

MIT Open Access Articles

Towards real-time monitoring of insect species populations

The MIT Faculty has made this article openly available. **Please share** how this access benefits you. Your story matters.

Citation: Ververloo, T., Duarte, F. Towards real-time monitoring of insect species populations. Sci Rep 14, 18727 (2024).

As Published: 10.1038/s41598-024-68502-8

Publisher: Springer Science and Business Media LLC

Persistent URL: <https://hdl.handle.net/1721.1/157744>

Version: Final published version: final published article, as it appeared in a journal, conference proceedings, or other formally published context

Terms of use: Creative Commons Attribution-NonCommercial-NoDerivs





OPEN Towards real-time monitoring of insect species populations

Titus Venverloo^{1,2✉} & Fábio Duarte¹

Insect biodiversity and abundance are in global decline, potentially leading to a crisis with profound ecological and economic consequences. Methods and technologies to monitor insect species to aid in preservation efforts are rapidly being developed yet their adoption has been slow and focused on specific use cases. We propose a computer vision model that works towards multi-objective insect species identification in real-time and on a large scale. We leverage an image data source with 16 million instances and a recent improvement in the YOLO computer vision architecture to present a quick and open-access method to develop visual AI models to monitor insect species across climatic regions.

The loss of biodiversity is a global crisis with profound ecological and economic consequences^{1–10}. Among the numerous threats to biodiversity, the rapid decline in insect populations is particularly concerning^{3–6}, as around 65% of insect species could go extinct over the next one hundred years. This could have disastrous consequences, as insects play critical roles in pollination and nutrient cycling, and act as a food source for other species^{2–4}. Hence, insect species abundance and diversity conservation are crucial to maintaining ecosystem stability^{2–4}.

Literature describing the dynamics of insect populations is growing, furthering our understanding of global biodiversity decline. Common drivers for the rapid decline in insect populations are habitat loss to agriculture and urbanization, water, air, and soil pollution including pesticides and fertilizers, pathogens and invasive species, and climate change⁵. Furthermore, ecological niche species are increasingly replaced by more generalist species, declining diversity while potentially stabilizing overall insect abundance^{11,12}. While some drivers of decline might be localized, global drivers such as climate change will affect every ecosystem on the planet^{5,9}. There is an ongoing discussion regarding the effect of climate change on insect populations in temperate regions of the globe, while for tropical regions there is a consensus that there will be large effects^{4–10,13}.

Challenges in insect conservation include accurate species identification, which is a very complex task considering the vast number of insect species^{1,14,15}, the enormous lack of spatial and temporal data covering insect species populations^{1,16}, and high uncertainty about species' ability to adapt to changing climate conditions^{4,13}. There is also plenty of evidence that conventional approaches are falling short in monitoring efforts, as manual classification requires extensive expertise and labor^{1,11}.

There are other concerns when it comes to the data utilized to describe the decline. For example, Crossley et al.¹² report no net abundance and diversity declines in long-term ecological sites in the United States of America, while Welto et al.¹¹ report that the lack of consistent sampling techniques across long-term monitoring sites has influenced those earlier findings^{11,12}. Another confounding factor is the seasonality of insect abundance, complicating objective quantification of decline⁶. Furthermore, we know very little about how extreme weather events might cause mass insect death episodes, further affecting the diversity and abundance of insects^{6,13,17}.

More effective and standardized monitoring of important taxa will allow for improved scientific consensus and ideally inform actions by governments to protect insect abundance and biodiversity across climatic regions.

Bridging the information gap

Data acquisition about insect species is being automatized with large-scale AI models. Currently, an effort similar to the one presented here, although on a much smaller scale, is already adopted for agricultural sciences, specifically focused on pest control efforts^{1,14,18}. Leveraging this approach across regions for the overall evaluation of insect abundance and biodiversity can standardize data collection while reducing the required effort involved¹⁵. Some initiatives already incorporate such large models¹⁹; however, they require manual collection of geolocated images²².

In a systematic literature review from 2023, the largest number of species included in a visual AI model was 40, trained on a dataset containing 4500 images¹. While the largest dataset included in the review contained

¹Department of Urban Studies and Planning, Senseable City Laboratory, Massachusetts Institute of Technology, Cambridge, USA. ²Senseable City Amsterdam, Amsterdam Institute for Advanced Metropolitan Solutions, Amsterdam, Netherlands. ✉email: tvenver@mit.edu

88,670 images, it had only 16 insect species and achieved a relatively low mean Average Precision (mAP) of 74%^{1,14}. Very few studies ventured beyond classifying a limited number of insect species, and are often focused on the most relevant species for their objectives, such as pest control^{1,14,18}.

Several technologies could help in acquiring better data, as covered by an extensive review¹⁵. Specifically, computer vision, acoustic sensors, radar and molecular methods are discussed to monitor insects. While the review highlights several studies that develop relevant technologies, they are often commercial products, such as Diopsis²¹, and are the result of an expensive development²⁰. Hence, open-source methods and tools are necessary to address this gap and extend the insect monitoring effort, including regions with low economic resources.

This paper proposes an AI model focused on insect species classification for the Western European region. This AI model, trained on 1.54 million web-scraped images, can classify 2584 insect species and could be deployed on images collected from high-definition cameras in urban, suburban, agricultural, and natural areas. For scalability to other geographic regions, we present a code repository which uses an existing 16 million image dataset to train custom AI models for local insect species of interest.

Results

Our dataset comprises images of 2584 insect species, totaling 1.93 million images. These images are split into 80% for training (1.53 million images) and 20% for validation (0.4 million images). A small sample of images is shown in Fig. 1. On average, each species is represented by approximately 770 images. This dataset has restricted access as some of the images might be copyright-protected. A smaller test dataset, containing 12,103 images, was collected from GBIF (Global Biodiversity Information Facility) and is accessible²². This smaller dataset is used to further validate the reported metrics from the validation dataset. The test dataset does not include any images utilized in the training of the model. Furthermore, we make available a code repository on how to utilize the GBIF framework²² to train custom YOLOv8 model for any region covered by the GBIF dataset.

The YOLOv8 model we developed achieved 82.3% Top 1 score on the validation dataset, which indicates how many times the model predicted the correct label with the highest probability. To our knowledge, this would make it the most accurate computer vision model to identify insect species at this scale. The accuracy, number of species included, and dataset size of previous literature^{1,14} are compared to our results in Fig. 2. The Top 5 score of 95%, also based on the validation dataset, further underscores the model's capacity to recognize insects. We also verified those metrics with the test dataset. The metrics from the test dataset are reported in Table 1. Table 1 also indicates that saving the Top 2 predictions might be worthwhile to improve the robustness of the monitoring effort, showing a 0.07 improvement.

While the model performs well overall, it does not perform uniformly across all species. Hence, a further validation step has been taken. First, we analyze the distribution of the number of images for each species (supplementary file 1). The analysis of the number of images indicates that the dataset has a long-tailed distribution, implying that for some species the model is trained with significantly less images than others. To test the model's abilities on these underrepresented species, we select 30 species in 6 different parts of the long-tail distribution for further validation, as shown in Fig. 3.

The 6 parts are:



Figure 1. A small sample of the collected images from the GBIF repository^{22,26}.

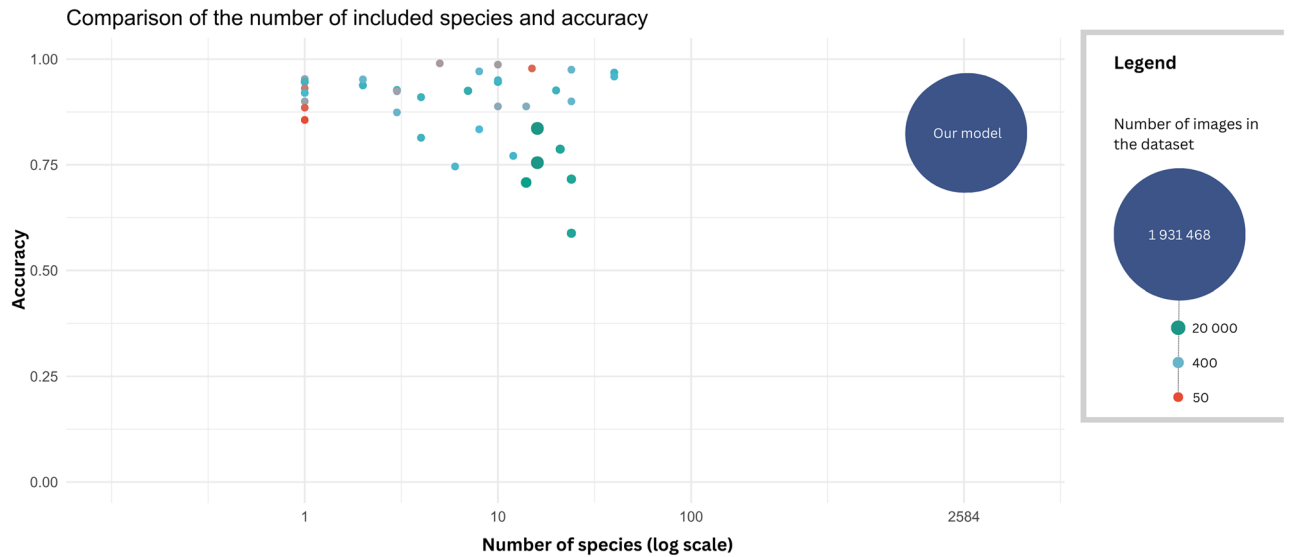


Figure 2. The presented dataset size, the number of included species, and achieved accuracy compared to other computer vision models included in systematic reviews^{1,14}. The blue dot indicates our results. Note that the x-axis is log-transformed due to the large increase in the number of included species.

	Top 1	Top 2	Top 3	Top 4	Top 5
Score	0.8287	0.8980	0.9258	0.9384	0.9443

Table 1. Metrics from the test dataset.

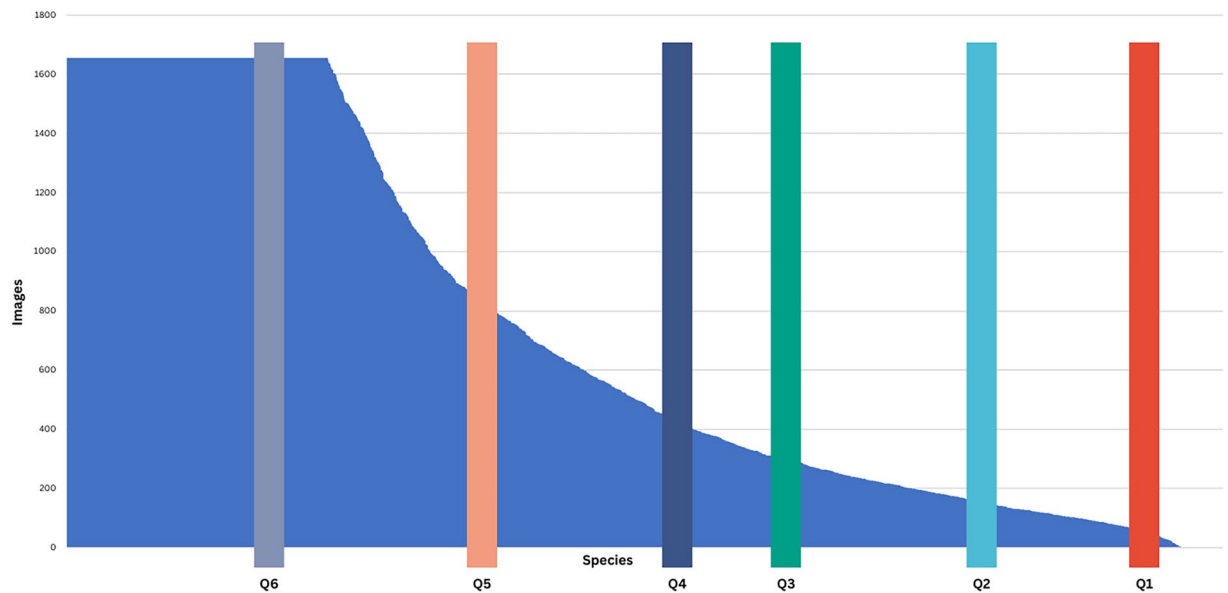


Figure 3. Showing the long-tailed distribution of number of images per insect species, highlighting the 6 selected parts of the distribution.

- Q1 with ~ 20 images
 - Species: *Lasioglossum pallens*, *Tapinoma erraticum*, *Gymnosoma dolycoridis*, *Sphecodes scabricollis*, *Cicada orni*
- Q2 with ~ 150 images
 - Species: *Arge dimidiata*, *Banchus pictus*, *Odontoscelis fuliginosa*, *Psylla buxi*, *Agrothereutes abbreviatus*
- Q3 with ~ 300 images

- Species: *Lejogaster tarsata*, *Lestiphorus bicinctus*, *Glischrochilus hortensis*, *Euodynerus dantici*, *Austrolimnophila ochracea*
- Q4 with ~ 400 images,
 - Species: *Scymnus nigrinus*, *Crepidodera plutus*, *Temnostethus pusillus*, *Heterarthrus vagans*, *Macropis fulvipes*
- Q5 with ~ 800 images
 - Species: *Limnia unguicornis*, *Empis stercorea*, *Phaonia fuscata*, *Tromatobia lineatoria*, *Cylindromyia bicolor*
- Q6 with ~ 1600 images
 - Species: *Asilus crabroniformis*, *Haematopota pluvialis*, *Baccha elongata*, *Andrena scotica*, *Plagioderia versicolora*

During validation, the 5 species in each of these 6 parts were separately analyzed (supplementary file 2). We find that the Top 1 scores decrease substantially for species represented with less than 800 images. For species with 150 to 800 images, the Top 1 scores range between 0.25 and 0.8, with an average for Q4 of 0.482, for Q3 of 0.644, for Q2 0.622, and for Q1 the Top 1 is 0 (Fig. 4). If we generalize these results and look at the distribution of images used for our model, our pre-trained AI model would be very accurate for ~ 1000 species, reasonable accurate for ~ 1100 species, and inaccurate for ~ 400 species.

We conduct a similar analysis for the Top 5 score, here we find that the model performs well, and the score remains stable between ~ 150 images to ~ 1600 images. For species with less than 150 images in the dataset the accuracy drops to 0 (Fig. 5).

Each prediction comes with a confidence score, which could be utilized to discard bad predictions improving overall accuracy. We plot the Top 1 confidence score in relationship to the Top 1 score in Fig. 6. For Q6 and Q5, we observe high confidence scores and high Top 1 scores. For Q4, Q3, Q2, we observe a near linear relationship between the confidence of predictions and the Top 1 score. The plot suggests that discarding predictions between 0 to 0.65 confidence would improve the useability of the model.

Discussion

The results of this study highlight the potential of computer vision in addressing the challenges associated with insect species identification and biodiversity conservation. The YOLOv8 model, trained on a large and diverse dataset, achieved impressive accuracy, demonstrating its effectiveness in recognizing insect species. However, the model is trained on a long-tailed distribution of images, meaning there is an uneven distribution of images per specie in the training data. This causes lower classification performance in tail categories compared to head categories.

There could be several solutions to circumvent this issue, including resampling the dataset, utilizing loss reweighting during the training or using semi-supervised methods to be able to effectively deal with less represented species. While this is a common issue in the field of image recognition, it is not easily resolved for new

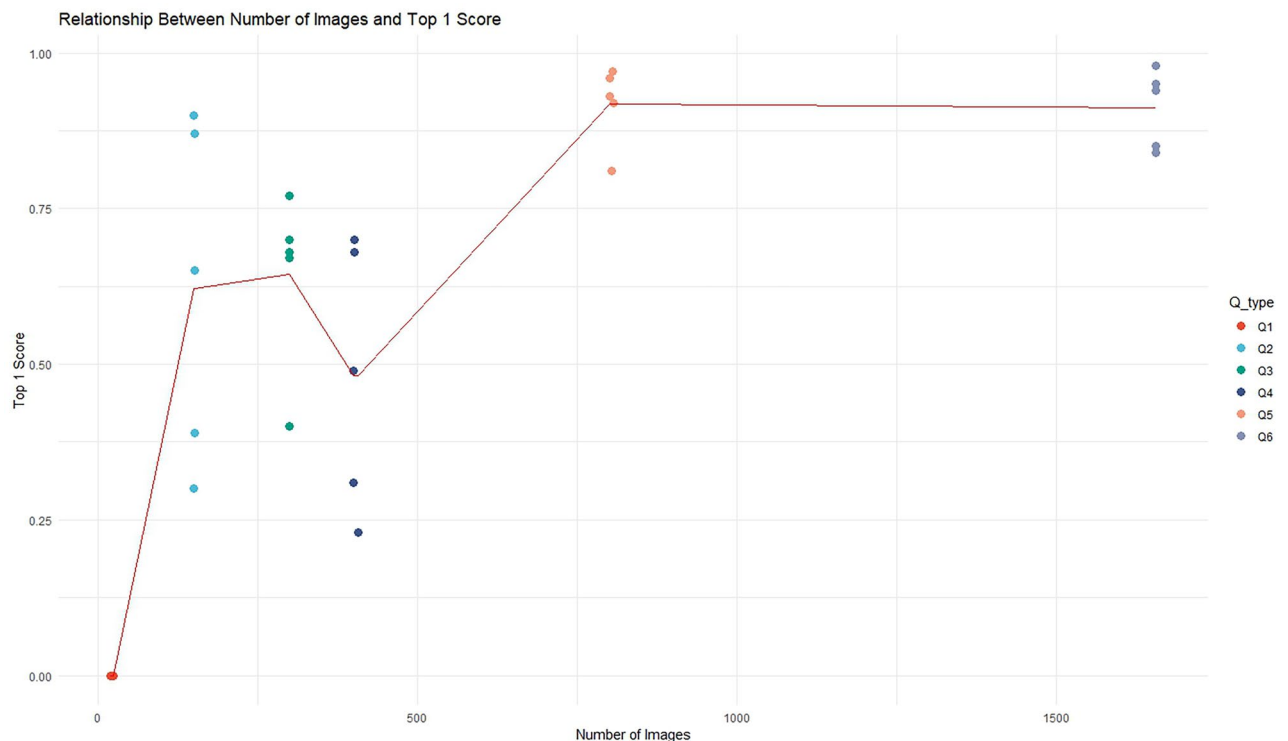


Figure 4. The relationship between the number of images per species and the Top 1 score for the presented model, based on the 6 parts of the distribution.

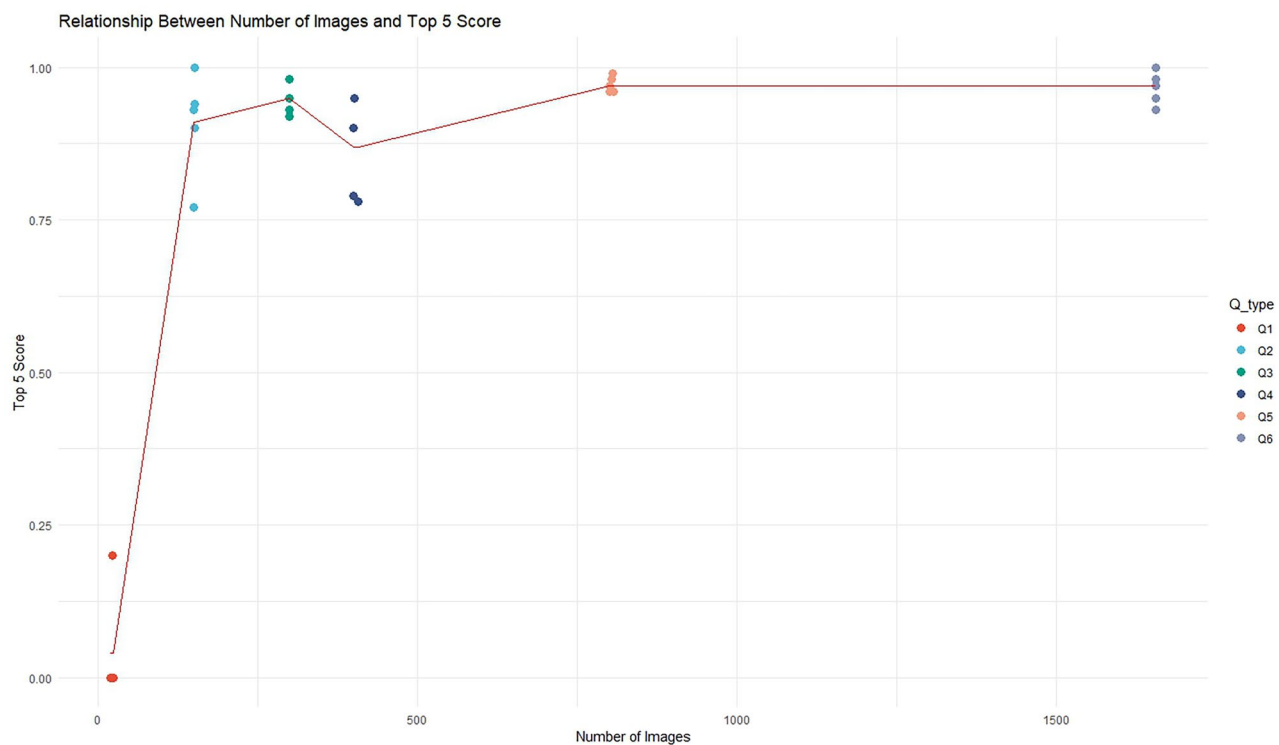


Figure 5. The relationship between the number of images per species and the Top 5 score for the presented model, based on the 6 parts of the distribution.

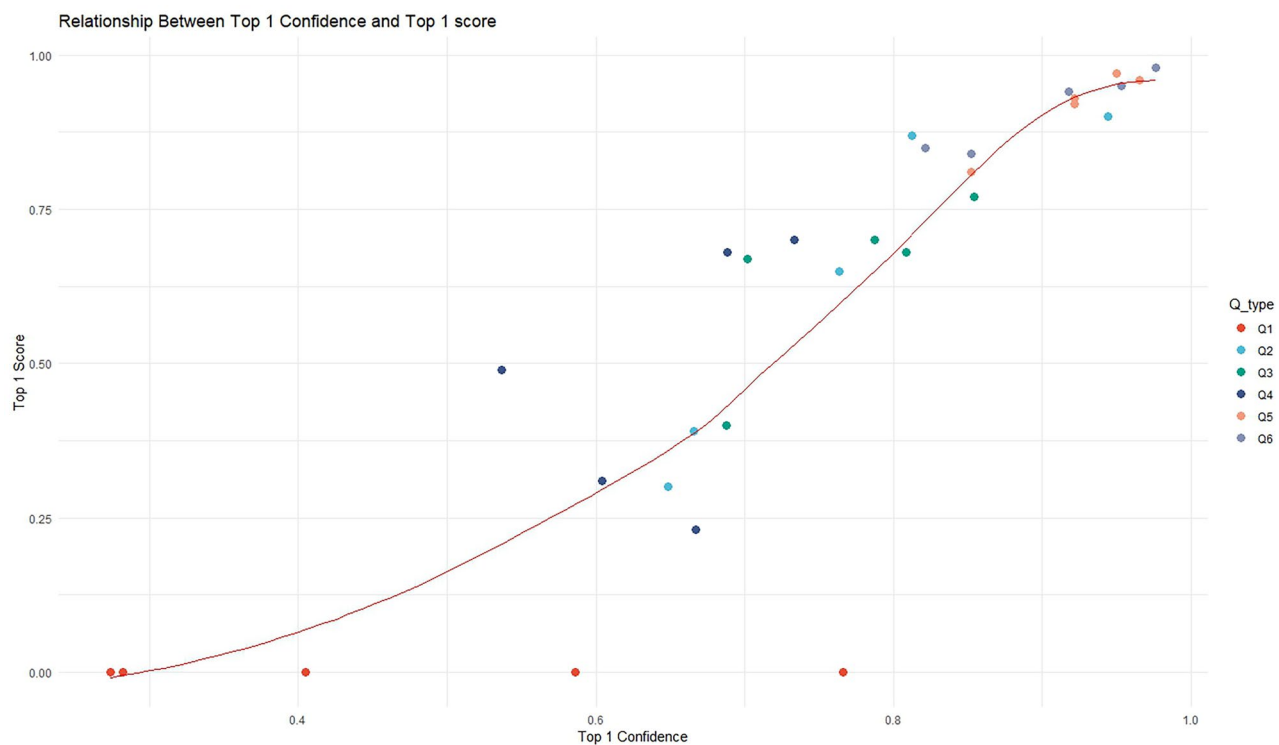


Figure 6. The relationship between the Top 1 confidence score and the Top 1 predictions for each of the 6 parts of the image dataset.

datasets. Hence, a future research direction is the utilization of the GBIF image repository incorporating methods to better deal with long-tailed distributions of classes. On the short term, discarding low-confidence predictions is an easily implementable solution. Additionally, the species in the tail end of the distribution are all rare species; thus, rebalancing the dataset might cause overprediction of very uncommon species. The primary objective of this contribution is to create a method to get a robust indicator of insect dynamics. To get this indicator, several rare species might not be relevant at this stage for initial monitoring setups. Efforts should be focused on selecting more abundant indicator species for the relevant ecosystems.

To make these computer vision developments useable, there should be a discussion on the monitoring efforts. Standardized monitoring with AI tools requires coordination between long-term research sites to formalize camera configurations, sample plot size, and type of plants in the monitored plot. Further research still must prove that computer vision systems remain reliable during in-the-wild deployments and that these sensing systems can operate autonomously and effectively. Additionally, the conventional monitoring setups, such as sweep netting, pitfall traps, malaise traps, light traps, berlese funnel traps, and visual surveys should not be replaced^{11,15}. These methods have their relevance in quantifying insect species; however, they often do not provide scientific data in the right granularity and in the right frequency for many analyses. There are also ways to combine these trap techniques and visual AI in parallel or in a complementary fashion^{11,15}.

Considering the large and pressing need to understand the dynamics of insect populations, more frequent measurements are vital. While image repositories are available^{15,22}, scientific publications on the application of large-scale visual AI are lacking. The absence of easy methods to train AI models, a lack of awareness and dataset availability, and the commercialization of monitoring technologies are delaying monitoring efforts. In this research, we present a possible path forward by providing a reproducible method to fetch an image database of species of interest, train AI models, and provide a novel large-scale AI model applicable to insect classification, which we tested for the purposes of this paper in the Western European region.

The presented computer vision model should be further tested and validated with deployments across multiple sites. The open-sourced code repository can be further improved on by incorporating methods to deal with the long tail distribution in the GBIF repository. Additionally, further technical developments could focus on multi-modal AI for the classification of insect. A conceivable application could be using visual recognition methods, where databases are more abundant, in combination with acoustic monitoring. The acoustic samples would then be labeled with a reliable visual classification prediction. This could create a large and needed acoustic data repository which scientists can use for more robust classification results.

Overall, this research represents a step forward in the automation of insect species identification for biodiversity conservation. The results underscore the potential of computer vision in combating biodiversity loss and offer promising directions for future research and conservation efforts.

Methods

Advancements in computer vision have paved the way for the automation of insect species identification at a larger scale. Convolutional Neural Networks (CNNs) have shown exceptional capabilities in image recognition tasks. While the AI field is progressing, insect population studies have yet to incorporate some of these techniques. For example, YOLO (You Only Look Once) is a real-time object detection system that has garnered attention for its speed and accuracy^{23,24}. YOLOv8, an improvement of the YOLO architecture, offers state-of-the-art performance in object detection²⁵ and is the architecture chosen for this article.

To create a comprehensive dataset for insect species identification, the lead author web-scraped almost 2 million images representing 2584 insect species. A small percentage of images was collected from search engines, while a large portion of images was collected from Observations.org²². Through this method, species were captured in various angles, lighting conditions, and backgrounds, which could ensure model robustness. The variety of angles is shown in Fig. 1. The lighting conditions were analyzed based on a representative subsample of images. Figure 7 shows the overall brightness distributions based on four metrics, mean brightness, standard deviation of brightness, the V channel of the images in the HSV format, and the L channel of the images in the LAB format. 10 images on the low and high side of the mean brightness distribution are shown in Fig. 8. The assessment of the brightness of the images also demonstrate the wide variety of backgrounds.

For the training of the AI model, the web-scraped dataset was divided into 80% training images and 20% validation images. The created dataset was used to train a novel AI model, relying on YOLOv8, where the number of species included in the model is larger by a factor of 64.6, expanding from a maximum of 40 species¹⁴ to 2584 species. Additionally, the reported dataset used for the training and validation is larger than previously reported datasets by a factor of 21.8, increasing from 88,000¹⁴ to almost 2 million images.

As the pre-trained model is specialized for the Western European context, a code repository was developed to replicate this method for other species in different climatic zones. The repository leverages a dataset with links to 16 million images of insects across a wide range of geographic regions. A region might have specific species of interest, or indicator species relevant to estimate ecosystem health. Hence these species names can be provided in a .csv file, after which the code repository downloads images of these species, if they are included in the image repository. The GitHub can be found at the Code Availability section, with detailed steps to create custom YOLOv8 models shown in Fig. 9.

To summarize, the GitHub repository requires two inputs from users: a simple csv file, with names of species, and a GBIF²⁶ image repository that includes those species. The user can choose to either use the prepared download²⁶, or create a download meeting their needs from GBIF. The prepared download includes links to images of the 16 million image data repository of GBIF²⁶. Once both the csv file and the GBIF dataset are provided, users can run two scripts to create a new custom YOLOv8 computer vision model and run a third script to obtain the predictions on other images.

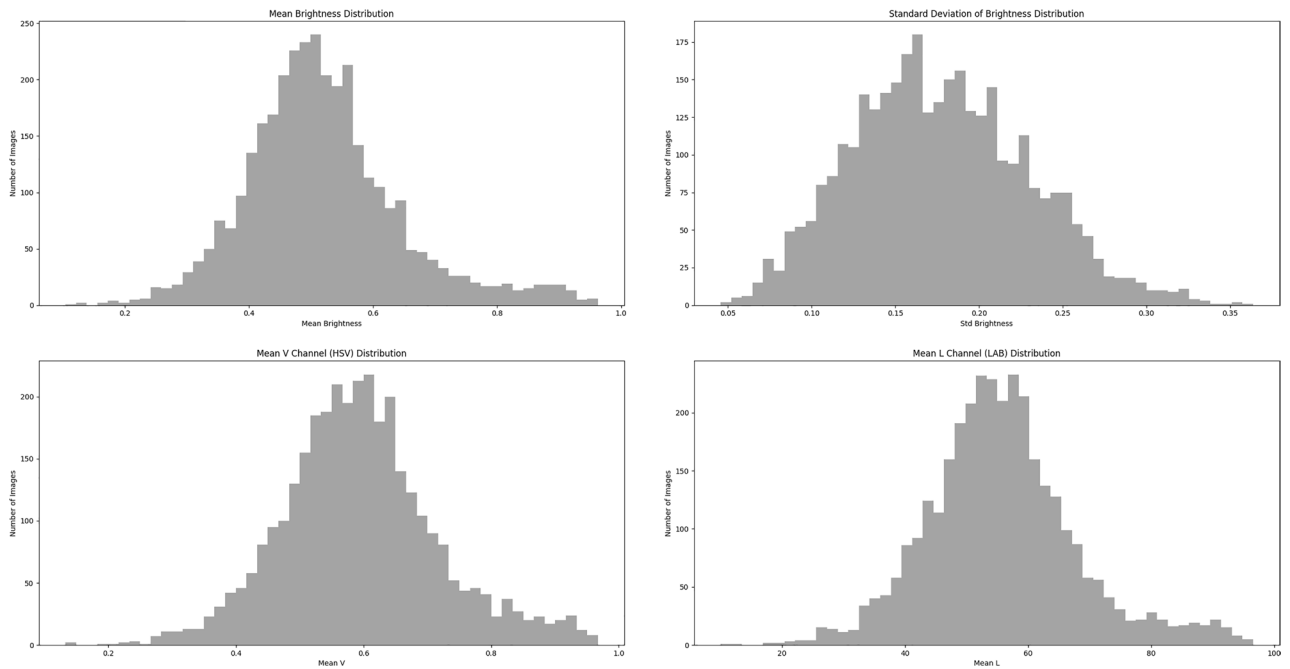


Figure 7. Brightness distribution of a subset of images in the dataset.

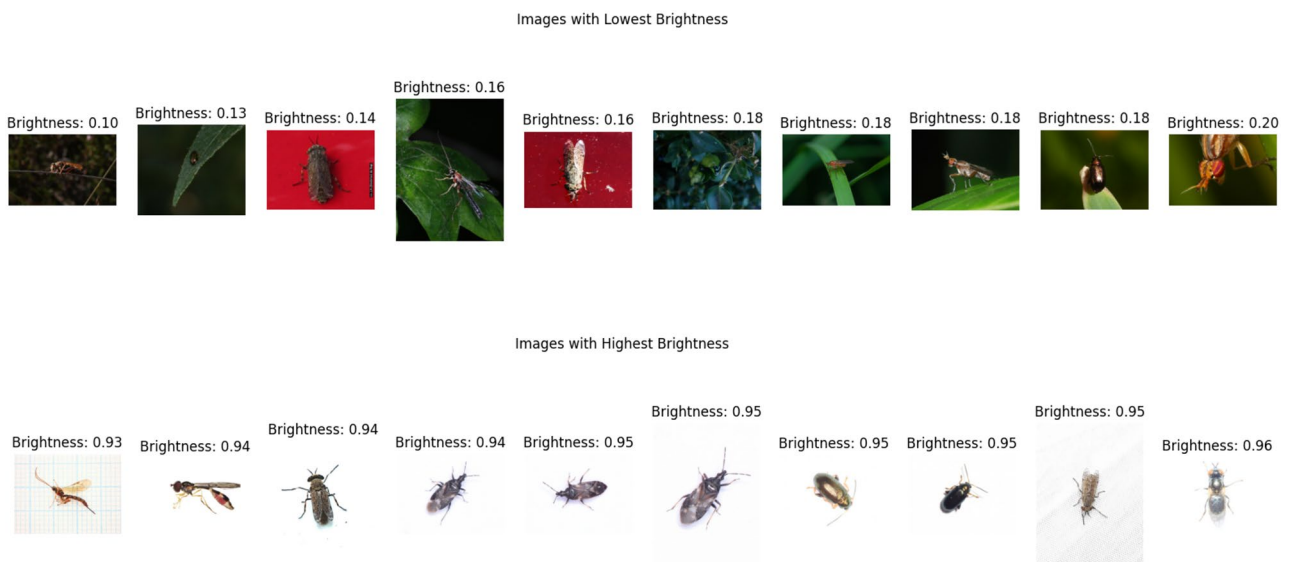


Figure 8. Sample of 10 low and high mean brightness images.

1. Collect_images.py
 - a. Collect images from GBIF in designated folder structure.
2. Train_validate.py
 - a. Train a YOLOv8 model relying on Ultralytics and report validation results.
3. Run_model.py
 - a. Finds images in a folder and runs the prediction model on those new images.

Schematic of processing

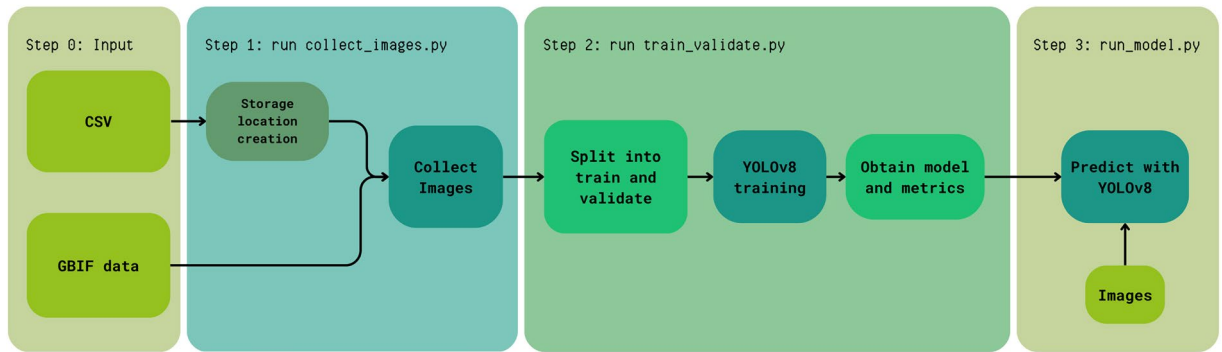


Figure 9. Schematic of the method, including the required processing steps to train custom YOLOv8 models for biodiversity tracking.

Data availability

Data availability Images can be downloaded from²⁶, GBIF Occurrence Download <https://doi.org/https://doi.org/10.15468/dl.dk9czq>.

Code availability

<https://github.com/Tvenver/Bplusplus>.

Received: 21 March 2024; Accepted: 24 July 2024

Published online: 12 August 2024

References

- Teixeira, A. C., Ribeiro, J., Morais, R., Sousa, J. J. & Cunha, A. A systematic review on automatic insect detection using deep learning. *Agriculture* **13**(3), 713 (2023).
- Wagner, D. L., Grames, E. M., Forister, M. L., Berenbaum, M. R. & Stopak, D. Insect decline in the Anthropocene: Death by a thousand cuts. *Proc. Natl. Acad. Sci.* **118**(2), e2023989118 (2021).
- Wagner, D. L. Insect declines in the Anthropocene. *Ann. Rev. Entomol.* **65**, 457–480 (2020).
- Duffy, K., Gouhier, T. C. & Ganguly, A. R. Climate-mediated shifts in temperature fluctuations promote extinction risk. *Nat. Clim. Change* **12**(11), 1037–1044 (2022).
- Sánchez-Bayo, F. & Wyckhuys, K. A. Worldwide decline of the entomofauna: A review of its drivers. *Biol. Conserv.* **232**, 8–27 (2019).
- Hallmann, C. A. *et al.* More than 75 percent decline over 27 years in total flying insect biomass in protected areas. *PLoS ONE* **12**(10), e0185809 (2017).
- Shaw, P. *et al.* African savanna raptors show evidence of widespread population collapse and a growing dependence on protected areas. *Nat. Ecol. Evol.* **8**, 1–12 (2024).
- Outhwaite, C. L., McCann, P. & Newbold, T. Agriculture and climate change are reshaping insect biodiversity worldwide. *Nature* **605**(7908), 97–102 (2022).
- Weaving, H., Terblanche, J. S., Pottier, P. & English, S. Meta-analysis reveals weak but pervasive plasticity in insect thermal limits. *Nat. Commun.* **13**(1), 5292 (2022).
- Harvey, J. A. *et al.* Scientists' warning on climate change and insects. *Ecol. Monogr.* **93**(1), e1553 (2023).
- Walti, E. A. *et al.* Studies of insect temporal trends must account for the complex sampling histories inherent to many long-term monitoring efforts. *Nat. Ecol. Evol.* **5**(5), 589–591 (2021).
- Crossley, M. S. *et al.* No net insect abundance and diversity declines across US Long term ecological research sites. *Nat. Ecol. Evol.* **4**(10), 1368–1376 (2020).
- Müller, J. *et al.* Weather explains the decline and rise of insect biomass over 34 years. *Nature* **628**, 1–6 (2023).
- Amarathunga, D. C., Grundy, J., Parry, H. & Dorin, A. Methods of insect image capture and classification: A systematic literature review. *Smart Agric. Technol.* **1**, 100023 (2021).
- van Klink, R. *et al.* Emerging technologies revolutionise insect ecology and monitoring. *Trends Ecol. Evol.* **37**, 872 (2022).
- van Klink, R. *et al.* Disproportionate declines of formerly abundant species underlie insect loss. *Nature* **628**, 1–6 (2023).
- Filazzola, A., Matter, S. F. & MacIvor, J. S. The direct and indirect effects of extreme climate events on insects. *Sci. Total Environ.* **769**, 145161 (2021).
- Martineau, M. *et al.* A survey on image-based insect classification. *Pattern Recognit.* **65**, 273–284 (2017).
- Stichting Observation International and local partners. Waarneming.nl. Waarneming.nl.
- Hogeweg, L., Zeegers, T., Katramados, I. & Jongejans, E. Smart insect cameras. *Biodivers. Inf. Sci. Stand.* **3**, e39241 (2019).
- Diopsis. Insecten | Diopsis.eu. Diopsis <https://diopsis.eu/insecten>.
- Observation.org. Observation.org, Nature data from around the World. Occurrence dataset <https://doi.org/10.15468/5nllie> Accessed via GBIF.org on 2024-01-19. (2024).
- Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* 779–788 (2016).
- Jiang, P., Ergu, D., Liu, F., Cai, Y. & Ma, B. A review of Yolo algorithm developments. *Procedia Comput. Sci.* **199**, 1066–1073 (2022).
- Ultralytics, Jocher, G., Chaurasia, A. & Qiu, J. Ultralytics YOLO. <https://ultralytics.com> (2023).
- GBIF.org (16 January 2024) GBIF Occurrence Download <https://doi.org/10.15468/dl.dk9czq>

Acknowledgements

We thank the Amsterdam Institute for Advanced Metropolitan Solutions (AMS Institute) and the MIT Senseable City Lab consortium, FAE Technology, MipMap, Samoo Architects & Engineers, GoAigua, DAR Group,

Ordinance Survey, RATP, Anas S.p.A., ENEL Foundation, the cities of Helsingborg, Regione Friuli-Venezia Giulia, Laval, and Stockholm, and all other members of MIT Senseable City Laboratory Consortium for supporting this research.

Author contributions

T.V. conceptualized, designed, and executed the research. T.V. created the code and the computer vision model. F.D. helped in shaping the research and revised the manuscript substantially. All authors participated in preparing the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1038/s41598-024-68502-8>.

Correspondence and requests for materials should be addressed to T.V.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Open Access This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

© The Author(s) 2024