# Landmarks Detection by Applying Deep Networks

Van-Linh LE[1,3], Marie BEURTON-AIMAR[1],
Akka ZEMMARI[1], Nicolas PARISEY[2]

linhlv@dlu.edu.vn/van-linh.le@labri.fr, beurton@labri.fr
akka.zemmari@labri.fr, nicolas.parisey@inra.fr

[1]LaBRI-CNRS 5800, Bordeaux University, France
[2]IGEPP, INRA 1349 Rennes, France
[3]ITDLU, Dalat University, Vietnam

**MAPR Conference**

Ho Chi Minh City, 5-6 April, 2018

# Context

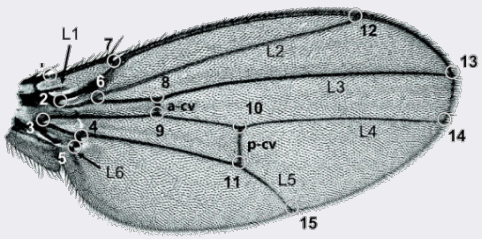


## Morphometry analysis

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

## Landmark

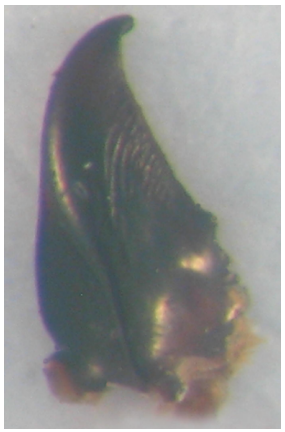
- A kind of **point of interest**
- A specific point defined by biologist. For example, intersection of veins on fly wing, the tip of beetle's mandible,. . .



# Dataset



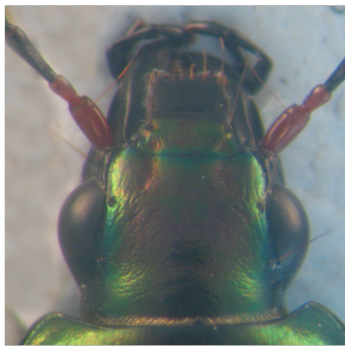
- Images have been taken from 293 **beetles**, seperate into 5 parts (images),
- Format: 2D in RGB color,
- Focus on **pronotum** images.



(a) Left mandible

(b) Right mandible

(c) Body

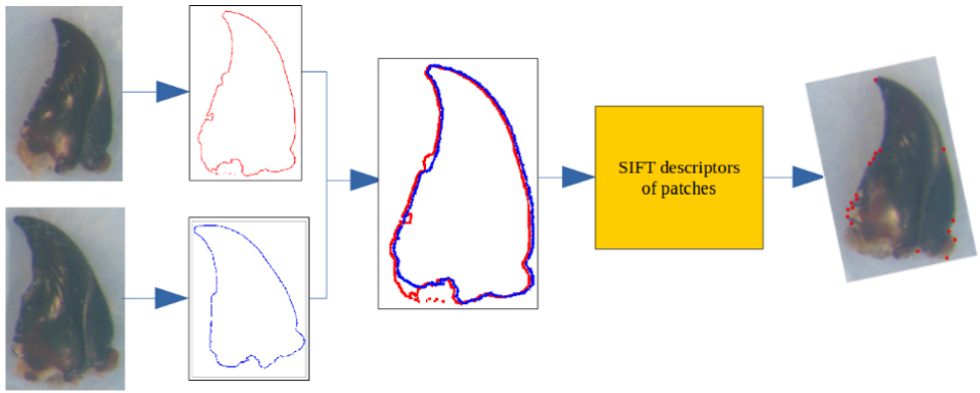


(d) Head

# Problems



With segmentable images:[1]

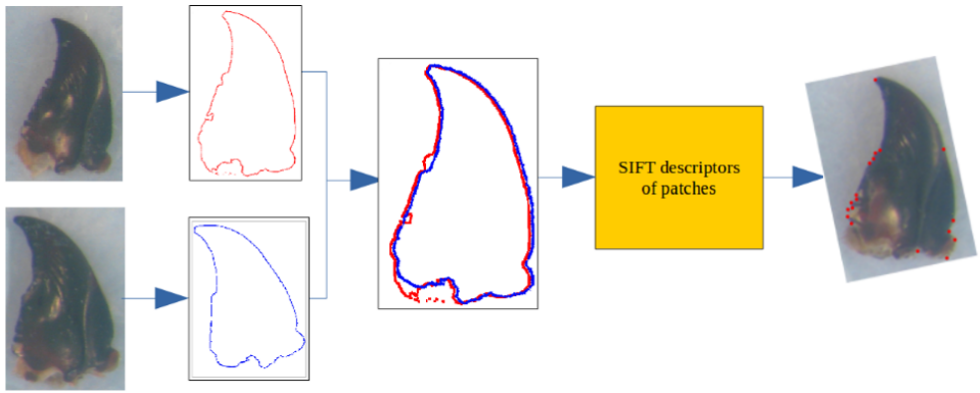



[1] Van-Linh Le, Marie Beurton-Aimar, Adrien Krähenbühl, and Nicolas Parisey. “MAELab: a framework to automatize landmark estimation." WSCG 2017.

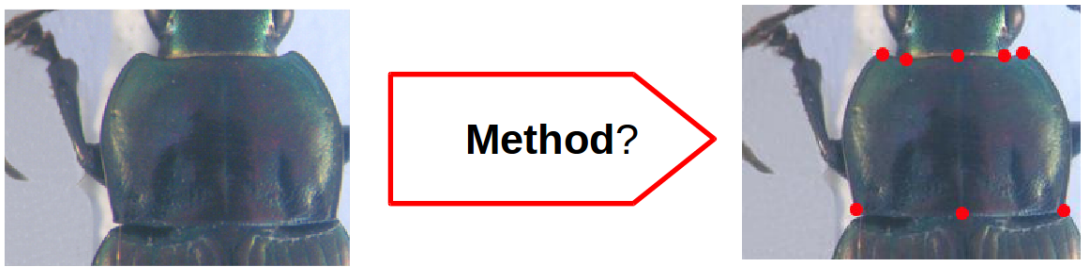
# Problems



With segmentable images:[1]




With un-segmentable images:

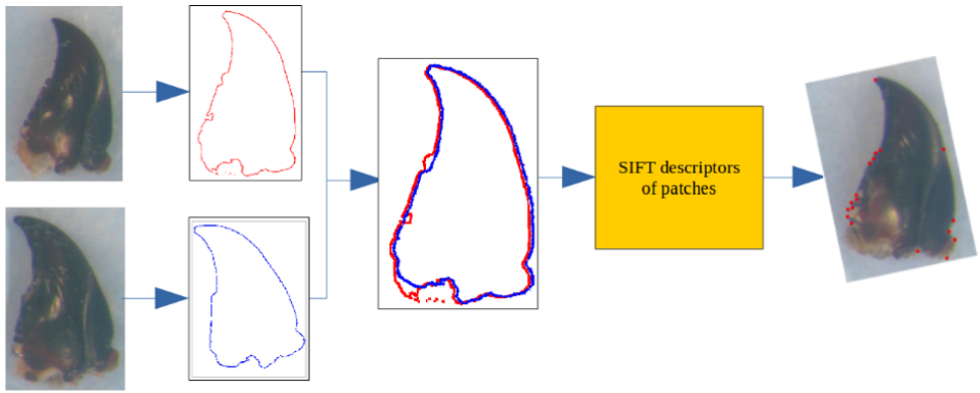



[1] Van-Linh Le, Marie Beurton-Aimar, Adrien Krähenbühl, and Nicolas Parisey. “MAELab: a framework to automatize landmark estimation." WSCG 2017.

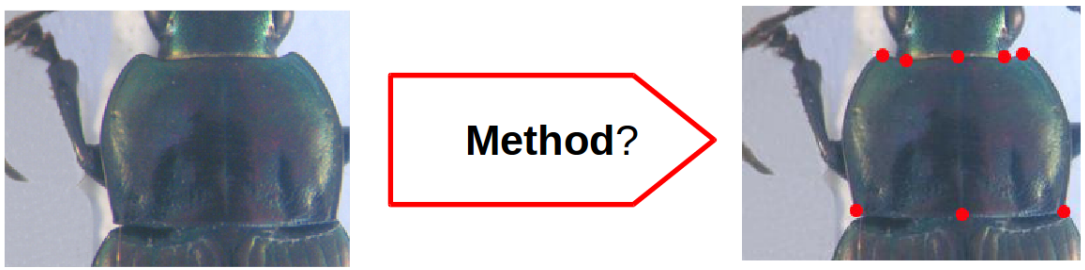
# Problems



With segmentable images:[1]




With un-segmentable images:




**How to predict the landmarks coordinates?**

[1] Van-Linh Le, Marie Beurton-Aimar, Adrien Krähenbühl, and Nicolas Parisey. “MAELab: a framework to automatize landmark estimation." WSCG 2017.

# Content

# Deep learning



## Definition

- A class of machine learning[1],
- Use a cascade of multiple layers for feature extraction and transformation,
- Learn multiple levels of representation in supervised or unsupervised.

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

# Deep learning



## Definition

- A class of machine learning[1],
- Use a cascade of multiple layers for feature extraction and transformation,
- Learn multiple levels of representation in supervised or unsupervised.

## Applications

- Computer vision (image recognition and classification)[2]
- Speech recognition[3]
- Question answering [4], language translation[5]

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

[2] A. Krizhevsky et al, “Imagenet classification with deep convolutional neural networks", 2012.

[3] T. N. Sainath et al, “Deep convolutional neural networks for lvcsr", 2013.

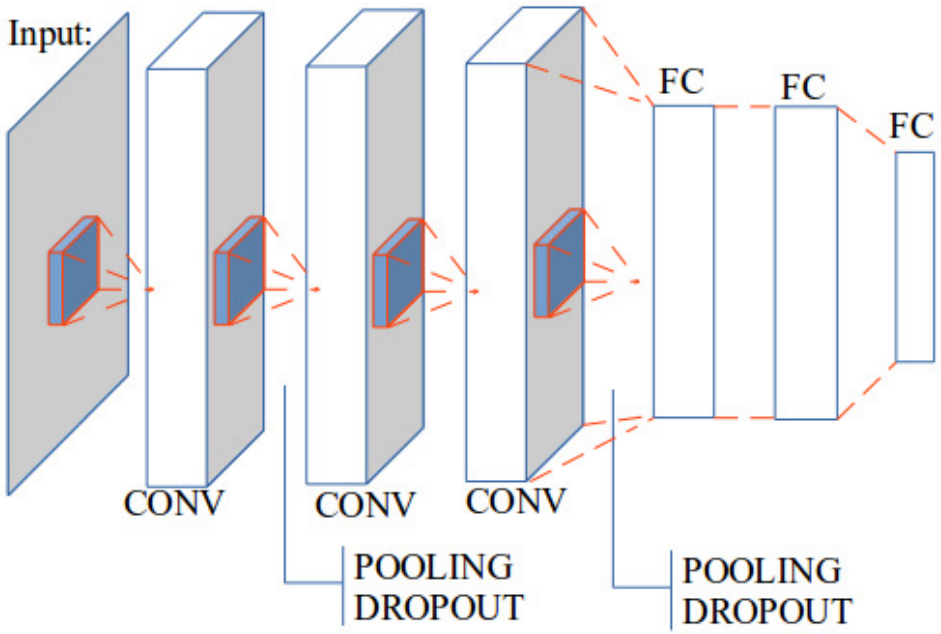
[4] A. Bordes et al, “Question answering with subgraph embeddings", 2014.

[5] I. Sutskever et al, “Sequence to sequence learning with neural networks", 2014.

# CNNs



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




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

# Network architecture

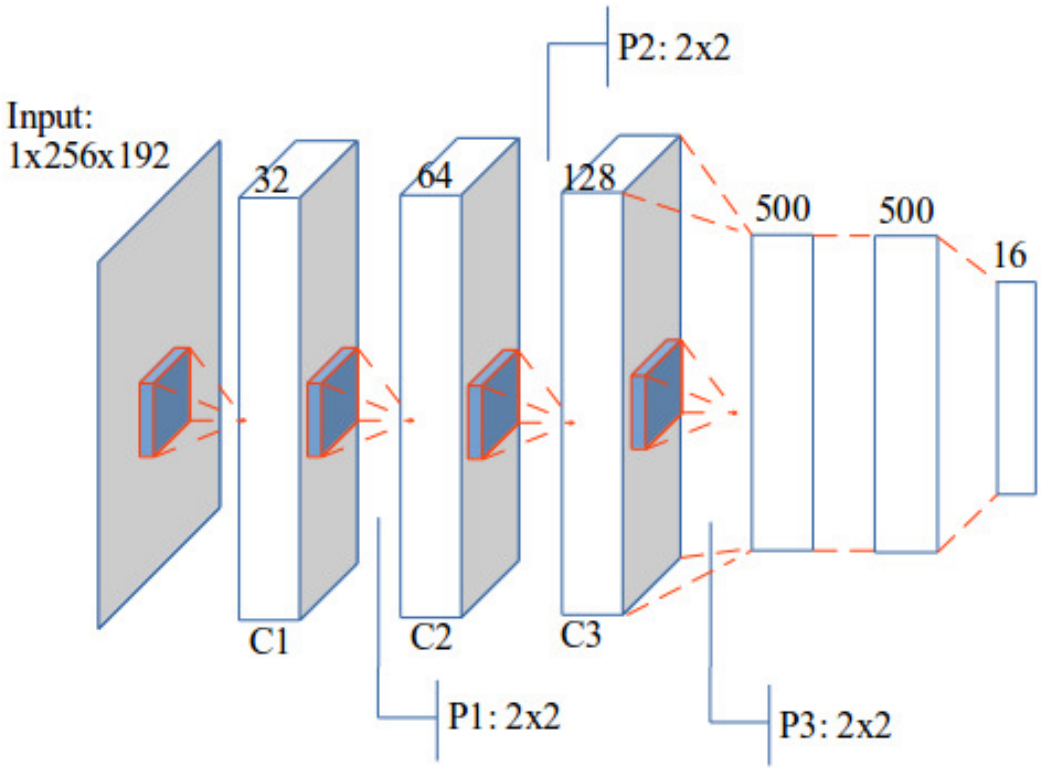


The first model includes:

- An gray-scale input,
- 3 CNN layers (C1, C2, C3),
- 3 POOLING layers (P1, P2, P3),
- 3 FC layers.

Problems:

- Output is not good enough,
- Overfitting.

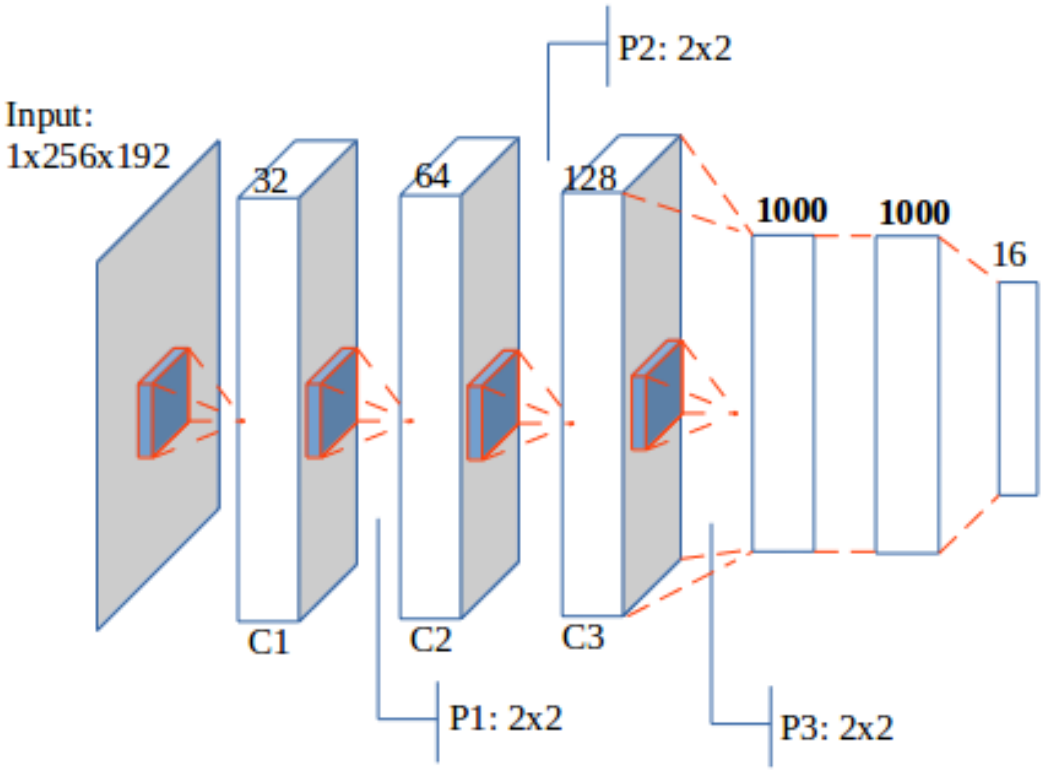


# Network architecture



The second model:

- Same architecture with the first one,
- Modify the output of FC layers (500 -> 1000),
- Result is not improved.

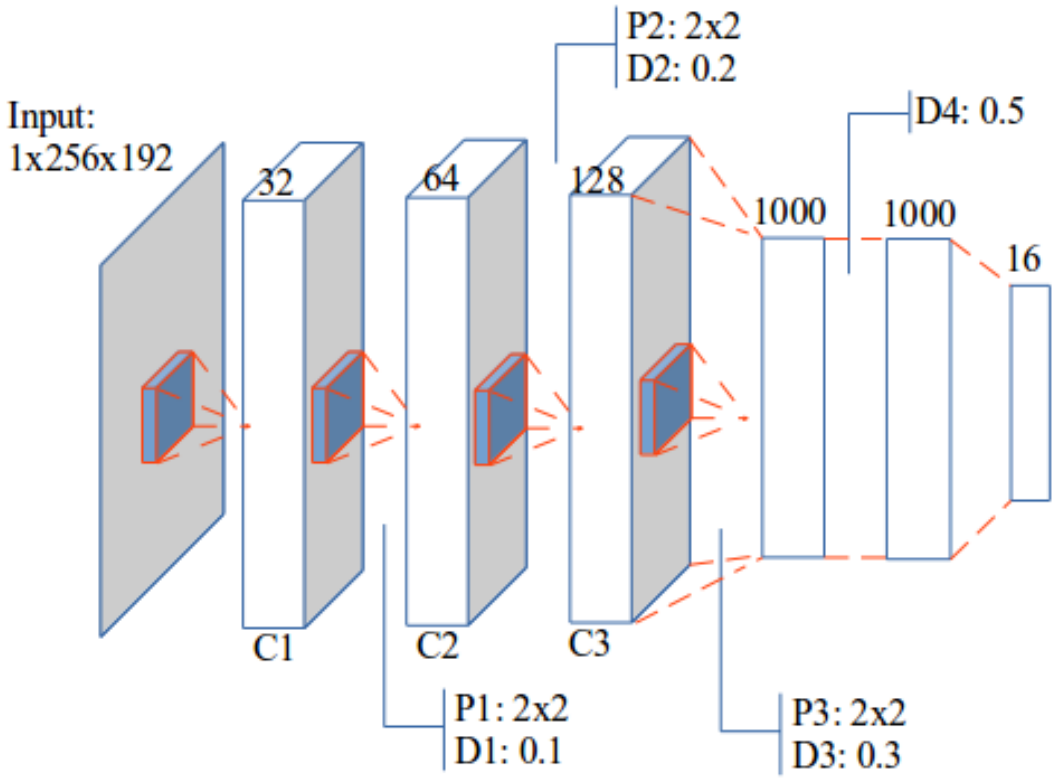


# Network architecture



The **third** model includes:

- Keep architecture of the second model,
- Adding 4 **DROPOUT layers** (D1, D2, D3, D4)



# Data augmentation

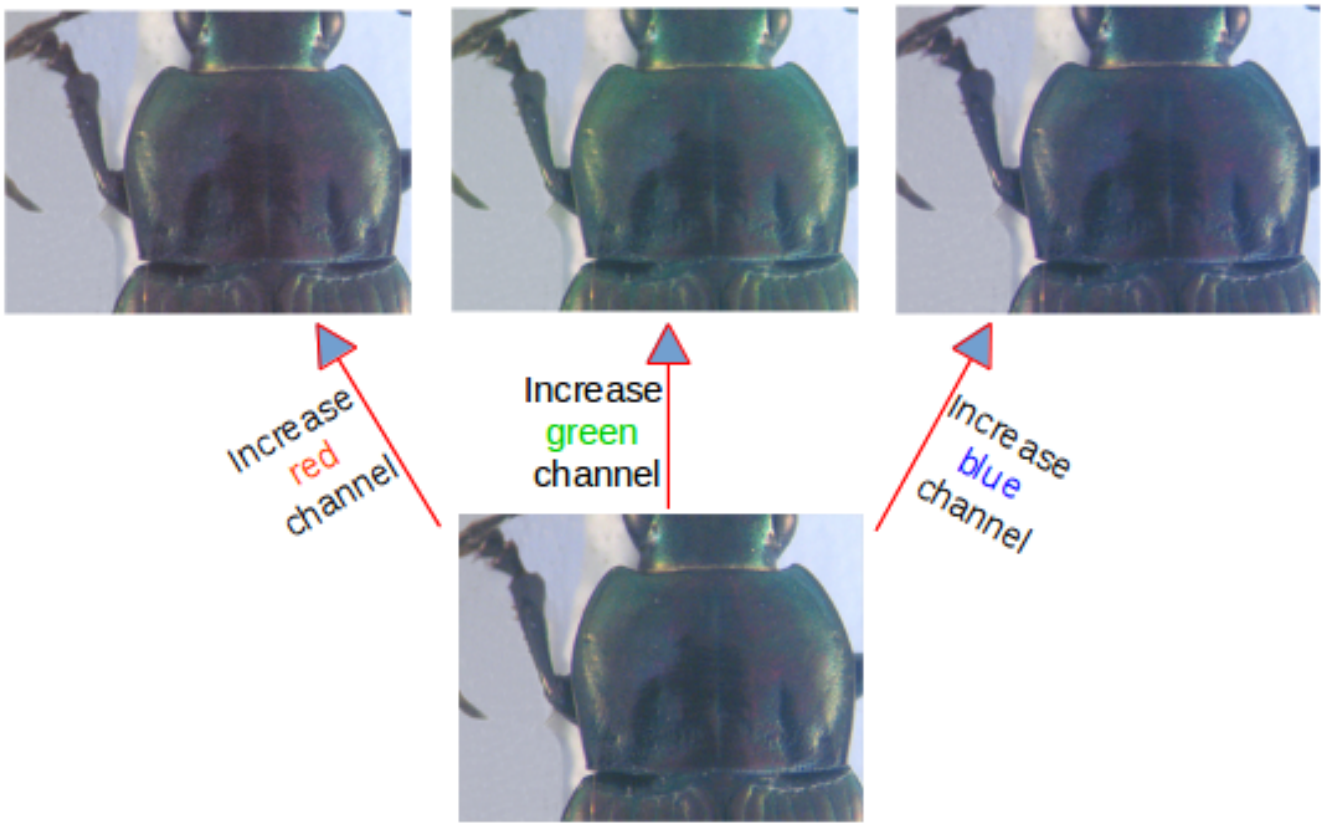

Dataset: 293 pronotum images in RGB format.

# Data augmentation



Augmentation methods:

- Increase the value of each channel,

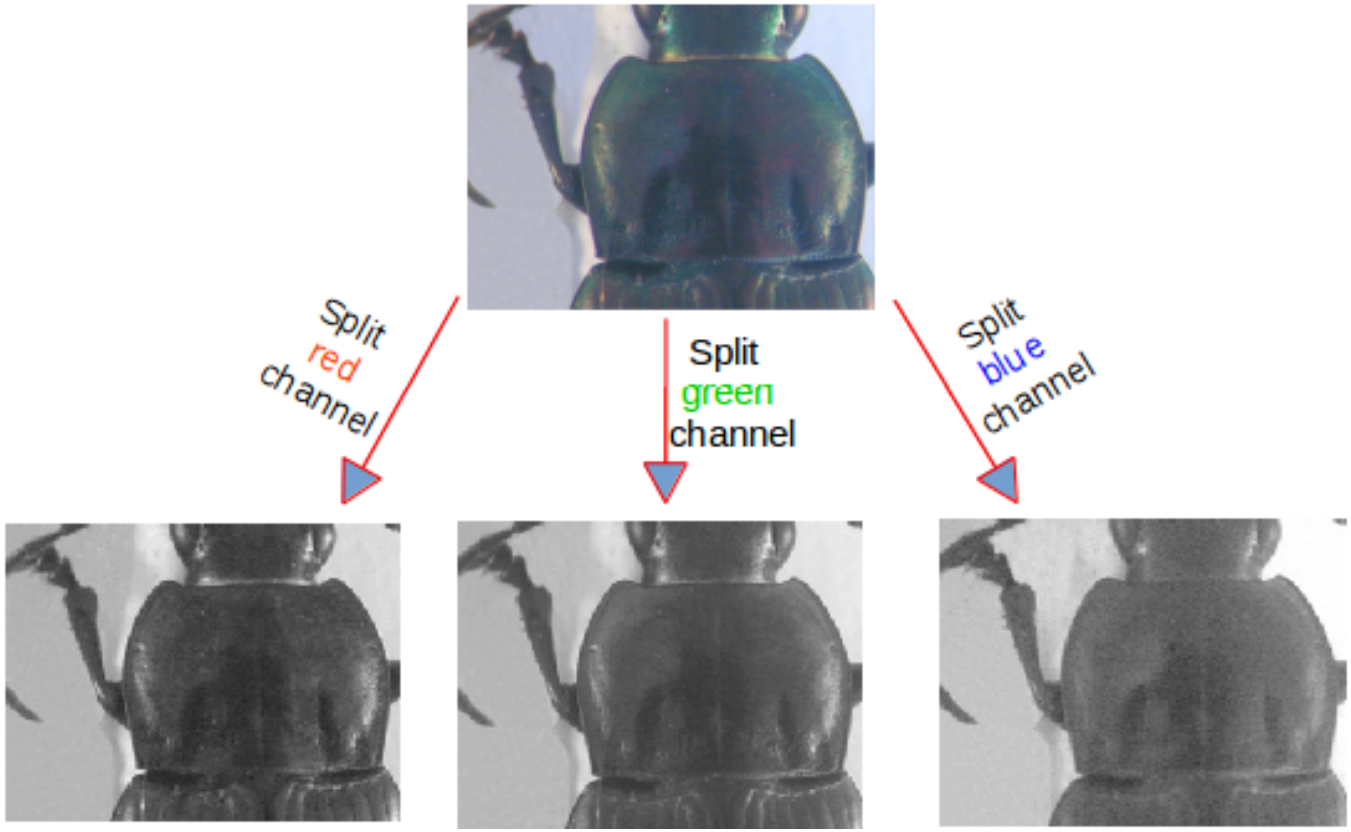


# Data augmentation



Augmentation methods:

- Split the channels.



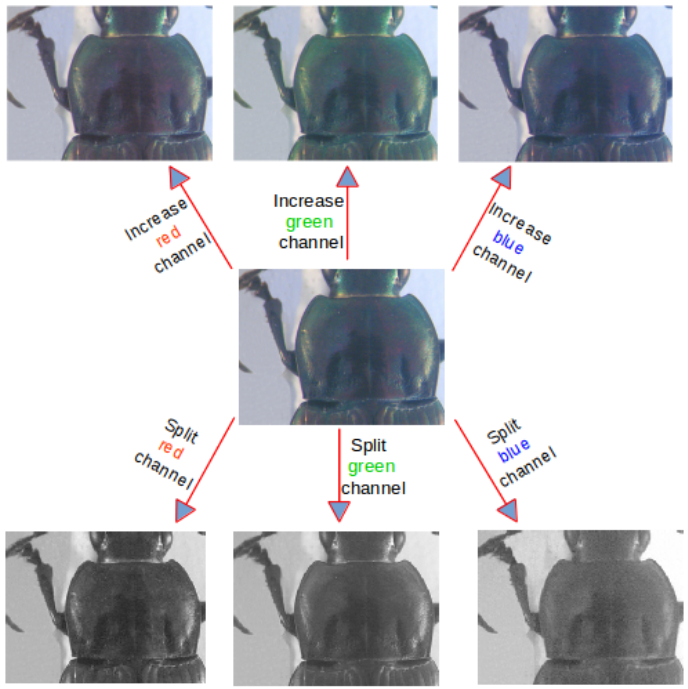
# Data augmentation



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

- Increase the value of each channel,
- Split the channels.

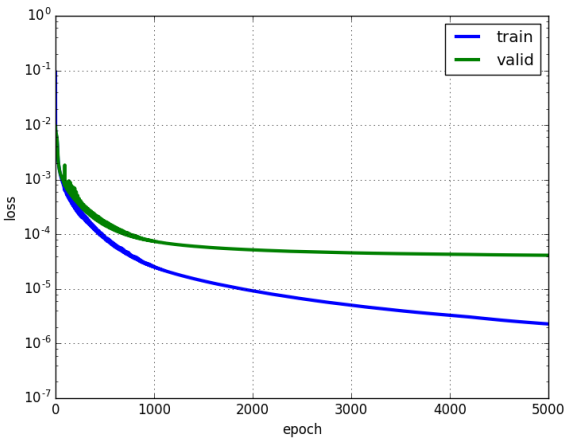
Total: $293 \times 7 = 2051$ images



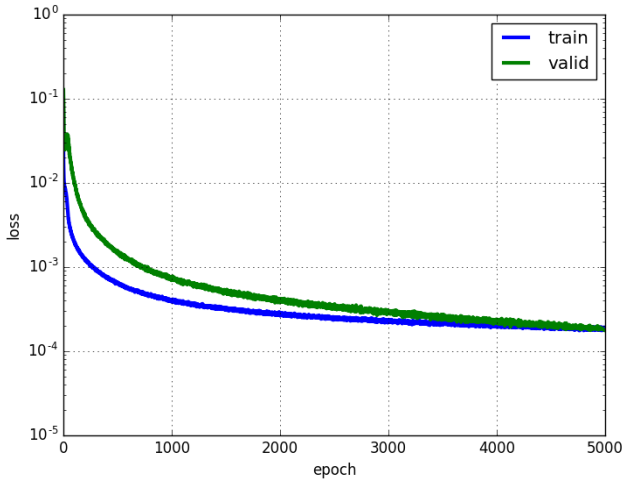
# Training



- Model: the third model in 5000 epochs[2]
- Training dataset: 1820 images ($260 \times 7$)
- Testing set: 33 images
- Images shows training and validation losses of the models. Blue curves are training losses, green curves are validation losses.
- Training time: 3 hours using NVIDIA TITAN X card.




(a) The first architecture



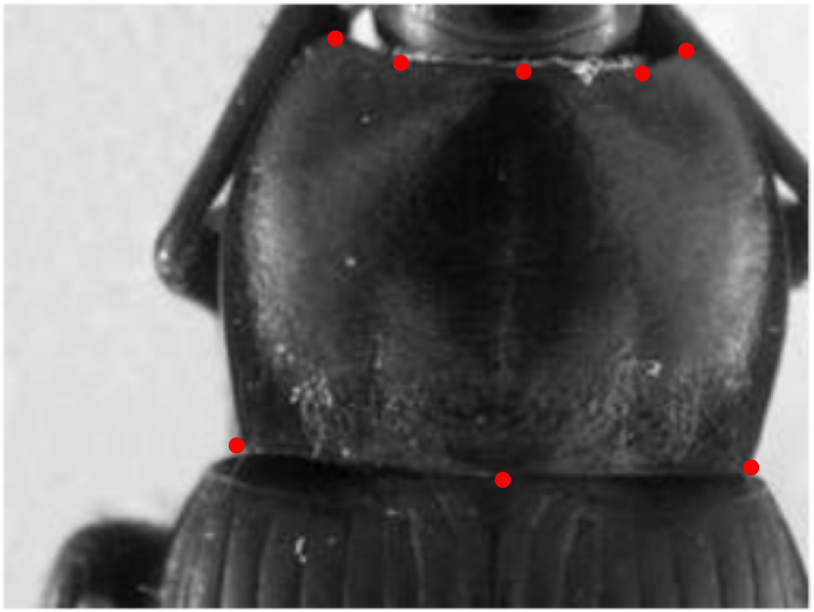

(b) The third architecture

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

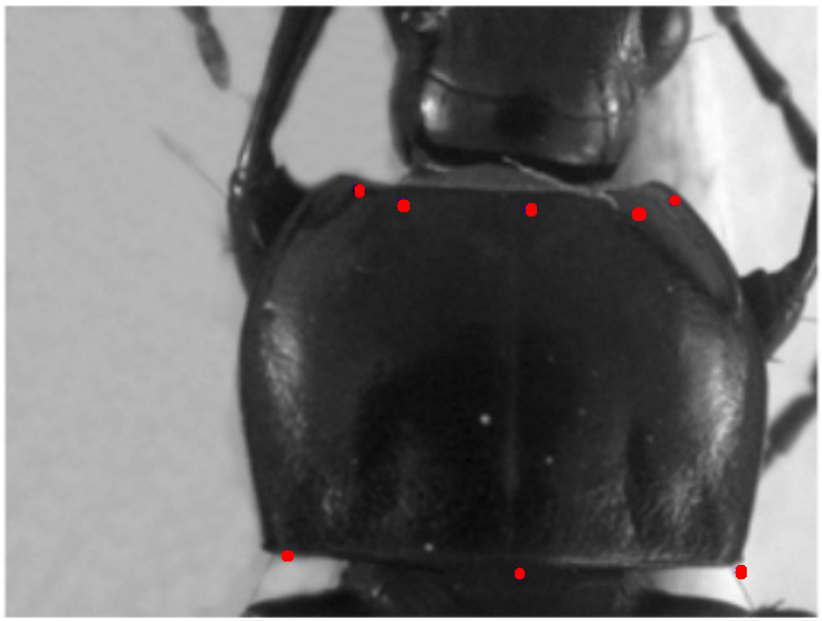
# Result
## Landmarks on images



Images show the result on testing images.



(a)



(b)

# Result
## Average distance



- Run the trained model to predict the landmarks on testing images,
- Calculate the distance between predicted landmarks and corresponding manual landmarks,
- Compute the average distance of all images per landmark.

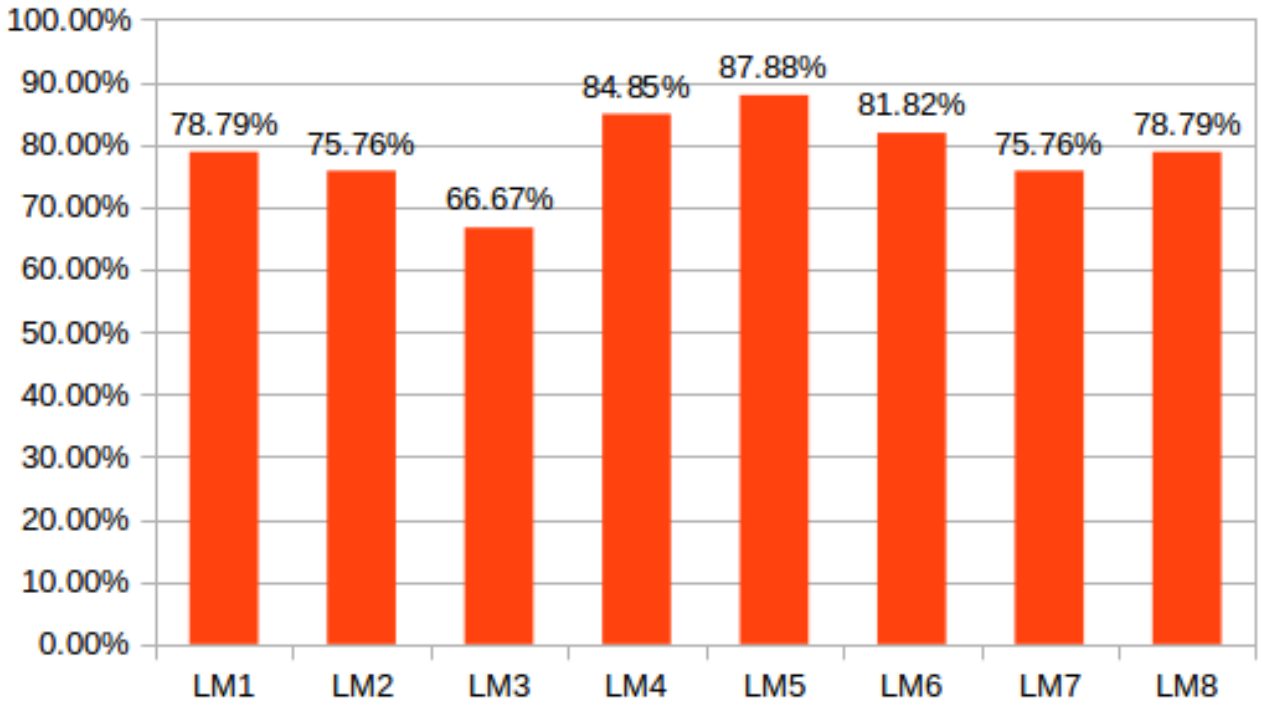
| #**Landmark** | **Distance** (in pixels) |
|---|---|
| 1 | 4.002 |
| 2 | 4.4831 |
| 3 | 4.2959 |
| 4 | 4.3865 |
| 5 | 4.2925 |
| 6 | 5.3631 |
| 7 | 4.636 |
| 8 | 4.9363 |

# Result
## Statistic on acceptable predicted landmarks



Chart shows the propotion of acceptable predicted landmarks

- Average accuracy: $\sim$ 75%
- Highest accuracy: 87.88%
- Lowest accuracy: 66.67%

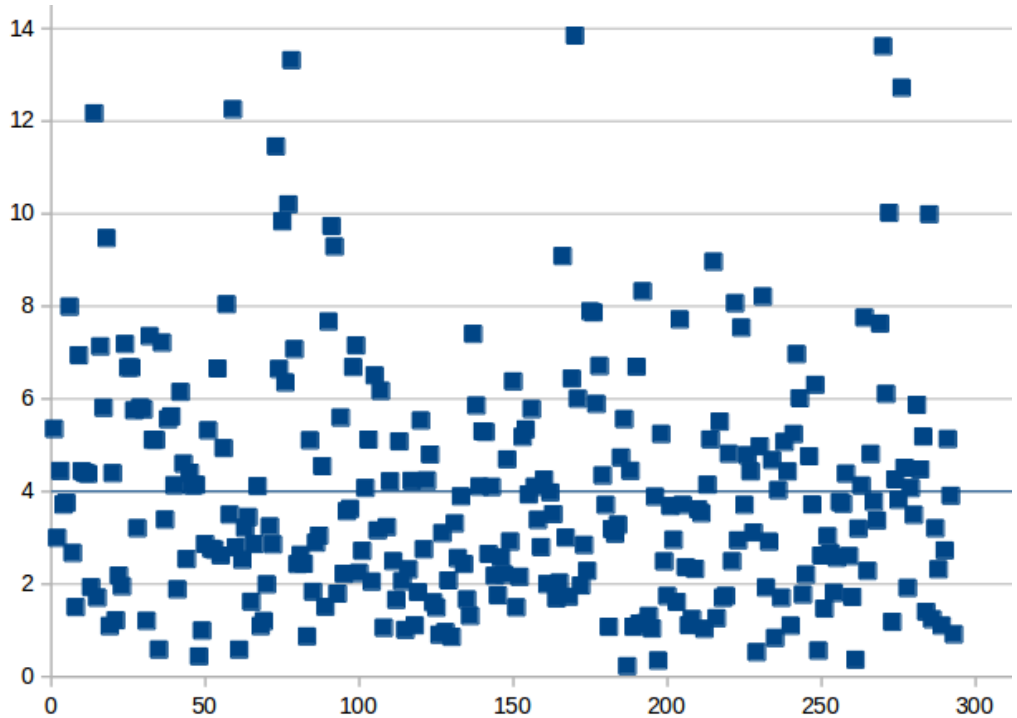


# Result

## Distribution of distance on the first landmark



- Good prediction: 56.66%
- Acceptable prediction: 40.27%
- Bad prediction: 3.07%



# Result
## Comparing with related works



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

| Metric | $\mathbf{r^2}$ | **EV** | **Pearson** |
|---|---|---|---|
| Cintast et al.[3] | 0.884 | 0.951 | 0.976 |
| Proposed architecture | **0.9952** | **0.9951** | **0.9974** |

[3] Cintas, “Automatic ear detection and feature extraction using geometric morphometrics and convolutional neural networks," IET Biometrics, vol. 6, no. 3, pp. 211–223, 2016

# Conclusion



## Conclusion

- Proposed a CNN to predict the landmarks on pronotum images.
- Proposed procedure to augment the dataset.
- The location of the predicted landmarks are acceptable with high accuracy ($\sim$ 75%). It allows to replace manual landmarks.

# Conclusion



## Conclusion

- Proposed a CNN to predict the landmarks on pronotum images.
- Proposed procedure to augment the dataset.
- The location of the predicted landmarks are acceptable with high accuracy ($\sim$ 75%). It allows to replace manual landmarks.

## Future works

Continue improving the landmarks coordinates by continuing on deep learning, *for example*, using transfer learning.

Thank you for attention!