Practical Tools

wildtag.ai: an open-access end-to-end offline AI-assisted desktop application for managing camera trap projects

Chris Sutherland[1] (0000-0003-2073-1751)
Oliver Hartley[1] (0000-0002-2194-8613)
Alessandro Araldi[1,2] (0009-0000-4731-8401)
Deon Roos[3] (0000-0003-4866-7472)
Xavier Lambin[3] (0000-0003-4643-2653)
Amber Cowans[1] (0000-0001-9092-6584)

[1] Centre for Research into Ecological and Environmental Modelling, University of St Andrews, UK.
[2] Research Department, Leopard Ecology & Conservation, Gaborone, Botswana
[3] School of Biological Sciences, University of Aberdeen, UK

Correspondence: css6@st-andrews.ac.uk

Abstract

1. Camera traps generate massive volumes of data, yet their decision-support potential is diluted by the bottleneck of manual processing. Automated classification has largely solved this, but classification alone does not remove the barriers to adoption: it must be coupled with the means to turn predictions into a verified, shareable dataset, which no existing tool does end-to-end, offline, and without programming.

2. The shift from a familiar manual workflow requires trusting new, often far less familiar, technology, and that apprehension is itself a barrier. One dichotomy compounds this barrier: camera-trap projects are increasingly delivered by teams (research groups, citizen-science projects), yet existing solutions prioritise either distribution (web-based platforms) or speed (local applications for bulk processing).

3. Addressing these core requirements will broaden access to AI-integrated camera-trap workflows and reduce the apprehension that deters adoption. Specifically, a tool that operates offline to keep data under the user's control, processes data efficiently in bulk, supports structured and distribution-ready validation with expert judgement in the loop, and produces interoperable, transparent, and shareable outputs would build the trust needed to drive adoption.

4. `wildtag.ai` integrates these competing priorities into a single, coherent workflow. Rather than trading distribution against speed, it treats camera-trap analysis as a managed, multi-contributor project. It is a free, openly available desktop application that runs entirely offline and includes automated detection and species classification, efficient and distribution-ready validation, and export to the Camtrap Data Package (Camtrap DP) standard. It builds on a curated selection of established models, bundled and hosted locally through a small registry, so that no coding, cloud service, or internet connection is required.

5. **Solution**: `wildtag.ai` offers the user community a tool to turn backlogs of images into verified, shareable data without specialist infrastructure, subscriptions, or loss of data control. This makes an ambitious camera-trap programme tractable for a small team or volunteer network. It is built to support the wider community: giving model developers an open route to reach practitioners, letting projects of any scale adopt a consistent workflow, and helping to democratise knowledge discovery by dismantling the cost, infrastructure, and expertise barriers that put AI-supported analysis out of reach.

Keywords: camera trap; species identification; deep learning; citizen science; data validation; Camtrap DP; biodiversity monitoring; offline software

1 Motivation

The development and increasing accessibility of automated detection and classification tools has overcome a key bottleneck in ecological workflows using camera trap data (Chalmers *et al.* 2023; Fennell *et al.* 2022; Norouzzadeh *et al.* 2021). AI-assisted data processing accelerates clearing empty frames (object detection) and identifying species (image classification) at rates that far exceed manual review (Norouzzadeh *et al.* 2018; Willi *et al.* 2019). While methodological development has been rapid, uptake has lagged (Rahman & Faria Akter 2025; Tuia *et al.* 2022), and the problem has shifted from "*can AI be used to reliably tag images?*" to "*how can users capitalise on the promise of established AI-integrated image classification?*". We believe that barriers to uptake can be overcome through user-focused tool development (De Freitas *et al.* 2023).

In our experience, one practical barrier to uptake is that no single tool spans the full data-to-decision path, i.e., from raw images to efficient classification and validation to decision-ready data (Besson *et al.* 2022; van Lunteren 2023). This data life-cycle involves several dependent tasks: automated classification, organisation and hosting of the model predictions, distribution of validation effort across a team, and standardised storage and reporting. Yet, available tools generally follow a design dichotomy (Table 1): cloud platforms support classification and collaboration but require accounts, uploads, connectivity, and the transfer of data to third-party servers, whereas offline desktop tools process data on local hardware but typically stop at prediction and export, and offer limited support for coordinated distributed validation. Each addresses important workflow components, but neither integrates all (Table 1).

This partial coverage forces a wholesale commitment to a partial solution, i.e., entrusting an entire project to a tool that handles only some of its stages, leaving the rest to be improvised. The resulting apprehension about reliability, loss of oversight, and the opacity of unfamiliar system dependencies is reasonable, even if the potential benefits are massive (Ammar *et al.* 2026; Rahman & Faria Akter 2025). `wildtag.ai` is our attempt at addressing this apprehension.

Rather than choosing between distribution and speed, or between automation and oversight, `wildtag.ai` treats camera-trap analysis as a single, managed, multi-contributor project spanning the whole workflow: a free, openly available desktop application that runs offline, processes data efficiently on local hardware, supports structured and distribution-ready validation with a human in the loop, and exports to a community data standard. Designed around the needs of practitioners rather than developers, `wildtag.ai` is intuitive, code-free, and fully offline, and is intended to broaden access to AI-assisted image processing.

2 Introducing `wildtag.ai`

`wildtag.ai` was designed around our experience as users of camera trap workflow tools and our work with the wider user community. Four constraints shaped our design decisions: users without a programming background; standard Windows laptops rather than servers or clusters; projects producing large volumes of images; and internet access that is unreliable or administratively restricted. Together, these constraints favour an easy-to-install, no-code tool that runs offline on modest hardware, rather than one built around bandwidth-intensive image uploads and downloads (van Lunteren 2023).

The application is lightweight (~644 MB), free to download and install, and organised around the main stages of an image-tagging workflow: processing, validation, summarising, and export, with a dedicated summary page that tracks progress (Figure 1). Importantly, a key feature of `wildtag.ai` is that validation can be done either by a single user or distributed across a team. All a project requires to begin is a folder of images and a spreadsheet of camera metadata; from these, `wildtag.ai` builds a consistent, self-documenting folder structure that every subsequent step reads automatically, with no configuration.

2.1 Image processing

In the processing step, a chosen object detector and species classification model are applied to clear empty frames and sort the remaining frames into species-specific folders. Because surveys can generate hundreds of thousands of images and take days on a standard laptop, progress is reported continuously and saved at regular intervals, so processing resumes where it left off in case there is a crash, power failure, or an unexpected system restart.

`wildtag.ai` is not a classification model; it hosts existing models and provides access to them in an embedded workflow without any coding requirements. Currently, we host the DeepFaune detector–classifier (Rigoudy *et al.* 2023), its regional extensions (Clarfeld *et al.* 2025), and SpeciesNet (Gadot *et al.* 2024), all established, openly published models whose performance has been independently reported. In doing so, `wildtag.ai` aims to promote open-access, benchmarked models and offers developers a platform to make models accessible to practitioners in a trustworthy and transparent way (Ammar *et al.* 2026). Updates to hosted

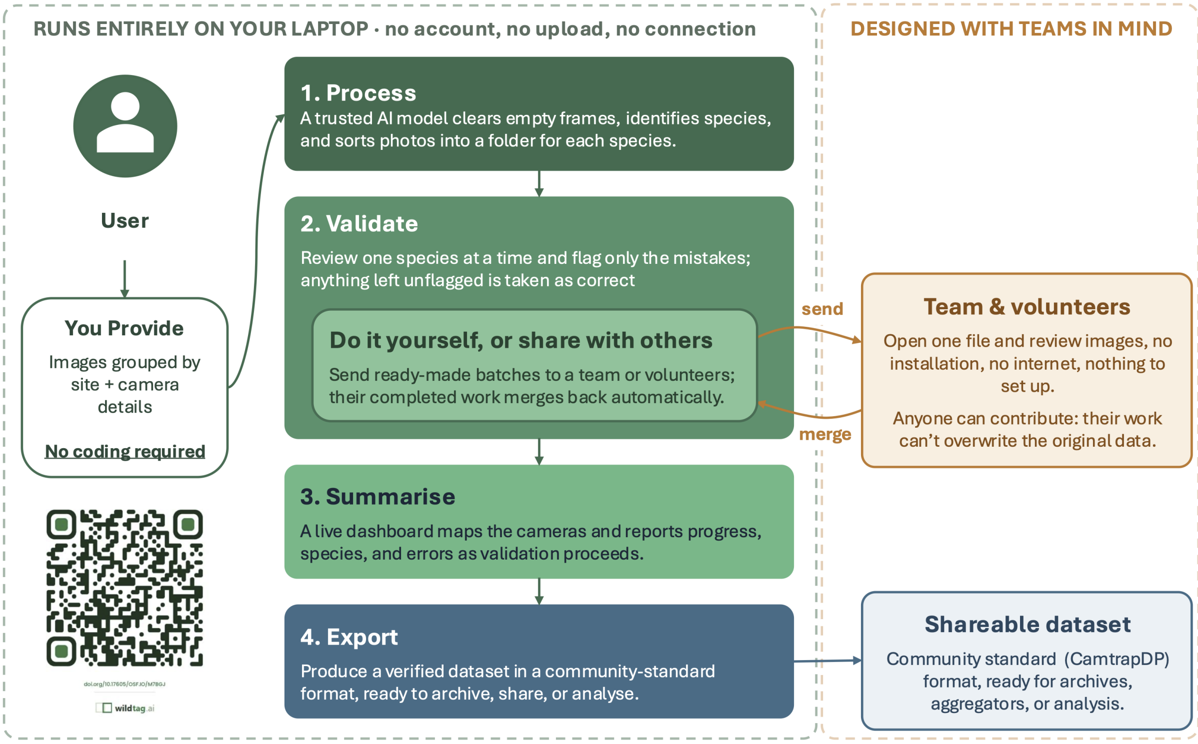

Figure 1: A conceptual overview of the `wildtag.ai` architecture and workflow.

models or new models can be added as they are published, meaning the workflow is not tied to any single model and extends readily to new species, regions, or survey types.

2.2 Validation

The `wildtag.ai` environment is built around efficient validation. Rather than presenting images for validation by site, in chronological order, or at random, classified images are organised into species-specific folders. Moreover, the validation process focuses only on correcting incorrect classifications, and images viewed but not corrected are treated as correctly labelled. This means reviewers verify one species at a time in a way that minimises clicking, making the task both more rewarding and more efficient (West & Pateman 2016).

Predictions are shown as a tiled viewing gallery, each detection shown with a bold bounding box, with muted bounding boxes around any other animals in the same photograph shown for context. Corrections are made against a fixed list of species, and if the desired label does not exist, labels can be added and persist throughout the project. Images containing people are blurred by default, complying with ethical and data protection requirements (Sandbrook *et al.* 2021). Performance is shown in real time through a confusion matrix summarising agreement between model predictions and validated labels as the reviewer works.

Critically, `wildtag.ai` facilitates distributed validation, directly addressing the bottleneck that even though image classification is automated, many, if not all, images must be validated (Willi *et al.* 2019; Cowans *et al.* 2026). The species-based organisation makes images distribution-ready, so batches of species-specific images can be sent to validators with relevant identification experience. Classified images are packaged into self-contained archives of configurable size, each bundling the `wildtag.ai` application together with a small, private copy of Python, so that a volunteer opens one file, reviews images with no installation, no administrative rights, and no internet connection required, and returns a single, automatically generated spreadsheet. Returned validations are merged back into the project with a click of a button, matched image by image. Crucially, this never alters the original detections: `wildtag.ai` keeps a permanent record of classification data separate from the record of what people have validated, so many contributors' work can be combined without risk of overwriting underlying data. The number of images shared can be adjusted to suit how the work will be done: small archives are easy to email or download for remote volunteers, while larger ones suit annotators working from a shared drive.

2.3 Summarising

Throughout, a data dashboard shows how the image classification and validation process is progressing. It allows mapping of camera locations and reports detections, species, and validation status. The summary dashboard and map update in real time as processing and validation proceed, so progress is visible at any point rather than only at the end.

2.4 Export

Throughout the workflow, data are stored and updated in a simple, standardised spreadsheet (a .csv file) with one row per detection, which includes the chosen model's classification and confidence score and the human validation status (along with other EXIF data). Every image and every detection (i.e., object within an image) is given a stable and reproducible unique identifier generated from the detection metadata (a *hash*). This means the same image always yields the same identifier, on any machine.

The required camera effort and deployment metadata follow Camera Trap Data Package (Camtrap DP) conventions from the outset (Bubnicki *et al.* 2024). This makes generating standard-compliant data straightforward - with a single click, users can save a project as a

Camera Trap Data Package.

2.5 Open access and availability

`wildtag.ai` is free and open. The application can be downloaded and installed from an OSF repository (Sutherland *et al.* 2026a) onto any Windows-based system. The instance is a static copy for publication here and for use with the example dataset; however, active development will continue on GitHub, where the source code is openly available (Sutherland *et al.* 2026b). Once the applications and chosen classifier are installed, the full workflow operates offline.

The classification models are hosted separately from the application and downloaded on first use. This makes the installer small, and users only download the models they need. This same mechanism is open to model developers: a published detector–classifier can be made available through `wildtag.ai` and hosted alongside the existing models, giving developers a direct route to practitioners while keeping the application lightweight (e.g., van Lunteren 2023).

Table 1: Capabilities of `wildtag.ai` compared with a representative selection of available options for camera-trapping image processing workflows. This table is not intended to be exhaustive, but instead a representative cross-section of peer-reviewed systems available to ecologists.

Capability	wildtag.ai	AddaxAI[1]	WildlifeInsights[2]	Agouti[3]	TrapTagger[4]
Cloud or local	Local	Local	Cloud	Cloud	Cloud
Account-free	Yes	Yes	No	No	No
Multi-model hosting	Yes	Yes	No	No	Yes
Geographic coverage	Global	Global	Global	Europe	Global
Distributed validation	Yes	No	Partial†	Partial†	Partial†
CamtrapDB export	Yes	Yes	Partial	Yes	No
Checkpoint and resume	Yes	Yes	–	–	–
Cost	Free	Free	Tiered	Free	Free
Compatibility	Windows	All	web	web	web

[1] van Lunteren (2023)
[2] Ahumada *et al.* (2020)
[3] Casaer *et al.* (2019)
[4] WildEye Conservation (2026)
† Roles can be allocated to project members.

3 A worked example

We provide a minimal working example (MWE) to illustrate the entire workflow. This example allows users interested in using `wildtag.ai` to use the application on a small, yet complete, data set before committing to a wholesale switch to a new workflow, which we hope will allow groups to make an informed decision about tool selection.

The instructions for the full workflow along with the example data set are available in the OSF repository (Sutherland *et al.* 2026a). The example comprises a collection of 16 camera-trap sites at an arbitrary location (St Andrews, Scotland). Every camera has a corresponding folder containing approximately 20 camera-trap images. The study area and camera-trap locations are generated for illustrative purposes, but the images are from a camera-trap study in the Cairngorms Connect restoration landscape as part of the Cairngorms Connect Predator Project (CCPP CCPP 2026). The example provides a walk-through of downloading `wildtag.ai`, installing a classification model, applying the model to the image data, individual and distributed validation, and monitoring performance and progress via the dashboard. Installation should take ∼10 minutes on a standard computer, with an additional 2 minutes to install the DeepFaune Europe model. Running the complete `wildtag.ai` pipeline end-to-end on the toy dataset takes 8-10 min for the AI classification and ∼15 minutes to fully validate the classifications.

As an example of how this scales to more realistic projects, we applied the `wildtag.ai` workflow to our CCPP data consisting of 472,287 images from 103 cameras. The AI classification of all images using DeepFaune Europe took 60.3 hrs on a standard HP desktop computer (HP Elite Tower 800 G9 Desktop PC; Intel Core i7-14700 CPU; 32 GB DDR5 RAM; Windows 11 Pro). A total of 15,592 images of 10 species of interest (out of 24observed) were distributed equally across five volunteers using the `wildtag.ai` distribution functionality, and validation of all these images took ∼11 hrs.

4 Discussion

Here we present `wildtag.ai`, a fully offline, user-friendly, code- and subscription-free tool for tagging and validating camera trap images that directly addresses commonly reported bottlenecks. Specifically, we integrate several practically important workflow components into a single workflow: object detection and species classification; targeted validation built around efficiency-through-distribution workflows; and standardisation of data generation and data sharing. With `wildtag.ai`, we aim to broaden access to the benefits of AI-assisted image processing.

Human-in-the-loop workflows support efficiency, but their uptake depends on how easily they mirror existing workflows and workflow bottlenecks (Chalmers *et al.* 2023). Rather than being built *for* ecologists, `wildtag.ai` has been co-developed *by* ecologists, ensuring our workflow organically maps solutions to these bottlenecks. The first solution is a feature of many workflows:

the high-confidence filtering out of blank images using an object detection stage, which usually comprises over 50% of images (Swanson *et al.* 2016; Penn *et al.* 2024; Willi *et al.* 2019). The second solution is to organise low-resolution copies of tagged images into tag-specific folders so that focal species validation can be prioritised, including 'cascaded validation', where commonly mistaken species are prioritised next. The third solution is easy parallelisation of the validation process across teams or volunteer groups.

We recognise that validation is critical to maintaining trust and confidence in data and future model training and development. We also recognise that, for completeness, projects typically strive to validate all non-blank images, and this remains a practical limitation in many real-world contexts. The architectural core of `wildtag.ai` addresses this directly: smart project organisation and targeted, distributed validation. The automatically generated project structure and one-click distribution and collection processes allow projects to capitalise on networks of potential validators (e.g., citizen science networks) and, in doing so, 'parallelise' the validation process in an organised, manageable, and sustainable way. This coupling of filtering out blank images and organising images into species-specific validation tasks has the added benefit of increased engagement levels (West & Pateman 2016; Robinson *et al.* 2021).

Several image processing options have been, and continue to be, developed to help ecologists leverage the potential of image classification algorithms (Table 1; see Morris 2026). The main point of difference of `wildtag` is the efficiency gains made by experience-driven solutions that address workflow bottlenecks. Specifically, `wildtag.ai` provides the following innovations, which we couple with examples of the efficiency gains we realised in the CCPP project.

- We use classification model predictions to organise images by species, which can be used to prioritise validation effort to species of interest rather than spending time looking at non-target species. For the CCPP data, 82% of the images were blank, and focal species represented just 3% of the data, i.e., validation was only required for 15,592 images rather than the 75,993 non-blank images.

- Images are presented in gallery view and coupled with an error-only correction process. Because most models perform reasonably well, the majority of images are correct, so this approach delivers efficiency gains by reducing the number of button clicks and multiview confirm-by-scanning. For our data, this resulted in validation rates of up to 1,400 images per hour, three times faster than published rates (Delisle *et al.* 2021).

- The ability to coordinate distributed validation offers efficiency gains through parallelising the validation process. This approach, a key feature of online platforms (e.g., Swanson *et al.* 2015), enables images to be validated simultaneously and volunteers to be matched with validation tasks that align with their knowledge, expertise, and interests. We distributed our validation among five validators, with each person taking 2.2 hours. Critically, by doing it synchronously, it took a total of 2.2 hours, rather than the 11 hours if the task was treated serially, i.e., the time savings scale with the size of the team of validators.

- We used design decisions that, by default, optimally but responsibly use the available computational resources on a user's computer (e.g., processing on multiple threads) and that deploy the classifier appropriately. Image classification of the example data using the DeepFaune Europe model took 8.5 minutes with `wildtag.ai` versus 34 minutes when using the alternative offline solution, `AddaxAI v7.2.1` (van Lunteren 2023) - a 4x time saving.

Comparing workflow times using our large CCPP is instructive. Assuming normal processing speeds of ∼450 images an hour Delisle *et al.* (2021) and that a detection model was used to filter out blanks (Beery *et al.* 2019), tagging all non-blank images to obtain a validated dataset on the 10 focal species would have taken 1,052 person-hours (131.5 working days). Using `wildtag.ai`, the same data was generated in 1% of the time (on the order of hours, not days). The AI classification is an additional time cost, but for this large project it is only an additional 3 days. The efficiencies we report will be project-specific, but the magnitude of the comparisons will hold, will scale with the size of the project, and, to the user community, are impactful.

What we present here is the first fully functioning version of `wildtag`. We believe we have balanced the trade-off between the complexity required for general tools that promise full end-to-end solutions, and the simplicity of developing specialised solutions that excel in specific tasks (von der Brüggen *et al.* 2022). Specifically, we developed `wildtag.ai` with responsiveness to the user community and generality in mind. Immediate feature additions are likely to include: making it operating-system-agnostic; allowing multiple validations per image; and formatting post-processed data into analysis-ready formats. All of these feature needs, and more, are expected as `wildtag.ai` gains traction. We have established a forum for users to share experiences and feature requests (https://groups.google.com/g/wildtagai; wildtagai@googlegroups.com), through which tool maintenance and development will be driven.

Model hosting, another democratising feature, is making an explicit and direct link between the development community, i.e., those who develop, train, and distribute classification models, and the user community, i.e., those who wish to embed classification models into their image processing workflows. We hope that our focus on hosting open-access models that are sufficiently documented and supported will encourage best practice and standardisation among the development community while simultaneously offering transparency and agency for users to support decisions around which models to use. Empowering decision-making is also supported by publishing small, manageable, but representative data sets that different models can be applied to quickly and without wholesale commitment.

Author contributions

Conceptualisation: *CS, OH, AA, DR, XL, AC*. **Methodology**: *CS, OH, DR, AC*. **Software**: *CS, OH*. **Validation**: *CS, OH, AC*. **Formal analysis**: *CS, OH, AC*. **Investigation**: *CS, OH, AC*. **Resources**: *CS, XL, AC*. **Data Curation**: *CS, OH, AC*. **Writing (Original Draft)**: *CS, OH, AC*. **Writing (Review & Editing)**: *CS, OH, AA, DR, XL, AC*. **Visualisation**: *CS, OH, AC*. **Supervision**: *CS*. **Project administration**: *CS*.

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Conflict of interest

CS is an Associate Editor at Methods in Ecology and Evolution and Journal of Applied Ecology, but played no part in the review process of this paper.

Data availability statement

All supporting information for this paper is available via a dedicated Open Science Framework (OSF) repository: https://osf.io/m7bgj/ (Sutherland *et al.* 2026a).

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