Ecological Informatics 76 (2023) 102150

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

A semi-automatic workflow to process images from small mammal camera traps

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ARTICLE INFO

Keywords:
Camera trap
Rodent
Automatic image classification
Adaptive monitoring
Data processing
Deep learning

ABSTRACT

Camera traps have become popular for monitoring biodiversity, but the huge amounts of image data that arise from camera trap monitoring represent a challenge and artificial intelligence is increasingly used to automatically classify large image data sets. However, it is still challenging to combine automatic classification with other steps and tools needed for efficient, quality-assured and adaptive processing of camera trap images in long-term monitoring programs. Here we propose a semi-automatic workflow to process images from small mammal cameras that combines all necessary steps from downloading camera trap images in the field to a quality checked data set ready to be used in ecological analyses. The workflow is implemented in R and includes (1) managing raw images, (2) automatic image classification, (3) quality check of automatic image labels, as well as the possibilities to (4) retrain the model with new images and to (5) manually review subsets of images to correct image labels. We illustrate the application of this workflow for the development of a new monitoring program of an Arctic small mammal community. We first trained a classification model for the specific small mammal community based on images from an initial set of camera traps. As the monitoring program evolved, the classification model was retrained with a small subset of images from new camera traps. This case study highlights the importance of model retraining in adaptive monitoring programs based on camera traps as this step in the workflow increases model performance and substantially decreases the total time needed for manually reviewing images and correcting image labels. We provide all R scripts to make the workflow accessible to other ecologists.

1. Introduction

The increasing use of automated sensor networks such as wildlife camera traps, phenology cameras and acoustic sensors has advanced ecological research by providing high-resolution and large-scale data for better understanding of ecological processes and improving ecological forecasting (Farley et al., 2018). Such sensor networks usually produce enormous amounts of data that need to be stored and processed, an often challenging task for ecologists. For example, camera traps, which have become widely used tools for wildlife monitoring in the last decades (Burton et al., 2015; Steenweg et al., 2017), can easily accumulate thousands of images in a short time. Traditionally, the images are reviewed by humans who manually extracted data such as the presence of a species or the number of individuals on the image. However, manual classification of images is very time consuming and has limited the use of camera trap data so far (Glover-Kapfer et al., 2019).

To overcome the challenge of manually processing huge amounts of data, artificial intelligence is increasingly used in ecology, for example to automate the classification of camera trap images (Christin et al., 2019). Deep neural networks are a type of machine learning models that have proven to be especially useful for image recognition (Krizhevsky et al., 2012) and have been applied for animal detection and classification with great success (e.g. Norouzzadeh et al., 2018; Tabak et al., 2019; Willi et al., 2019; Zualkernan et al., 2022). These models can for example separate empty images from images containing an animal (e.g. Beery et al., 2019), identify species, count individuals, and categorize animal behaviour with an accuracy that matches or even outperforms humans (Norouzzadeh et al., 2018). However, developing and training neural networks require programming skills and have therefore often been tasks for computer scientists (Tabak et al., 2020). To facilitate the use of machine learning in ecology, several neural networks trained on large image data sets are now publicly available via simple user

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https://doi.org/10.1016/j.ecoinf.2023.102150
Received 19 January 2023; Received in revised form 26 May 2023; Accepted 27 May 2023
Available online 5 June 2023

interfaces. For example, Tabak et al. (2020) developed the R-package 'Machine Learning for Wildlife Image Classification (MLWIC2), which provides functions for classifying new camera trap images with the provided models and for training new classification models using own images. Besides tools for automatic image classification, a range of software tools for camera trap data management and image annotation have been developed since the use of camera traps became popular (see review by Young et al., 2018). More recently, machine learning has been implemented in annotation programs to allow for semi-automatic workflows which combine automatic classification and human labeling. AIDE (Annotation Interface for Data-driven Ecology) is a open-source web framework for image annotation that also provides tools for training machine learning models (Kellenberger et al., 2020). Timelapse (http://saul.cpsc.ucalgary.ca/timelapse/) is an open-source annotation software that incorporates the output from a machine learning model and can be used to verify and correct model labels. However, Timelapse works only with the output from a specific detection model, the MegaDetector (Beery et al., 2019), and is therefore not suitable if another model type was used for automatic classification.

Most camera trap studies have so far focused on large mammals (i.e. carnivores and ungulates) (Burton et al., 2015) and thus, tools for automatic image classification have also been developed with a focus on these animal groups (e.g. Norouzzadeh et al., 2018; Tabak et al., 2019; Beery et al., 2019). Nevertheless, small mammals, such as rodents and shrews, represent the most abundant and specious orders of mammals (Wilson and Reeder, 2005) and studying their population dynamics is important because many rodent species pose risks to humans as vectors of zoonoses (Meerburg et al., 2009a) or crop pests (Meerburg et al., 2009b). Furthermore, they often exert key ecosystem functions (Ims and Fuglei, 2005; Boonstra et al., 2016; Andreassen et al., 2020). In the last years, camera traps have been increasingly used to monitor small mammals which opens new possibilities to study their ecology (Rendall et al., 2014; Kleiven et al., 2022). However, camera trapping of small animals is challenging because they are less likely to trigger motion-sensor cameras. The cameras must be placed close to the animals, both to trigger the camera and to allow identification of cryptic small mammal species from the images (Glen et al., 2013). In addition, small mammals often move in dense vegetation near the ground or under snow during winter in northern environments. Thus, camera traps specifically adapted to target small mammals are often necessary (Mos and Hofmeester, 2020; Kalhor et al., 2021). One possibility that has been successfully implemented to monitor ground-dwelling small mammal communities is placing the camera in a box or a tube that can be entered by small animals (Soininen et al., 2015; Mos and Hofmeester, 2020; Mölle et al., 2022; Gracanin et al., 2022). In order to efficiently analyse images from small mammal camera traps, the implementation of automatic image classification is necessary. Since available pre-trained classification models are trained on image data sets dominated by larger animals, they can not be applied to images from small mammal camera traps. Thus, models specifically trained for the classification of small mammal species with images from specific small mammal camera traps will be necessary.

Many ecological studies are based on long-term monitoring, as this is needed to quantify ecological responses to potential drivers, evaluate the impact of management actions, understanding complex ecosystem dynamics and providing core ecological data for statistical and theoretical models (Magurran et al., 2010; Lindenmayer et al., 2012). Camera traps are efficient tools for long-term monitoring of animal populations if they are combined with complete and flexible workflows for image processing. Besides automatic image classification, such workflows should include a quality check where the model performance is evaluated, followed by a step where automatic image labels can be reviewed and corrected manually. Although many tools for camera trap image processing are available already, they are not easily streamlined into a complete workflow because different software tools and platforms have been developed for different tasks. In addition, these tools are often not particularly flexible and it might be difficult to adjust them to the different needs of different monitoring programs such as those based on camera traps designed to target small mammals. Furthermore, most of the available tools focus on either automatic or manual image classification, although a combination might often be most appropriate. In many cases, neural networks will rather accelerate manual classification than completely replace it (Vélez et al., 2022; Greenberg, 2020) because the transferability of neural networks to new images is known to be problematic (Norouzzadeh et al., 2018) and classification models usually perform better for some species than for others. Thus, the importance of verifying automatic image labels has been emphasized (Christin et al., 2021).

In this study, we propose a semi-automatic workflow for processing and classifying images from small mammal camera traps that accommodates some of the challenges faced when initiating long-term, adaptive monitoring programs. The workflow includes organising and preparing raw images retrieved from the camera traps, automatic image classification, a quality check of the automatic image labels and the correction of wrong labels. In addition, we incorporate training a classification model and retraining the model with new images in the workflow. We demonstrate the workflow using images from a long-term small mammal monitoring program in Arctic tundra. Since there are no pre-trained classification models for the targeted small mammal community publicly available yet, we also trained a model for the classification of images from a typical arctic small mammal community (voles, lemmings, shrews and mustelids).

The complete workflow is performed in the statistical software R (R Core Team, 2022), a programming language used by most ecologists (Lai et al., 2019). Thus, the use of R instead of python, the leading programming language for deep learning tasks (Raschka et al., 2020), will likely lower the threshold for ecologist of implementing automatic image classification in their workflows. Most available frameworks for automatic image classification come as tools with a graphical user interface or as R packages. Such tools and packages are designed to be user-friendly with the aim to make machine learning models available for ecologists without programming experience (Tabak et al., 2020). However, they are often difficult to modify and researchers are then obliged to develop their own tool for their specific needs instead of using existing ones. Thus, we provide R-scripts for all steps of the workflow, including training an image classification model with the hope that this will facilitate the implementation of automatic images classification in workflows of ecologists. The scripts are very flexible and even if some coding experience is required, we think they can be easily adapted to other studies by ecologists with an average knowledge of R.

2. Description of the workflow

The semi-automatic workflow includes a processing pipeline from images downloaded in the field to a quality checked data set ready to be used in ecological analyses. In addition, we give an example for training an image classification model in R and for adapting the model to new data without the need of computer vision expertise. (Fig. 1).

2.1. Image preparation

First, after retrieving the images from the cameras, we recommend renaming all images with a unique name. Camera trap images are usually automatically named with a generic name such as 'IMG_0001.JPG' by the camera and thus, images from different camera traps have the same names. This will cause confusion in monitoring programs with many cameras running over a long time. Furthermore, image metadata saved with the image, such as date and time when the image was taken or temperature can be extracted and saved in a metadata-file within the same step.

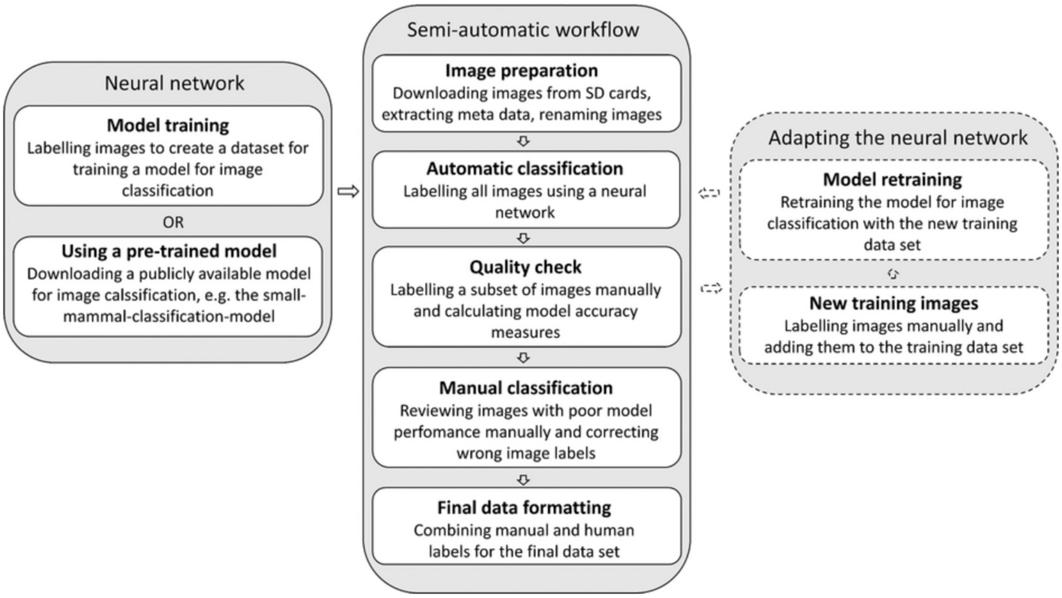

Fig. 1. The steps of a semi-automatic workflow for classifying camera trap images.

2.2. Automatic classification

Then, all images are labeled automatically using an image classification model. Since monitoring small mammals communities with camera traps is an emerging field with no available pre-trained models, we focus on the typical situation where there is need to train the classification model with images from the targeted community. Alternatively, a pre-trained, publicly available model such as our small mammal classification model can be utilized. The output of classification models is a value between 0 and 1 per class, describing the confidence of the model that the image belongs to a certain class. The class with the highest confidence is usually extracted as the automatic image label. Our model can be run on a normal laptop to classify images automatically, however, a GPU is strongly recommended to train a model in a reasonable time.

2.3. Quality check

Image classification models often generalize poorly to new data (Norouzzadeh et al., 2018), and thus, verification of the automatic image labels after classifying new images is important. The quality check therefore includes labeling a subset of images manually and calculating accuracy measures such as prediction accuracy, precision, recall and F1 score (Sokolova and Lapalme, 2009). We suggest a quality check in three steps that allows evaluation of (i) overall and (ii) per-class model performance as well as (iii) setting a confidence threshold. i) For calculating overall model accuracy we recommend labeling a random subset of images manually. ii) Since image data sets are often unbalanced, classes with few images might not be sufficiently represented in the random subset. In order to calculate per-class model accuracy, we recommend labeling a random subset of images of each class in addition (e.g. 100 images per class). iii) To determine a confidence threshold (confidence level above which model labels are deemed to have high accuracy and thus can be accepted), we recommend to select random images per confidence class for manual labeling, i.e. images classified with a confidence between 0.1 and 0.2, 0.2 and 0.3 and so on. Prediction accuracy can then be calculated for each confidence class.

2.4. Model retraining

Based on the quality check, the researcher can decide whether model performance is satisfactory or if the model performance should be improved by selecting new training images and retraining the model. If images from new sites have been classified, model performance can be improved by including images from these sites in the training data set. If the model had problems with some classes; e.g. identification of some species, it might help to include more images of these species in the training data set. When selecting new training images, the model output from the original model can be helpful to find images that meet a certain criteria, e.g. to find images of a certain species. However, all training images should be reviewed manually instead of relying on model outputs only to avoid misclassified training images.

2.5. Manual classification

If the model performance is in general satisfying, but poor for a specific type of images, for example for images with low confidence or for images of one species, the labels of these images should be reviewed manually and corrected if necessary.

2.6. Final data formatting

The automatic and manual image labels are combined in the final data set that then can be used in ecological analyses. The data set provides image metadata, class-specific observations (i.e. automatic and manual image labels) and image quality information.

3. Case study

We here demonstrate all steps of the semi-automatic workflow presented in Fig. 1 adapted to the development of a long-term, camera trap-based monitoring program of an Arctic small mammal community. A more detailed figure of the workflow specific to this case study is provided in the Appendix A. All R scripts needed for the workflow and detailed instructions for using the scripts and following the workflow are available on GitHub (https://github.com/hannaboe/camera_trap_workflow). We also provide our classification model and the training data set which can be used to retrain the model together with additional images.

3.1. Monitoring program and image data set

Long-term monitoring of small mammals within the the Climate-ecological Observatory for Arctic Tundra (Ims et al., 2013) was initiated with 44 camera trap sites on the Varanger Peninsula in Northern Norway in 2014 (Mölle et al., 2022). More traps were gradually added in the following years, resulting in a total of 92 camera trap sites by 2020. The camera traps established during these years were located in two habitats (hummock tundra and snowbed habitat), and two study areas (Komagdalen and Vestre Jakobselv) (Fig. 2). The target species of the monitoring are Norwegian lemmings (*Lemmus lemmus*), voles (*Myodes rufocanus* and *Microtus oeconomus*) as well as their predators, stoats (*Mustela erminea*) and least weasels (*Mustela nivalis*). Furthermore, shrews (*Sorex ssp.*) and small birds are also frequently recorded.

The camera trap was developed by Soininen et al. (2015) and consisted of a Reconyx camera (Customized from Reconyx S750, Reconyx Inc., Holmen, WI, USA) mounted on the ceiling of a metal box that functions as a tunnel where small mammals can pass through (Fig. 3). The cameras were programmed to take motion sensor images with two images per trigger and a quiet period of one minute between consecutive trigger events. In addition, to monitor the functionality of the camera traps (battery life, intrusion with snow, ice, and water), two time-lapse images were taken per day. Most images are empty or contain a single animal on the floor of the box in a relatively fixed distance from the camera lens. However, animals have different positions and sometimes only parts of the animal is visible in the openings of the box. Snow, ice, water and vegetation can accumulate in the boxes and a cause variable background (Fig. 4).

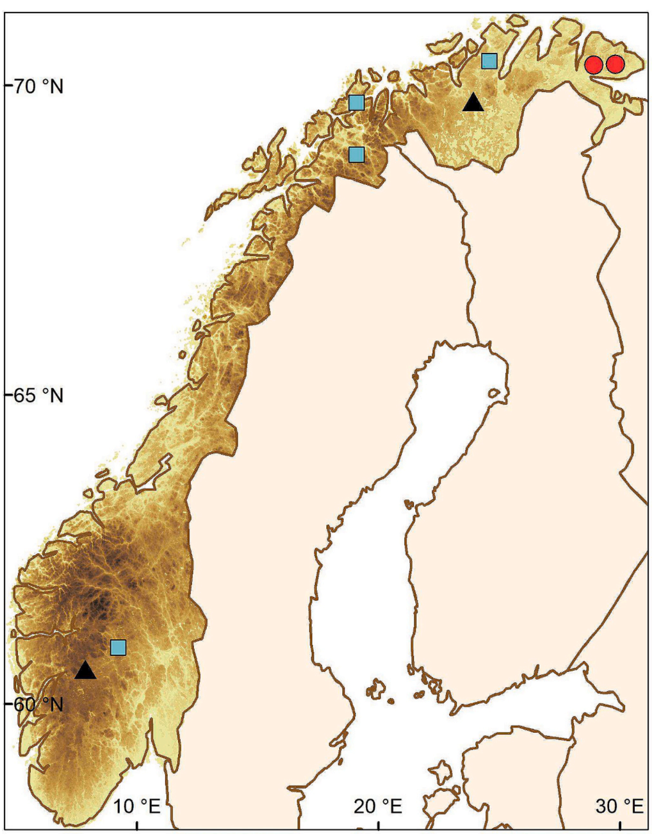

Fig. 2. The location of the two camera trapping areas (Komagdalen and Vestre Jakobselv) of the small mammal long-term monitoring program on the Varanger peninsula are represented with red dots. The location of other small mammal camera trapping areas in Valdres, Kirkesdalen, Håkøya, Porsanger (from South to North) are represented with blue squares. Images of these areas where used to extend the training data set. The location of the small mammal camera trapping areas in Joatka (Northern Norway) and Finse (Southern Norway) are represented with black triangles. Images of these areas are used as an out-of-sample data set for model validation.

In summer 2020, the long-term monitoring program was extended with 72 new camera trapping sites on the Varanger Peninsula. These sites were established in the same two study areas as before (Komagdalen and Vestre Jakobselv), but in two new habitats (heath and meadow). A similar camera trap set up as for the initial traps was used, but a new camera model (Customized from Reconyx Hyperfire II, Reconyx Inc., Holmen, WI, USA) was deployed inside the boxes, and the boxes had a darker painted floor. Since the trigger speed of the new camera model was slower, which leads to blurred images when animals pass through the camera box with high speed, a low metal barrier was installed in the middle of the box to slow down the animals (Fig. 4 A, C and E show boxes with the metal barrier). The changes of the camera trap setup (modified boxes and new camera model) and the addition of the new trap sites (habitats) made it necessary to assess whether this had an effect on the performance of the initially trained classification model.

3.2. Model training

To develop the classification model, we used the images taken between summer 2014 and summer 2020 in hummock tundra and snowbed habitat on the Varanger peninsula (original camera traps). Since our data set was unbalanced with a lot of empty and vole images, but fewer images of stoats, least weasels and birds, we included images from other smaller small mammal camera trapping programs across Norway in the training data set to increase the number of images of rare species. Furthermore, including more localities might potentially increase the transferability of the model to new camera trap sites. These camera traps are located in Porsanger, Kirkesdalen, Håkøya and Valdres with 3–15 camera traps per locality (Fig. 2).

We selected 59000 images for model development from all available images taken between summer 2014 and summer 2020. The images were sorted in 6 animal classes (voles, lemmings, shrews, least weasels, stoats and birds), one class for empty images if there was no animal on the image and one class for bad quality images if it was not possible to decide whether the image was empty or not. Bad quality images are for example blurry images, images from boxes full of snow, water or vegetation or images of humans or landscapes taken when the camera was set up. All training images from the Varanger peninsula, Porsanger, Kirkesdalen, Håkøya and Valdres were selected manually and only images that could be easily sorted in one of the categories were included the training data set. We tried to create a balanced training data set by selecting images from all camera traps and by selecting a similar number of empty images and images of abundant species (voles, lemmings and shrews). However, there was still an unbalance between abundant and rare species (Table 1). We did not include difficult images in the training data set (i.e. images where only a small part of the animal was visible or blurry images) since the quality of the training data set is important for the accuracy and the reliability of a neural network (Kavzoglu, 2009).

The selected 59000 images were then split in a training and an internal validation data set (90% for training, 10% for validation). For testing the final model on an independent out-of-sample data set, we used images from small mammal camera trapping programs in Joatka (Northern Norway) and Finse (Southern Norway) (Fig. 2). The trapping program in Joatka was started in 2020 and includes 20 camera traps. The trapping program in Finse was started in 2021 with 8 camera traps. Both programs use the same camera trap set up as in the new habitats on the Varanger peninsula. To create a realistic data set, we labeled a random subset of the available images from Joatka and Finse manually and used these 6252 images as an out-of-sample data set (Table 1).

We trained a deep neural network in R (R Core Team, 2022) using the R-package keras (Chollet et al., 2017), an interface to TensorFlow (Abadi et al., 2015) for R. We used the ResNet50 architecture (for details about the model architecture see He et al., 2016) with an adam optimizer (Kingma and Ba, 2014). We trained the model from scratch for 55

Fig. 3. The camera trap developed by Soininen et al. (2015) consists of a Reconyx camera that is mounted on the ceiling of a metal box that can be entered by small mammals. The camera traps are protected with stones when placed in the field.

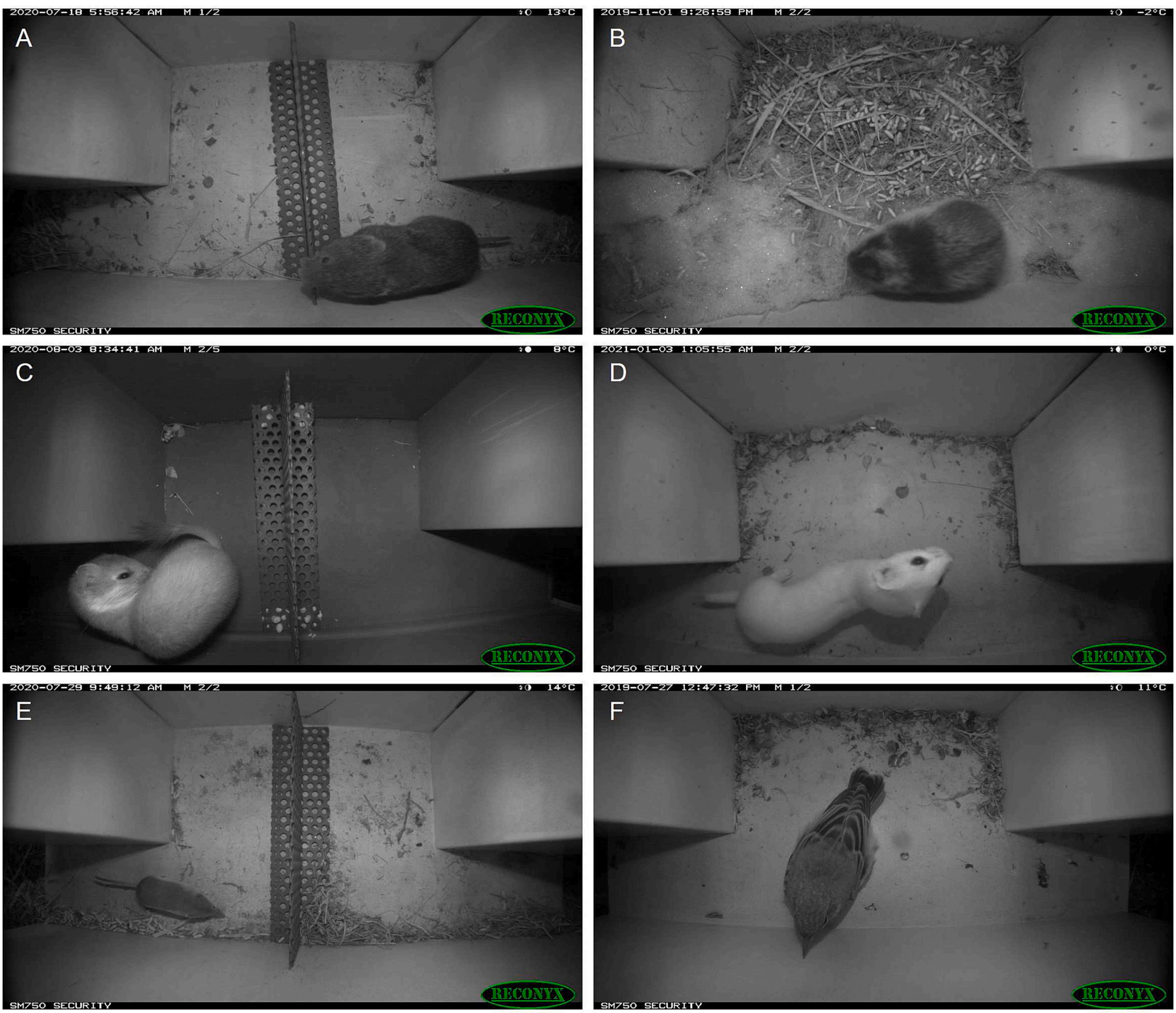

Fig. 4. Example images of a vole (A), a lemming (B), a stoat (C), a least weasel (D), a shrew (E), and a bird (F).

epochs with a one-cycle learning rate policy with a minimum learning rate of 0.000001 and a maximum learning rate of 0.001 (Smith, 2018). We explored different hyper-parameters and choose the ones that gave the best results for training the final model. All images were resized to 224 x 224 pixels previous to training and image augmentation (shifts, horizontal flips, rotations, zooms and shears) was applied to expand the

Table 1
Number of training images, validation images (used for model validation during model training) and out-of-sample test images (used for external model validation after training was finished) as well as number of new images selected from the images taken between summer 2020 and summer 2021 for model retraining.

Class	Number of training images	Number of validation images	Number of out-of-sample test images	Number of new training images for model retraining
Bad quality	6453	677	549	306
Bird	3382	219	119	195
Empty	9444	979	3301	533
Least weasel	1725	98	69	424
Lemming	9449	967	647	449
Shrew	9265	962	584	416
Stoat	4024	438	64	425
Vole	9894	1024	919	528
TOTAL	53636	5364	6252	3276

training data set. The models were trained on a cloud service with 1 GPU, 4 CPUs and 16 GB RAM provided by Sigma2 - the National Infrastructure for High Performance Computing and Data Storage in Norway.

We evaluated the model performance on the validation data set and the out-of-sample test data set by calculating model accuracy as the number of correct predictions divided by the number of all images as well as precision, recall and F1 score for each class (Appendix B):

$$Precision = \frac{TP}{TP + FP} \quad (\mathrm{TP = Truepositives})$$

$$Recall = \frac{TP}{TP + FN} \quad (\mathrm{FP = Falsepositives})$$

$$F1 = 2*\frac{precision*recall}{precision + recall} \quad (\mathrm{FN = Falsenegatives})$$

3.3. Data processing and semi-automatic workflow

To demonstrate the workflow and to test the transferability of the model to new sites and camera trap modifications, we used all images taken on the Varanger peninsula between summer 2020 and summer 2021 (also including images from the original camera trap set up).

After the images were downloaded from SD-cards in the field, we prepared the images by extracting meta data such as date, time and temperature from the images. Then, all images were renamed with a unique name including camera-site-id and the date when the image was taken. We classified all images automatically using our model and extracted the class with the highest confidence from the model output, which was used as the automatic image label.

We then quality checked the automatic image labels from the model in three levels: First, we calculated overall model accuracy for each camera trap type (i.e. original camera traps in hummock tundra and snowbed habitat and new camera traps in heath and meadow habitat). We did this by selecting 1000 random images per camera trap type, labeled them manually, and compared manual and automatic image labels. Second, to evaluate model performance for each class, we selected additional 200 random images per class and camera type and labeled them manually. We then calculated precision, recall and F1 score for each camera trap type using the 1000 random images and the 200 images per class. Since some classes are much more common than others, including a fixed number of images per class (i.e. 200) increased the proportion of rare classes in the validation data set relative to the complete data set. Thus, model performance would be overestimated for rare classes and underestimated for abundant classes. Therefore, the number of true positives, false positives and false negatives was corrected for the proportion of each class in the complete data set (see Appendix C). We also visualized these results in form of a confusion matrices (without correction) for each camera trap type using the R package caret (Kuhn, 2008). Third, to determine the confidence level above which the automatic image labels can be accepted, we selected 200 images per confidence class (0–0.1, 0.1–0.2, …, 0.9–1.0) and per camera trap type for calculating accuracy for each confidence class.

After the quality check, we decided to improve model performance by retraining the model with some of the new images (see Section 3.4 for model retraining). We re-classified all images with the retrained model and repeated the quality check. Based on the different quality measures, we decided which automatic image labels we will accept and reviewed the remaining images manually.

3.4. Model retraining

From all images taken between summer 2020 and summer 2021 we added 3276 new images to the training data set and retrained the model from scratch on the original and the new training images using the same hyper-parameters as for the original model. When selecting the new training images, we tried to select the same number of images from all camera trap sites and classes. Since images with stoats, least weasels and birds were underrepresented in the original training data set, we selected almost all images of these classes. If we selected many images from one site, we also selected some extra empty images, as well as images of other classes if available, from the same site and taken during the same period in order to prevent the model from associating the image background with a certain class. We did not take this into account when selecting the original training images and therefore also added some images from the previous years to the training data set. We then retrained the neural network as described before.

4. Results of the case study

4.1. Model validation

Prediction accuracy of the small mammal classification model after training for 55 epochs evaluated on the validation data set was 98.2% and 82.1% evaluated on the out-of-sample data set. After retraining the model with new images, prediction accuracy was 98.0% evaluated on the validation data set and 94.8% evaluated on the out-of-sample data set.

The retrained model performed well for the classes with many training images (F1 score between 0.98 and 0.99 for the validation data set and F1 score above 0.9 for the out-of-sample data set), whereas model performance was poorer for the classes with less training images (stoat, least weasel and bird). Model precision, recall and F1 score for each class as well as confusion matrices for the validation and the out-of-sample data set are given in Appendix B.

4.2. Classification and quality check of new images with the original model

Between summer 2020 and summer 2021, the original camera traps in hummock tundra and snowbed habitat took 368735 images and the newly established camera traps in meadow and heath habitat took 70279 images. These images were automatically classified with our small mammal classification model.

The quality check showed that overall prediction accuracy was 95.3% for the original camera traps and 90.7% for the new camera traps (calculated using 1000 manually labeled images per camera trap type). Prediction accuracy increased with model confidence (Fig. 5). 88.2% of the images from the original camera traps and 73.7% of the images from the new camera traps were classified with a confidence above 0.9.

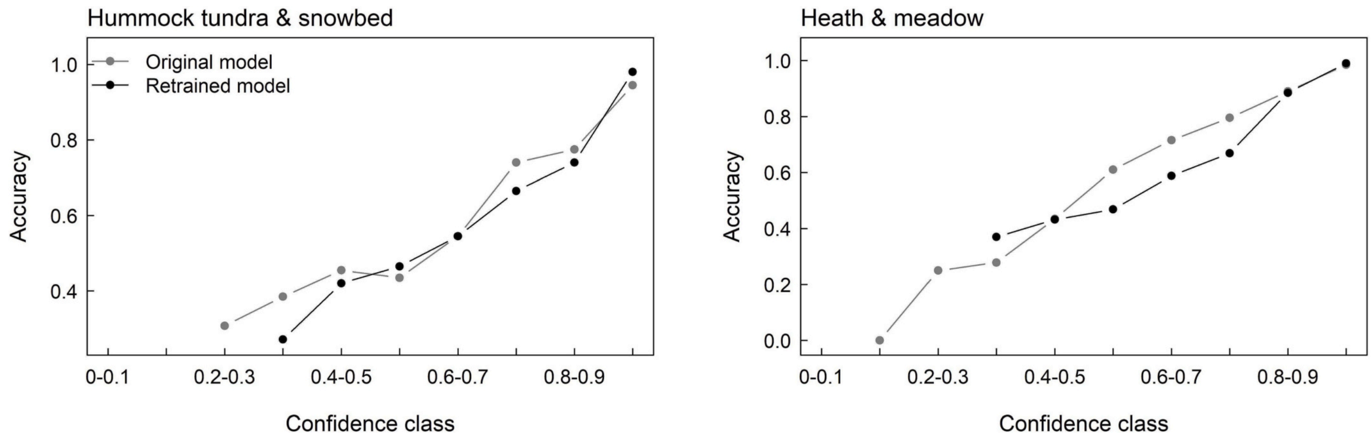

Fig. 5. Prediction accuracy of images that were classified with a confidence between 0 and 0.1, between 0.1 and 0.2, …, and between 0.9 and 1.0 with the original and the retrained model. Prediction accuracy was calculated using 200 randomly selected and manually labeled images per camera trap type (original camera traps in hummock tundra and snowbed habitat and new camera traps in heath and meadow habitat) and confidence class.

4.3. *Classification and quality check of new images with the retrained model*

After classification of the new images taken between summer 2020 and summer 2021 with the retrained model, overall prediction accuracy was 98.4% for the original camera traps and 97.5% for the new camera traps. Retraining the model increased the percentage of images classified with a confidence above 0.9 for both camera trap types. 97.9% of the images from the original camera traps and 94.9% of the images from the new camera traps were classified with a confidence above 0.9 with the retrained model (Fig. 5).

Retraining the model with images from 2020–2021 also improved model precision and recall of all classes. While model performance of the original model was poor for some classes, it was acceptable for the updated model with F1 scores above 0.8 for all classes (Table 2 and Fig. 6).

Table 2
Precision, recall and F1 score for the 8 classes in the new data sets from 2020–2021 predicted using the original (numbers in brackets) and the retrained classification model (bold numbers). The new data sets include the images taken between summer 2020 and summer 2021 with the original camera traps in hummock tundra and snowbed habitat and the new camera traps in heath and meadow habitat. The values presented here were corrected for the proportion of each class in the complete data set. The correction and the uncorrected values are shown in Appendix C.

	Hummock tundra & Snowbed			Heath & Meadow		
Class	Precision	Recall	F1	Precision	Recall	F1
Bad	(0.69)	(0.86)	(0.77)	(0.83)	(0.84)	(0.84)
quality	**0.89**	**0.79**	**0.83**	**0.93**	**0.96**	**0.95**
Bird	(0.47)	(0.82)	(0.60)	(0.17)	(0.14)	(0.15)
	0.89	**0.87**	**0.88**	**0.90**	**0.98**	**0.94**
Empty	(0.99)	(0.95)	(0.97)	(0.95)	(0.96)	(0.96)
	0.99	**0.99**	**0.99**	**0.99**	**0.99**	**0.99**
Least	(0.39)	(0.98)	(0.56)	(0.10)	(0.96)	(0.18)
weasel	**0.87**	**1.00**	**0.93**	**0.72**	**1.00**	**0.84**
Lemming	(0.79)	(1.00)	(0.88)	(0.67)	(0.96)	(0.79)
	0.80	**1.00**	**0.89**	**0.85**	**0.99**	**0.92**
Shrew	(0.56)	(0.77)	(0.65)	(0.81)	(0.71)	(0.75)
	0.89	**0.86**	**0.87**	**0.97**	**0.97**	**0.97**
Stoat	(0.35)	(0.80)	(0.49)			
	0.82	**1.00**	**0.90**			
Vole	(0.93)	(0.95)	(0.94)	(0.96)	(0.85)	(0.90)
	0.99	**0.97**	**0.98**	**0.99**	**0.96**	**0.97**

5. Discussion

We present a semi-automatic workflow for the classification of small mammal images that is adapted to the challenges associated with the development of long-term monitoring programs based on camera traps. We demonstrate the application of the workflow using images from long-term monitoring of a small mammal community in Arctic tundra. Since most available models for automatic classification of camera trap images are designed for larger animals, we trained a classification model for the identification of a typical northern small mammal community with voles, lemmings, mustelids and shrews. Species composition of small mammal communities may differ substantially at smaller scales than large mammal communities. Hence, training a classification model with images from the targeted community may be a required task at the onset of new small mammal monitoring programs. Our model had an accuracy of 94.8% evaluated on images from two new study areas indicating that the model can be applied by other small mammal monitoring programs that use the same camera trap set up and target a similar species community. We trained the model and constructed the entire workflow in R, to demonstrate that extensive machine learning knowledge or programming skills in python are not needed to implement automatic classification in camera trap studies. Instead, we believe that ecologists that are proficient R users are able to adjust our scripts to train their own model or retrain our model and set up their own workflow. We illustrated the proposed workflow by processing new images, including images from new camera trap sites with modified camera traps. This is a typical situation during the course of long-term monitoring programs where new data is coming in periodically and new sites or new camera models might be added. The flexibility, transparency, and required skill level make our workflow an especially useful tool for ecological long-term monitoring programs of small mammals that generate large camera trap data sets.

Our workflow includes a relatively extensive quality check of automatic image labels. Such a check is crucial, as machine learning models usually decrease dramatically in accuracy when they are applied to new data (Schneider et al., 2020). Hence, the verification of automatic image labels has been emphasized by several authors (Christin et al., 2021; Vélez et al., 2022). In our case study, the original model classified the new images with a prediction accuracy over 90%, which is very high when a classification model is transferred to new data (Schneider et al., 2020). However, a drop of prediction accuracy from 98% to 90% from one year to the next can compromise the temporal consistency of data from a long-term monitoring program. We show that if retraining the model with new images is part of the workflow, model performance for new images can be strikingly increased (to 97.5% for the the new camera

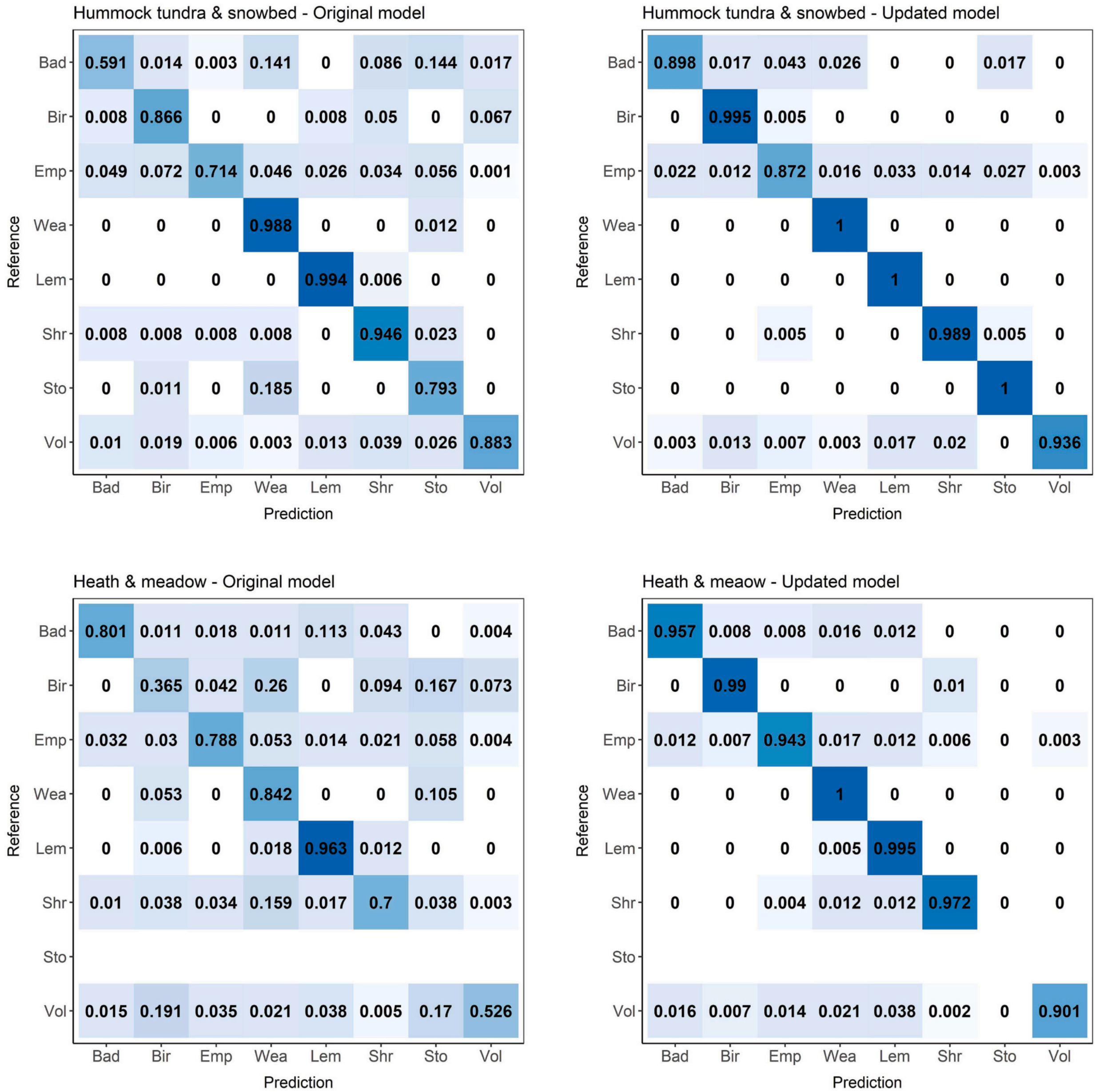

Fig. 6. Confusion matrix (percentage of correct labels for each class) showing the performance of the original and the retrained classification model on new data sets from 2020–2021. The new data sets include the images taken between summer 2020 and summer 2021 with the original camera traps in hummock tundra and snowbed habitat and the new camera traps in heath and meadow habitat. (Bad = Bad quality, Emp = Empty, Bir = Bird, Vol = Vole, Wea = Least weasel, Lem = Lemming, Shr = Shrew, Sto = Stoat).

traps and 98.4% for the old camera traps). Even if overall prediction accuracy was high, the quality check revealed that images classified with a confidence above 0.9 had a prediction accuracy around 99%, while images classified with a confidence between 0.8 and 0.9 had a prediction accuracy around 80%. Therefore, we decided to accept all model labels with a confidence above 0.9 and labeled the remaining images manually. Furthermore, we also discovered differences in model performance for the different classes, i.e. our model performed poorly for stoats and least weasels. Since these are considered key species of the particular monitoring program, we also labeled all images of these classes manually. Another reason for an extensive quality check is that image data sets usually contain some images that are difficult for a classification model. For example, our data set contained one camera trap with a dead lemming. Images from this box were all labeled as 'lemming' although the correct label would be 'empty'. Furthermore, the boxes often get filled with snow during winter, and sometimes the snow patches have similar shapes and colour as mustelids in winter coat and are therefore labeled as 'stoat' or 'least weasel'. We also recorded a new (i.e. not included in the training data set) mustelid species (mink) on some images from the new camera traps placed in habitats closer to aquatic environments than the original trap sites. If enough images of all classes and confidence-levels are reviewed in a quality check, these issues are likely to be discovered and can then be corrected.

Our workflow minimized the effort of human labeling through retraining the model with new images. Retraining the model with 3276 out of over 400.000 new images was enough to increase model accuracy as well as the percentage of images that were labeled with high confidence. This meant that only around 10.000 images were classified with a confidence below 0.9 and had to be reviewed manually, compared to around 60.000 images without retraining the model. We thus saved about 70 h of manual image labeling when estimating that a human will label about 700 images per hour. Besides saving a lot of time, reducing the number of manually labeled images might also increase the accuracy of the data set. Human accuracy is likely to decrease if a large data set has to be reviewed because humans might be more prone to make mistakes when looking at images for hours and days. Furthermore, a small data set can often be labeled by experts whereas the help from less experienced assistants, who often obtain lower accuracies, is needed for labeling a large data set (Norouzzadeh et al., 2018). Therefore, we think an extensive quality check to identify images for which the model performs poorly and correcting the labels of these image as well as possibly retraining the model with new images are important steps of the workflow when a model is applied to new data. This will often be the case when camera traps are used in long-term monitoring programs (Bodesheim et al., 2022). Typically, a model is trained on images gathered over some years and will then be used to automatically classify images from the following years. We used a simple way to retrain the model by manually selecting new training images and training a new model on the updated training data set. We found this method to result in a model that is performing well on the new data set and to be simple enough to be implemented by ecologists. However, more advanced techniques where algorithms are used in an active learning loop to select images that are most relevant for model improvement can be tested (Kellenberger et al., 2020; Norouzzadeh et al., 2021) if our method does not result in a satisfactory model.

We developed the workflow for images from camera traps specifically designed for recording small mammals. These images are relatively easy for model development and transferability since all images have the same distance to the objects and usually contain only one individual animal. Thus, the workflow can directly be transferred to other small mammal camera trap studies by using the provided R scripts and instructions (https://github.com/hannaboe/camera_trap_workflow). If the same or similar species are targeted as in our data set (voles, lemmings, mustelids, shrews and small birds), our small mammal classification model can be used for automatic classification. We also provide our training data set, so the model can be retrained with images from other localities to increase model performance. If species composition differs from our data set, a new model could be trained using transfer learning with our model as a base-model. With transfer learning, good model performance can be reached even if the training data set is small (Weiss et al., 2016). Several studies successfully trained models with around 1000 images per class when using transfer learning (Shahinfar et al., 2020; Ferreira et al., 2020). Thus, new projects that are building on our model do not have to put a lot of effort in creating a large training data set to train their own models.

To our knowledge, our workflow is the first approach that gathers and streamlines all steps of a processing pipeline for small mammal camera trap images using automatic classification within one platform. Due to its flexibility, the workflow is especially well suited for adaptive monitoring programs (Likens and Lindenmayer, 2018; Ims and Yoccoz, 2017), where monitoring targets, design and technologies are optimized over time. By providing R scripts, we also open the possibility for other ecologist to further develop the workflow and target it to their specific needs. Deep learning is a fast developing field (Minar and Naher, 2018) and as new methods, such as new model architectures, become available, they can be implemented to improve the workflow. In addition, we also provide R-shiny-apps, which are as flexible as R scripts, for the more time consuming steps of the work (quality check and correction of model labels). After the apps have been adjusted to the study, they can be used without knowledge of R and volunteers can help with labeling images manually. Thus, although many tools for processing camera trap images have been developed in the last years, we anticipate that the workflow presented here can help other research programs to develop their own routines for processing camera trap images and to incorporate automatic classification in their workflows.

CRediT authorship contribution statement

Hanna Böhner: Conceptualization, Data-curation, Formal-analysis, Investigation, Methodology, Project-administration, Software, Validation, Visualization, Writing-original-draft, Writing-review-editing. **Eivind Flittie Kleiven:** Conceptualization, Data-curation, Investigation, Validation, Writing-review-editing. **Rolf Anker Ims:** Conceptualization, Funding-acquisition, Investigation, Validation, Writing-review-editing. **Eeva M. Soininen:** Conceptualization, Funding-acquisition, Investigation, Project-administration, Resources, Validation, Writing-review-editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All R scripts together with a some example images and detailed instructions how to set up the workflow are available on GitHub (https://github.com/hannaboe/camera_trap_workflow). The small mammal classification model as well as the images used for training, validating and testing the model are available at https://doi.org/10.5281/zenodo.7801786.

Acknowledgements

We thank Siw Killengreen and Ingrid Jensvoll for initiating the development of small mammal cameras in COAT, Jan-Erik Knutsen, Torunn Moe and Leif-Einar Støvern for help with field logistics, and everyone who has participated in camera trapping field work on the Varanger Peninsula since 2014: Siw Killengreen, Ingrid Jensvoll, Leif Einar Støvern, Dorothee Ehrich, Francisco Javier Ancin Murguzur, Jonas Mölle, Mathias Leines Dahle, Kjerstin Mæland, Jarad Mellard, Mike Murphy, Jan-Erik Knutsen, Per Aspaas, Xavier Lambin and Julia Mikhailova. The camera trapping infrastructure has been funded by the Fram Centre and the Research Council of Norway (Grant No. 245638). The same grant, together with UiT-The Arctic University of Norway has provided salary funds. This study is a contribution from the Climate-ecological Observatory for Arctic Tundra (COAT). We thank Nina E. Eide for providing images from the small mammal camera trapping program in Finse, Southern Norway. The images were stored and processed on resources provided by Sigma2 - the National Infrastructure for High Performance Computing and Data Storage in Norway

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, athttps://doi.org/10.1016/j.ecoinf.2023.102150.

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