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Can citizen science and social media images support the detection of new invasion sites? A deep learning test case with *Cortaderia selloana*

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ABSTRACT

Deep learning has advanced the content analysis of digital data, unlocking opportunities for detecting, mapping, and monitoring invasive species. Here, we tested the ability of open source classification and object detection models (i.e., convolutional neural networks: CNNs) to identify and map the invasive plant *Cortaderia selloana* (pampas grass) in mainland Portugal. CNNs were trained over citizen science images and then applied to social media content (from Flickr, Twitter, Instagram, and Facebook), allowing to classify or detect the species in over 77% of situations. Images where the species was identified were mapped, using their georeferenced coordinates and time stamp, showing previously unreported occurrences of *C. selloana*, and a tendency for the species expansion from 2019 to 2021. Our study shows great potential from deep learning, citizen science and social media data for the detection, mapping, and monitoring of invasive plants, and, by extension, for supporting follow-up management options.

1. Introduction

Assessing the state of ecosystems and their drivers of change over time and space is paramount for supporting informed decisions in environmental management (Karr et al., 2008; Vos et al., 2000; Yoccoz et al., 2001). Monitoring the state of ecosystems has become a common practice to assess ecosystem integrity and health (Karr et al., 2008), nevertheless, for more effective environmental management it is also essential to monitor the ecological drivers of ecosystem change (Rapport and Hildén, 2013). Among the major drivers of ecosystem change are invasive alien species (IPBES, 2019), i.e., species that are introduced to new geographic areas, becoming self-sustaining, spreading, and leading to major impacts on the environment or society (Iannone III et al., 2020; Richardson et al., 2011).

Monitoring invasive alien species can be a costly and time-consuming activity, specifically when performed systematically by experts on the field (i.e., in situ surveys; Johnson et al., 2020). As complementary or even alternative approaches, monitoring invasive alien species from volunteer-based initiatives (e.g., community or citizen science; Vendetti et al., 2018; Eritja et al., 2019; Price-Jones et al., 2022), Earth Observations (e.g., using UAVs or satellite; Bradley, 2014; Pettorelli et al., 2014; Reddy et al., 2021), and other remote sensors (e.g., camera traps, geolocation devices) has gained an increased popularity to boost data collection and quality in regards to invasive alien

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species (e.g. Rassati et al., 2016, Dash et al., 2019; and see discussion on Juanes, 2018).

Digital data from social media platforms (e.g., Flickr, Twitter) is also becoming a promising source for species observations and occurrences (Edwards et al., 2021; Toivonen et al., 2019), including on invasive alien species (Allain, 2019; Blood, 2016). Social media data encompass images created and shared by people online that can contain large and useful information about the natural environment (Di Minin et al., 2015). Such data content often includes georeferenced meta-data and specific time stamps (Gliozzo et al., 2016), being useful, for instance, in mapping animal and plant species distributions across large study areas (ElQadi et al., 2017; Jeawak et al., 2018).

The last decade has also seen enormous technological advances in our ability to identify, access, and analyse online digital data (Farley et al., 2018; Hampton et al., 2013; Runting et al., 2020). The use of artificial intelligence, and specifically of machine learning and deep learning algorithms, such as Convolutional Neural Networks (CNNs), have led to significant progress in environmental monitoring from online digital images, including, for instance, the recognition and surveillance of plant diseases (e.g., Abade et al., 2021), the classification of land cover (ElQadi et al., 2020; Xu et al., 2017) or the detection and classification of animals in camera traps (Tan et al., 2022), requiring a low degree of human supervision (Lusch et al., 2018).

Despite the opportunities of online digital data (e.g., Allain, 2019; Daume, 2016) and artificial intelligence (e.g., Bonin-Font et al., 2021; Elias, 2023; Lake et al., 2022) for environmental monitoring, their combined application in the field of invasive alien species is still in its infancy. In this study, we aim to contribute to advance this field by testing the ability of using pre-trained and open source deep learning models to support the monitoring of invasive alien plants on social media images. Using *Cortaderia selloana* (Schult. & Schult.f.) Asch. & Graebn (pampas grass) as a test species in mainland Portugal, we specifically set out to understand the extent to which the combination of deep learning and social media information can be used in: (i) the identification and detection of invasive alien plant species in online digital images; and (ii) the detection and mapping of previously unreported locations of invasive alien plants. The results of our exploratory approached are discussed in the context of monitoring efforts on *C. selloana*, and more broadly the lessons learned that inform conservation action and management for invasive alien plant species.

2. Methods

2.1. Test species - *Cortaderia selloana*

Cortaderia selloana, originally from South America, has been introduced worldwide, mainly as ornamental in lawns and gardens (Başnou, 2009; Montserrat, 2009). It shows characteristic plumes which are often used for aesthetic purposes and displayed on social media platforms. In many Mediterranean and temperate locations of Europe, Africa, Australia, New Zealand, and North America, *C. selloana* is widespread and considered an invasive alien (Başnou, 2009; Bellgard et al., 2010; Starr et al., 2003). In Europe, *C. selloana* is widespread in France, Italy, Spain, United Kingdom, and Portugal, with predictions showing a potential increasing expansion, driven by climate change and urbanization (Brunel et al., 2010; Pardo-Primoy and Fagúndez, 2019; Tarabon et al., 2018). Being an opportunistic species, *C. selloana* occupies disturbed habitats, and is often found in urban and industrial areas or along road and railways (Domènech and Vilà, 2007; Pardo-Primoy and Fagúndez, 2019; Pausas et al., 2006).

C. selloana has many negative impacts on native biodiversity (e.g., changes soil nutrient properties and community structure; creates barriers to the movement of fauna, uses the resources available to other species.; Domènech et al., 2006), economies (e.g., forestry production systems; Gadgil et al., 1992) and human health and well-being (e.g., allergies and respiratory diseases, Rodríguez et al., 2021). Indeed, it achieves the highest impact score across scales (using Generic Impact Scoring System - GISS) when compared with other alien grasses (Nkuna et al., 2018).

In Portugal, the species has been listed in the Decree law No. 92/2019 (national regulation of invasive alien species; Environment Ministry, 2019), meaning that a legal scheme for the control, custody, introduction into nature and repopulation is established. Nonetheless, management actions aiming to eradicate, or more reasonably, to control and contain its spread are extremely costly and can have low effectiveness, because the species can withstand harsh climatic conditions, has a deep root system and an outstanding seed dispersal capacity (Gosling et al., 2000; LIFE STOP Cortaderia, 2020; Popay et al., 2003; Suárez et al., 2022). Monitoring the spread of *C. selloana* species is therefore a pressing need for the early detection of new occurrence locations in an attempt to prevent widespread invasion and establishment.

2.2. Methodological framework

This study was conducted by a multidisciplinary team with expertise in both ecology/botany and computational sciences. Our automated image analysis approach followed four main steps presented in Fig. 1. In Step 1, we collected the online digital images from citizen science and social media platforms (see Section 2.3. Data collection). In Step 2, our imagery dataset (3274 images) was manually annotated and labelled based on whether it contained or not the species of interest (see Section 2.4. Data labelling). In Step 3 we applied different deep learning classification and object detection models (i.e., to identify and detect the presence of the species *Cortaderia selloana* in each image; see Section 2.5. Model implementation). Finally, in Step 4, we used the georeferenced information and time span of each image where the *C. selloana* was identified by the models, to map the potential occurrence of the species over time (see Section 2.6. Spatialization and mapping).

2.3. Data collection

Our data collection involved two different imagery datasets. The first dataset was used to train the CNNs, while the second dataset was used to test the transferability and generalization of the model. For the first dataset (train dataset hereafter), we compiled 2273 images displaying *Cortaderia selloana* and taken in Portugal until December 2022. Images were compiled from the citizen science platforms Invasoras.pt (https://invasoras.pt/; 1926 images) and iNaturalist (https://www.inaturalist.org/; 347 images). From the set of 2273 images, only those containing the species inflorescences (pampas) were retained, resulting in a total of 1323 images. The 1323 images were manually verified, and low resolution, blurred a,nd/or irrelevant (e.g., paintings and drawings) images were removed, resulting in a final set of 1237 images. A similar number (1237) of outdoor images without *C. selloana* (including images of streets, landscapes, wide-open shots of nature, close-up shots of animals and/or plants, among others) was additionally collected from Flickr, resulting in 2474 images for subsequent analysis.

The second dataset (transferability dataset hereafter), consisted of publicly available images taken in Portugal from four social media platforms: Facebook (https://www.facebook.com/), Flickr (https://www.flickr.com/), Instagram (https://www.instagram.com/) and Twitter (https://twitter.com/). Image collection was done in March 2023 by searching for common names of *C. selloana* in Portuguese (e.g., "Erva das pampas", "Capim das pampas"), thereby avoiding collecting images outside of Portugal, as well as the scientific name of the species (i.e., "*Cortaderia selloana*"). To ensure time and resource efficiency in transferability and generalization analyses, we collected a sample of images from each social media platform (a random set of 100 per platform, resulting in a total of 400 images; see Table A.1). We also collected the same number (400) of outdoor images without the *C. selloana* from Flickr, a social media platform with a vast number of outdoor photographs taken and uploaded by the public, with possibility of

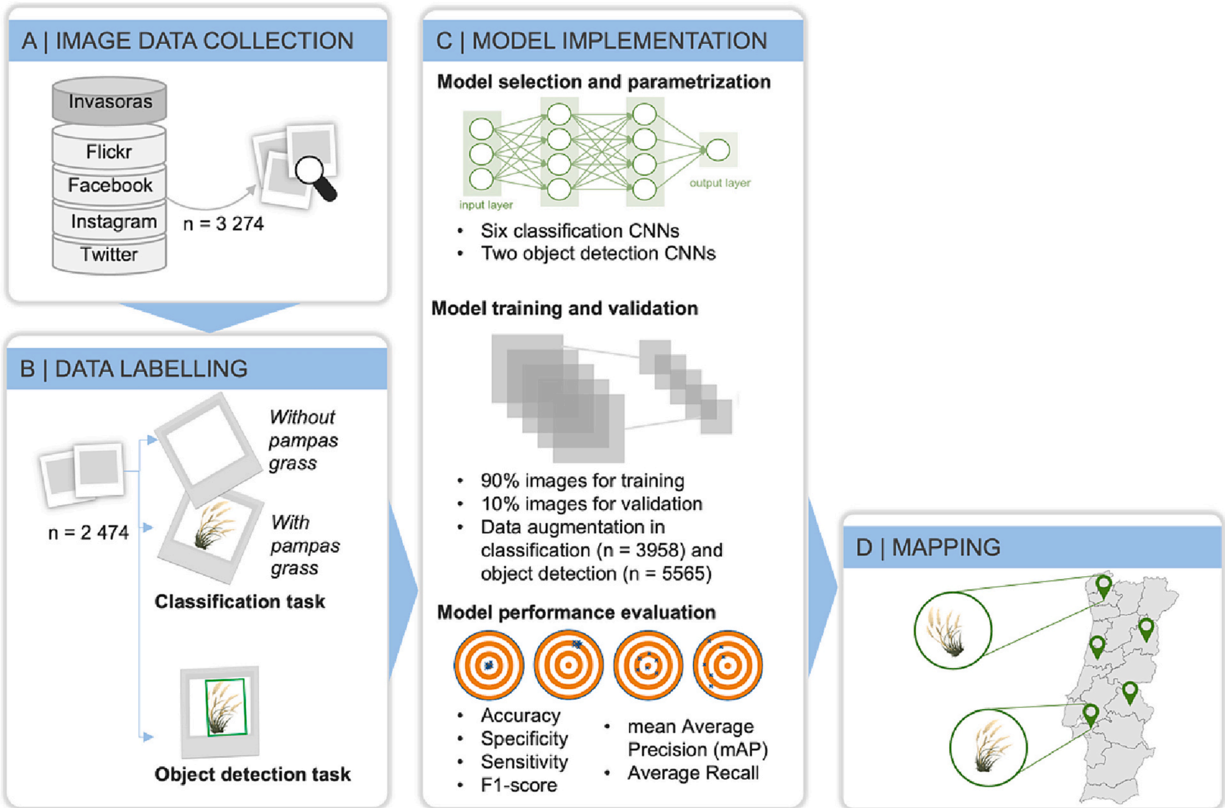

Fig. 1. Methodological framework adopted to identify the invasive alien test species *Cortaderia selloana* in online digital images from social media (A), based on the examination of image content with or without *C. selloana* and the species position in the image (B), and using classification and object detection models (CNNs). Images where the species has been correctly identified by the models were mapped to see the georeferenced location of the species from 2019 to 2021 (D).

downloading public information automatically, therefore maximizing time and resource efforts. The final size of the transferability set was 800 images.

Image collection for Facebook, Instagram, and Twitter was conducted manually. For Invasoras.pt. and Flickr, we used a Python 3.8.13 (https://docs.python.org/3.8/reference/) script based on URL scraping (for Invasoras.pt). Also, for Flickr we use its Application Programming Interface (API) to automate the search and scraping of images. Information on the geolocation (at city level) and time span of each image was also gathered, manually (for instance, by checking the location tagged by the users) or automatically, whenever publicly available (resulting in 144 geotagged images). Data collection methods were minimized to extract only absolutely necessary data from publicly available posts and avoiding the collection of potentially sensitive, private, and personal information, thus respecting the user's privacy and the platform's terms of use (Di Minin et al., 2021).

2.4. Data labelling

We considered two different types of CNNs: classification and object-detection based. For the classification CNNs, each image was manually checked to verify the presence or absence of the species, using a binary classification: (a) "With *Cortaderia selloana*", if the image content displayed at least one *C. selloana* ($n = 1237$; Fig. 2a), and (b) "Without *Cortaderia selloana*" if the *C. selloana* was absent in the outdoor environment ($n = 1237$; Fig. 2b). For the object detection CNNs, whenever an image exhibited the *C. selloana* ("*Cortaderia selloana*"), the position and presence of the species in the content of the image was manually annotated by drawing a labelling box around the space of the species in the image (Fig. 2c). The labelling procedure was done using labelImg (https://github.com/tzutalin/labelImg), a Python graphical image annotation tool that saves annotations as XML files in PASCAL VOC format. It was conducted by the same author (ASC), with expertise in both ecology and computer sciences, and previous experience in data annotation and labelling and species identification, thereby minimizing any bias or else maintaining any potential bias as systematic.

2.5. Model implementation

We first selected the CNNs architectures to be implemented (Section 2.5.1). After that, we trained, validated, and tuned the CNNs using the 5-fold cross validation method, along with other performance improvement strategies (Sections 2.5.2 and 2.5.3). Then, we evaluated the model's performance by applying commonly adopted classification metrics (Section 2.5.4). Lastly, we tested the transferability and generalization capacity of both classification and object detection CNNs when applied using social media images (Section 2.5.5).

2.5.1. Model selection and parametrization

For the classification task, before the implementation of deep learning models, all images were resized to the same resolution (227×197 pixels) by considering the mean dimensions of the set, and then normalized to the [0,1] range (Na and Fox, 2020). Then, six open source CNNs were selected: VGG16 (Simonyan and Zisserman, 2015), ResNet50, ResNet101 (He et al., 2016), Inception-v3 (Szegedy et al., 2016), DenseNet201 (Huang et al., 2017) and EfficientNetB0 (Tan and Le, 2019). These algorithms were selected because of their ease for transfer learning and high performance on similar classification tasks (Arun and Viknesh, 2022; Vallabhajosyula et al., 2022). For model optimization, we used the Adam optimizer algorithm (Kingma and Ba, 2015), a batch size of 10 and 100 epochs. The learning rates were chosen from empirical trials over 100 epochs, with and 10^{-4} and 10^{-6} showing

Fig. 2. Examples of images included in the classification task: (a) "With *Cortaderia selloana*", from Invasoras.pt., (b) "Without *Cortaderia selloana*", from Flickr. The image also shows an example of an image labelled for the object detection task (c) "*Cortaderia selloana*", from Invasoras.pt.

the best performances. We also implemented an early stop approach, with a patience value of 16 to regularize the model and minimize the loss function (binary cross entropy). The early stop approach is a common technique in machine learning to halt the training process of a model prematurely if performance on a validation dataset fails to improve beyond a predefined threshold, thereby preventing overfitting and conserving computational resources.

For the object detection task, we used three open source CNNs pre-trained for a diversity of object detection goals: Faster R-CNN ResNet50 (Ren et al., 2015), Faster R-CNN ResNet101 (Ren et al., 2015) and Faster R-CNN Inception-v2 (Szegedy et al., 2016). For each network we established 200,000 number of steps per epoch, a batch size of 1 and a L2 regularization penalty of 10^{-2}. The maximum number of the checkpoint file to be evaluated was set to 1. As in every optimization problem, we aimed to minimize the loss function, while maximizing the model's performance. To do so, we followed two metrics - total loss and average inference time per image – which although not constituting evaluation metrics, support the choice of the most accurate and computationally efficient model (i.e. the lower the total loss, the better the model; the shorter the average inference time, the most computationally efficient the model). The total loss is usually computed as the sum of the classification (loss of the classifier that determines the type of target object) and localization losses (loss of the regressor that generates a rectangular box to locate the target object), while the average inference time per image corresponds to the amount of time taken by the models to process a new image and make a prediction. Details on both classification and detection CNNs description, parameterization and implementation can be found in the Supplementary Material.

2.5.2. *Model training and validation*

For the classification task, the performance of the models was evaluated using 5-fold cross validation over the dataset described in Sections 2.3 and 2.4, as this approach provides a robust and unbiased estimate of a model's performance while also guiding effective hyper-parameter tuning for improved overall performance (James et al., 2023). The dataset was divided into 5 subsets, and, at each iteration of the 5-fold cross validation, one was used to evaluate the models using the performance metrics that will be presented in Section 2.5.4. The remaining 4 subsets were used for training (90% of the images) and validation (10% of the images).

To enhance the performance of our classification and detection models while also avoiding overfitting, we increased the size of the training dataset through a data augmentation approach. This approach involves artificially increasing the diversity of a dataset by applying various transformations to the existing data samples, such as rotation, flipping, or cropping. These transformations modify the appearance of the original images, thereby creating new variations that can help improve the model's ability to generalize across different scenarios and conditions. Specifically, for the classification models, we used four transformations per image that were selected considering the visual characteristics of plant species, as well as the typical properties of citizen-science and social media images. An example of such was the adoption of the horizontal flipping instead of the vertical flipping, as the former would not be reasonable for terrestrial plants. These transformations were implemented using the data generator available in Keras (Chollet, 2015): horizontal flip, zoom (range of 0.2), width shift (range of 0.2) and height shift (range of 0.2). For the object detection models (following the same logic of the previous ones), we implemented five random transformations per image using the "data augmentation options" parameter of the TensorFlow configuration file: horizontal flip, image scale, adjust contrast, adjust brightness, and adjust saturation. Both original and transformed images were considered for training, resulting in a final dataset of 3958 (for the classification models) and 5565 (for the object detection models) images.

2.5.3. Transfer learning

To improve the performance of our models, we applied a transfer learning strategy, which consisted of initializing each CNN with weights of open source CNNs pre-trained on databases with similar characteristics to our dataset. Specifically, we used CNNs pre-trained with the ImageNet database (https://www.image-net.org/), for the classification task. For the object detection task, we used CNNs pre-trained with the Microsoft Common Objects in Context (MS COCO; https://cocodataset.org/#home) and iNaturalist (https://www.inaturalist.org/) databases (see Supplementary Material for details).

To achieve a good balance between generalization and specificity of image classification for the classification models, the first CNN model layers were kept frozen during training with transfer learning, while three fully connected layers in VGG16 and EfficientNetB0, and one fully connected layer in ResNet50, ResNet101, Inception-v3 and DenseNet201, were re-trained (fine-tuned) using our training dataset. Before the output layer, we also included an additional dense layer with 128 units and a rectifier linear unit activation function (ReLU), to enhance the model's adaptation to the classification task. ReLU is a mathematical function commonly used in deep learning approaches that replaces negative input values with zero, enabling the model to learn nonlinear relationships and facilitate faster convergence during training. Lastly, the output layer was modified to fit a binary classification (with 2 units).

In the object detection models, all the parameters in the configuration files were kept the same as the ones used during the original training of the networks (https://github.com/tensorflow/models/tree/master/research/object_detection/samples/configs), except for the number of classes, which we changed to 1 in order to fit our detection goals (the "*Cortaderia selloana*" class).

2.5.4. Model performance evaluation

The performance of each classification model (VGG16, ResNet50, ResNet101, Inception-3, DenseNet201 and EfficientNetB0) was evaluated based on commonly adopted classification metrics (Tharwat, 2018; Table 1): accuracy (ACC), specificity (or True Negative Rate: TNR), sensitivity (recall or True Positive Rate: TPR) and f1-score (F_1). For the classification task, the term positive stands for the presence of *Cortaderia selloana* in the images ("With *Cortaderia selloana*"), whereas the negative stands for *C. selloana* absence ("Without *Cortaderia selloana*"). The evaluation metrics were then calculated as the mean of the performance metrics obtained over the 5 different folds (see Section 2.5.2). Finally, we used a paired samples *t*-test, with a confidence interval of 0.05 (Hsu and Lachenbruch, 2005) to test for significant differences in classification metrics between each pair of the five CNN models, for both learning rates (10^{-4} and 10^{-6}).

The performance of each object detection model (Faster R-CNN ResNet50, Faster R-CNN ResNet101 and Faster R-CNN Inception-v2) was evaluated using the MS COCO detection metrics and the PASCAL VOC detection metrics (Table 1): mean Average Precision (mAP) and Average Recall (AR). Both MS COCO and PASCAL VOC are widely used benchmarks for object detection in computer vision, allowing models to generalize effectively across various object categories and complex scenes (MS COCO; Lin et al., 2014), as well as to ensure standardized evaluation and facilitate consistent comparisons across different studies (PASCAL VOC; Everingham et al., 2010). The mAP was computed over different Intersection over Union (IoU) thresholds in the case of the models pre-trained on the MS COCO dataset and over a 0.50 IoU threshold in the models pre-trained on the iNaturalist dataset. IoU thresholds represent the ratio between the area of the intersection and the area of the union of the predicted and actual bounding boxes (Rezatofighi et al., 2019). On the other hand, the AR was calculated only for the models pre-trained on the MS COCO dataset, over 1, 10 and 100 detections, as predefined by the transfer learning architecture (see Table A.9).

Table 1
Evaluation metrics considered in the classification and object detection models evaluation, with respective example. TP represents the True Positives, TN the True Negatives, FP the False Positives and FN the False Negatives.

Metric	Example
Classification models	
Accuracy	Calculates the level of correctly classified images as "With *Cortaderia selloana*" and as "Without *Cortaderia selloana*" by the model.
Specificity	Shows the proportion of correctly classified images as "Without *Cortaderia selloana*" by the model, in relation to all actual "Without *Cortaderia selloana*" images.
Sensitivity (or recall)	Shows the proportion of correctly classified images as "With *Cortaderia selloana*" by the model, in relation to all actual "With *Cortaderia selloana*" images.
F1-score	Calculates the level of correctly and incorrectly classified images as "With *Cortaderia selloana*" and "Without *Cortaderia selloana*" by the model.
Object detection models	
mean Average Precision (mAP)	Indicates the proportion of correctly detected images as "*Cortaderia selloana*" by the model, in relation to all actual and predicted "*Cortaderia selloana*" images.
Average Recall (AR)	Shows the proportion of correctly detected images as "*Cortaderia selloana*" by the model, in relation to all actual "*Cortaderia selloana*" images.

2.5.5. Model testing

The six classification and three object detection models trained with the citizen science images were used to classify and detect the *Cortaderia selloana* in social media images. For the classification models, all images were resized to the same resolution as the training ones ($227\times$ 197 pixels), and then normalized to the [0,1] range (Na and Fox, 2020). Model performance on the new images was evaluated using the metrics previously described, with the aim of assessing the CNN models transferability and generalization capacity.

2.6. Mapping

Used the information on the time span of each georeferenced image containing the *Cortaderia selloana* to map the potential location of the species between 2019 and 2021. Due to lack of information on geolocation and time span, only images from Flickr and Instagram were used in the mapping exercise. Procedures were conducted in QGIS3.10 (QGIS.org, 2019).

3. Results

3.1. Identifying the Cortaderia selloana in citizen science images

When using the classification task for discriminating pictures "With *Cortaderia selloana*" from those with "Without *Cortaderia selloana*" (Fig. 3a and b), the considered CNNs showed high performance (e.g., with f1-score values above 96.16%; Table 2) and few significant differences in their performance metrics ($p < 0.05$; see Table A.8 for full results). Overall, the best performance results were obtained by the DenseNet201 with the learning rate of 10^{-4} in terms of accuracy (99.07%) and f1-score (99.06%) values, followed by the EfficientNetB0 with the same learning rate (10^{-4}), which also showed high accuracy, sensitivity, and f1-score (99.03%). In the case of the Desenet201 model, only 0.8% of the images displaying the *C. selloana* were confused by the model as showing no *C. selloana* (false negatives; Fig. 3c). Likewise, from the images showing no *C. selloana*, in 0.8% of the cases DenseNet201 incorrectly predicted the class "With *Cortaderia selloana*" (false positives; Fig. 3d). A similar pattern was verified for the remaining CNN models

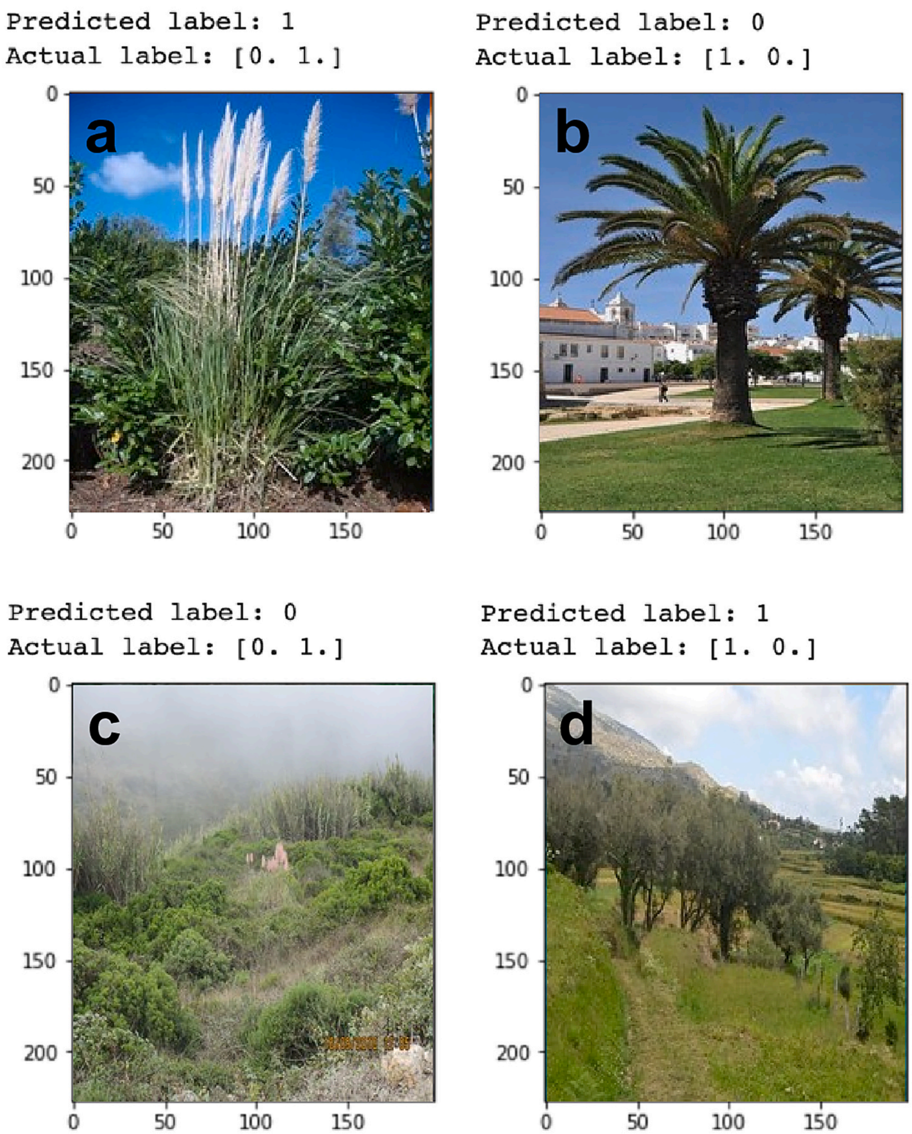

Fig. 3. Examples of images where the classification models correctly predicted and failed to predict: (a) *Cortaderia selloana* (true positives), (b) absence of *C. selloana* (true negatives), (c) *C. selloana* (false negatives) and the (d) absence of *C. selloana* (false positives). 0 – "With *Cortaderia selloana*", 1 – "Without *Cortaderia selloana*".

(see confusion matrices in Tables A.4 and A.5).

Overall, the classification models mostly failed to classify images in which *C. selloana* is in the background, reduced in size or barely visible (e.g., Fig. 3c), as well as images displaying plants with similar features to *C. selloana* ones (e.g., Fig. 3d).

When using the object detection models (Faster R-CNN ResNet101, Faster R-CNN ResNet50 and Faster R-CNN Inception-v2) performances differed depending on the transfer learning weights (MS COCO versus iNaturalist; Table 3). Overall, object detection models pretrained in the MS COCO dataset showed the most satisfactory results (Table 3), with Faster R-CNN ResNet50 showing the highest performance in terms of mean Average Precision (94.11%).

In general, the object detection model with overall best performance, i.e., Faster R-CNN ResNet50 with MS COCO weights, failed mostly to detect images displaying more than one *C. selloana*, especially if they are in the background, reduced in size or barely visible (Fig. 4).

3.2. Identifying the Cortaderia selloana in social media images

The models pre-trained over the citizen science images showed to be very effective when applied to the social media images (Figs. A.1a and A.1b), with high performances (e.g., f1-score values above 93.09%; Table 4). Unlike the training task, the best results were obtained by EfficientNetB0 with a learning rate of 10^{-4}, in terms of accuracy (97.50%), sensitivity (96.00%) and f1-score (97.46%), followed by Inception-v3 with the same learning rate (10^{-4}), which also showed high accuracy (96.88%), sensitivity (94.00%), specificity (99.75%) and f1-score (96.78%). In the case of the EfficientNetB0 model, only 4% of the images displaying the *Cortaderia selloana* were confused by the model as showing no *C. selloana* (false negatives; Fig. A.1c). Likewise, from the images showing no *C. selloana*, in 1% of the cases EfficientNetB0 incorrectly predicted the class "With *Cortaderia selloana*" (false positives; Fig. A.1d). A similar pattern was verified for the remaining CNNs (see confusion matrices in Tables A.6 and A.7).

Regarding the object detection task, the models pre-trained over the citizen science images also showed a satisfactory performance when applied to the social media images (Table 5), with mean Average Precision above 76.85%. Similar to the training set, the best results were obtained by the models pre-trained in the MS COCO dataset, with Faster R-CNN Inception-v2 showing the most satisfactory mean Average Precision results (81.71%; Fig. A.2).

Table 2
Performance metrics for both learning rates scenarios trained for each classification model (mean ± standard deviation of the five folds). ACC – Accuracy, TPR – Sensitivity, TNR – Specificity and F_1 – F1-score. Light grey cells highlight the best performance results for learning rate and metric.

Classification models	lr = 10^{-4}				lr = 10^{-6}			
	ACC	TPR	TNR	F_1	ACC	TPR	TNR	F_1
VGG16	98.46 ± 0.93	98.69 ± 0.81	98.21 ± 1.73	98.47 ± 0.91	97.45 ± 0.34	96.92 ± 0.70	97.98 ± 1.04	97.44 ± 0.35
ResNet50	98.46 ± 0.72	98.38 ± 0.66	98.54 ± 1.18	98.46 ± 0.71	96.20 ± 0.98	95.69 ± 1.82	96.69 ± 1.43	96.16 ± 1.07
ResNet101	98.59 ± 0.88	98.04 ± 1.52	99.11 ± 0.34	98.57 ± 0.91	96.85 ± 0.91	95.77 ± 1.58	97.90 ± 0.41	96.79 ± 1.00
Inception-v3	98.91 ± 0.49	98.62 ± 0.75	99.19 ± 0.28	98.90 ± 0.50	97.09 ± 1.14	94.99 ± 1.78	99.18 ± 0.65	97.02 ± 1.17
DenseNet201	99.07 ± 0.46	99.03 ± 0.62	99.11 ± 0.44	99.06 ± 0.47	98.22 ± 0.60	97.32 ± 0.9	99.11 ± 0.79	98.20 ± 0.64
EfficientNetB0	99.03 ± 0.52	99.03 ± 0.72	99.03 ± 0.47	99.03 ± 0.51	97.33 ± 0.94	96.84 ± 1.63	97.82 ± 0.34	97.31 ± 0.99

Table 3
Performance metric (mAP@0.50IOU; mean average precision), average inference time per image and total loss (sum of the classification and localization losses) for each model. Light grey cells highlight the best model results for performance (mAP), total loss and speed.

	Faster R-CNN ResNet101 iNaturalist	Faster R-CNN ResNet101 MS COCO	Faster R-CNN ResNet50 iNaturalist	Faster R-CNN ResNet50 MS COCO	Faster R-CNN Inception-v2 MS COCO
Average inference time per image (ms)	395	106	366	89	58
mAP@0.50IOU	89.78	93.41	90.63	94.11	93.87
Total loss	1.22	0.53	1.27	0.61	0.55

3.3. Mapping the spatial distribution of Cortaderia selloana

Overall, when analysing the spatial patterns of *Cortaderia selloana* potential occurrences (Fig. 5), we observed a pattern of increased detections of the invasive species across time and in new locations, with few species' observations in 2019 and more than double the number of observations in 2021. In comparison with the reported locations from the citizen science platform, social images show 11 new location instances of the species, particularly in the North, Coastline and South regions of Portugal (Fig. 5a).

4. Discussion

4.1. General performance over Cortaderia selloana identification in citizen science images

In this study we aimed to investigate the potential of using publicly available classification and object detection models over online digital images to monitor invasive alien plants, using the *Cortaderia selloana* in Portugal as a test case. Promising opportunities of combining deep learning approaches with online digital data have already been suggested in previous applications addressing ecological and environmental challenges (Hartmann et al., 2022; Sujatha et al., 2021; Valarmathi et al., 2021). Our results also showed a high performance of deep learning tools to identify the *C. selloana* in citizen science and social media images, with the potential for identifying new locations of *C. selloana* in Portugal.

4.2. Model performance over Cortaderia selloana identification in citizen science images

From the different models considered in our study, the classification model DesenNet201 (with a learning rate of 10^{-4}) and the object detection mode Faster R-CNN ResNet50 (pre-trained on the MS COCO

Fig. 4. Examples of images where the Faster R-CNN ResNet50 with MS COCO weights failed to design and predict *Cortaderia selloana* object detection boxes (left images – detected boxes; right images – real boxes). (a) with *C. selloana* in the background, reduced in size or barely visible; (b) with more than one *C. selloana*.

Table 4
Performance metrics of each model in the test set (for both learning rates scenarios). ACC – Accuracy, TPR – Sensitivity, TNR – Specificity and F_1 – F1-score. Light grey cells highlight the best performance results for learning rate and metric.

Classification models	lr = 10^{-4}				lr = 10^{-6}			
	ACC	TPR	TNR	F_1	ACC	TPR	TNR	F_1
VGG16	94.88	90.00	99.75	94.61	95.75	94.50	97.00	95.70
ResNet50	96.25	93.25	99.25	96.13	94.63	91.75	97.50	94.47
ResNet101	96.00	92.50	99.50	95.85	95.00	93.25	96.75	94.91
Inception-v3	96.88	94.00	99.75	96.78	93.50	87.50	99.50	93.09
DenseNet201	96.13	93.00	99.25	96.00	96.25	93.25	99.25	96.13
EfficientNetB0	97.50	96.00	99.00	97.46	93.62	89.50	97.75	93.35

dataset) achieved the most promising results over citizen science images (i.e., maximum f1-score of 98.20% and mean Average Precision of 94.11%). Previous studies classifying and detecting plant species in digital images also highlighted the performance of DenseNet201 (Haupt et al., 2018), and Faster R-CNN ResNet50 (Li et al., 2021). The densely connected architecture associated to DenseNet201 is particularly robust and easy to implement and re-train, as it substantially reduces the complexity and number of parameters, alleviates the vanishing-gradient problem, and reinforces feature propagation and reuse (Huang et al., 2017). Faster R-CNN ResNet50 is a very fast Region Based Convolutional Neural Network that benefits from residual connections and batch normalization to extract features at deeper layers (He et al., 2016). All these particularities were probably the main drivers of the accurate results observed for these two architectures.

When comparing the best classification model DenseNet201 (with a learning rate of 10^{-4}) with the object detection one Faster R-CNN ResNet50 (with MS COCO weights), we could notice slightly higher performances for the classification model. This may be attributed to the transfer learning procedure adopted when implementing the classification models, which can improve image classifications of digital platforms to produce more robust and reliable identification of invasive plant species (Cabezas et al., 2020). Considering that object detection models required a greater hyperparameter tuning to achieve stable and satisfactory evaluation results, our results might suggest the preferable use of classification models to monitor and map the distribution of the *Cortaderia selloana* efficiently and with less complexity.

Table 5
Performance metric (mAP@0.50IOU; mean Average Precision), average inference time per image and total loss (sum of the classification and localization losses) in the test set. Light grey cells highlight the best model results for performance (mAP), total loss and speed.

	Faster R-CNN ResNet101 iNaturalist	Faster R-CNN ResNet101 MS COCO	Faster R-CNN ResNet50 iNaturalist	Faster R-CNN ResNet50 MS COCO	Faster R-CNN Inception-v2 MS COCO
Average inference time per image (ms)	395	106	366	89	58
mAP@0.50IOU	76.85	79.23	74.93	80.80	81.71
Total loss	2.24	1.14	2.24	1.20	1.08

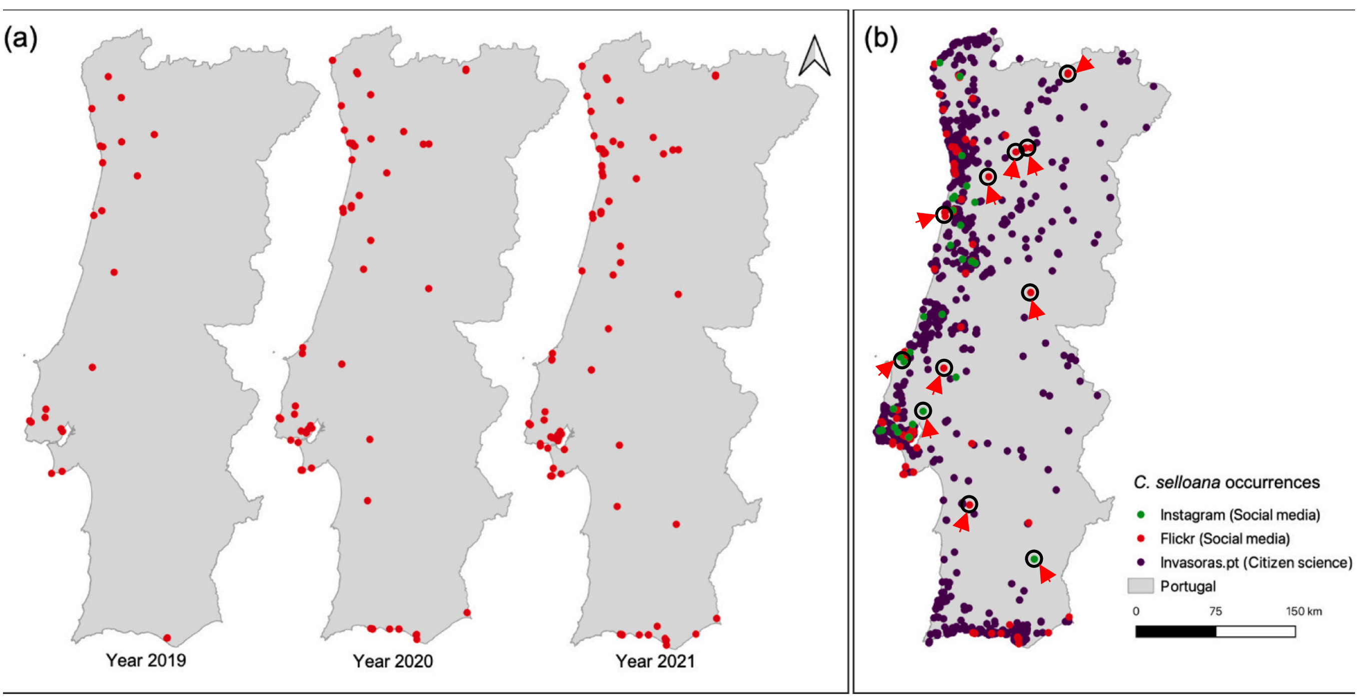

Fig. 5. Spatial distribution of *Cortaderia selloana*: (a) for Flickr across 2019, 2020 and 2021, (b) for Instagram, Flickr and Invasoras.pt. Black circles and red arrows indicate new potential locations in relation to the data available on Invasoras.pt. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.3. Model performance over Cortaderia selloana identification in social media images

When we applied the pre-trained models with the citizen science imagery to the social media images, we observed a general decrease in model performance (maximum f1-score of 96.13% for DenseNet201 and mean Average Precision of 81.71% for Faster R-CNN ResNet50). However, although the decrease was more pronounced for the object detection models, it was minor, not compromising the efficiency and accuracy of the models to classify and detect the *Cortaderia selloana*. This supports the assumption that pre-trained models could still be useful to identify invasive plant species in different online image sources. The loss of model efficacy can be associated with the social media images properties, as these platforms typically resize and recompress images with their own preferred settings, resulting in lower resolution and quality. Also, in social media images, the *C. selloana* is more likely to be present in the background, at smaller dimensions, as users tend to take pictures at other environmental attributes (e.g., selfies, landscapes). This can compromise the performance of the models associated to lower image quality and resolution (Talebi and Milanfar, 2021).

Still, from the different models considered, EfficientNetB0 and Faster R-CNN Inception-v2 performed best on social media images. These results agree with previous applications on biodiversity using EfficientNetB0 (Hassan et al., 2021), and Faster R-CNN Inception-v2 (Moniruzzaman et al., 2019). Regarding the performance of each pre-trained model, EfficientNetB0 with a learning rate of 10^{-4} and Faster R-CNN Inception-v2 pre-trained on the MS COCO dataset performed better compared to the remaining architectures. These results also suggest that classification models present a higher efficiency and performance when applied to images containing different proprieties and sources, which makes them robust tools to support the identification of *C. selloana*. Identifying this species in pictures is very straightforward and simple, as *C. selloana* contains several specific features (such as the pampas) that make it very characteristic and difficult to be confused with other plant species. Moreover, there are no other plant species in Portugal (our study area) with the same features as *C. selloana.* Both of these particularities may be the source of the high results observed in this study.

4.4. Monitoring the invasive alien Cortaderia selloana from online digital images

Our methodological approach showed to be promising at identifying and classifying *Cortaderia selloana* in digital images and, therefore, supporting the monitoring of the distribution of this species. Other studies have also showed the potential of using digital data and tools, such as Google Street View, to track the spread of *C. selloana* (Pardo-Primoy and Fagúndez, 2019), as well as to understand public perceptions (Roldão Almeida et al., 2023) and to redirect citizens actions (Marchante and Marchante, 2016). Nevertheless, studies including either citizen science or social media data to map and monitor the distribution of invasive alien species are still scarce. As a popular ornamental species, *C. selloana* particularly arouses public interest, which is reflected in the frequency of social media posts. Thus, data from these online platforms is particularly promising for monitoring the distribution of *C. selloana*, with users from different locations posting several pictures of the species (in our specific case, we obtained around 4483*C. selloana* pictures, however many more could be collected).

The images we collected allowed us to complement citizen science distribution information about the species, by suggesting new potential locations of *C. selloana* in Portugal based on social media. The location of the images containing *C. selloana* could eventually suggest a tendency for increased species occurrences in Portugal from 2019 to 2021. Increased overall distribution of *C. selloana* in Portugal is naturally expected because of the species high invasiveness and fast spread facilitated by a warming climate and urbanization (Tarabon et al., 2018). Yet, it is important to view these results with some caution. For instance, we cannot discard the possibility of getting more species data locations because of a higher internet penetration or even social media use, similar to what might happen with other data sources (i.e., the more people engaged, the more data we may get: Ghani et al., 2019). Also, we only considered images showing the plumes of the invasive alien *C. selloana*. Monitoring the species outside of its blooming season, as well as detecting immature individuals, is constrained, as it can be confused with other plant species with similar vegetative characteristics. This may hinder our approach's ability to identify pioneer populations in new areas, which could impact its effectiveness as an early alert system for invasive plants monitoring. Advancing detection of *C. selloana* outside its flowering season will require using imagery datasets that include a broader range of plant life stages and phenological states. For that, exploring other architectures, such as NasNet (Zoph et al., 2018), GoogLeNet (Szegedy et al., 2015) or Inception-ResNet (Szegedy et al., 2017) and techniques would also be a necessary step for model performance improvement and tuning (e.g., Cluster-Based Over Sampling).

4.5. Opportunities and limitations for monitoring invasive alien plants

Even though our study is only exploratory, several issues need to be emphasised for the general detection, mapping, and monitoring of invasive alien plants. The process of acquiring data from citizen science or social media platforms can be quite easy, either through an API, or other scrapping methods, enabling the relatively fast and automated collection of big digital data. Yet, not all social media and citizen science platforms allow data scrapping, according to the terms and conditions of use of each platform. Likewise, the use of deep learning can automate the process of detecting invasive alien plants from big digital images, making the monitoring of invasive alien species more time-, and perhaps, cost-effective when looking into large geographic areas and time periods, compared to other conventional methods (e.g., field surveys; Qian et al., 2020). However, advancing such big analysis will also require developments to infrastructures and programming skills, which may not be accessible to a wide research community.

Metadata associated with online digital images, such as coordinates and time span, can be used to identify locations potentially occupied by invasive alien plants (supporting the early detection of the species) and as input data in modelling frameworks to further explore potentially suitable areas for the species occurrence (e.g., Species Distribution Models or Habitat Suitability Models; César de Sá et al., 2019; Robinson et al., 2018). Online platforms have a large user base and far-reaching audience, which can greatly increase the coverage and visibility of invasive alien species monitoring and detection efforts in near real-time. However, user-generated content, particularly on social media, does not always include georeferenced or time information, and in some cases this information is not sufficiently precise for accurate mapping of invasive alien species. Inevitably, this limits our capacity to use this type of data for some contexts, particularly if the aim is informing management activities. Furthermore, there is no guarantee that the quality and resolution of publicly available images will enable precise identification of the species. Incorporating other forms of online data, such as textual information (e.g., tags, captions, comments) may further improve the generalization of deep learning tools for invasive alien species detection, mapping, and monitoring (Jeawak et al., 2018; Tateosian et al., 2023; Terry et al., 2020). Lastly, the spatial concentration bias of social media images, particularly the prevalence of photo captures in some areas at the expense of other areas (e.g., due to accessibility limitations, appealing attributes, among others; Di Minin et al., 2015), may also lead to limitations in the detection of invasive plants (and other species or natural assets).

Nonetheless, we are confident that the technology-driven approach followed in this study provides valuable contributions to the development of a widespread and dynamic monitoring system where social media users become passive contributors of the monitoring process (Marchante and Marchante, 2016). Under proper developments, the information generated by the monitoring system for (near) real-time detection and identification of invasive plants across locations can contribute to timely intervention measures, such as containment of further occurrences, also serving as a guideline to time and cost-effectiveness management. As such, the outcomes of this study, even if preliminary, show potential for aiding government authorities, stakeholders, or other organizations in their decision-making processes, including on resource allocation for invasive species management, and focused collaboration between the public and environmental agencies. If further developed, our methodological approach may contribute or complement to improve existing invasive species monitoring efforts. In practice, our monitoring tool can support the development of user-friendly interfaces or mobile applications that allow stakeholders, such as environmental researchers and land managers, to easily access and detect the *Cortaderia selloana* in digital images (Hussien et al., 2023). By analysing geotagged social media images, our approach can be used to create distribution maps of the invasive species infestations, allowing to identify areas of high invasion risk (Allain, 2019). It can also contribute to implement automated strategic monitoring programs that regularly scan social media platforms for images containing the *C. selloana*, aiding authorities to track the distribution of the species. Furthermore, our models can complement existing databases or mapping platforms to provide comprehensive information on the distribution and dispersal of *C. selloana* (Reeves et al., 2021). These applications have the potential to support the identification of priority areas for eradication efforts, the efficient allocation of resources, and the evaluation of the success of management interventions over time. Still, we are also aware of potential barriers in the acceptability and confidence of using artificial intelligence tools and user-generated contents by these organizations, especially in the context of social issues like ethics and fairness (Whittlestone et al., 2019). To promote acceptability and proper use, it is essential to highlight the transparency and fairness in the overall workflow adopted, addressing any biases or ethical concerns associated with deep learning applications and the use of personal data. The collaborative nature of our approach, where the public contributes through citizen-science and social media platforms, can foster a sense of shared responsibility, which usually increases the trust in these methods (Liberatore et al., 2018).

CRediT authorship contribution statement

Eva Malta-Pinto: Writing – review & editing, Writing – original draft, Conceptualization. **Siham Tabik:** Writing – original draft, Software, Methodology, Conceptualization. **Tom August:** Writing – original draft, Software, Methodology, Data curation. **Helen E. Roy:** Writing – original draft, Investigation, Funding acquisition. **Ricardo Correia:** Writing – review & editing, Data curation. **Joana R. Vicente:** Writing – original draft, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Ana Sofia Vaz:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

None.

Data availability

In agreement to the FAIR principles and to promote reproducibility, both the code and data used in this analysis have been made publicly available along with the necessary metadata to reproduce the analysis. The code that was used to perform the *Cortaderia selloana* classification and object detection tasks using python language (version 3.10.12), based on TensorFlow and Keras libraries, can be found on Github: https://github.com/anasccardoso/Deep-learning-Cortaderia-selloana.git. This repository was created by ASC (email: sofia.cardoso@cibio.up.pt) in 2023 and has all the material that was used to perform the analysis, including metadata, programming scripts, excel files and TensorFlow records (TFRecord), which can also be found at Zenodo (https://doi.org/10.5281/zenodo.8348734), due to Github memory constrains. The author's experimental environment consisted of a Jupyter notebook from Google Colab, with the following features:-

12.68GB of RAM;-

78.19 GB of Disk space;-

Tesla T4 GPU (provided free of charge by the platform).

The analyzed citizen science and social media data, and its associated metadata, are available at Zenodo: https://doi.org/10.5281/zenodo.8348734. The data were collected by ASC (email: sofia.cardoso@cibio.up.pt) in 2023 and includes 3274 images.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2024.102602.

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