Landmarks prediction on Beetle anatomical by applying Convolutional Neural Network

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Abstract

In morphometric studies, landmarks are regarded as one of important properties to analyze the object's shape. Especially in biology, collecting complete landmarks give us the information of the oganism. From that, the biologists can study the complex interactions between evolution of the oganism and environment factors. In the context of this study, we focus on one of the most common insect of North-Western France, Carabidae (Beetle). Landmarking manually will be a time-consuming process. In order to investigate the posibility of automatic identify the landmarks on Beetles, we propose a convolutional neural network (CNN) to predict the landmarks on the parts of Beetle: pronotum, head, and body. The proposed model will witnessed on the datasets includes 293 images (for each part) in different sizes. The experiments will be done in two directions: training the model from scratch and using fine-tuning. During the experiments, the coordinates of automatic landmarks will be evaluated by comparing with the manual coordinates, which are given by the biologists.

1 Introduction

Morphometric landmarks are important features in biological investigations. They are use to analyze the shape of the organisms. Depending on the organisms, the number of landmarks on their shapes is different. When we consider the position of the landmarks with the shape, most of landmarks are located on the edges, for example, the landmarks on wings of Drosophila fly [**?**]. Besides, we can also see the landmarks which stayed inside the anatomical part, i.e, landmarks on pinna of human ears [**?**]. Currently, the landmarks are set manually by the biologsits. However, landmarking manually will be a time-consuming process and difficult to pre-process. Consequently, a process that proposed automatically the coordinates of landmarks could be interested.

In image processing, segmentation is a most often step of the methods. In some cases, the object of interest is easy to extract and can be analyzed with the help of a lot of very well-known image analysis procedures. The result of segmentation step is very useful for many purposes. Depending on purpose of the applications, the object can be segmented or un-segmented before continuing the futher steps. Landmarks setting is no different. In a previous study [**?**], we have analyzed two parts of beetle: left and right mandibles. These parts are easy to segment. In that work, we have applied a set of algorithms based on segmentation, image alignment and SIFT [**?**] to detect the landmarks on mandibles.

Unfortunately, the images of other parts are not simply as the mandibles. Besides the main objects, we have also the different parts, i.e, we have a part of head and the legs in pronotum images. The image becomes very noisy. If we would like to segment the object as traditional processes, the process may have consumed a lot of time and difficult to choose a proper method.

This is the reason that we turn the landmarking problem on some parts of beetle (i.e, pronotum, head, and body) to a way of analyzing images without the segmentation step.

As the beetles have not been dissected, their anatomical parts have not been set apart. So image segmentation of each part, as they are still attached to the whole specimen, is problematic and has been given up. Coordinates of manual landmarks for each part have been provided and are considered as the ground truth to evaluate the predicted ones by our methods. Fig.1 shows the parts of beeltes and their manual landmarks what we are looking for.

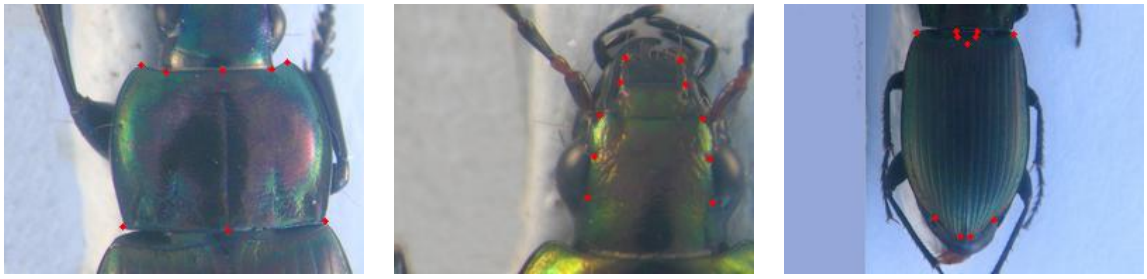


Figure 1: The dataset images with their manual landmarks.
From left to right: pronotum, head, and body

To achieve the landmarks prediction, we have proposed a CNN model [**?**] by using Lasagne library [**?**]. In the first evaluation, the proposed model has been trained from scratch on the dataset of each part. In the second step, the evaluation has been modified to use a fine-tuning [**?**] stage.

Our contributions in this study are as follows: In the next section, we present the related works about automatic estimation landmarks on 2D images. The architecture of proposed network will be presented at section **??**. In section **??**, we describe the process to augment the dataset. All the experiments of our model will be shown in section **??**. It includes the results to evaluate the model and comparison between two working strategy on neural networks.

2 Dataset

The data includes images in three sets of the beetle: pronotum, body, and head (Fig.2). Each dataset includes 293 color images. For each dataset, the images are divided into two subsets: training and validation (called training set) include 260 images, and the testing set has 33 images. To have enough images for training process, the training sets have been combined together. Then, the training dataset was enlarged to 5460 images (1820×3) following the way that we change the values of pixels on the images. At this time, we have enough the images for training. However, another problem has occurred: the number of landmarks of each part is different: 8 landmarks on pronotum part, 11 landmarks on the body part, and 10 landmarks on the head part. We see that the trained model will be fine-tuned on pronotum dataset. So, we kept the number of the landmark on pronotum as a reference and we suppress some landmarks on body and head part. Specifically, we have removed *three* landmarks on the body part ($1^{st}, 6^{th}, 9^{th}$) and *two* landmarks on the head part ($5^{th}, 6^{th}$).

3 The model

In this study, we use the model that we have used to train on pronotum dataset. The network consists on three repeated-structure of a convolutional layer followed by a maximum pooling layer and dropout layer. The depth of convolutional layers increases from $32, 64$, and 128 with different size of the filter kernel: $3 \times 3, 2 \times 2$, and 2×2. All the kernels of pooling layers have

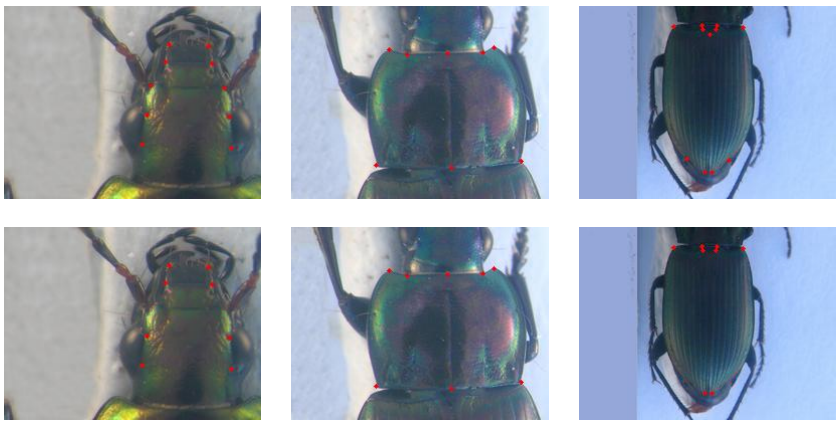


Figure 2: The dataset images. *Top row*: The images with their manual landmarks. *Bottom row*: The training images (some landmarks have been removed on head and body parts)

the same size of 2×2. The dropout probability values used for dropout layers are $0.1, 0.2$, and 0.3. Then, three full connected layers have been added to the network. A dropout layer with probability of 0.5 was added between the first two full connected layers. The outputs of the full connected layers are $1000, 1000$, and 16, respectively. The output of the last full-connected layer corresponds to 8 landmarks (x and y coordinates) which we would like to predict (Fig. 3).

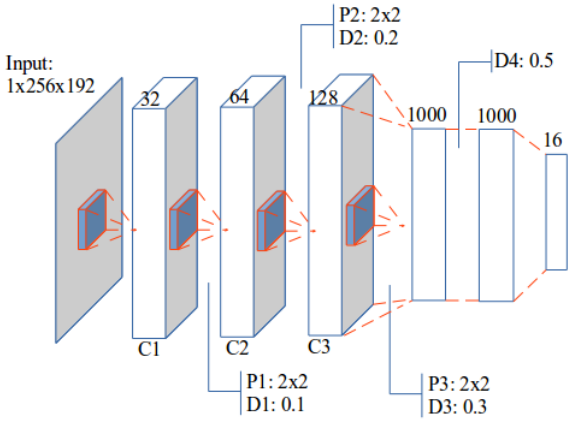


Figure 3: The architecture of CNN model

The parameters of CNN are shown in Table.x.

Parameter	Initial value	End value
Epochs	10000	
Training batch size	128	
Testing batch size	128	
Learning rate	0.03	0.0001
Momentum	0.9	0.9999

Table 1: The network parameters in proposed model

4 Experiments

4.1 Training on three parts of beetle

The dataset includes 5460 images was trained on the model with 10000 epochs[1]. The images are randomly divided into training set and validation set followed the ratio 6 : 4. The learning rate began at 0.03 and decreased to 0.00001 during training. In vice versa, the momentum started at 0.9 and increasing to 0.999 at the end of the training process.

Fig.4 shows the losses during training process. At the beginning, the validation loss is always higher than the tranining loss, but from the 2000 epochs, the training loss begins stable while the validation loss continue to decrease. At the end of training, the losses values are 0.00029 and 0.00009 for training and validation, respectively.

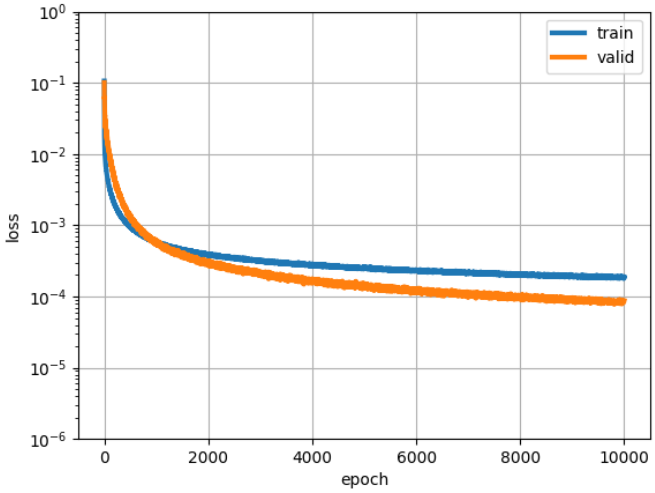


Figure 4: The losses during training on the images of three parts

Fig.5 shows the predicted landmarks on some images in test set.

4.2 Fine-tuning on pronotum dataset

The trained model have been continued to fine-tune [1] with pronotum dataset. To get all predicted landmarks for the pronotum images, a scenario to choose the test images is executed. For each round, we have chosen 33 images for the test set, the remaining images have been put to training test. Table.2 shows the losses during fine-tuning on different dataset of pronotum images.

Fig.6 shows an example of the losses during fine-tuning and corresponding predicted landmarks on the test set.

After fine-tuning, the predicted landmarks of all images are provided. To evaluate the effects of fine-tuning, we calculated the distance between the predicted landmarks and corresponding manual landmarks. A statistic on the distance of each landmarks is also computed.

Table.3 shows the average error distance given by each landmark. The values in **Distance 1** and **Distance 2** columns present for the average distance of all landmark when the pronotum images were trained from scratch and fine-tuning, respectively. From the Table. 3, the result from fine-tuning is significantly improved ($\sim 38\%$)

[1]An epoch is a single pass through the full training set

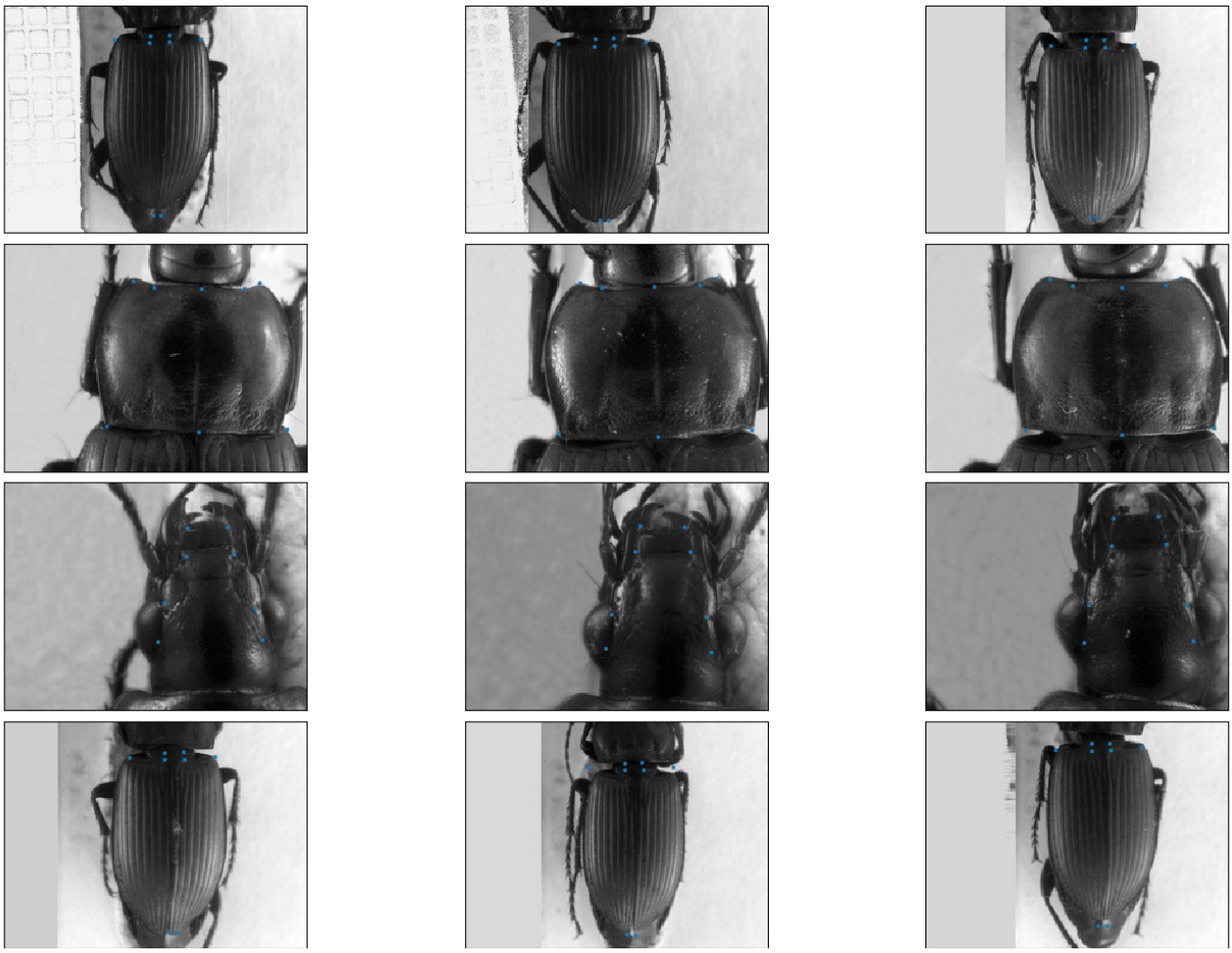


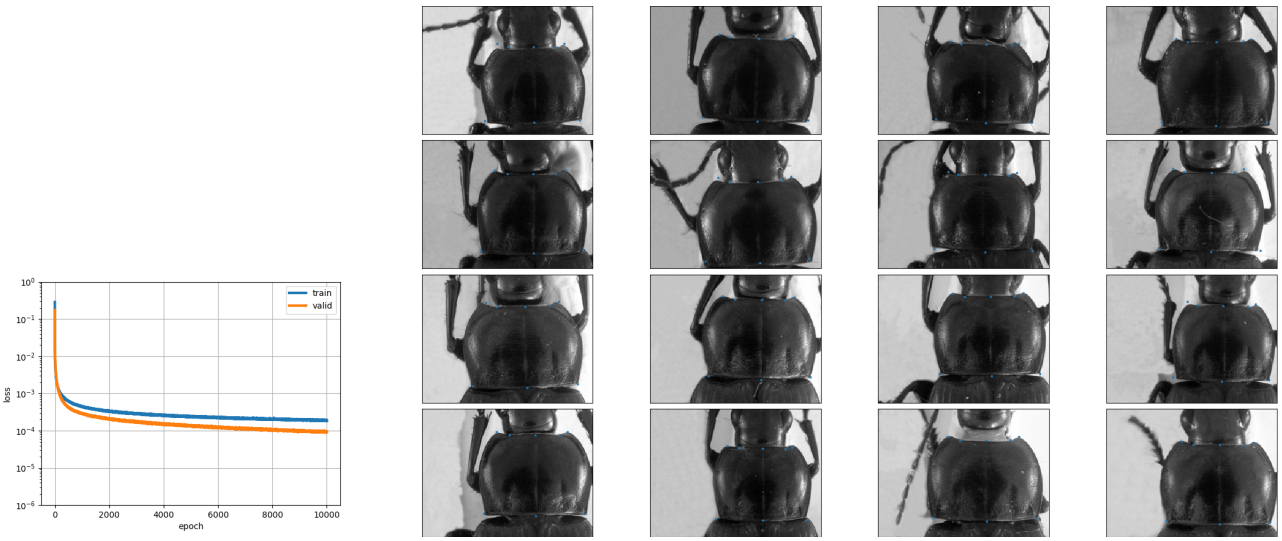
Figure 5: The blue points present for the predicted landmarks on the images in test set

Round	Training loss	Validation loss
1	0.00019	0.00009
2	0.00018	0.00010
3	0.00018	0.00010
4	0.00019	0.00008
5	0.00019	0.00009
6	0.00018	0.00008
7	0.00019	0.00008
8	0.00018	0.00006
9	0.00018	0.00009

Table 2: The losses during fine-tuning model

5 Conclusions

A CNN model has been trained on a dataset that includes the images of three parts of beetle. The trained model then has been fine-tuned with the pronotum dataset. Comparing the losses when we trained the pronotum from scratch, the losses during fine-tuning has been improved 40% on validation test. Besides, the coordinates of predicted landmarks are also more accuracy than the last result (training from scratch) (Table.3). From the result, we can see that fine-tuning has affected to the results from CNN. However, the effects still limits in our case. The



(a) Training losses and validation loss

(b) A pronotum with predicted landmarks

Figure 6: An result example when fine-tuning the trained model on pronotum dataset

#Landmark	Distance 1	Distance 2
1	4.002	2.486
2	4.4831	2.720
3	4.2959	2.652
4	4.3865	2.771
5	4.2925	2.487
6	5.3631	3.049
7	4.636	2.684
8	4.9363	2.871

Table 3: The average error distance per landmark.

experiments of the techniques on fine-tuning need to do to reach to the result as we expect.

References

[1] Jason Yosinski, Jeff Clune, Yoshua Bengio, and Hod Lipson. How transferable are features in deep neural networks? In *Advances in neural information processing systems*, pages 3320–3328, 2014.