Invertebrates Detection with YOLOv5: Towards Study of Soil Organisms Using Deep Learning

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Dataset

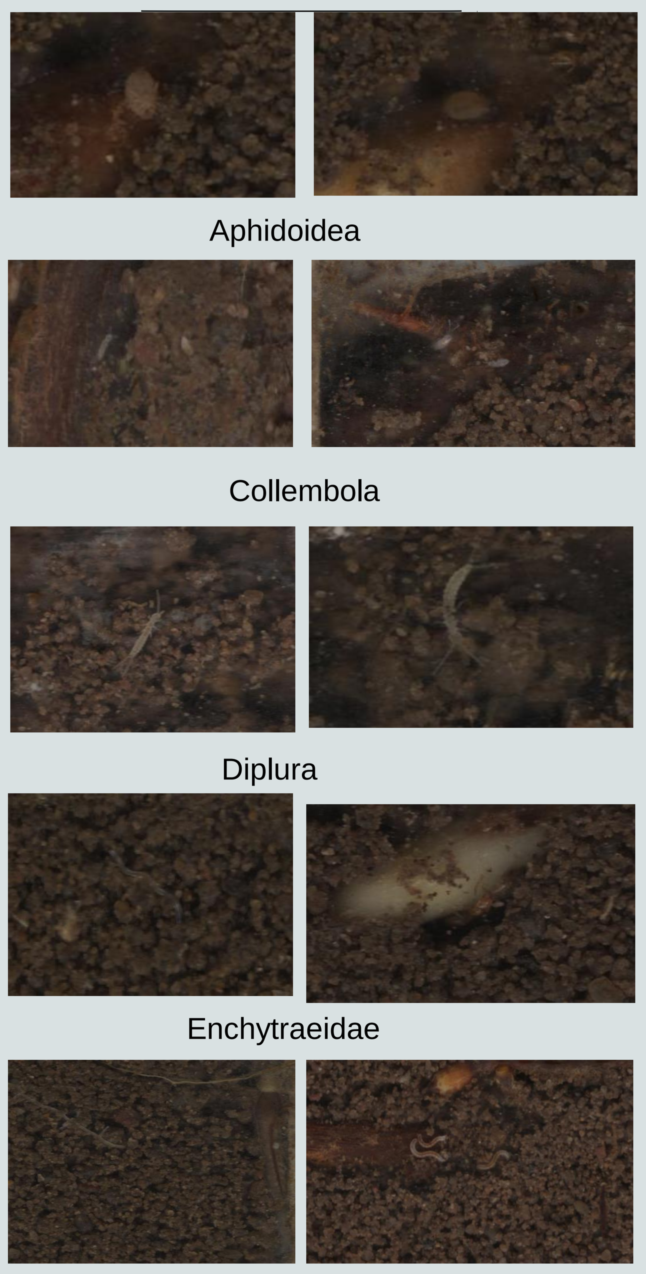


Fig. 1. Dataset description

Visual Result

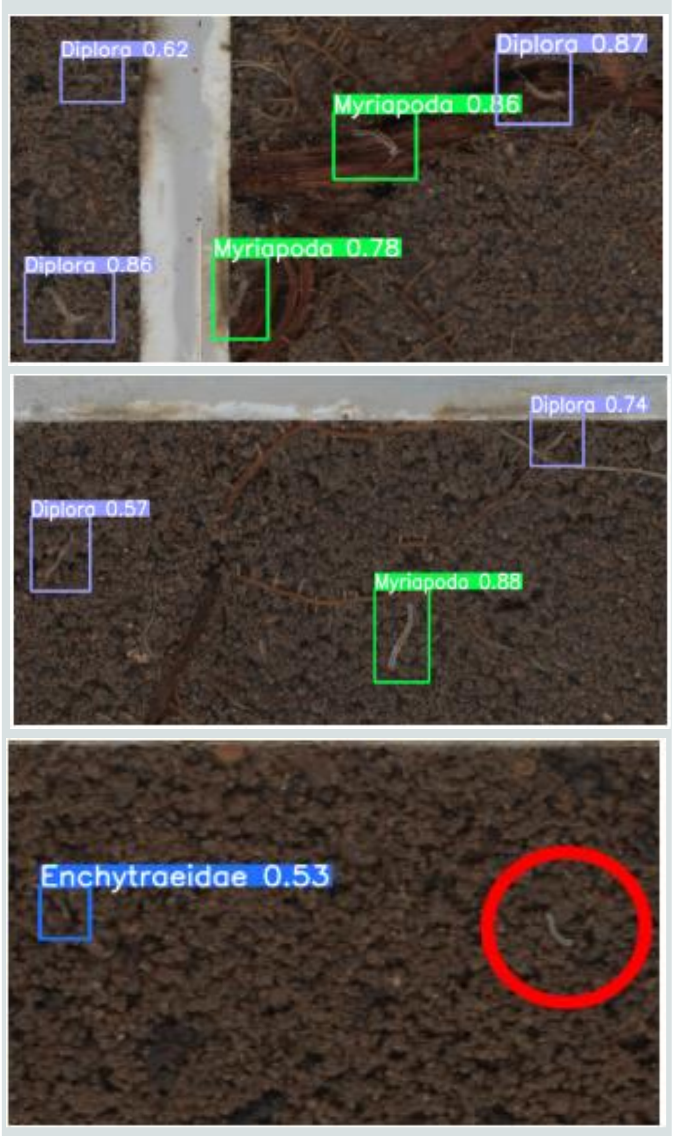


Fig.7. Examples of invertebrates' detection in underground scanned images: from left to right, true positives (myriapods and diplura –diplora–), false positives (2 roots detected as diplura), and false negative (undetected myriapod, circled in red). Images of size 449×760 , 434×908 and 356×573 respectively.

Overview

The investigation of the complicated underground life via automatic technique is in high demand in recent days. Using Convolutional Neural Network (CNN) to detect soil invertebrates is an interesting approach, although most studies on the topic have focused on other solutions. The creation of state-of-the-art technique through this work will be a significant step in soil ecology, bio-science and agriculture in effectively exploring the different types of invertebrates, their behaviors and interactions. In this paper, generating and annotating images containing seven classes of invertebrates is firstly presented. Then various automatic detections of the invertebrates using YOLOv5 algorithm on these images are performed and evaluated. detection, invertebrate dataset, YOLOv5, cluttered background. Roughly the work involves:

- **Soil fauna, invertebrate detection:** First effort using deep learning
- **Dataset:** Generating and annotating the dataset
- **Yolov5:** Using Yolov5 and optimizing for small and complex object detection
- **Evaluation:** The preliminary evaluation is promising.

Introduction

The study of biological diversity and activity in soil is a very challenging topic [1] [2]. Knowledge on organisms' activity and its interactions is important, since it is at the core of ecosystem functioning. Preserving, enhancing and managing soil biodiversity is crucial for a sustainable development of our societies. Except for some emblematic organisms (as, e.g., earthworms [3] [4], ants or roots [5] [6]), there is unfortunately limited knowledge on soil fauna. Most soil organism monitoring techniques are invasive and require soil excavation (coring, hand sorting, etc.). In particular, biologists lack information on the spatial and temporal distribution of soil organisms. The installation of waterproof scanners in fixed locations allows the acquisition of in situ images of soil. These image-based monitoring techniques generate larger datasets in terms of size than those usually handled [7]. Therefore, the manual analysis of the images is very time-consuming, especially since many images do not contain any organisms. In addition, there is a bias inducted by the observer with subjective decisions making about the information to extract [8]. Thus, the development of image-based biodiversity monitoring must be accompanied by the development of automated and reliable analysis tools. In the state of the art, there is currently no work for detecting soil organisms in the soil using Neural Networks (NN) on images. Only detection by X-Ray tomography, or through acoustic systems could be found as in [9]. Besides, some recent work has shown progress in invertebrate automatic detection, but only out of the soil [10]. In this contribution, efforts have been made to automate the detection of objects of interest (soil fauna) in images of truffle soil with little variation in humidity. All the images used are scans of the same soil area, therefore the background is almost the same in all of the images. The YOLOv5 [11] algorithm has been used and trained to automatically detect the invertebrates, and assign a label to each object. This involves image dataset creation, annotations, feeding the annotated data to the deep neural network (here YOLOv5 models), training the network and consequently detect the invertebrates with the correct labels. The performance of the proposed system is evaluated with standard evaluation metrics, and the obtained results are in free form although usable by non-computer specialists. The main purpose of this work consists in showing pioneer results in automatic invertebrate detection in soil images. This contribution paves the way for further progress in this field. There are 2 main challenges in this study:

- The size of the invertebrate is very small compared to the image resolution: few pixels are available for the model to deduce feature characteristics from each type of invertebrates.
- The images contain cluttered backgrounds, which makes it harder for the model to make reliable predictions.

Implementation

Dataset Creation: A ground truth dataset of the pre-processed fauna images has been created using Plainsight™ software.

Evaluation Metrics: Precision and Recall based on confusion matrix has been used for the evaluation.

YOLOv5: YOLOv5 offered by Ultralytics [11], YOLOv5s, YOLOv51, etc.

Optimization: Ephos, Hyper-parameter, Initial learning rate (LR0), Scale

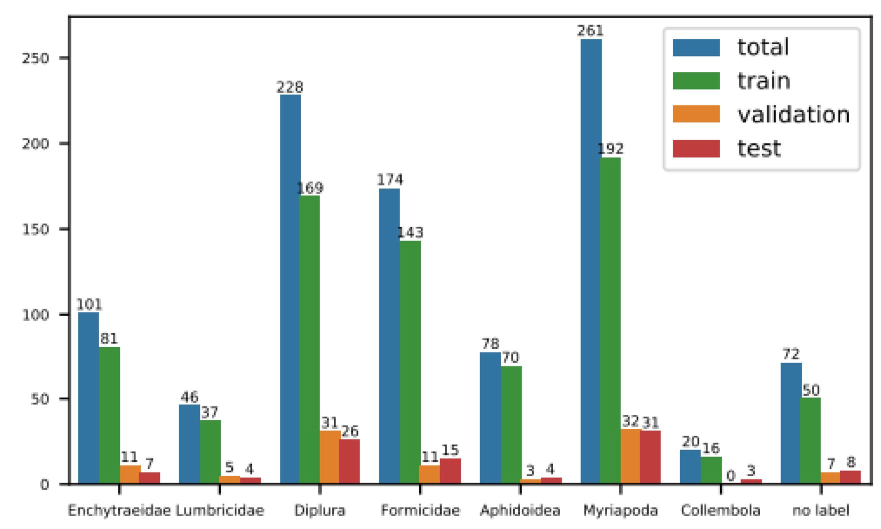


Fig. 2. Composition of the full dataset for train, validation and test

Evaluation & Result

Training and Validation: (A) Single Invertebrate Detection

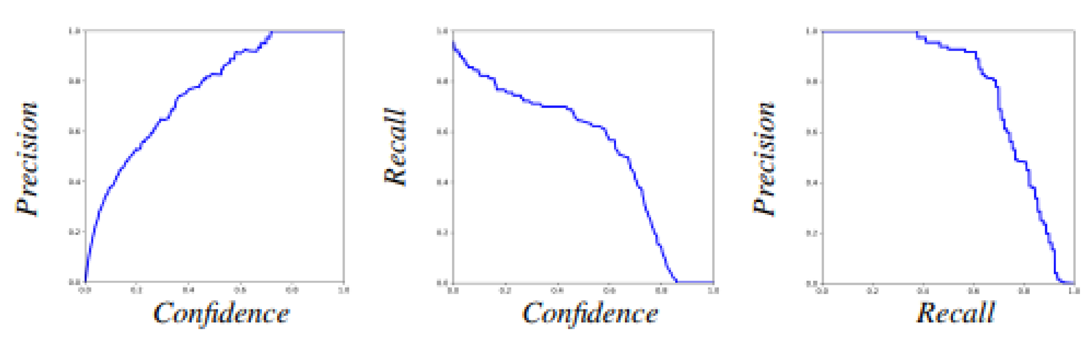
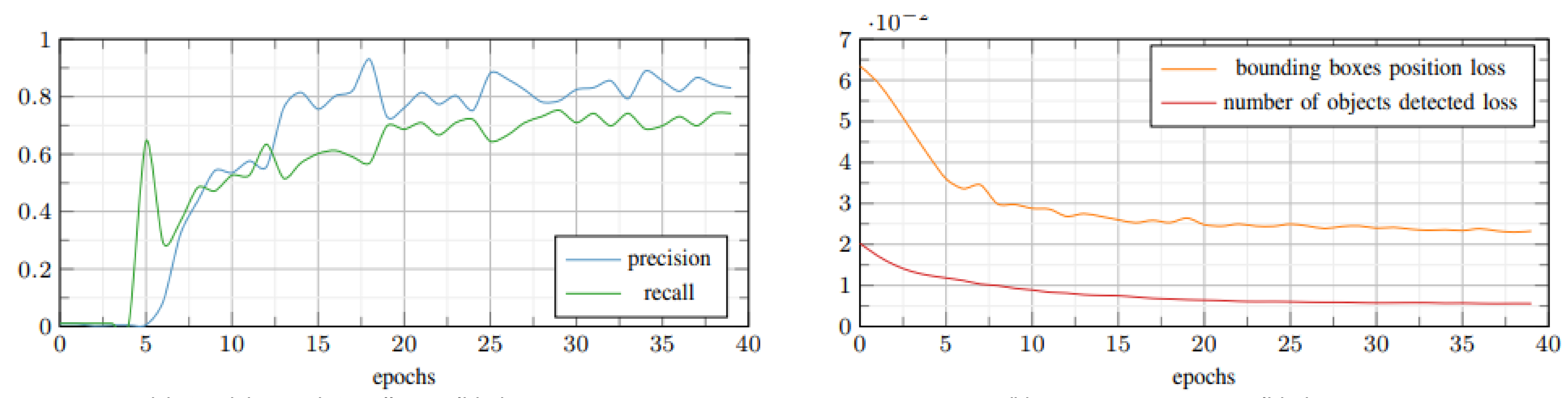


Fig.5. Metrics for single invertebrate detection model on test set

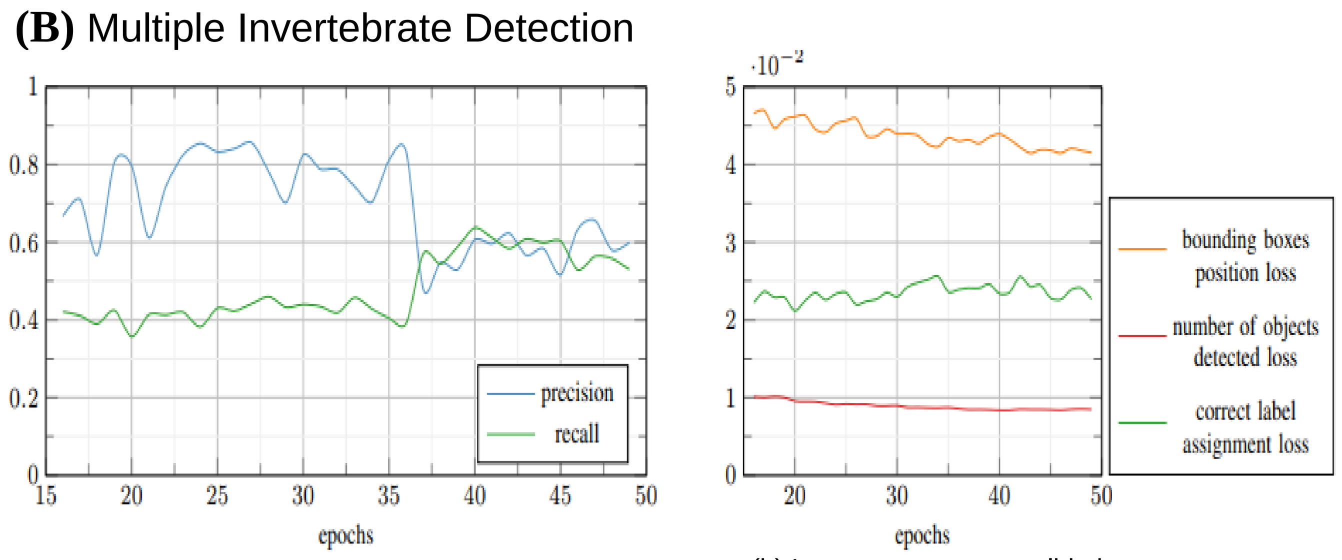


(a) Precision and Recall on validation set

(b) Loss measures on validation set

Fig. 3. Metrics for single invertebrate detection model on validation set.

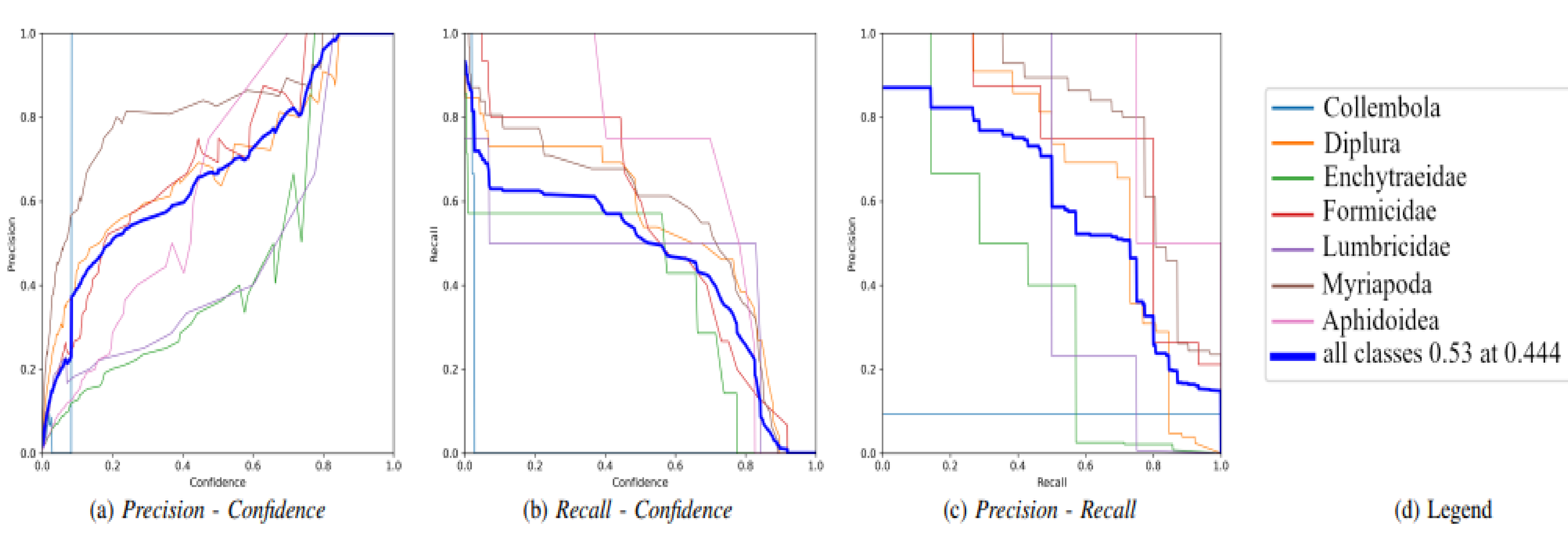
(B) Multiple Invertebrate Detection



(a) Precision and Recall on validation set

(b) Loss measures on validation set

Fig. 4. Metrics for 7 invertebrates' detection model on validation set



(a) *Precision - Confidence*

(b) *Recall - Confidence*

(c) *Precision - Recall*

(d) Legend

Fig. 6. Metrics for 7 invertebrates' detection model on test set.

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