Towards landmarks prediction with Deep Network

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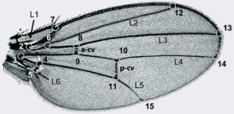
Context

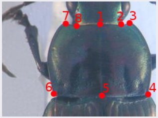
Morphometry analysis

- Used to study the complex interaction between the morphometry of species and environmental factors.
- Characterize information of biological species such as shape, sizes, or **landmarks**,. . . .

Landmark

- A kind of **point of interest**
- A specific point defined by biologist. For example, intersection of veins on fly wing, the corner of beetle's pronotum shape,. . .

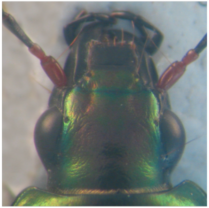




Dataset

- Images have been taken from 293 **beetles**, seperate into 5 parts,
- Format: 2D in RGB color,
- Focus on **pronotum** images.

Body part/elytre



Head part/tete

Pronotum part

Landmark setting

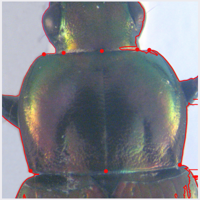
Manual landmarks

- Time-consuming
- Difficult to reproduce

Problems

Pronotum image:

- Not precised: contains also a part of head and body
- Difficult to segment this object
- The landmarks are set both on the shape and inside the object



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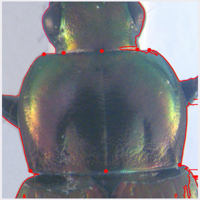

How to automatically predict the landmarks coordinates?

Content

Deep learning

Definition[1]

- A class of machine learning methods.
- Use a cascade of multiple layers for feature extraction and transformation.
- Learn multiple levels of representation in supervised or unsupervised mode.

[1] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, no. 7553, pp. 436–444, 2015

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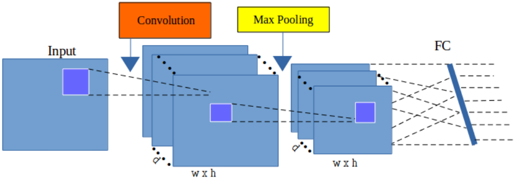
Applications

- Computer vision (image recognition and classification)
- Speech recognition
- Question answering, language translation, . . .

[1] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, 2015

Convolutional neural networks

- Consists an input, an output and multiple hidden layers[1]
- Arranges the data in 3 dimensions: *width, height and depth*
- Classical layers: **convolutional** layers, **pooling** layers, **dropout** layers, **full-connected** layers, . . .

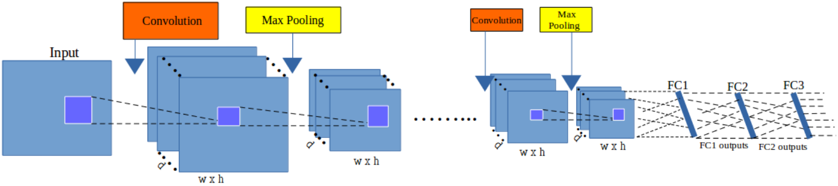


[1] Y. LeCun et al, "Convolutional networks and applications in vision", 2010.

First architecture

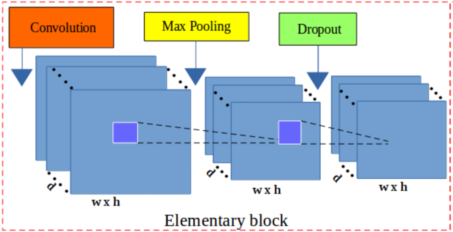
The first applied networks:

- Repeat the pair of convolutional and maximum pooling layers
- Trying to adjust the parameters of the layers



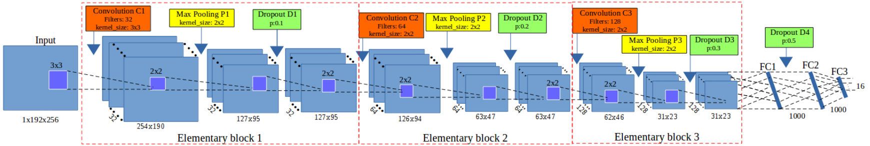
Elementary block:

- A **convolutional** layer
- A **maxixum pooling** layer
- A **dropout** layer



The proposed model:

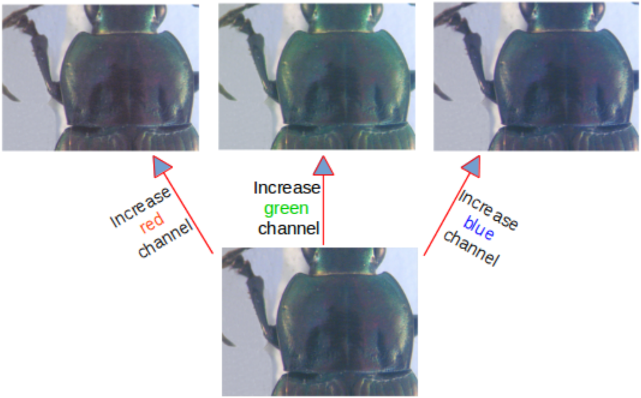
- **Three elementary blocks**
- **Three full-connected** (FC) layers
- A dropout layer was inserted between the first and the second FC layer



Data augmentation

Dataset: 293 pronotum images in RGB format.
Augmentation methods:

- Increase the value of each channel



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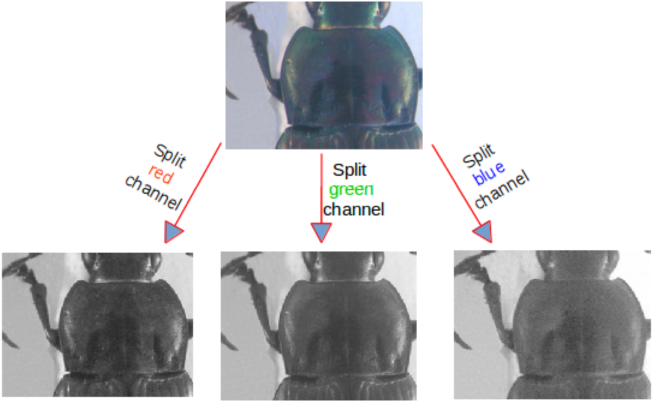
- Split the channels



Data augmentation

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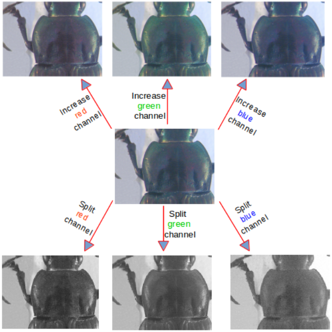
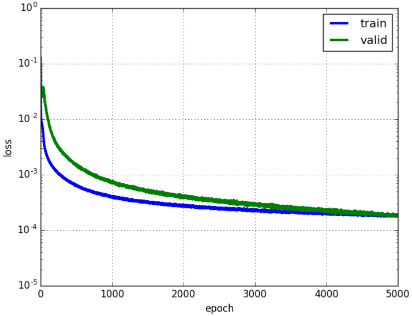
$\Rightarrow$ Total: $293 \times 7 = 2,051$ images



Training

- Training dataset: $1,820$ images (260×7)
- Apply the cross-validation to select training and testing data
- Training parameters: momentum ($0.9 \rightarrow 0.9999$), learning rate ($0.03 \rightarrow 0.00001$), 5000 epochs[1]
- Image shows training and validation losses of the model
- Training time: 3 hours using NVIDIA TITAN X card



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

First results

Correlation metrics and landmarks on the images

- Quality metrics: coefficient of determination (r^2), explained variance (EV), Pearson correlation.

Metric	$\mathbf{r^2}$	**EV**	**Pearson**
Proposed architecture	**0.9952**	**0.9951**	**0.9974**

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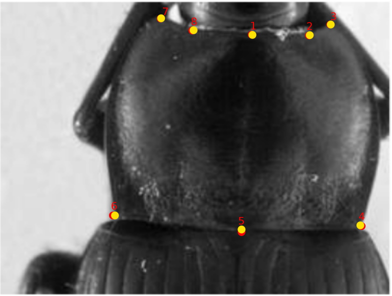
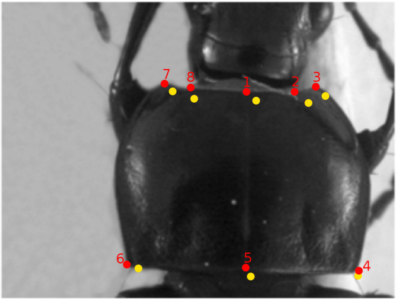
- Display the landmarks on the images:



(a)



(b)

First results
Average distances

- Calculate the distance between predicted landmarks and corresponding manual landmarks.
- Compute the average distance by landmark.

Landmark	**Distance** (in pixels)
1	**4.002**
2	4.4831
3	4.2959
4	4.3865
5	4.2925
6	**5.3631**
7	4.636
8	4.9363

The statistic of average distances on all images per landmark.

Transfer learning/Knowledge transfer

- Re-use model developed for a specific task/dataset to lead another task on another dataset
- **Fine-tuning**: retrain a pretrained model
- **Model Zoo** (Caffe library): people share their pre-trained networks.

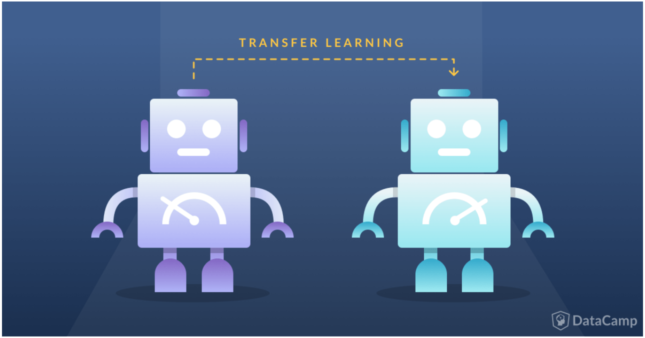
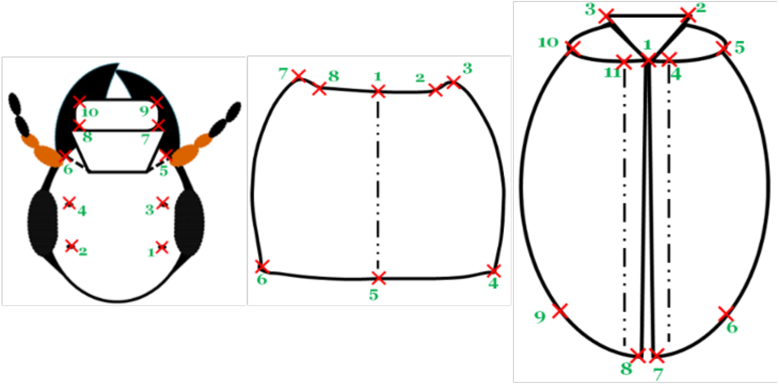


Image source: **DataCamp**

Fine-tuning our model

- Estimated landmarks on pronotum images when fine-tuning on **VGG-16, VGG-19, ResNet50** have not been improved
- Train the model on a dataset including the images of 3 parts of beetles: head, body and pronotum parts **(**5, 460 **images)**
- Fine-tune pretrained model on pronotum dataset



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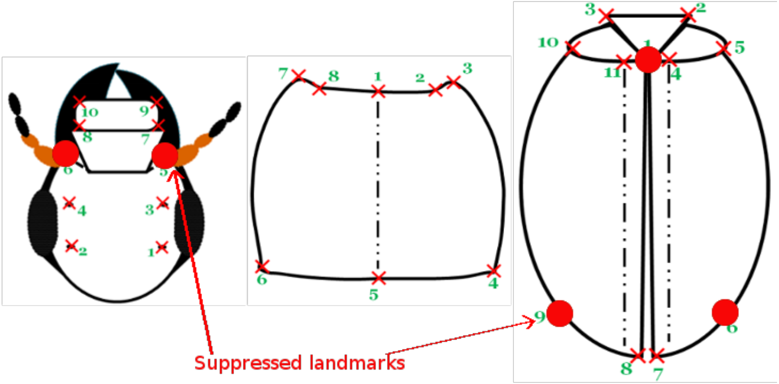
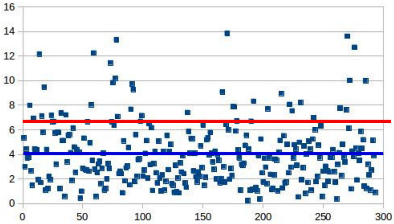


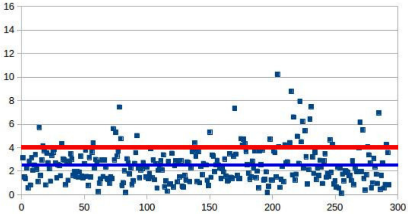
Comparing the average distances between two processes: training from scratch and fine-tuning.

Landmarks	From scratch		With fine-tuning	
	Average	SD	Average	SD
LM1	**4.002**	**2.5732**	**2.486**	**1.5448**
LM2	4.4831	2.7583	2.7198	1.7822
LM3	4.2959	2.7067	2.6523	1.8386
LM4	4.3865	3.0563	2.7709	1.9483
LM5	4.2925	2.9086	2.4872	1.6235
LM6	**5.3631**	**3.4234**	**3.0492**	**1.991**
LM7	4.636	2.8426	2.6836	1.7781
LM8	4.9363	3.0801	2.8709	1.9662

- The distribution of distance of the best result (1^{st} landmark)

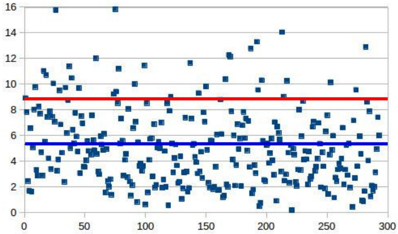


(a) Training from scratch



(b) With fine-tuning

- The distribution of distance of the worst result (6^{th} landmark)



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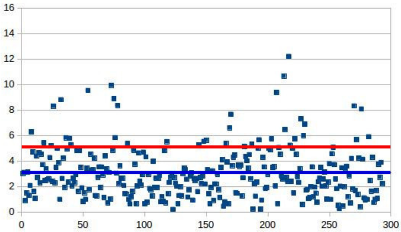

(b) With fine-tuning

Conclusion

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- Propose a new CNN architecture with elementary blocks to predict the landmarks on pronotum images.
- Propose a new procedure to augment the dataset.
- Apply fine-tuning to improve the quality of predicted landmarks.
- The predicted landmarks able to replace the manual landmarks without segmentation step.

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Future works

- Applying the method on body and head parts
- Going deeply how to design the right pre-training model

Thank you for attention!