how far the smart bridge could be installed from the camera, (c) how well the solar panel functioned under different light levels, and (d) how well the artificial intelligence algorithm performed with different image backgrounds (open areas, farmland and forest). We chose the testing locations based on qualitative differences in vegetation structure, light availability and image background (Table 1). In summary, the smart bridge and solar panel were installed together on a tree 2–6 m above the ground level at a distance of 5–20 m from the camera trap. Camera traps were installed on a tree approximately 40–50 cm above the ground level, perpendicular to and approximately 4 m from the centre of well-used elephant paths.

We compared results from field testing with benchmark data from two systems operated in a private urban setting in the Netherlands for 3 months.

3.2 | Data analysis

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

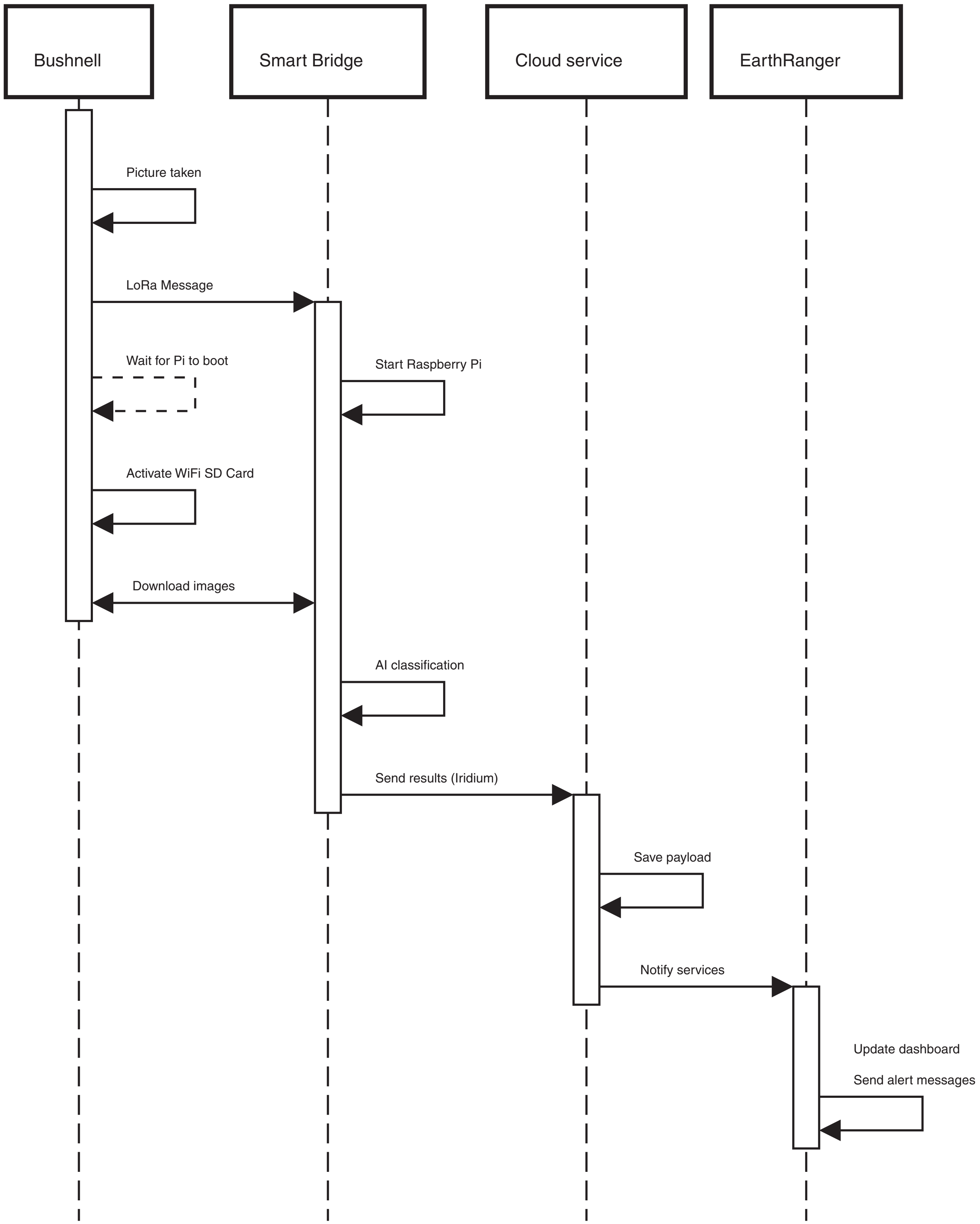

FIGURE 2 Diagram showing the stepwise logic between the Bushnell™ camera trap capturing an image and sending an alert via the smart bridge. The total duration of the entire process is approximately 7 min under optimal conditions.

TABLE 1 Description of test locations and field conditions with qualitative descriptions of light availability (light: low, medium, high), distance between camera and smart bridge (bridge: near <5 m, moderate 5–10 m, far 10–20 m), the positioning of the Smart Bridge (bridge position) and image background (considered important for artificial intelligence performance)

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	Moderate	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 small river	17	High	Far	Approximately 5 m above ground level on a large tree trunk	Green vegetation with some brown forest floor
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

We assessed artificial intelligence model performance (Kappa statistics, precision, recall, accuracy, balanced accuracy and F1 score, see (Kuhn, 2020)) on the newly captured images by comparing the artificial intelligence-generated image labels with 'expert' labels. Expert labels were created for each image after the field test by first processing the captured images using the Mbaza AI software (Whytock et al., 2021) and manually validating all results (co-author RW).

4 | RESULTS

A total of 814 images were captured during the field test (Table S2) and alerts for 588 images were successfully transmitted to the backend. Of the 226 alerts not received, 72 were from Cayette, where we installed the smart bridge just 2 m above ground level under a dense forest canopy, and it was unable to connect to the Iridium network. A further 154 alerts not received were from Forest East because the smart bridge unexpectedly ran out of battery after just 6 days caused by a problem with the charging circuit that was later solved. We removed a further 17 images which had no timestamp (human error during camera setup) and which could not be used to evaluate alert time delays, leaving $n = 571$ alerts from four systems for the analysis. A detailed breakdown of battery life and power consumption is given in Supplementary Material and Figures S3 and S4.

4.1 | Alert times

There was a median 7.35 min time difference between capturing an image and sending an alert ($n = 4$ camera stations). Median, minimum and maximum alert times are given in Table S1 for each location. Of the four systems, Kazamabika had the slowest median alert time (306.3 min) and some alerts were delayed for days (outliers in Figure 3) because the smart bridge was not well positioned and could not connect to the iridium network. A total of 296 (52%) of alerts were received within 15 min or less (Figure 3; Figure S5).

4.2 | Artificial intelligence model accuracy and interpreting alerts

Overall model accuracy on new data collected during the field test ($n = 571$ images) was 84%, with a Kappa statistic of 0.74. For the elephant class, precision was 82% and recall 86%, with a balanced accuracy of 86%. All test statistics for all classes and a confusion matrix are given in Table S2 and Figure S6.

5 | DISCUSSION

Sending real-time alerts from ecological sensors such as camera traps in areas with poor data connectivity is complex and involves integrating a large number of potentially complex hardware and

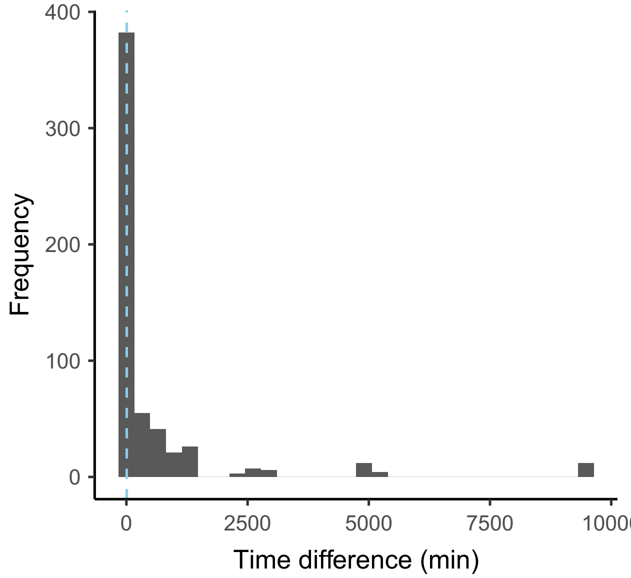

FIGURE 3 Histogram showing time difference between image capture and alert transmission time. The dashed line shows the median alert time of 7.35 min.

software components. Our results demonstrate that these components can be successfully integrated to achieve reliable, near real-time alerts from camera traps under challenging field conditions.

5.1 | Problems and solutions

A total of 588 alerts were generated by our four systems during 18 days of field-testing, and the final total could have been as high as 814 if all alerts had been transmitted and received. This is a substantial amount of data to interpret on a rolling basis with just four active camera systems and three AI label classes. In future, we recommend using approaches such as 'vote-counting' (e.g. sending single alerts for a sequence of images based on the most common species label) to reduce the total number of alerts. This would also reduce data transmission costs, which is likely to be an important consideration for many end users.

Our system does not currently send images directly but this would be possible using an on-demand approach. For example, users could request certain images or an image series by sending a message (relayed via satellite) to the smart bridge. The main limitations to implementing this is achieving a reasonable trade-off between image quality and transmission costs. For example, sending an extremely compressed thumbnail (Figure S7) would cost $2 USD per image with a $20 per month contract on the Iridium network.

Future generations of camera traps might run artificial intelligence models on the camera hardware directly instead of using a separate smart bridge. However, if the goal is to transmit real-time data from cameras installed near the ground (i.e. below 2 m) for wildlife monitoring, then developers should be aware that it will be difficult to achieve network connectivity under a dense forest canopy. We were not able to send any alerts from Cayette forest patch, where the smart bridge was installed just 2 m above the ground level, but increasing this height to 4 m or greater resolved this issue. The wireless smart bridge, which can be mounted high in a tree, might therefore be a useful design feature for future edge computing solutions.

5.2 | Potential applications beyond our case study

Our results show that we have created a viable hardware solution for running powerful artificial intelligence algorithms in the field and transmitting results over a satellite network. The computing power of the Raspberry Pi 4 is currently underused and there is scope for integrating artificial intelligence models with other sensors, such as microphones for bioacoustic research. There are already a substantial number of open source Raspberry Pi projects available for ecological research (Jolles, 2021), and many of these could be integrated with the smart bridge with relatively minimal effort.

6 | CONCLUSION

We have shown that it is possible to send reliable, real-time information from camera traps over the Iridium satellite network by integrating an artificial intelligence model, off-the-shelf camera traps and custom hardware. Our solution does not depend on installation of additional network infrastructure in the landscape and can be deployed in the field by non-experts from anywhere on earth. However, scaling up our system will require engineering expertise and potentially commercial production. We hope that the broader solutions presented here can inform future efforts to successfully design and deploy robust, connected camera traps that provide real-time insights for conservation and ecology.

AUTHOR CONTRIBUTIONS

Robin Whytock contributed to the system design, co-wrote the manuscript, collected the data and analysed the data. Thijs Suijten designed the system, co-wrote the manuscript and collected data. Tim van Deursen co-designed the system and collected data. Jędrzej Świeżewski created the AI model. Hervé Mermiaghe co-designed the pilot. Nazaire Madamba and Narcisse Mouckoumou collected data. Aurélie Flore Koumba Pambo supervised Robin Whytock and co-wrote the manuscript. Joeri Zwerts, Laila Bahaa-el-din, Stephanie Brittain, Anabelle Cardoso and Brice Momboua supplied data for the AI model and co-wrote the manuscript. Philipp Henschel, Christopher Orbell and Lee White supplied data for the AI model and contributed to the system's design. David Lehmann contributed to the system's design and co-wrote the manuscript. Loïc Makaga collected data. Donald Midoko Iponga co-wrote the manuscript. Katharine Abernethy co-wrote the manuscript and co-designed the pilot.

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CONFLICT OF INTEREST

Q42 is a commercial entity that develops hardware and software for industry applications. Q42's contribution to this study was done by their 'Hack the Planet' non-profit initiative that provides services to third-sector or academic clients working on solving social and environmental issues. Appsilon is a commercial business that develops software and data analytic platforms for industry. Appsilon's contribution to this study was done by their 'AI for Good' initiative that provides services to third-sector or academic clients working on solving social and environmental issues. The African Conservation Group is a commercial entity that funds the forestLAB research group at the University of Stirling. Robin Whytock is a Director of Digital Forest UK Ltd that provides technology solutions for sustainable land management. The work described here precedes this appointment and this work was the outcome of noncommercial academic research (see Author affiliations).

PEER REVIEW

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DATA AVAILABILITY STATEMENT

Firmware for the camera trap extension module: https://doi.org/10.5281/zenodo.7258377. Firmware for the smart bridge: https://doi.org/10.5281/zenodo.7258404. Software to run the Raspberry PI 4 Compute Module: https://doi.org/10.5281/zenodo.7258413. Files for the smart bridge hardware and camera extension: https://doi.org/10.5281/zenodo.7258419. Code for the data analysis presented in the paper: https://doi.org/10.5281/zenodo.7258440.

ETHICS STATEMENT

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

RESEARCH PERMISSIONS

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

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SUPPORTING INFORMATION

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

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