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1 **CORIGAN : Assessing multiple species and**
2 **interactions within images**

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17

18 **Abstract**

- 19 **1.** Images are resourceful data for ecologists and can provide a more
20 complete information than other methods to study biodiversity and the
21 interactions between species. Automated image analysis however often
22 relies on extensive datasets, not implementable by small research teams.
23 We are here proposing an object detection method that allows the analysis
24 of high-resolution images containing many animals interacting in a small
25 dataset.
- 26 **2.** We developed an image analysis pipeline named 'CORIGAN' to extract the
27 characteristics of the community. CORIGAN is based on the YOLOv3 model
28 as the core of image detection. To illustrate potential applications, we use
29 images collected during a sentinel prey experiment.
- 30 **3.** Our pipeline can be used to detect, count and study the physical
31 interactions between various animals. On our example dataset, the model
32 reaches 86.6% precision and 88.9% recall at the species level or even at
33 the caste level for ants. The training set required fewer than 10 h of
34 labelling. Based on the pipeline output it was possible to build the trophic
35 and non-trophic interactions network describing the studied community.
- 36 **4.** CORIGAN relies on generic properties of the detected animals and can be
37 used for a wide range of studies and supports. Here, we study
38 invertebrates on high-resolution images, but the same processing can be
39 transferred for the study of larger animals on satellite or aircraft images.

40 **Keywords:** Image processing, Animal detection, Interaction study,
41 Convolutional Neural Network, Trophic networks, Sentinel prey study, On-field
42 image

43 **1. Introduction**

44 Understanding the functioning of ecosystems depends on accurate information
45 on biodiversity, species behaviour, trophic and non-trophic interactions, and
46 other ecosystem properties. Such information can be very useful for biodiversity
47 conservation, invasive species monitoring, and biological pest control (Reid *et al.*
48 2005).

49 However, classical methods used to sample biodiversity or to identify the
50 behaviours of species are often either time consuming, information-poor, or
51 expensive. Depending on the studied species and objectives of the studies,
52 these methods include direct observation, the use of trap cameras, Barber traps,
53 sentinel prey, or satellite images for instance. Among these methods, camera
54 observations have several advantages and present few biases. For the study of
55 arthropods with sentinel preys, Grieshop *et al.* (2012) demonstrate the
56 usefulness of the collected data and mentioned as only limits of this techniques
57 the small sampling window of a camera and the time investment needed for
58 image analysis. In fact, ecologists and biologists are therefore increasingly using
59 automated methods to analyse images (Pimm *et al.* 2015).

60 To date, one of the most developed applications of computer vision in ecology is
61 the identification of species (Wäldchen, Mäder & Cooper 2018; Weinstein 2018).
62 In comparison with species identification, the counting of objects and the
63 describing of animal behaviours and interactions are less developed applications
64 of computer vision in ecology (Weinstein 2018). Furthermore, the existing
65 methods to identify, count, or describe animals are often designed for specific
66 uses and rely on extensive datasets and citizen science initiatives (Norouzzadeh
67 *et al.* 2018; Willi *et al.* 2018).

68 In the current manuscript, we describe the CORIGAN pipeline that uses object
69 detection to identify and locate numerous small objects in high-resolution images
70 and uses these detections to compute information about species interactions. We
71 illustrate how CORIGAN can be applied on a small custom dataset of images of
72 invertebrate communities from a sentinel prey experiment in a tropical
73 agrosystem.

74 **2. Materials and methods**

75 **2.1. Overview**

76 **2.1.1. Image and detection processing**

77 We use the YOLOv3 Convolutional Neural Network (CNN) (Redmon *et al.* 2018) as
78 core of our image-processing pipeline. This model outputs the bounding box
79 coordinates of the objects it recognizes on an input image. As this model is best
80 fit for small images featuring large objects, we have developed an image-
81 processing pipeline inspired from satellite images analysis methods (Van Etten,
82 2018) to be able to work with high-resolution images featuring numerous small
83 objects. The image-processing is summarized in Fig. 1 and details on image
84 labelling, processing and CNN training are presented in Supplementary Material
85 1. Images are first sliced into $n_{slices} \times n_{slices}$ pixel slices with a given *overlap* to
86 reduce the risk of an object being cut in non-identifiable parts.

87 For model training, ground truth labels of the train dataset are recomputed within
88 each slice referential with P_{object} and P_{slice} parameters to handle how small and
89 large labels will be recomputed. The CNN is then trained on this new dataset.
90 Here, we have performed data augmentation as Redmon *et al.* (2018) and payed
91 particular attention to overfitting, given the size of our example dataset.

92 For model testing, detection is performed on slices using trained model weights
93 and a separate test dataset. These detections are then merged back together
94 within the referential of the original image. The overlap of the slicing may
95 generate duplicates and a refining of the detections with *Overlap Threshold (OT)*
96 and *Confidence Threshold (CT)* parameters is performed to suppress duplicates.
97 Refined detections are then compared with ground truth to assess the
98 performances of the model. Detected and ground truth bounding boxes are
99 compared using Intersection over Union (IoU), which is the ratio between the
100 area of intersection and the area of union of two bounding boxes. An IoU of 1
101 indicates that the detected box and ground truth box overlap perfectly.
102 Detections are accepted as True Positive (TP) if $IoU > 0.5$ and if the detected
103 class is correct. Otherwise, the detection is considered as False Positives (FP). As
104 well, duplicates are considered as FP. If a ground truth object is missed, it is
105 considered as False Negative (FN). Overall performances are assessed with
106 precision, recall and F1-score.

$$107 \text{ precision} = \frac{TP}{TP + FP}$$

$$108 \text{ recall} = \frac{TP}{TP + FN}$$

$$109 F1 = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$$

110 For each class, the Average Precision (AP) is computed as the area under the
111 precision-recall curve. AP is used to compare performances between classes.

112 Once the model shows acceptable performances and the best processing
113 parameters determined, the pipeline can be used to study interactions between
114 animals.

115 **2.1.2. Interactions**

116 Since we observe animals on a 2D surface, we can thus use the intersection of
117 bounding boxes to detect physical interactions between two individuals. There
118 may be intersections of bounding boxes without real physical contact but the
119 intersection of bounding boxes ensures that animals are within very close range
120 to each other. We chose to consider this as a physical interaction, as this means
121 that at least one of the participants of the interaction is willing to engage physical
122 contact with the other.

123 To provide further nuances, interactions may be characterized depending on the
124 known or observed behaviour of a species towards another. In our example,
125 interactions between predators and prey are labelled as *predation* if the prey is
126 alive and *scavenging* if the prey is already dead at the beginning of the
127 experiment. Interactions between two predators of different species are labelled
128 as *competition*, whereas interactions between two predators of the same social
129 species are labelled as *cooperation*. Finally, animals whose behaviour towards
130 others where not clearly identified are labelled as *undefined*. Moreover, the
131 number of individuals of a predator species interacting with a prey on an image is
132 counted, providing information about the predator unit investment needed for
133 the capture of a prey during a predation event. All results are exported in csv
134 dataframes. R scripts are provided for analysis and production of graphics.

135 **2.2. Example dataset**

136 To illustrate how CORIGAN can assess multiple species and interactions within
137 images, we have conducted sentinel prey experiments, using eggs and dead or
138 alive adults of *Cosmopolites sordidus* and larvae of *Metamasius sp.* as prey under
139 the camera.

140 Detailed protocol is presented in Supplementary Material 2. These experiments
141 have produced 1240 images of 3000x 4000 pixels and we have used 95 images
142 as training dataset, 95 different images as test dataset and 1191 to study
143 invertebrate interactions. Training and test dataset feature 4087 invertebrates
144 belonging to 24 classes: these include 21 species and morphospecies; three ant
145 species are further labelled to caste level (minor or major workers). For the sake
146 of clarity, results are here presented with these classes summarized into seven
147 super-classes (ant, cockroach, weevil, spider, larva, egg, slug) but see Table 1 in
148 Supplementary Material 3 for complete results on all classes. An output example
149 for a test image of this dataset is shown Figure 2.

150 **3. Results**

151 **3.1. Network performance**

152 Given our dataset, we choose $n_{slice} = 416$ pixels and an *overlap* of 0.2. Each
153 original image then generates 108 slices. Labels are kept for $P_{object} = 0.4$ and
154 $P_{image} = 0.5$. We choosed an *OT* of 0.4.and a *CT* of 0.2. Details on the choice of
155 values of these parameters are provided in Supplementary Material 1.

156 Given our hardware (detailed in Supplementary Material 1), training on 95
157 images (corresponding to 10 260 slices) required about 24 h. Tests on 93 original
158 images (meaning 10 044 slices) required < 5 min. The presented state of the
159 network shows maximal test performance and a test loss to training loss ratio of
160 1.01.

161 The model had a precision of 86.6%, a recall of 88.9%, and an F1-score of 87.8%
162 on detailed classes. If classes are summarized into super-classes, precision,
163 recall, and F1 increased to 89.6%, 91.2%, and 90.4% respectively. AP for the
164 different super-classes are shown on Table 1.

165 **3.2. Interaction analysis**

166 All interactions between animals are displayed on Figure 3. Such a matrix can be
167 used to show the importance of intra-specific interactions. For instance, our
168 example shows numerous intraspecific interactions for the ants *Pheidole*
169 *radoszkowskii* and *Solenopsis geminata*. Interspecific interactions can be shown as
170 an interaction network and qualified given the participants of the interaction (Fig.
171 4).

172 The number of predators interacting with a prey on an image are shown on
173 Table 2. For example, smaller ants (e.g. *P. radoszkowskii*, *S. geminata*) need to
174 invest more individuals for the capture of one prey than larger ants (e.g.
175 *Odontomachus bauri*)

176 **4. Discussion**

177 **4.1. Time investment to apply the method**

178 For our example, labelling (train and test datasets) took 12h of human work. This
179 time can as well be reduced with the use of active learning methods(Qiu *et al.*
180 2016). Using our method, with accurate knowledge of the imaged species, a
181 dataset achieving 90% precision requires less than a day of work and is
182 applicable by small research teams working on custom datasets.

183 **4.2. Interaction and predation definition**

184 In the current research, we assessed interactions between two individuals as the
185 overlapping of bounding boxes. A source of error while studying interactions is
186 the confusion between species of similar size and general morphology. The high
187 number of interactions between *P. radoszkowskii* and *S. geminata*, for example,
188 was an artefact mostly due to confusion between the two classes. In images

189 displaying an *S. geminata* attack on *Metamasius* larvae, 1050 of 9436 *S.*
190 *geminata* were also incorrectly detected as *P. radoszkowskii*, resulting in the
191 generation of false positives. These confusions mostly occur in complex, crowded
192 scenes, which are difficult to assess even for a human observer (see Figure 5).

193 **4.3. Robustness of the method**

194 One problem facing deep-learning methods, especially with small datasets, is
195 overfitting. Here, despite the limited amount of training data, our model was not
196 overfitted, as indicated by the test loss to training loss ratio and the test
197 performances. Our model is robust partly as a consequence of the slicing of the
198 original image. With the slicing of original images, the model does not learn
199 directly from the original images but from the slices after pre-processing (with
200 our example parameters, this means a 108 times larger dataset). Furthermore, a
201 vast majority of the slices show background that provides various details and
202 shapes at a precise level (branches, soil particles, etc.) that could have been
203 confounded with invertebrates. These details are learned by the model and
204 reduce possible confusion. This effect could be associated with hard negative
205 mining, which has been a successful strategy to improve neural network
206 performance (e.g. Ogier Du Terrail & Jurie 2017; Sun, Wu & Hoi 2018). Data
207 augmentation is also important for ensuring robustness (Godfellow *et al.*, 2016),
208 particularly with small datasets. Performances and robustness of the model
209 depends on the dataset but the use of high-resolution images and slicing ensures
210 a relative robustness even for small datasets.

211 **4.4. Further improvements**

212 To reduce the risk of false positives and false negatives (especially when dealing
213 with unknown species), hierarchical classification approaches could be
214 developed. These methods are a known technique to improve model

215 generalisation and have been shown relevant for handling biological data
216 (Redmon & Farhadi 2016; Colonna, Gama & Nakamura 2018).

217 In our example dataset, images were taken with short time steps and are not
218 independent, leading to a possible bias in the frequency of interactions. This bias
219 could be overcome by the tracking of individuals over multiple images (e.g. see
220 Romerri-Ferrero *et al.* 2019).

221 **5. Acknowledgements**

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223 Investments for the Future Program, referred as ANR-16-CONV-0004. The Ph.D.
224 thesis of P. Tresson was funded by CIRAD and #DigitAg grants.

225 **6. Author contributions**

226 Pa.T., D.C., Ph.T., and W.P. conceived of research idea. Pa.T. implemented and
227 evaluated the methods and led the writing of the manuscript. D.C. and S.R.
228 conducted the field study. D.C., C.P., and Pa.T. contributed to the labeling task.
229 L.B.B. initiated the project. All authors contributed critically to the drafts and
230 gave final approval for publication.

231 **7. Data accessibility**

232 [Code is available on Github]

233 [Dataset will be available online on CIRAD Dataverse <https://dataverse.cirad.fr/>]

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281

282 **Table 1.** *AP per super-classes. This underlines a limitation of the use of deep*
 283 *learning with small datasets, as class imbalance can lead to poor performances*
 284 *on rare classes. See Table 1 in Supplementary Material 3 for detailed results on*
 285 *all classes.*

Super-classes	Classes	Training examples	Test examples	AP (\pm SD)
Ant	10	1467	1395	0.84 \pm 0.29
Cockroach	3	35	31	0.18 \pm 0.15
Egg	1	89	85	0.85 \pm 0.00
Larva	1	296	294	0.94 \pm 0.00
Slug	2	16	14	0.63 \pm 0.55
Spider	6	18	14	0.64 \pm 0.50
_Weevil	1	173	167	_0.90 \pm 0.00

286

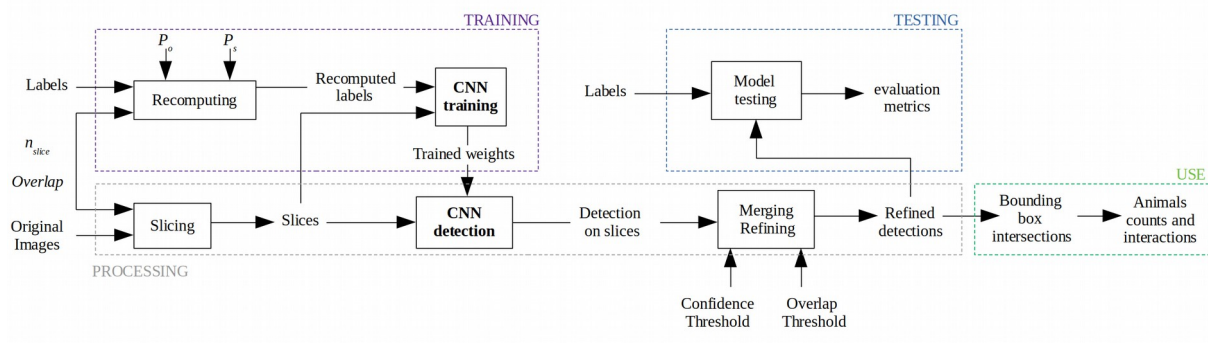
287

288 **Table 2.** Mean (\pm SD) numbers of predators surrounding an individual sentinel
 289 prey (\pm standard variation) as detected by automated image analysis. The values
 290 in parentheses (*n*) are the number of predation events recorded between the two
 291 species. *msp* = morphospecies, and *Na* indicates cases where predator was not
 292 detected in interaction with the prey.

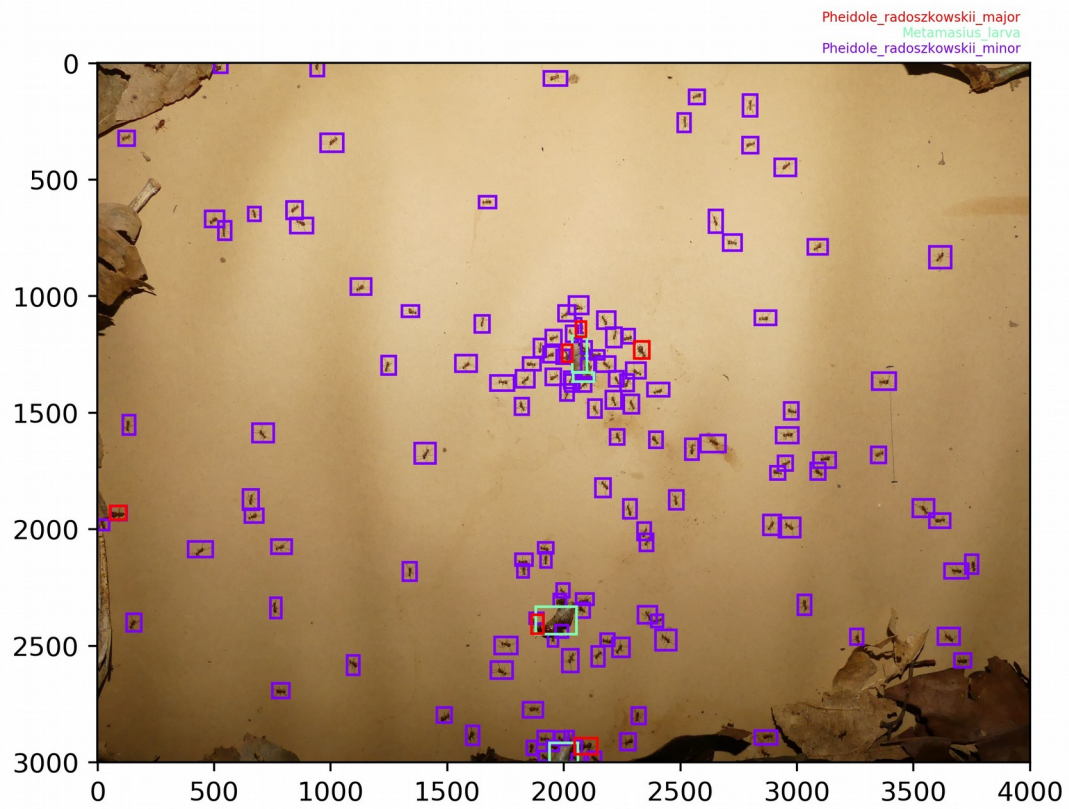
Predator	Metamasius larva (<i>n</i>)	Cosmopolites sordidus carcass (<i>n</i>)	Cosmopolites egg (<i>n</i>)
Blattidae <i>msp1</i>	1.05 \pm 0.22 (19)	1.00 \pm 0.00 (2)	<i>Na</i>
<i>Camponotus atriceps</i> minor	<i>Na</i>	1.00 \pm 0.00 (6)	<i>Na</i>
<i>Camponotus atriceps</i> major	<i>Na</i>	1.00 \pm 0.00 (1)	<i>Na</i>
<i>Nylanderia msp1</i>	1.00 \pm 0.00 (1)	1.00 \pm 0.00 (3)	<i>Na</i>
<i>Odontomachus bauri</i>	1.16 \pm 0.37 (6)	1.00 \pm 0.00 (10)	<i>Na</i>
<i>Pheidole radoszowskii</i> minor	3.03 \pm 2.25 (153)	1.03 \pm 0.16 (35)	<i>Na</i>
<i>Pheidole radoszowskii</i> major	1.37 \pm 0.61 (45)	1.00 \pm 0.00 (2)	<i>Na</i>
<i>Solenopsis geminata</i> minor	3.47 \pm 2.05 (120)	1.94 \pm 0.46 (347)	1.00 \pm 0.00 (2)

293

294

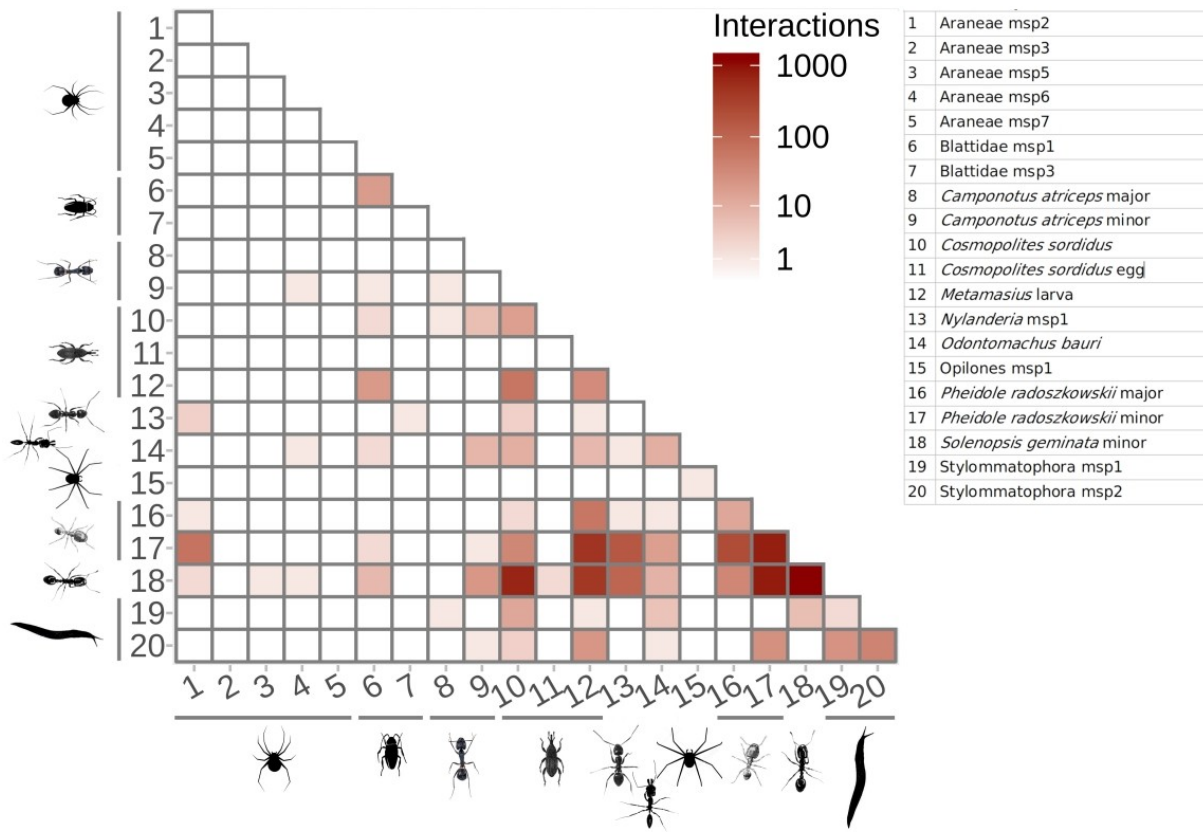


296 | **Figure 1.** Overview of the proposed method.



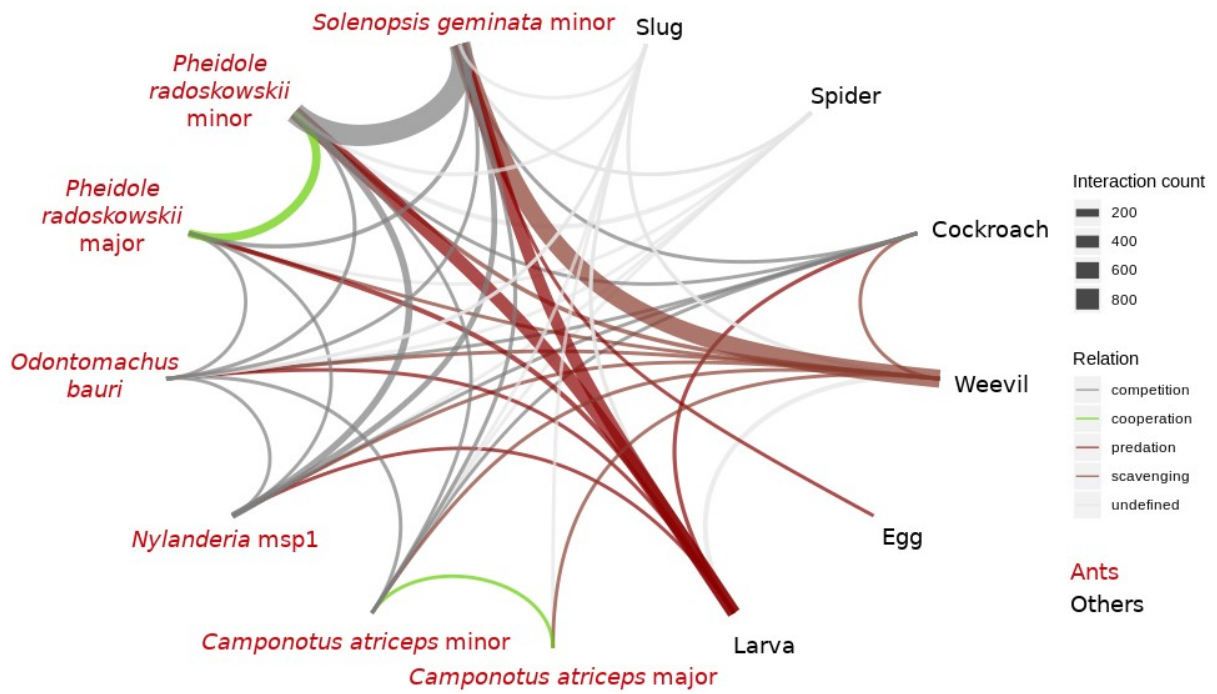
298 **Figure 2.** Output of the pipeline for an image of the test dataset. Values on x
 299 and y axes are pixel coordinates.

300



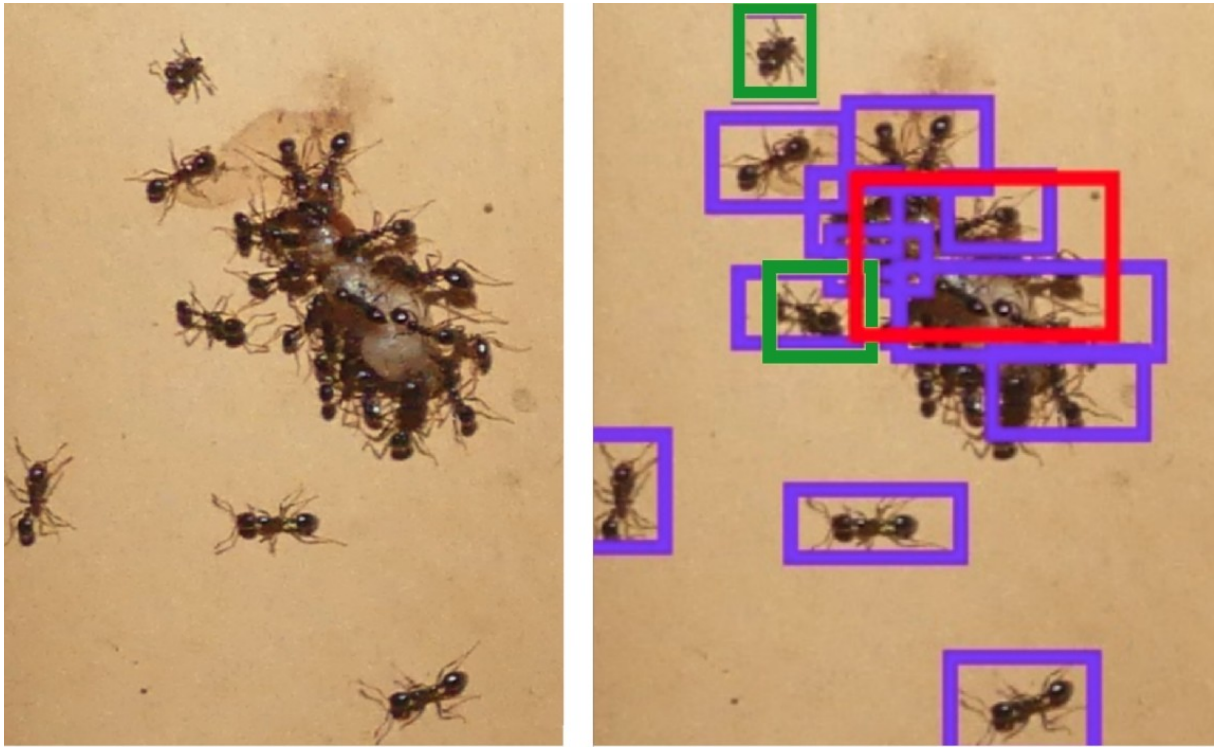
301 **Figure 3.** Interaction matrix showing interactions on our example dataset.

302



303 **Figure 4.** Trophic and non-trophic interaction network between species of the
 304 observed community.

305



Pheidole radoszkowskii minor
Solenopsis geminata minor
Metamasius larva

306 **Figure 5.** Example of complex situation leading to misclassifications, FP and FN.
307 Some minor worker of *Solenopsis geminata* were confused with minor worker of
308 *Pheidole radoszkowskii*, another species of the *Myrmicinae* subfamily and of
309 similar size.