cibio InBIO RESEARCH NETWORK Biodiversity and Evolutionary Biology
U.PORTO BIOPOLIS FCT Fundação para a Ciência e a Tecnologia MINISTÉRIO DA CIÊNCIA, TECNOLOGIA E ENSINO SUPERIOR

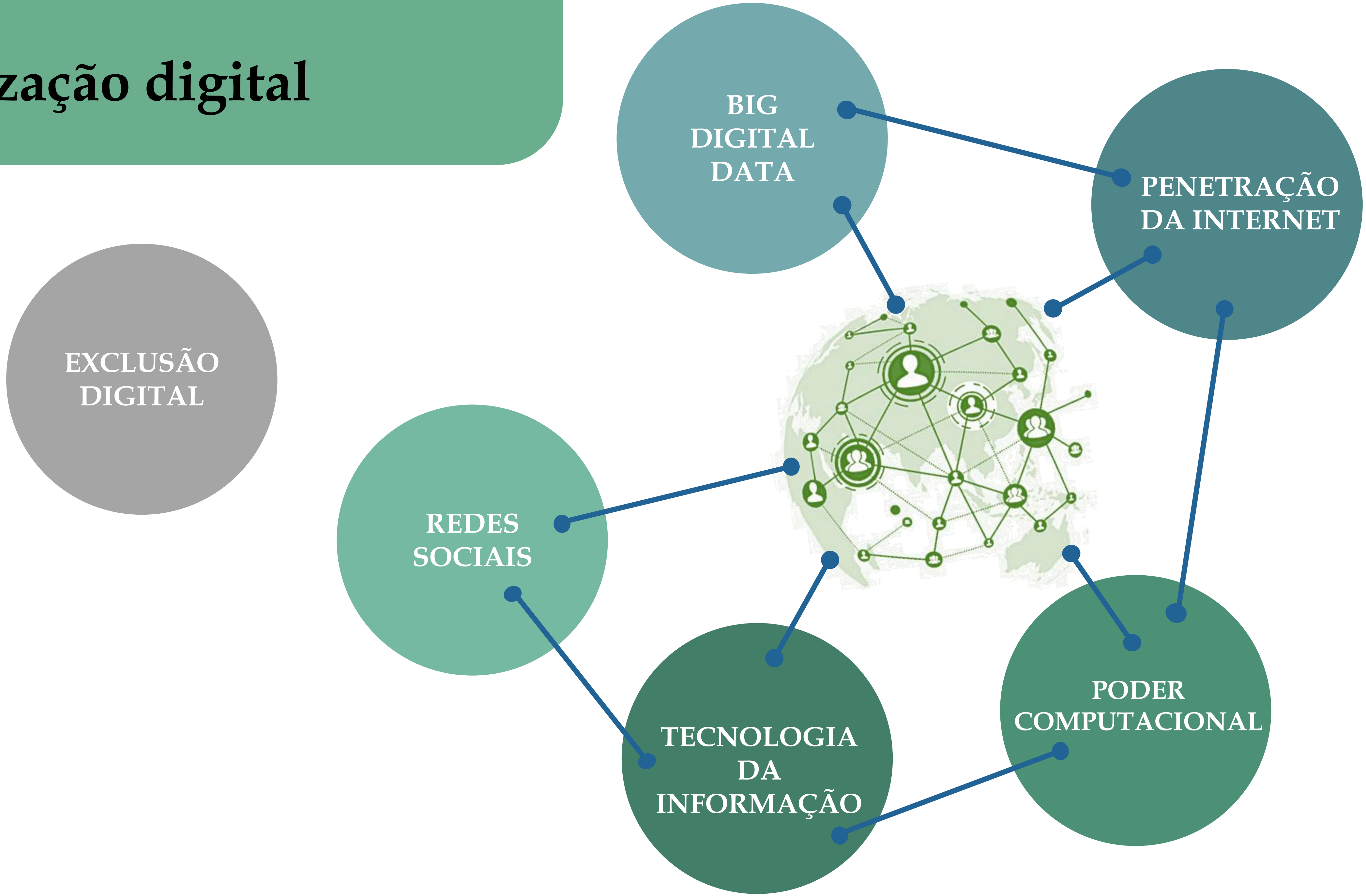
Capturar, etiquetar, detetar:

O papel da ciência cidadã e das redes sociais na monitorização de plantas invasoras

Ana Sofia Cardoso

Eva Malta-Pinto; Siham Tabik; Tom August; Helen E. Roy; Ricardo Correia; Joana R. Vicente; Ana Sofia Vaz

Globalização digital



Dados Digitais

Toivonen et al. 2019.
https://doi.org/10.1016/j.biocon.2019.01.023

DEEP LEARNING

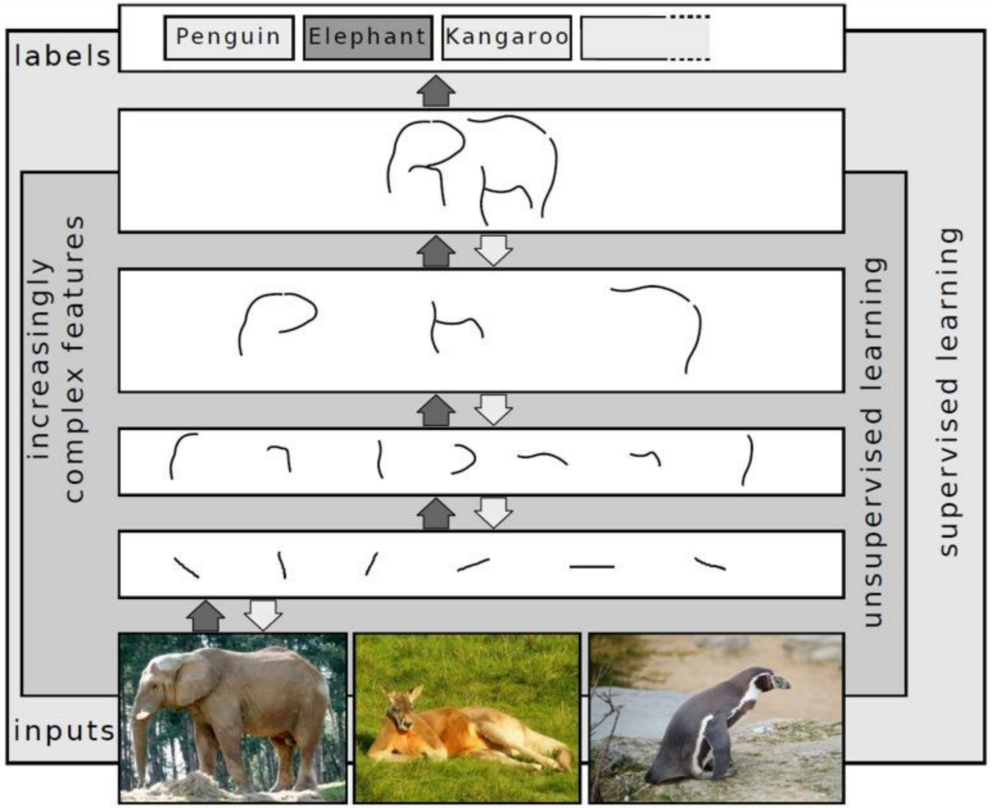
Aprendendo Representações Hierárquicas

Utiliza várias camadas para progressivamente extrair características de nível superior dos dados de entrada, de forma semelhante ao funcionamento do cérebro humano

nature COMMUNICATIONS

Perspectives in machine learning for wildlife conservation

Devis Tuia[1,17], Benjamin Kellenberger[1,17], Sara Beery[2,17], Blair R. Costelloe[3,4,5,17], Silvia Zuffi[6], Benjamin Risse[7], Alexander Mathis[8], Mackenzie W. Mathis[8], Frank van Langevelde[9], Tilo Burghardt[10], Roland Kays[11,12], Holger Klinck[13], Martin Wikelski[3,4], Iain D. Couzin[3,4,5], Grant van Horn[13], Margaret C. Crofoot[3,4,5], Charles V. Stewart[14] & Tanya Berger-Wolf[15,16]

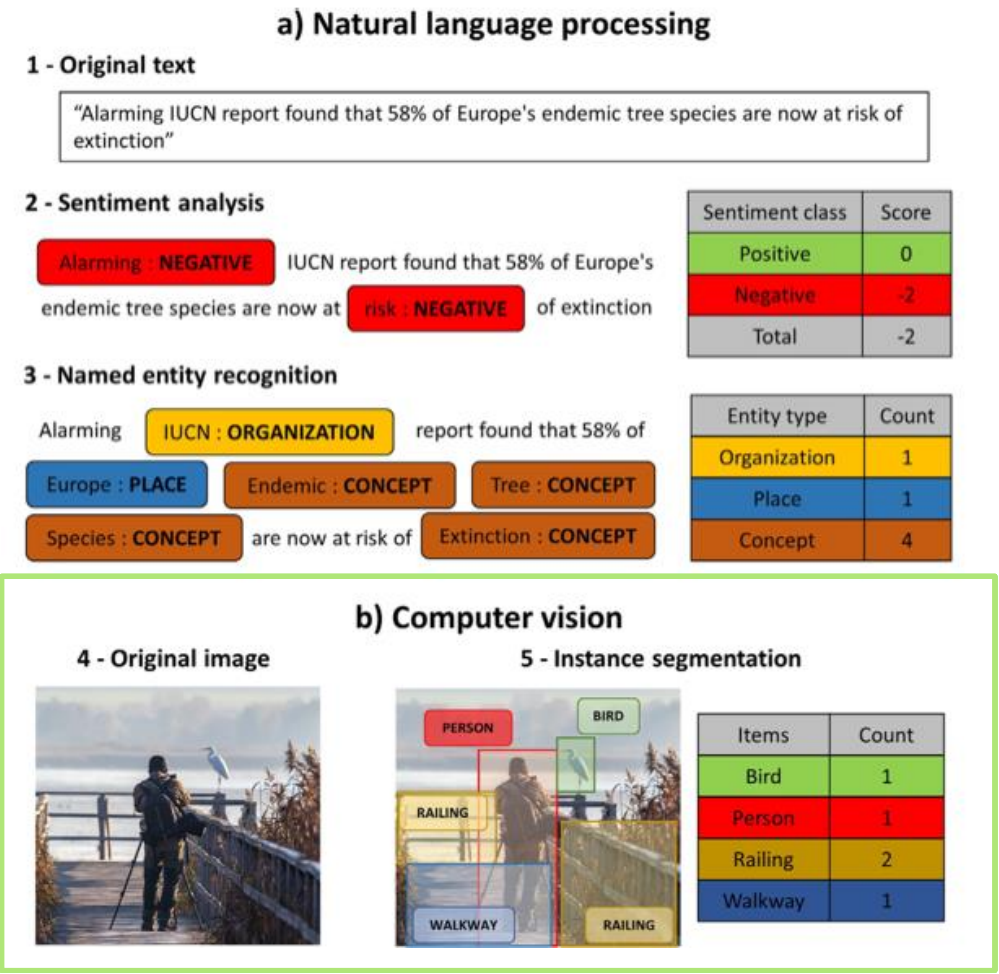


Schulz et al. 2012.
doi: 10.1007/s13218-012-0198-z

Current Biology
Magazine

Deep learning for environmental conservation

Aakash Lamba[1], Phillip Cassey[1], Ramesh Raja Segaran[1], and Lian Pin Koh[1,2,3,*]



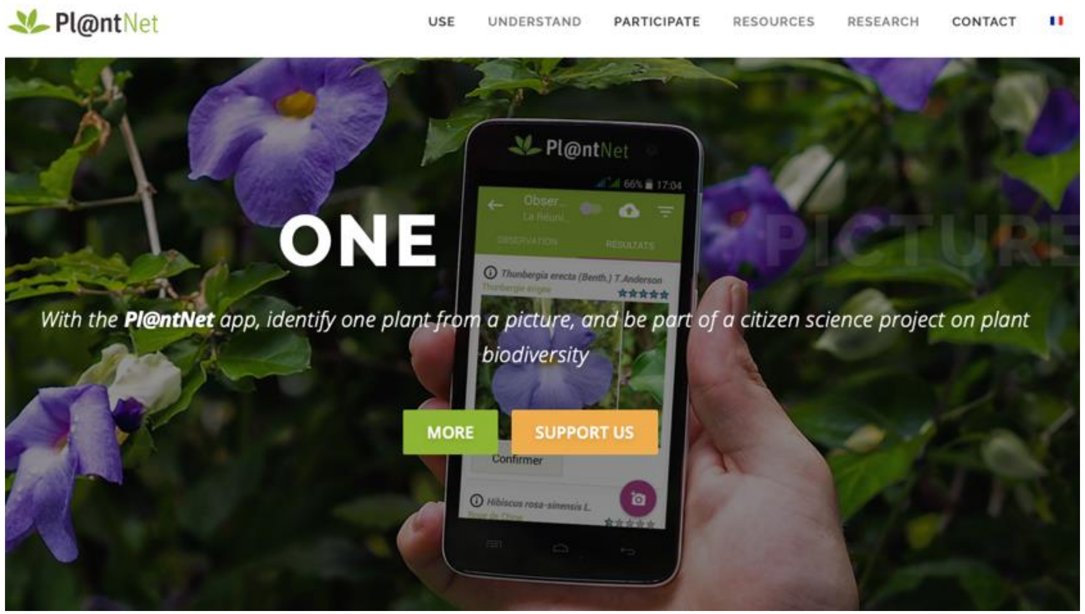
Correia et al. 2021.
doi: 10.1111/cobi.13706

Visão Computacional na Ciência Cidadã

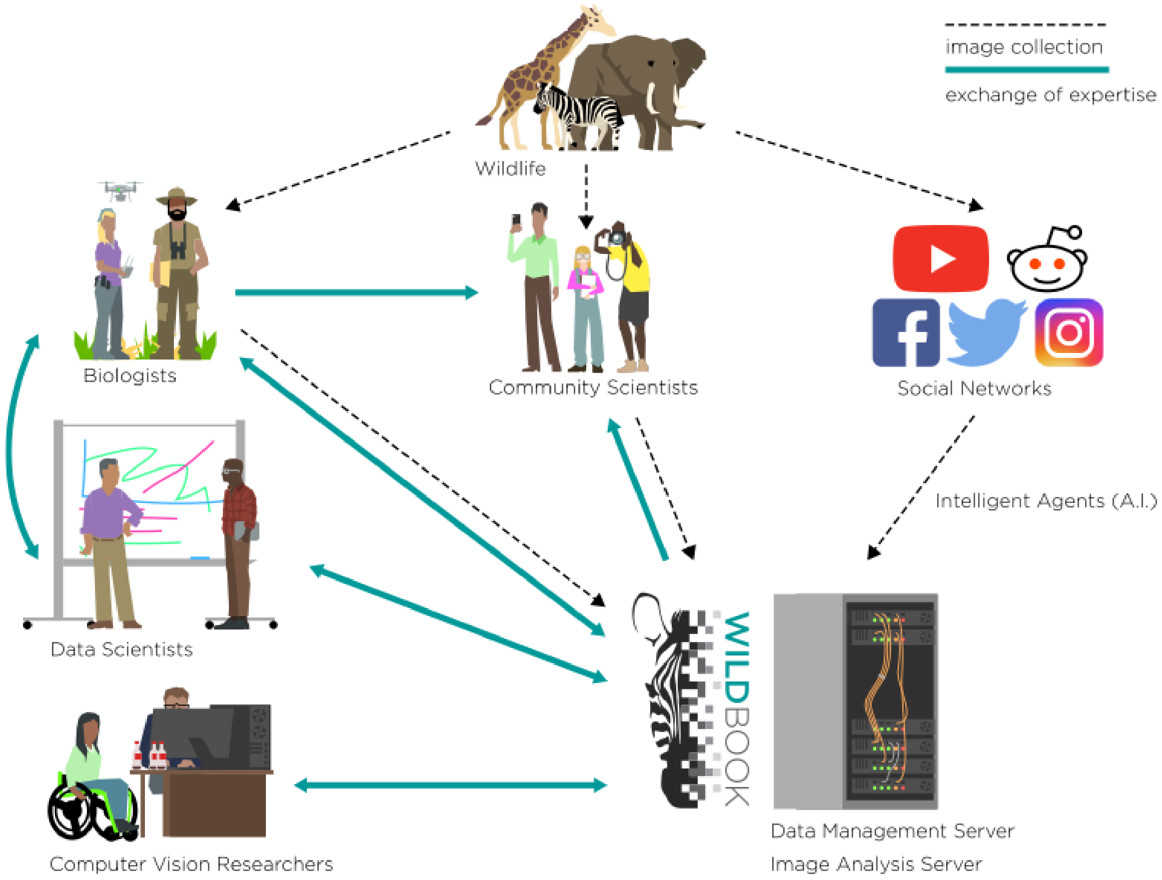
Patterns

AI Naturalists Might Hold the Key to Unlocking Biodiversity Data in Social Media Imagery

Tom A. August,[1,5,*] Oliver L. Pescott,[1] Alexis Joly,[2] and Pierre Bonnet[3,4]

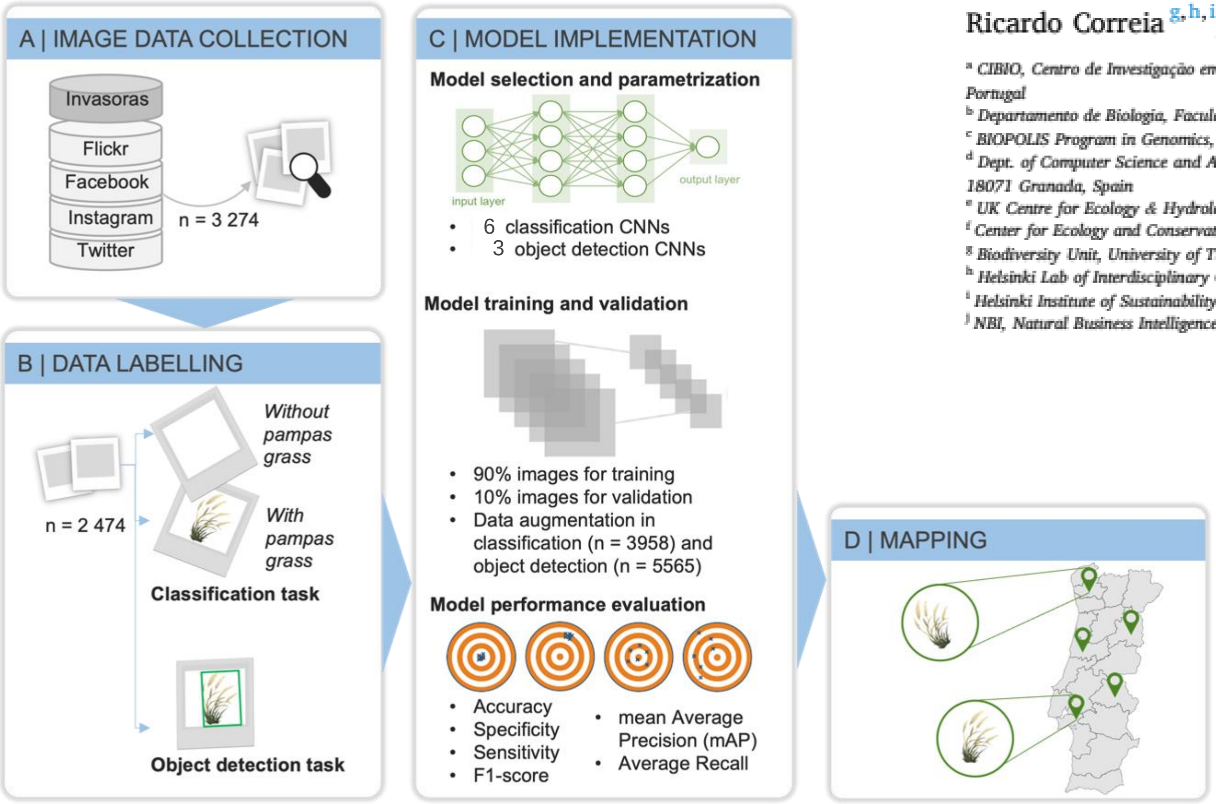


https://plantnet.org/en/



Tuia et al. 2022.
doi: /10.1038/s41467-022-27980-y

Monitorização de plantas invasoras



Contents lists available at ScienceDirect

Ecological Informatics

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

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

Ana Sofia Cardoso [a,b,c,*], Eva Malta-Pinto [a,b,c], Siham Tabik [d], Tom August [e], Helen E. Roy [e,f], Ricardo Correia [g,h,i], Joana R. Vicente [a,b,c], Ana Sofia Vaz [a,b,c,j]

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[b] *Departamento de Biologia, Faculdade de Ciências, Universidade do Porto, 4099-002 Porto, Portugal*
[c] *BIOPOLIS Program in Genomics, Biodiversity and Land Planning, CIBIO, Campus de Vairão, 4485-661 Vairão, Portugal*
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[f] *Center for Ecology and Conservation, University of Exeter, Penryn Campus, Cornwall, TR10 9FE, UK*
[g] *Biodiversity Unit, University of Turku, 20014 Turku, Finland*
[h] *Helsinki Lab of Interdisciplinary Conservation Science (HELICS), Department of Geosciences and Geography, University of Helsinki, Helsinki, Finland*
[i] *Helsinki Institute of Sustainability Science (HELSUS), University of Helsinki, Helsinki, Finland*
[j] *NBI, Natural Business Intelligence, Régia Douro Park, Andrães, Vila Real, Portugal*

Introdução

Espécies introduzidas por seres humanos em novas áreas geográficas, que se espalham rapidamente, tornando-se abundantes e causando grandes impactos no meio ambiente e na sociedade.

- ✔ Plantas invasoras entre os principais impulsionadores da **mudança socio ecológica**
- ✔ Ferramentas de vigilância com sistemas mais **dinâmicos automatizados**
- ✔ A gestão requer deteção e **monitorização** precoces
- ✔ Análise de redes sociais em conjunto com ferramentas de **deep learning como uma abordagem emergente**

NeoBiota 71: 165–188 (2022)
doi: 10.3897/neobiota.71.79597
https://neobiota.pensoft.net
RESEARCH ARTICLE
A peer-reviewed open-access journal
NeoBiota
Advancing research on alien species and biological invasions

Leif Howard[1,2*], Charles B. van Rees[1,3*], Zoe Dahlquist[1],
Gordon Luikart[1,2], Brian K. Hand[1,2]

1 Flathead Lake Biological Station, University of Montana, Polson & Missoula, MT, USA **2** *Wildlife Biology Program, University of Montana, Missoula, MT, USA* **3** *River Basin Center, University of Georgia, Athens, GA, USA*

Applications in Plant Sciences

Species distribution modeling based on the automated identification of citizen observations

Christophe Botella[1,2,3,4], Alexis Joly[1], Pierre Bonnet[3,5,7], Pascal Monestiez[4], and François Munoz[6]

Conservation Biology

Invasion Culturomics and iEcology

Ivan Jarić[1,2*] Céline Bellard[3] Ricardo A. Correia[4,5,6,7] Franck Courchamp[3] Karel Douda[8] Franz Essl[9] Jonathan M. Jeschke[10,11,12] Gregor Kalinkat[10] Lukáš Kalous[8] Robert J. Lennox[13] Ana Novoa[14] Raphaël Proulx[15] Petr Pyšek[14,16] Andrea Soriano-Redondo[17,18] Allan T. Souza[1] Reut Vardi[19] Diogo Veríssimo[20,21,22] and Uri Roll[23]

Rev Fish Biol Fisheries (2021) 31:909–922
https://doi.org/10.1007/s11160-021-09667-7
ORIGINAL RESEARCH

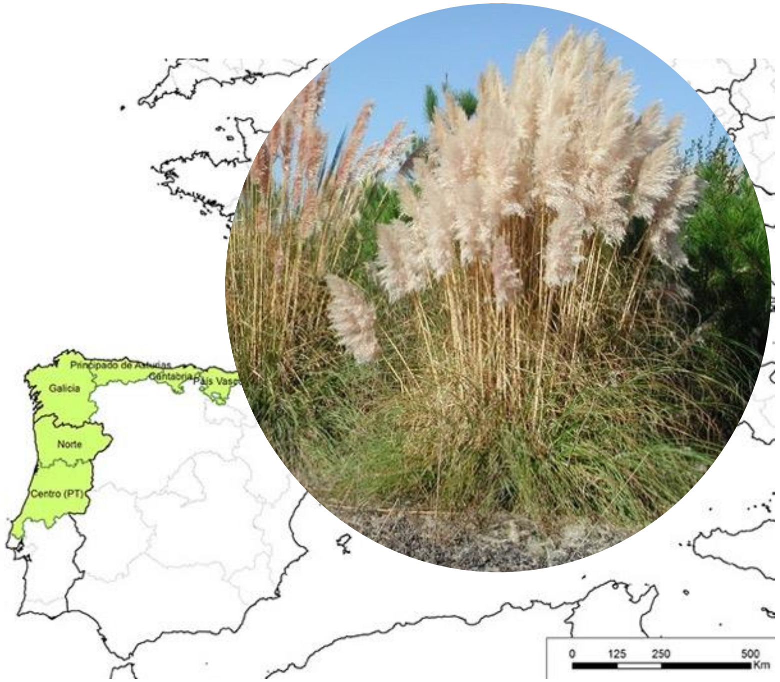
Deep learning algorithm as a strategy for detection an invasive species in uncontrolled environment

Ángel Trinidad Martínez-González · Víctor Manuel Ramírez-Rivera · J. Adán Caballero-Vázquez · David Antonio Gómez Jáuregui

Objetivos

(1) Os algoritmos de deep learning podem suportar a **identificação automatizada de plantas invasoras** em imagens das redes sociais?

(2) Em que medida as imagens das redes sociais informam sobre **novas potenciais ocorrências de plantas invasoras**?



Abordagem

Recolha de imagens para treino

Classificação e anotação das imagens

iNaturalist

invasoras.pt

flickr

twitter

Instagram

facebook

Abordagem

Treinar os modelos → Aprendizagem por transferência → Avaliação → Testar os modelos – conjunto de dados de teste

Classificação

1. VGG16
2. ResNet50
3. ResNet101
4. InceptionV3
5. DenseNet201
6. EfficientNetB0

Deteção de objetos

1. Faster R-CNN ResNet50
2. Faster R-CNN ResNet101
3. Inception-v2

TensorFlow Keras

MS COCO

ImageNet

iNaturalist

- Accuracy
- Sensitivity
- Specificity
- F1-score

- mAverage Precision (mAP)
- Total loss

flickr

twitter X

Instagram

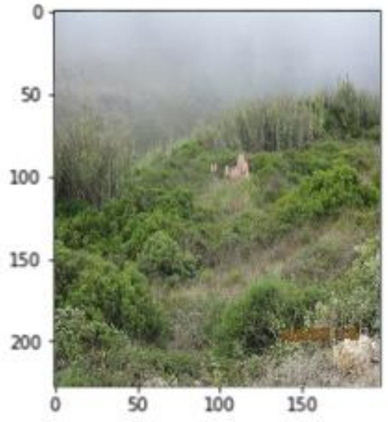
facebook

Resultados

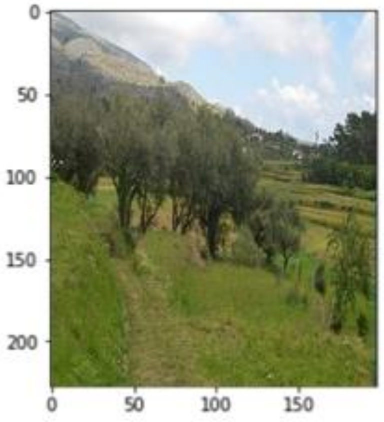
Treino dos modelos

	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

Falsos negativos



Falsos positivos



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

Previsto Real

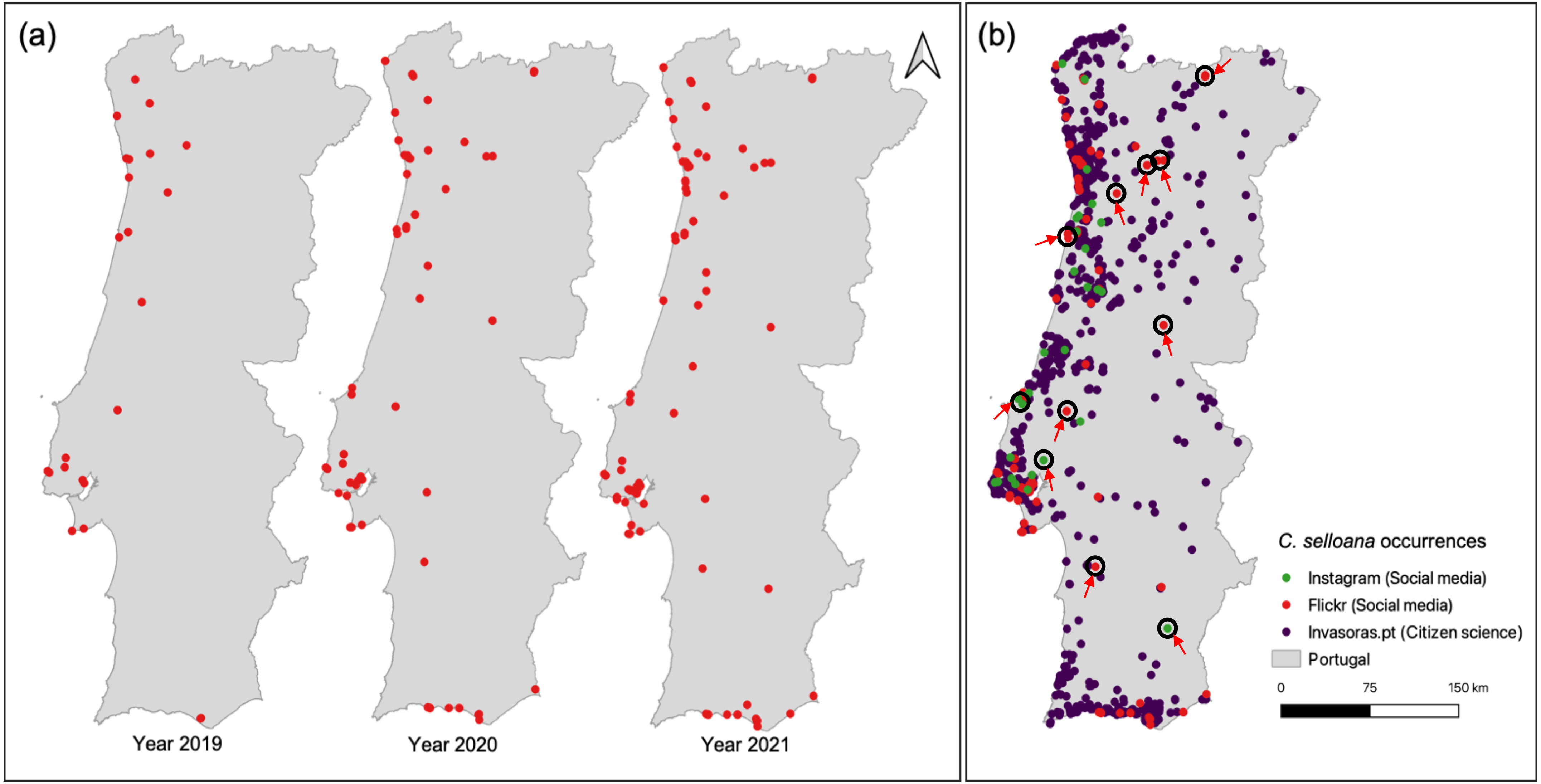
Resultados

Teste dos modelos

	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

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

Resultados



(a)
Year 2019
Year 2020
Year 2021
(b)
C. selloana occurrences
Instagram (Social media)
Flickr (Social media)
Invasoras.pt (Citizen science)
Portugal
0
75
150 km

Conclusões e próximos passos

- ✓ Possíveis limitações relacionadas com:

    Estado fenológico da planta invasora;

    Maior penetração da internet ou uso das redes sociais;

    Viés espacial das redes sociais.

- ✓ Incluir imagens com o estado fenológico completo da espécie invasora, bem como outros tipos de dados online (por exemplo, texto)

Contents lists available at ScienceDirect

Ecological Informatics

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

Mining Twitter to monitor invasive alien species — An analytical framework and sample information topologies

Stefan Daume *

Muito obrigada!

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2021.05426.BD
2022.06965.PTDC

SCAN ME

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Tom August

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RESEARCH NETWORK
Biodiversity and Evolutionary Biology

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