Taxonomic classification of ants (Formicidae) from images using deep learning

Marijn J. A. Boer [1,2,*]

Abstract
The diverse and species rich group of ants consists of important biodindicators for ecosystem health and could be surrogates for overall species richness, but identifying ant species is hard and requires specialists. In the field of computer vision, machine learning has shown promising results in species identification and could greatly speed up and improve taxonomic accuracy. While previous work has been conventional in that features needed to be extracted, here, deep learning (in the form of a convolutional neural network) is proposed to learn features automatically in order to classify ant species. Such a system could answer whether ant species could be discriminated using deep learning, insight that will be contributed to Naturalis's broader computer vision project. The use of ant images will also raise questions on the use of different castes and different image shot types, which will be combined to a multi-view approach. For a more scalable approach a dataset with the 97 most imaged species (10,204 images) has been harvested from AntWeb. The dataset shows little difference in shot type, but there is a problematically large distribution on the width of the image dimension which has to be solved before training. Still undecided, there are two options for training and validating the classifier; (1) use an existing, already promising CNN or (2) design an CNN and start simple, expanding after each evaluation. After training the network is evaluated using a top-1 and top-5 accuracy test and hopefully even classify morphospecies to valid species.

Keywords
Convolutional Neural Network — Image Classification — AntWeb — Ants — Formicidae

1 *Rutger Vos Lab, Endless Forms, Naturalis Biodiversity Center, Leiden, Pesthuislaan 7, 2333 BA, Leiden, Netherlands*
2 *Masterstudent Biology; Evolution, Conservation and Biodiversity, Institute of Biology Leiden, Sylviusweg 72, 2333 BE, Leiden, Netherlands*
*** Corresponding author**: marijn.boer@naturalis.nl

1. Introduction

1.1 Taxonomy and the ants

The family of the ants (*Formicidae*) is a large and diverse group within the insect order, sometimes exceeding other groups of insects in local diversity by far. They are globally found (with the exception of Antarctica) and play an important role in a lot of ecosystems [1]. To get a good understanding of their role in ecosystems, it is important to have information on their species richness and other indicators of diversity. With this information, ants can also act as a biopredictor for the health of ecosystems, which is in return important for species conservation [2]. Furthermore, arthropods are found to be good surrogates of predicting species richness patterns in other groups of animals [3]. This may even be possible using morphospecies as taxa [4], but for that you still need a species concept.

Understanding which species there are, is complex and specialists are generally required for correct identifications. Ant taxonomists use distinct characters, sometimes varying for genus and species, to identify species. Examples of these characters are antennae, hairs, carinae, thorax shape, shininess of the body. And still, it is difficult to identify species correctly, because for example (1) some ant species are very cryptic or sibling species, (2) species have different castes and intercastes and (3) male individuals are underrepresented in descriptions and collecting.

1.2 Computer Vision

Research in the field of computer vision shows prior art on insect identification from images. Wang et al. [5] designed an identification system to identify insects at the order level, including ants. They used 7 geometrical features in their system and accuracy reached 97%. In other research the wing outline is used for insect identification [6]. Automating identification could greatly speed up taxonomic work and improve accuracy [7].

Automatic identification on species level has been subject of research for a while now. Machine learning (ML) is applied on morphometrics of butterflies [8] with success. This was also done, using

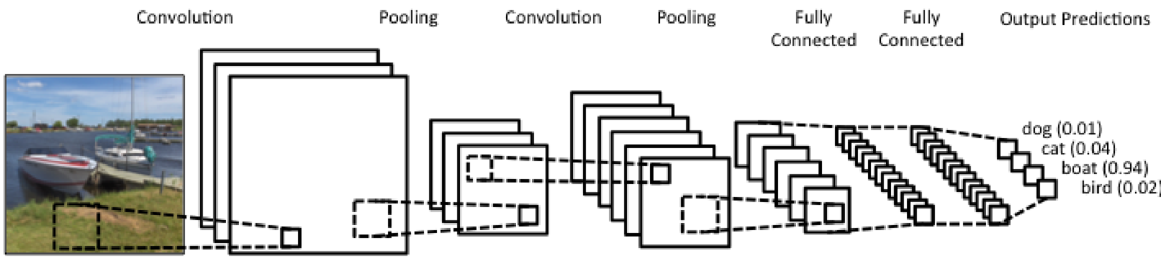

Figure 1. A simple representation of a Convolutional Neural Network. Source: clarifai.com/static/images/cnn.png

wing morphometrics of honey bees [9, 10]. And it is not limited to insects or even animals, as researchers designed a system to automatically identify 184 American trees using leaf morphometrics and color distributions with great success [11]. Others found that it was possible to use ML for classifying orchid species [12, 13]. Almost all of previous research exploit metrical features and morphometrics, but this still would need the guidance from a human.

1.3 Deep learning

This is were deep learning (DL) is a more promising identification tool. In the past 5 to 7 years, DL attracted lots of attention in research and methods and algorithms have greatly improved [14]. DL allows a machine to learn features by itself, instead of conventional ways where features need to be introduced to the machine [14, 15]. DL has shown to perform much better when looking at multiple features, instead of a single one, as in conventional ways [16]. A successful DL algorithm is the convolutional neural network (CNN), mostly used for image classification and preferably trained using GPUs. These computationally intensive networks are designed to process (convolve) 2D data (mainly images), using typical layers as convolutional and pooling layers [14]. A typical and simple representation of a CNN can be seen in Figure 1 on page 2. In a few years CNNs have advanced a lot [17] and different studies have shown promising results. CNNs have been used in plant identification identification [18, 19], plant disease detection [20] and even identification of underwater fish images [21], all with promising results. A more practical example is the classification of different qualities of wood for industrial purposes [22]. However, as promising as it sounds, DL still has some (mostly non-programming) obstacles to overcome [23]. *(Discussion? → Impact on taxonomic research? → Automation of species identification. What will it do to taxonomy and collections? [7, 24, 25]).*

1.4 Paving the way

The aim of this research is to explore the possibilities on automatic insect identification using DL. Because of these rapid improvements in deep learning, a convolutional neural network is proposed for automatic species identification. This research uses a difficult dataset, ants (in contrast e.g. to colorful and pattern-rich butterfly), but if it shows promising results, it could potentially pave the way in insect classification. Furthermore, it could hopefully benefit Naturalis' goal of initializing an image classification system for own use. In order to also explore the CNN-field a trial will be started to incorporate a "three type view per specimen" approach. Almost all imaged specimens on AntWeb follow the same procedure of head, dorsal and profile shot type images. The combination of these three images per specimen could potentially produce a higher accuracy than when using only one image, just because there is more data to train on. Because this is a fairly new and undiscovered field, with only 2 articles found so far [26, 27].

Some questions have to be answered so a promising CNN can be designed that classifies images of ants, but the main research question is *"Can ant species be discriminated from images using deep learning?"*. To answer this question, subquestions need to be answered while exploring subsets of the data. Three important subquestion will be if (1) *"three shot types are classifying the species more accurately than a single shot view?"*, or (2) *"which shot type will classify species more accurately?"* and (3) *"which image quality has the best accuracy vs.*

training speed?". In relation to the image quality there is also a image dimension problem, as not all images have the same width.

And then there is the problem of different castes. Will there be any problems using males, queens or workers; alate (winged) or dealate (non-winged) queens; major and minor workers; ergatoid and intercastes specimens? Ergatoids (productive) and inter-castes (non-productive) denotes the wingless individuals that look like the intermediate of a queen or male and a worker [28]. And what happens when morphospecies are incorporated, as they could be viewed as real species. Once the network is running with fair accuracy, how will it handle *indet* species? Most of these problems can be overcome, but there are others that can not. AntWeb has amber resin and fossil specimens, specimens with broken or lost body parts (e.g. antennae), and even some incorrect identifications. For example, there is debate on North American and European *Lasius spp.* [29].

Programming code and documentation will be available for open access (MIT licensed) and published when the project is finished on URL: `github.com/naturalis/FormicID`.

2. Proposed Approach & Methods

The first trials will be on a relatively small dataset with a simple neural network to make the project more scalable and research more comprehensible. After evaluation of these results, new elements can be added to increase complexity and answer more complex questions. Each time after training where success is reached, extra dimensions of training data can be added. The following points line up examples of additions for increasing the complexity of this research:

- Use RGB images instead of grayscale
- Increase in image quality from low quality to medium quality
- Using all the valid species on AntWeb
- Including morphospecies
- Including alate queens and/or dealate queens and/or males and/or ergatoid specimens
- combining head, profile and dorsal shot views as a multi-view experiment

2.1 AntWeb

The data for this research is administered on the web page of AntWeb (URL: `antweb.org`), a website that provides a considerable amount of information on the incredible diverse group of ants (Formicidae) [30]. The website has an extensive and well documented database of ant records. Specimens are, among lots of other things, taxonomically classified, ecologically documented and imaged, almost all with superb accuracy and finesse. Data from AntWeb can be accessed using the websites API (version 2 [31] or version 3 beta [32]). Using programming scripts the catalog number, scientific name, shot type and the images for a specimen is harvested. AntWebs API version 2 doest not support to filter for different castes when harvesting information, but with the updated version (version: 3 beta) it should be possible. At the moment version 2 is used, so all castes are represented when scraping images, which could give rise to problems. Furthermore, images on AntWeb are, for a significant part, all divided in 3 shot types per specimen; head, dorsal and profile views. Because of server restrictions images have to be downloaded in batches. AntWeb provides 4 different qualities of images, from lowest to highest; low, medium, thumbview, high. A representation of a species can be seen in Figure 2 on page 3.

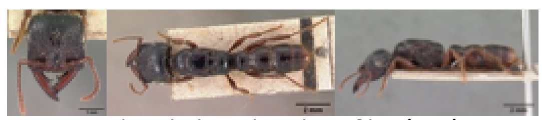

Figure 2. A head, dorsal and profile view image of *Amblyopone australis*. Images are in color and downloaded at the lowest quality.

2.2 Data preparation and processing

The first dataset for this research needed to be comprehensible, so a start can be made on the architecture of the neural network and fine-tuning all the algorithms. Images need to be in a grayscale format, evenly sized, correctly named and organized. Below a description is given on the first created dataset for this research, in order to compute a neural network and get preliminary results, before adding extra information to increase complexity.

2.2.1 *FormicID-97*

This first dataset, called *FormicID-97*, was made to have about 100 species (or classifiers). After ranking the most imaged species (combined for head, profile and dorsal views) a cut was made around a 100 species for a number of images. At this cut, the lowest ranking species had 68 images and the cut needed to be made at 101 species. This accounted for 10,225 AntWeb images. Out of these 101 species, 4 species were actually not representing real species, but the aggregated records of specimens that could not be identified to species in that genus. These groups were *Camponotus indet, Cremagotaster indet, Pheidole indet* and *Polyrhachis indet* and they were removed from the dataset, because it is unknown to see which species these specimens represent and even if they are the same species. Furthermore, a total of 21 specimens did not have valid URL's to images therefore could not be downloaded automatically. The dataset ended up with 97 species and a total of 10,204 images, which were downloaded to a directory and correctly named. All images were downloaded in color, at the lowest quality available. Images will be converted to grayscale speed up training in the first few trials.

The distribution of these species is shown in Figure 3 on page 5. This dataset is made up of head, profile and dorsal shot images of these species, but this is not evenly distributed as can be seen in Figure 4 on page 6. The dataset still needs to be filtered on castes, to get a worker only dataset.

Image height is at a constant 122 pixels for all images, but image width varies a lot as can be seen in Figure 5 on page 6. This problem could be potentially be solved using 1 or more of three methods. The first option is to squash the image to a square and thereby have all the images in the same dimensions. This would however change the shape of species, which could be an important classifying factor. The next option is to keep the aspect ratio, but to crop the image to the center using a set height and width. But this could erase parts of the body. The last option is to add black borders (i.e. zero's) on the image and then crop to get the desired height and width. The problem here is that this would add noise to the dataset, which the network would need to learn to ignore. The choice for one of these methods has not been made yet.

The file sizes are distributed rather normally around are around 20 kilobytes (Figure 6 on page 6). At the moment of writing all *FormicID-97* images are downloaded. The dataset will to be cleaned of non-workers castes and of problematic images. Then all images will be converted to grayscale images and resized to all have the exact same size. In order to increase the dataset, image augmentation can be applied, meaning that copies of images will be shifted, rotated and flipped vertically and added to the dataset.

In the first experiment *FormicID-97* will be split in three groups: head, profile and dorsal shots. This will ensure that the network is only training on a specific shot type and can not get confused by multiple views of a species. Results will show which shot type will better classify an image at species level. At this moment the dataset contains all types of castes; workers, alate and dealate queens, males and possible ergatoid or intercaste specimens. The combination of workers, queens and males will probably already make classification more complicated, but adding these intermediate forms will increase this even more.

For training purposes the 3 shot type-datasets will be split in training, validation and test sets, respectively in an 8:1:1 ratio, while keeping the species ratios intact.

2.3 Network architecture

All programming will be written in Python 3.6. For deep learning Keras will be used[33], with Tensorflow as backend [34]. There are two options in using a convolutional neural network (CNN).

1. The first option is to use an existing and promising CNN. There are multiple candidates for this and they all try to better the other. Below is a list of candidate CNNs:
    - *Resnet* [35]
    - *Inception-v4* / *Inception-ResNet* [36],
    - *DenseNet* [37]
    - *Xception* [38]
    - *GoogleNet* [39]
    - *VGGNet* [40]
2. They other option is to build a new neural network. This networks architecture will start as a relatively simple 3 layer network.

Furthermore, when designing a network there are a lot of things one need to think about. Below is a list of design choices that are made for this research. For now these are with reservation.

- Programming the network in Keras [33] using Python 3.6
- Use dropout [41]
- Choose NADAM as optimizers[42] (other possible optimizers are ADAM [43] or SGD [44, 45]
- Use Batch normalization [46]
- Perofrm parameter optimization [47]
- Visualizing the CNN architecture [48, 49, 50]
- Validation of network using different methdos (e.g. KNN or k-Fold cross-validation)

2.4 Testing network

The network will be tested for best top-5 accuracy and top-1 accuracy using the trained network. If

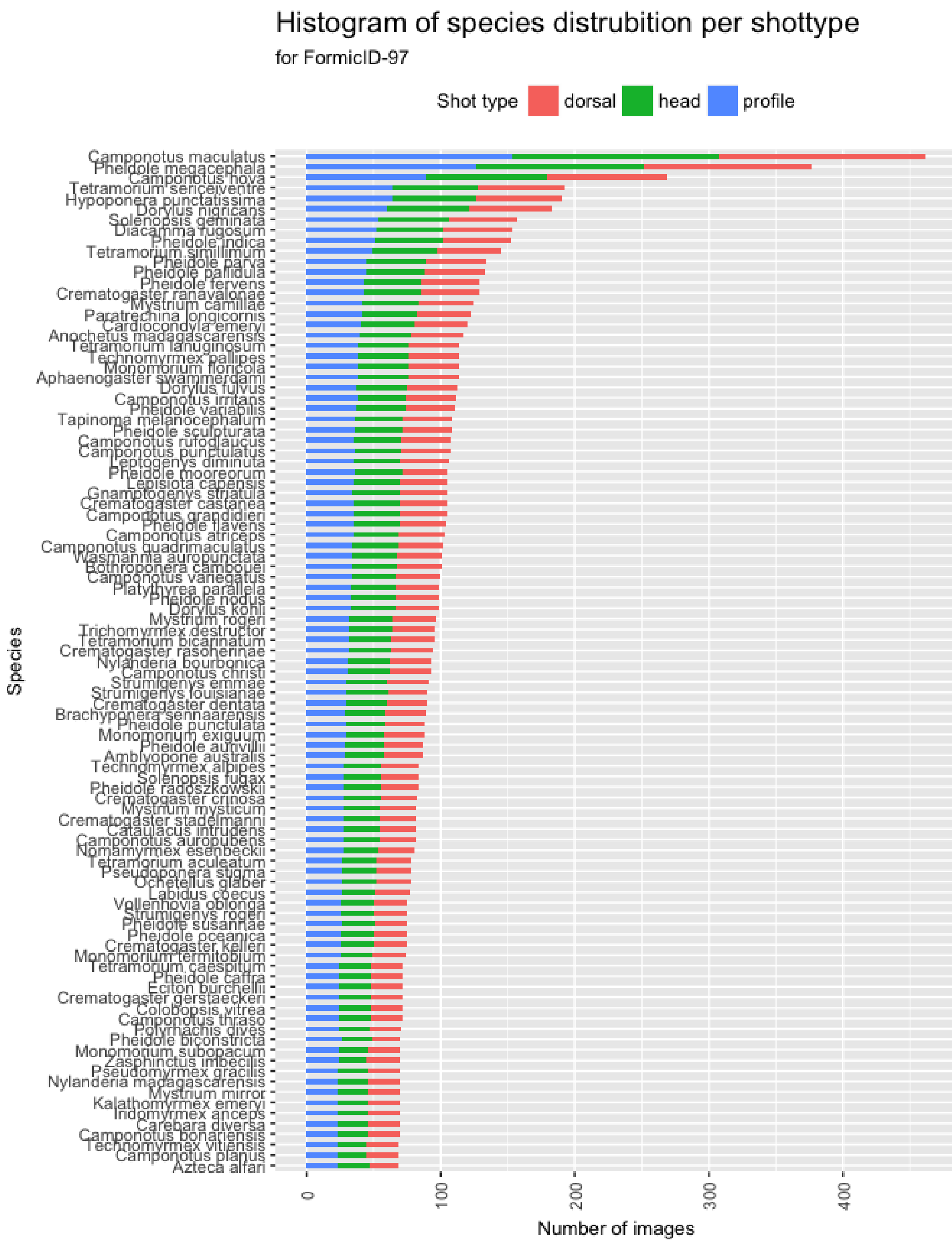

Figure 3. Histogram showing the distribution for the 97 most imaged species. Images are divided in dorsal (red), head (green) and profile (blue) views. Distribution ranges from the most imaged *Camponotus maculatus* with 462 images to *Azteca alfari*, *Camponotus planus* and *Technomyrmex vitiensis* with 68 images.

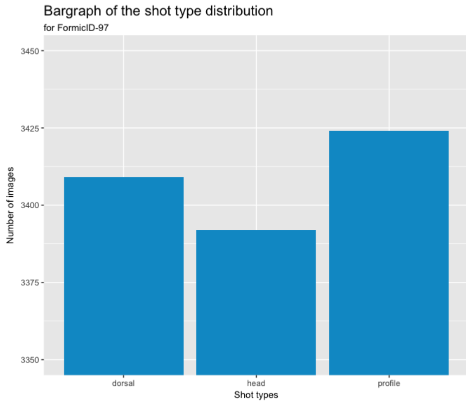

Figure 4. Bargraph showing the distribution for different shot types for the *FormicID-97* dataset. The y-axis is zoomed in from 3350 to 3450 in order to see a difference, but in fact the difference is very small.

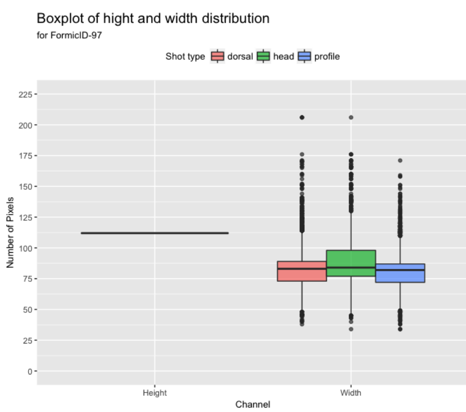

Figure 5. Boxplot showing the distribution for the number of height and width pixels for the *FormicID-97* dataset. Height is the same for all image, at exact 122 pixels.

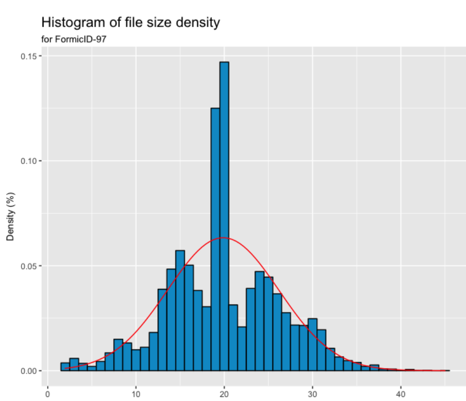

Figure 6. Distribution of the file size of the file sizes of all the RGB images from *FormicID-97*. The mean is 19.88 Kb.

accuracy is high *indet* species could be tested to see which species they could represent.

2.5 Timeline

Figure 7 on page 7 shows the time schedule for this internship. The project start was on September 25th, 2017 and the deadline is set on July 31th, 2018. The proposal deadline is on is February 6th, 2018, accompanied by the proposal presentation. The end presentation will be planned later on. In December, 2017 the project was on a pause for 6 weeks for the purpose of education (course: Methods in Biodiversity Analysis - Leiden University) and a 2 week vacation. The timeline shows different parts of this project per week and in some weeks, subjects overlap, meaning that work will be combined or split in that week.

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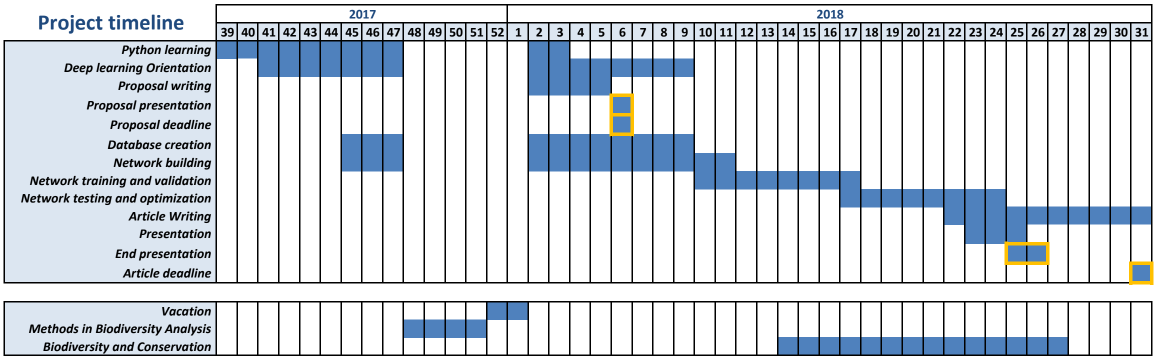

Figure 7. Timeline of the project. Orange boxed weeks represent deadlines. The bottom three parts of the timeline are not part of the actual project.

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