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- Trapper: https://gitlab.com/trapper-project/trapper
- Trapper AI Manager : https://gitlab.com/trapper-project/trapper-ai
- Trapper AI Worker : https://gitlab.com/trapper-project/trapper-ai-worker
- Trapper CS: https://gitlab.com/trapper-project/trapper-frontend

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1. Abstract

Effective wildlife monitoring is essential for biodiversity conservation and sustainable management, particularly in the face of rapid environmental changes and human-wildlife interactions. Advances in camera trap technology and citizen science, here used to denote non-professional involvement in scientific research, irrespective of citizenship status, have revolutionized ecological data collection, providing scalable and non-invasive methods for tracking species distribution, abundance and behaviour across large spatial and temporal scales. However, challenges in managing the vast datasets generated, ensuring user engagement and addressing privacy concerns persist. To address these issues, we introduce Trapper Citizen Science (Trapper CS), an open-source platform combining artificial intelligence-based data processing pipelines with citizen science to enhance wildlife monitoring efforts. Trapper CS supports automated data processing, provides user-friendly interfaces and real-time species identification, while promoting collaboration and data sharing through standardized protocols and data formats (Camtrap DP). With applications spanning research, management and citizen engagement, Trapper CS exemplifies a novel approach to integrate technology and public participation for addressing global wildlife challenges. This paper discusses the platform's architecture, functionality and applications, highlighting its potential to contribute to more effective wildlife monitoring and management.

2. Introduction

2.1. Wildlife monitoring in the digital age

Wildlife plays essential ecological roles, supporting biodiversity and human well-being (Sandifer et al. 2015). However, anthropogenic pressures, such as urbanization, deforestation, and climate change, are accelerating biodiversity loss and disrupting population dynamics (Butchart et al.

2010; Townsend et al. 2008). Some species, such as ungulates and large carnivores in the northern hemisphere, have increased due to land use changes and conservation (Chapron et al. 2014; Linnell et al. 2020), intensifying human-wildlife interactions and requiring new management approaches (Roman et al. 2015). Effective management demands large-scale, long-term ecological monitoring (Steenweg et al. 2017; Stephens et al. 2015).

Camera traps have proliferated in recent decades due to technological advances and the need for cost-effective, non-invasive monitoring (Ahumada et al. 2020; Delisle et al. 2021). They enable continuous observation across taxa and ecosystems without disturbing animals (Wearn and Glover-Kapfer 2019) , and support studies of behaviour, abundance, phenology, and community dynamics (Burton et al. 2024; Hofmeester et al. 2020; Steenweg et al. 2017; Veldhuis et al. 2020). This has transformed ecological research and enabled deployment in both terrestrial and marine systems (O'Brien and Kinnaird 2013; O'Connell et al. 2011). As climate-driven changes accelerate, real-time monitoring becomes critical. Yet, the volume of image data presents processing challenges (Norouzzadeh et al. 2018). Platforms like Trapper, Agouti, Wildlife Insights, Sentinel, TrapTagger, WildID, AddaxAI (formerly EcoAssist), and MammalWeb aim to improve data workflows and foster collaboration (Ahumada et al. 2020; Bubnicki et al. 2016; Conservation X Labs 2025; ENETWILD Consortium et al. 2022; Hsing et al. 2022; Lunteren 2023; WildEye 2025; WildID 2021). Still, lack of interoperability and metadata standards limits integration and reuse. Recent work has highlighted that without centralized repositories and standardized metadata formats, even extensive investments in camera trap networks can fall short of their potential, due to limitations in collaborative analysis, image processing capacity and model-ready data outputs (Bruce et al. 2025). Camtrap DP addresses this by providing a standardized, flexible data model, comprising Deployments, Media and Observations tables, that facilitates seamless data exchange and integration across systems (Bubnicki et al. 2024). As a community-developed standard under the Biodiversity Information Standards (TDWG), Camtrap DP is currently the most mature and widely supported proposal for harmonizing camera trap data. Citizen science, here defined as the involvement of non-professionals in scientific research and knowledge production, supported by advancements in technology and reduced costs, has become integral to ecological monitoring (Adam et al. 2021; Green et al. 2020; 2023). We acknowledge ongoing debate around the term 'citizen science', particularly in North America where 'community science' is increasingly preferred to avoid implications related to citizenship status (Cooper et al. 2021). However, we use 'citizen science' here because it remains more widely used in Europe and is more specific in denoting voluntary participation in formal scientific inquiry. From here on, we use the term 'citizen science' to refer inclusively to all forms of non-professional involvement in scientific research, irrespective of participants' legal citizenship status. Citizen science extends sampling across space and time and provides valuable data on species' responses to environmental change (Green et al. 2023; Willi et al. 2019; Jiguet et al. 2007). Camera traps uniquely engage both professionals (e.g. Snapshot USA; Rooney et al., 2025) and citizens (e.g. Candid Critters, Snapshot Serengeti, MammaleWeb), contributing to research and public engagement (McShea et al. 2016; Parsons et al. 2018; Swanson et al. 2015; Hsing et al. 2022; Lasky, Parsons, Schuttler, Hess, et al. 2021). This inclusive approach does not only contribute to outcomes in science, but also creates a collaborative bridge between the general public, wildlife research and advanced technological applications (Jansen et al. 2024; Lasky, Parsons, Schuttler, Mash, et al. 2021; Swanson et al. 2015). While many citizens, such as naturalists and hunters, contribute to wildlife observation through camera traps, the lack of centralized open-source and citizen-science-oriented platforms that implement professional camera trap know-how and workflows for sharing and managing data means much of its potential remains untapped. It is often crucial that such platforms are run by trusted regional organizations (Urbano et al. 2021), as not all participants are willing to share their data directly with large global repositories (as e.g. Wildlife Insights) due to legal and/or trust issues. To be effective, platforms must be customizable, support varying engagement levels, implement standards like Camtrap DP (Bubnicki et al. 2024), and be open-source to allow integration with other tools and services, including publicly available AI models for image and video processing.

Thus, establishing accessible and user-friendly platforms that encourage citizens to contribute their data to coordinated monitoring programs, while supporting professional camera trap data management, processing and standardization in the backend, are foundational. Once established, they allow integration of deep learning, reducing human workload while maintaining classification accuracy (Willi et al. 2019). Given the rapid pace of AI development, open-source and modular design are essential to ensure platforms can efficiently incorporate new methods and stay at the forefront of analytical capability. This layered approach not only scales up monitoring efforts but also enables real-time data analysis, providing critical insights into ecological trends and facilitating timely conservation actions.

2.2 Limitations faced by collectors and users of camera trap data

Camera trap data collection by citizen scientists and its use by researchers and managers face several persistent barriers. A central challenge is the sheer volume of data generated (Fig. 1; Norouzzadeh et al., 2018), which remains time-consuming to process and often requires manual intervention (but see Zampetti et al., 2024) despite advances in deep learning (e.g. CNNs, Vision Transformers, Vision Language Models) that enable automated species identification (Beery et al. 2019; Dussert et al. 2024; Weinstein 2018). Most existing closed-source platforms are not AI-extensible, limiting integration of custom or regional models and preventing rapid adoption of new image recognition methods.

Usability is another major issue, particularly in citizen science, where platforms often lack intuitive interfaces suited for non-expert users (Fig. 1). This can deter engagement and restrict the reach of participatory monitoring efforts (Ahumada et al. 2020; Hsing et al. 2022). Privacy concerns further complicate data sharing, especially for images containing humans or sensitive species. For instance, some contributors, such as hunting teams, may be unwilling to share data on animal densities or locations openly, though they may do so with trusted organisations, research bodies or agencies. Without flexible, customizable platforms, this kind of controlled sharing remains difficult.

Moreover, many systems lack support for standardized data exchange, which hinders interoperability and scientific collaboration. Camtrap DP (https://camtrap-dp.tdwg.org), as the most advanced global standard, should be fully supported to enable streamlined sharing. Probably one of the most relevant aspects, however, is the easy extraction of population-level metrics for use by managers, enabling near-real-time decision-making and practical application of monitoring data.

Together, these barriers underscore the need for integrated, open-source platforms that combine usability, privacy protection, extensibility and standardized data handling. While initiatives like MammalWeb and Wildlife Insights address some of these issues, a comprehensive, community-oriented solution is still lacking.

2.3 A solution to overcome identified barriers: an open-source citizen science platform - Trapper CS

To overcome the barriers outlined in Fig. 1, we present *Trapper Citizen Science* (Trapper CS), an open-source platform designed to promote citizen science engagement in ecological research and wildlife management using camera traps. Built on the flexible Trapper backend (Bubnicki et al. 2016), Trapper CS allows extensive customization, including AI modules, making it suitable for a wide range of projects. The platform combines scalable deep learning-based image recognition with active citizen and stakeholder participation, enabling efficient data aggregation, processing and sharing (Fig. 2). A key strength is its accessible design: a user-friendly interface and personalized dashboards help engage non-experts while maintaining scientific utility. Project coordinators can configure data attributes for collection and analysis to match project-specific goals.

Trapper CS's Python-based backend enables integration of custom AI models and analytical tools, supporting advanced processing and visualization (e.g. via Jupyter Lab). It also provides programmatic access to annotated images via API, facilitating continuous model training to maintain high species identification accuracy (Fig. 2). By adopting the Camtrap DP standard for data exchange (Bubnicki et al. 2024), the platform ensures interoperability and supports collaborative workflows among researchers and stakeholders. This integrated, open-source approach not only improves data management but fosters broader engagement and data reuse, enhancing the impact and scalability of wildlife monitoring

3. Description of Trapper CS

3.1 Trapper in the backend

Trapper CS builds on the open-source database platform Trapper (Bubnicki et al. 2016), designed to standardize, organize and manage camera trap data. Originally developed to address the growing volume and complexity of multimedia data in ecological research, Trapper has since evolved into a scalable, multi-platform system supporting collaborative data access and integration of AI tools. It is regularly updated and maintained by the Open Science Conservation Fund and partners.

The current beta release, Trapper 2.0, includes modules for citizen science (frontend), AI-based image processing (Trapper AI), and expert curation (Trapper Expert). Key features include open-source licensing, support for image and video processing, customizable classification attributes, Camtrap DP compliance, and tools for advanced analysis. The platform can be deployed locally or on cloud infrastructure and is already in use across major European research institutions. A detailed technical summary of Trapper's architecture, installation options and data management capabilities is provided in Appendix S1, Text S1.

3.2 AI model

Trapper AI integrates deep learning into camera trap workflows for detecting animals and classifying species in camera trap data. It consists of two components: the *Trapper AI Manager*, which organizes and queues processing tasks and *Trapper AI Worker*, which processes images using AI models and supports flexible deployments from local machines to cloud servers (Appendix S2, Fig. S1). Trapper AI supports popular architectures (e.g., YOLOv8, RT-DETR, ViT) and includes pre-trained models like MegaDetector and the Trapper AI Species Classifier, achieving high accuracy in European mammal classification (F1-score 95%, mAP 93%) using a dataset of over 400,000 images from five countries. The system is extensible, allowing users to configure new models and workflows with minimal effort. Full technical specifications, supported architectures, and deployment details are provided in Appendix S1, Text S2.

3.3 Trapper CS

The Trapper Citizen Science (CS) interface has been designed to support non-expert users in engaging with wildlife monitoring via camera trap data. The interface is currently accessible in multiple languages, including English, Swedish, German and Polish (with a possibility to add more), with a simple language-switching option in the top-right corner. Users can switch between different projects they have access to and access a comprehensive overview of each project. Projects can be designated as either public or private. Public projects are accessible to all registered users, who can view and contribute to them freely. In contrast, private projects are only visible to users who have been explicitly granted access. A left sidebar provides easy navigation to sections such as Dashboard, Upload, Images, Deployments, Classification View and Teams.

The CS interface, an extension of the Trapper platform, aims to streamline complex data flow, organization, sharing and classification processes into a more simplified and intuitive experience for users on various devices, including PCs, laptops, tablets and phones (with currently limited mobile functionality). Core functionalities include a basic upload page, a carefully designed classification interface and a viewing area for classified images, with plans for future enhancements like data analysis and mapping tools (Fig. 3). The design prioritizes an attractive, modern and user-friendly layout, developed by UX/UI designers in collaboration with users (stakeholders, citizen scientists, and the community of Trapper users) to best meet their requirements. The following sub-sections give an overview of each component of the Trapper CS interface. Additional technical information and more detail along with user interface screenshots can be found in Appendix S2, Text S1 & Figure S1-S7.

3.3.1 Data upload

Users can upload large batches of images and associate them with deployments using coordinates or an interactive map. Metadata such as camera model, bait type, and habitat can be added. Trapper CS automatically generates database objects and applies AI-based detection (via MegaDetector by default), anonymization of humans and vehicles, and species classification. Administrators can select different AI models available in Trapper AI Manager.

3.3.2 Dashboard and user insights

The dashboard displays project-wide and individual user statistics, including the number of deployments, images, camera trap days, and classification summaries. It visually differentiates user contributions and offers easy access to messages, settings, and navigation options, facilitating user engagement and oversight.

3.3.3 Image and deployment view

Trapper CS offers users a comprehensive interface for browsing and managing both images and deployments. The image view includes powerful filtering options that allow users to sort images by species, location, deployment, classification status and more. Metadata such as observation type, ownership, and AI versus human validation status are displayed alongside thumbnails, offering quick insight into image content. An image can be opened in detail to reveal full metadata and classification history, along with a map showing the camera trap's geographic location.

The deployment view complements the image browser by giving users access to camera trap metadata, including coordinates, deployment periods and the number of recorded sequences. Deployments can be explored in list or map views and filtered by user or project-defined attributes. Users can edit or delete their own deployments and adjust timestamps in bulk to correct for common field-based errors. These functionalities make it easier to manage large volumes of data while preserving accuracy and traceability within collaborative projects.

3.3.4 *Spatial visualization*

An integrated map-based GIS view shows deployment locations using Leaflet and OpenStreetMap. Users can explore spatial patterns, switch between map/list views, filter deployments, and preview associated media. Basemaps are customizable, and shared deployments can be viewed collaboratively.

3.3.5 *Classification interface*

The classification module is a comprehensive and visually appealing interface designed to facilitate the object-based and AI-assisted classification of camera trap images by users. It displays AI-filtered images (animal, blank, human, vehicle), allowing users to refine labels and attributes (e.g., species, behaviour, age, sex) at the object level using bounding boxes, with an easy way of creating, edition and managing bounding boxes. Forms are dynamic so that it adapts to project needs. Tools for classification include brightness/contrast filters and bulk classification functions. Users flagged as experts can approve or correct others' classifications allowing a robust feedback mechanism for training new AI models.

3.3.6 *Teams and data sharing*

The Teams module supports collaborative classification efforts by allowing data sharing among defined user groups with geographic boundaries. Admins create teams, invite members, , define shared regions (via maps or GPX), and assign access permissions. Members can classify shared images while retaining control of their own contributions.

3.3.7 Export

Data can be exported from the Trapper backend as CSV or in Camtrap DP format, including both tables and metadata. This facilitates integration with platforms like GBIF and reduces the burden of manual metadata preparation.

3.4 Potential risks and concerns

The use of camera trap data in citizen science initiatives presents potential risks, notably concerning privacy and data security. Location sharing of sensitive species or habitats can expose them to risks, including illegal targeting or human interference, necessitating strict measures to secure sensitive data. Privacy is another critical issue, particularly when images capture humans. These images must be handled carefully to protect identities, often through blurring or other anonymization techniques (Ahumada et al. 2020). Ensuring that privacy protocols are robust and meet legal and ethical standards is essential to build trust and encourage broader participation among citizen scientists and the general public. To address concerns around privacy and data security in citizen science, Trapper CS incorporates several protective measures. Human and vehicle anonymization is automatically applied during image processing to protect personal identities, supporting ethical standards and legal compliance. For sensitive species, Trapper CS offers a notification system that alerts project administrators to the presence of such data, which enables them to manage access appropriately. Additionally, when exporting data using the Camtrap DP format, administrators can choose to omit image URLs for designated species by marking them as private. This ensures that sensitive ecological information is not publicly exposed and enhances trust among contributors.

3.5 Open-source approach and customization possibilities

Trapper CS, as an open-source platform, allows for significant customization, empowering users to develop additional functionalities suited to specific research or management needs. For example, users can create a custom landing page with an interactive analytical dashboard to visualize data in real time or design team-specific functionalities that support collaborative research workflows. This open-source model facilitates flexibility in design, enabling the integration of diverse analytical tools and modules, such as custom AI models and data analysis pipelines or unique data visualization options, thus enhancing the adaptability and applicability of the platform for diverse ecological and wildlife management contexts.

4. Discussion: Challenges, wider lessons and future work

This paper presents Trapper CS, an open-source platform that combines AI-based processing of large camera trap datasets with citizen science participation. It addresses major challenges in ecological monitoring, such as data management, real-time species identification, user engagement and data standardization, offering a promising model for integrating technology with public collaboration. Here, we outline key opportunities and challenges that inform its future development and broader application.

A key challenge is ensuring the platform remains usable for diverse stakeholders. Outputs like density estimates must be both easy to access and relevant for wildlife managers, requiring alignment between model results and management needs. Interfaces also need to support users with limited technical skills. Currently, only administrators can export data, but allowing users to download their contributions (e.g., as .csv) could increase engagement. This could be part of a future module offering personal data exploration. Structured feedback from interviews, surveys and testing will help improve functionality and integration into monitoring workflows. Iterative, stakeholder-driven development is essential for adoption and long-term impact

Trapper CS must be adaptable across varied wildlife management contexts and countries. Although already used by the Swedish Association for Hunting and Wildlife Management, wider testing is needed to assess its relevance elsewhere. In regions where hunters and local stakeholders contribute to monitoring, the platform has strong potential. Promoting standardized data formats and cross-border collaboration can support international efforts to harmonize monitoring and improve data quality.

Viltbild strongly motivated the collaboration between SLU, the Swedish Association for Hunting and Wildlife Management, the Open Science Conservation Fund and the Mammal Research Institute. Across Europe, hunters contribute to monitoring many taxa, especially ungulates and small game (Cretois et al. 2020). Their routinely collected data (e.g. hunting bag, carcass and non-invasive sampling) offer insights on genetic composition, species population or traits and community composition (Cretois et al., 2020). n Sweden, with over 100,000 hunters using camera traps, these data are widespread but often remain local. Centralizing them could unlock significant potential for national monitoring. Moreover, hunter engagement can improve species monitoring beyond traditional programs, providing valuable insights into species' life history parameters and responses to environmental change. With their strong ecological knowledge, hunters can help with the identification of species in the images, increasing the human-annotated dataset. The involvement of hunters, who regularly observe and interact with nature, can bridge a vital gap between scientific research and practical management efforts.

New camera technologies, such as models that transmit images via email, could greatly enhance Trapper CS by removing the need for manual SD card retrieval. This functionality would support an automated early warning system for threats like African swine fever or invasive species, triggering real-time alerts from AI detection. Such tools align with existing systems like Sentinel or AddaxAI (Conservation X Labs 2025; Hack the Planet 2025; Lunteren 2023) and align closely with Trapper CS's mission to provide timely and actionable insights, further supporting proactive wildlife management strategies. The Trapper team has already developed a system architecture for such functionality, making this a realistic direction for future development.

Integrating deep learning models that extract ecological information from images would reduce reliance on manual annotation and strengthen monitoring workflows. While tools like MegaDetector provide coarse filtering (animals, vehicles, humans, blank; Beery et al., 2019), tasks, such as distance estimation, individual tracking or behaviour classification, remain underdeveloped or require field-based calibration or reference imagery (Haucke et al. 2022; Henrich et al. 2024; Johanns et al. 2022). Emerging methods using CNNs, Vision Transformers and Visual Language Models show promise (Dussert et al. 2024; Graving et al. 2019). Developing new workflows that automate downstream steps, such as density estimation via the Random Encounter Model or Camera Trap Distance Sampling (Howe et al. 2017; Rowcliffe et al. 2008), would further enhance analytical capacity. Embedding these capabilities into platforms like Trapper CS would enable end-to-end automation from raw data to ecological inference, thereby supporting more efficient and scalable wildlife management.

Citizen scientists are increasingly seen as full partners in wildlife research, contributing beyond data collection to project design and interpretation (Hinojosa et al. 2021; Pandya 2012). This transition, inspired by platforms like iNaturalist, highlights the need for well-designed user interfaces, intuitive workflows and a strong understanding of user motivations. Sustaining engagement requires meaningful feedback, letting users interact with data and understand how it's used. Studies stress the importance of feedback loops, visualisation tools and communication that is two-way and rewarding (Truong and van der Wal 2024; van der Wal et al. 2016; Zhou et al. 2020). These findings suggest that future platforms should prioritise attractive and accessible visualisations of collected data and may also benefit from integrating light gamification elements, such as achievement badges or team-based challenges, to support user commitment and data quality.

Ensuring international data standards will also be critical to maintaining data quality and comparability as citizen scientists increasingly take on more independent roles in initiating and managing wildlife monitoring projects. Without consistent structures, integrating data across platforms and regions becomes difficult, limiting reuse and large-scale ecological analysis. Standardised data frameworks are essential to enable investigations of ecological questions across broad spatial scales, for example along latitudinal gradients, where coordinated analyses can reveal macroecological patterns and responses to environmental change. In this context, the development and adoption of the Camtrap DP represent a major step forward (Bubnicki et al. 2024). Camtrap DP provides a standardized, machine-readable format now used by platforms like Trapper and Agouti and supported by GBIF and the Atlas of Living Australia (Bruce et al. 2025; Reyserhove et al. 2023; Robertson et al. 2014). As these standards become widely adopted, they offer a concrete foundation for building interoperable and scalable systems that support both local engagement and global synthesis. Promoting their use within platforms like Trapper (CS) is not just a technical necessity, but essential for keeping data usable over time.

Maintaining open-source software over time is a substantial challenge, particularly in academia where funding is short-term and project-based (Easterbrook 2014; Prlić and Procter 2012). While important work has been done to develop tools for wildlife monitoring, these efforts frequently remain isolated, with each research group building its own platform or application. This fragmentation limits long-term sustainability, reproducibility and the broader impact of software tools. A shift toward collaborative development, seen in fields like bioinformatics (Cock et al. 2009), could improve long-term impact by stabilizing codebases and pooling expertise. Without it, ecological tech risks duplication and inefficiency.

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6. Author contributions

Author contributions are described using the CRediT taxonomy. Magali Frauendorf (MF), Jakub W. Bubnicki (JWB), Piotr Tynecki (PT), Filip Ånöstam (FÅ), Łukasz Wałejko (LW), Joris P. G. M. Cromsigt (PGMC), Fredrik Widemo (FW), and Tim R. Hofmeester (TRH) contributed to this work as follows: Conceptualization - MF, JWB, FÅ, TRH; Funding acquisition - FÅ, TRH, JPGMC, FW; Project administration – TRH, FÅ; Software – JWB, PT, LW; Validation – MF, FÅ, THR; Visualization – MF; Writing original draft – MF; Writing review editing – MF, JWB, PT, FÅ, LW, JPGMC, FW, THR.

7. Conflict of interest statement

None to declare.

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9. Figure captions

Figure 1: Overview of the barriers limiting use of camera trap data in combination with citizen science and the proposed solutions. Icons used in this figure were sourced from The Noun Project (licensed version).

Figure 2: Key factors enhancing wildlife monitoring and management through Trapper CS. Icons used in this figure were sourced from The Noun Project (licensed version).

Figure 3: Overview of the main components and functionalities of Trapper CS. Icons used in this figure were sourced from The Noun Project (licensed version).

10. Figures

Figure 1

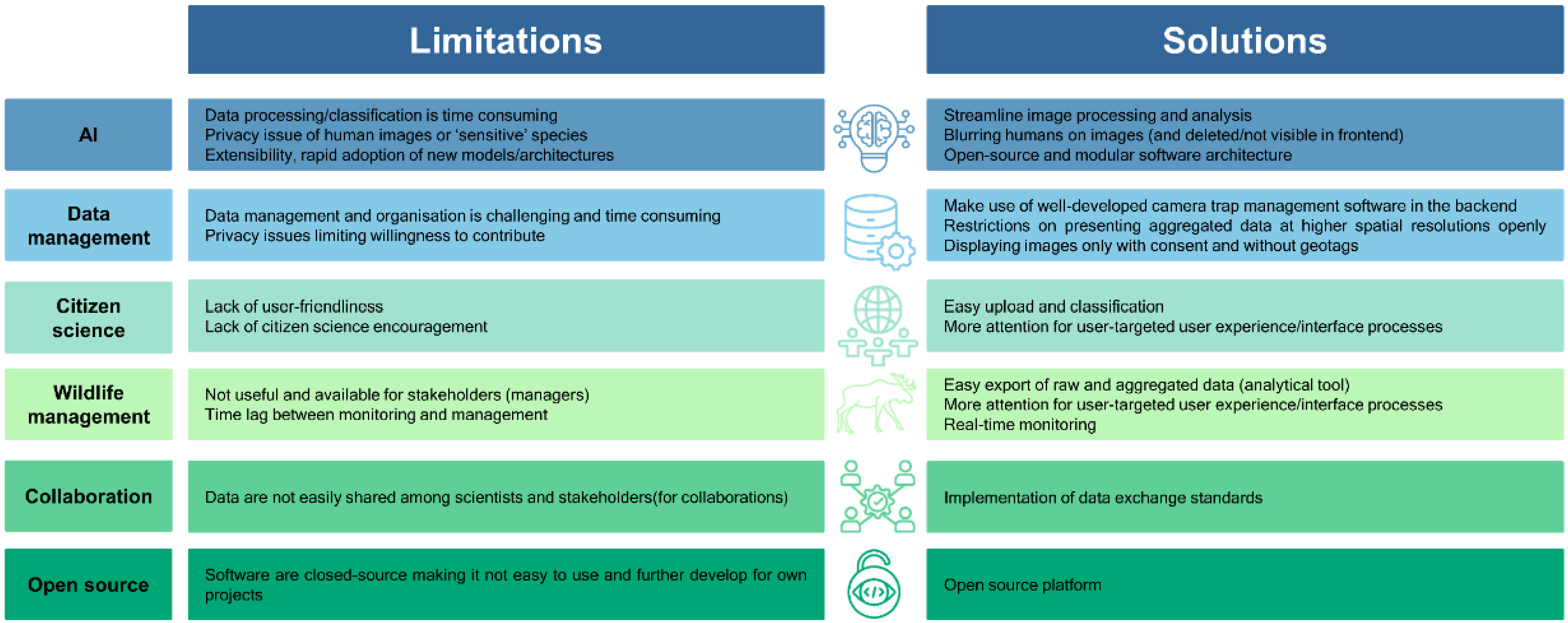


Figure 2

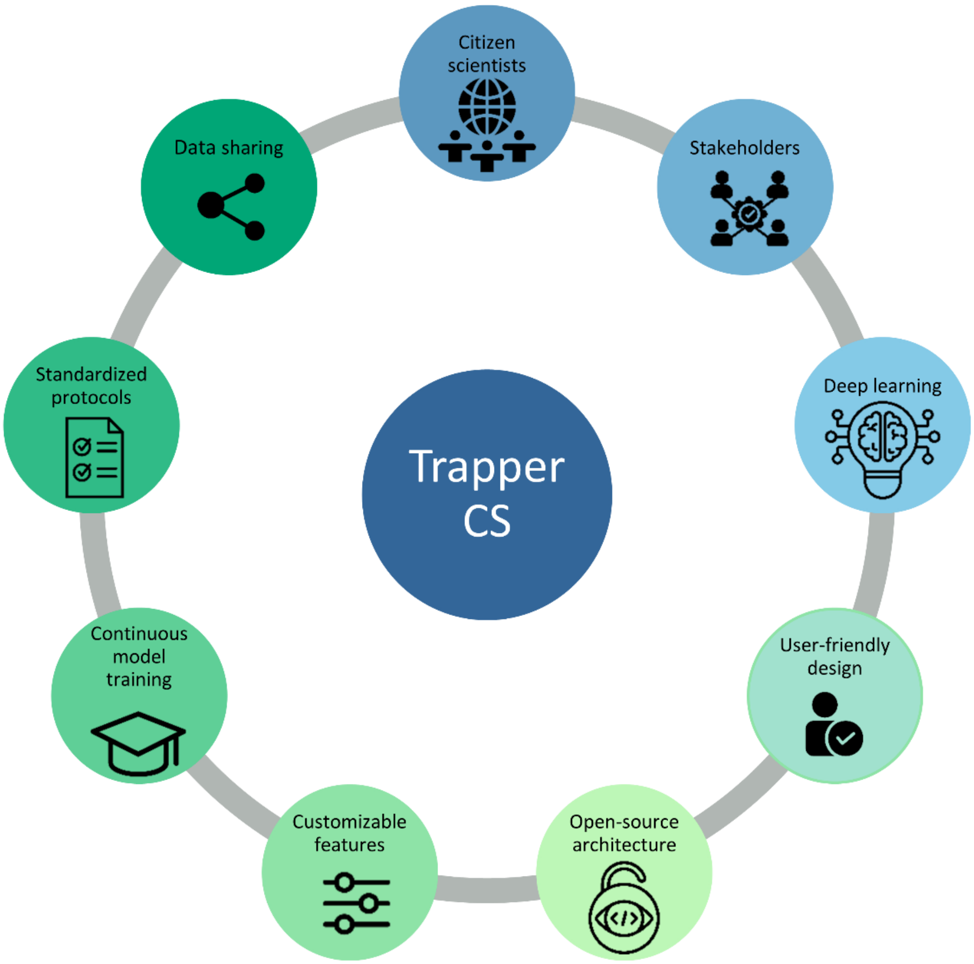
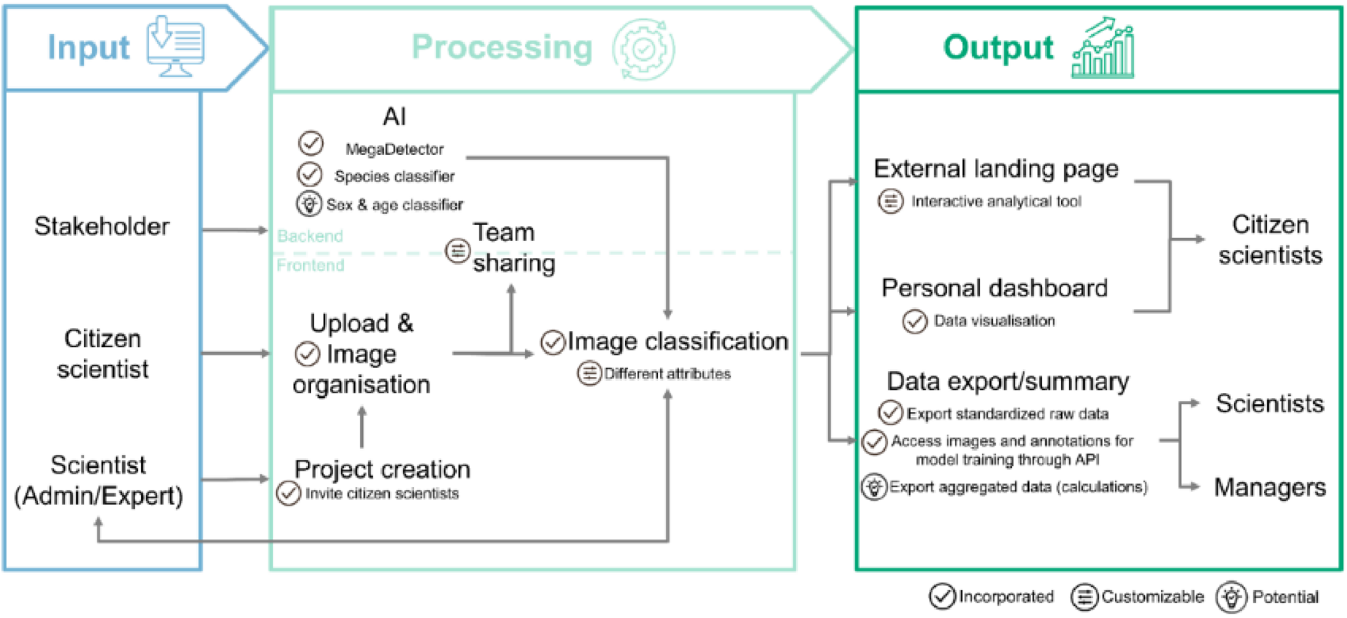

Citizen scientists
Stakeholders
Deep learning
User-friendly design
Open-source architecture
Customizable features
Continuous model training
Standardized protocols
Data sharing
Trapper CS

Figure 3



11. Supporting Information

Appendix S1: Technical details

Appendix S2: User interface and functional features of the Trapper Citizen Science platform