

Multiple Monkey Pose Estimation Using OpenPose

Salvador BLANCO NEGRETE ⁽¹⁾

Rollyn Labuguen ⁽¹⁾ , Jumpei Matsumoto ⁽²⁾ , Yasuhiro Go ^(3,4) ,
Ken-ichi Inoue ⁽⁵⁾ , Tomohiro Shibata ⁽¹⁾

⁽¹⁾ Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Japan

⁽²⁾ Systems Emotional Science, University of Toyama, Japan

⁽³⁾ Cognitive Genomics Research Group, ExCELLS National Institutes of Natural Sciences, Japan

⁽⁴⁾ Department of System Neuroscience, National Institute for Physiological Sciences Okazaki, Japan

⁽⁵⁾ Department of Neuroscience, Primate Research Institute, Kyoto University, Japan

blanco.negrete@gmail.com



Motivation

Animals are widely used for experiments

Why Monkeys ?

Nonhuman primates more closely mirror human physiological and behavioral features.

Manual Annotation vs Computer Based Analysis

Manual :

- Subjective
- Changes by person
- Takes a lot of time

Computer Based :

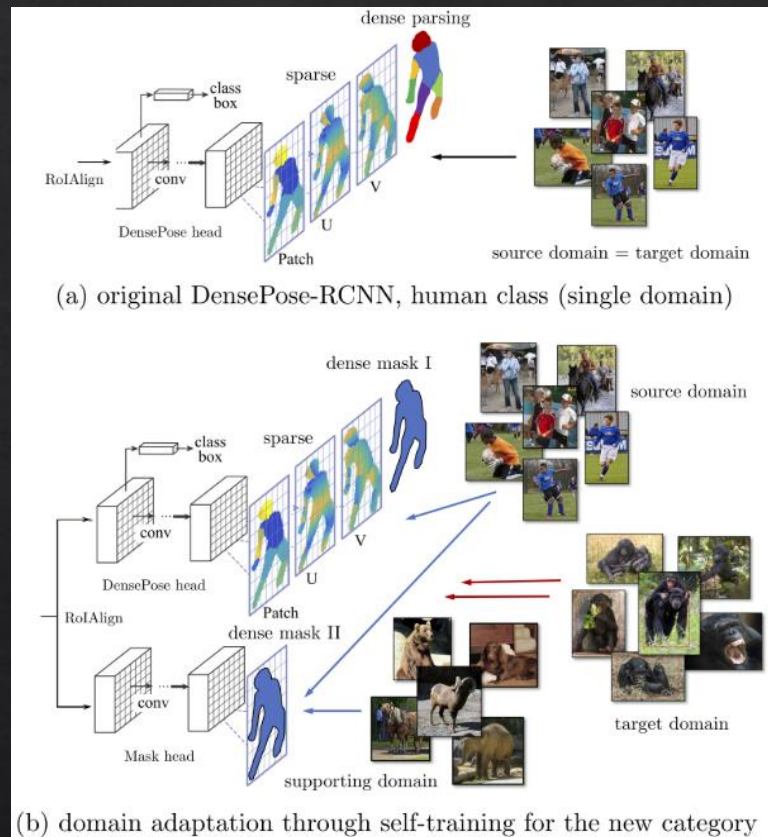
- Quantitative
- Unbiased
- Replicable
- Automated
- Sophisticated data analysis
- Less intrusive

Ethical considerations (Three Rs):

- Replacement: Replace the use of animals
- Reduction: Obtain more information from animals.
- Refinement: Alleviate or minimize potential pain, suffering or distress.

Transferring Dense Pose to Proximal Animal Classes

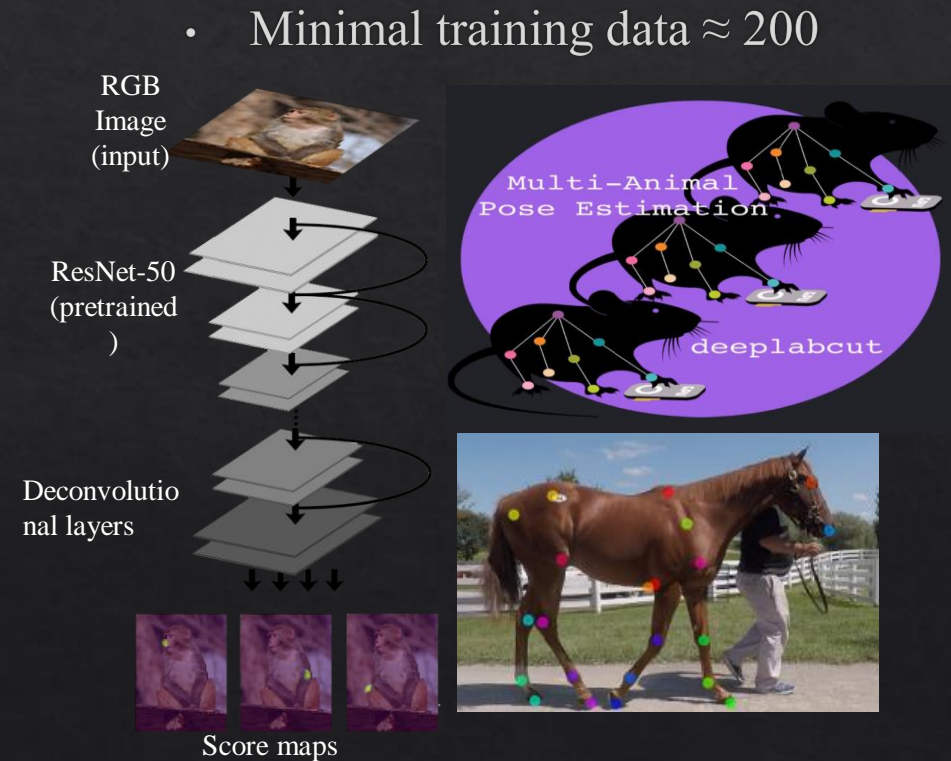
Sanakoyeu Artsiom, Khalidov Vasil, McCarthy Maureen S., Vedaldi Andrea, Neverova Natalia



<https://arxiv.org/abs/2003.00080>

DeepLabCut

Alexander Mathis, Pranav Mamidanna, Taiga Abe, Kevin M. Cury, Venkatesh N. Murthy, Mackenzie W. Mathis, Matthias Bethge (Submitted on 9 Apr 2018)



<https://arxiv.org/abs/1804.03142>

<https://github.com/AlexEMG/DeepLabCut>

OpenPose

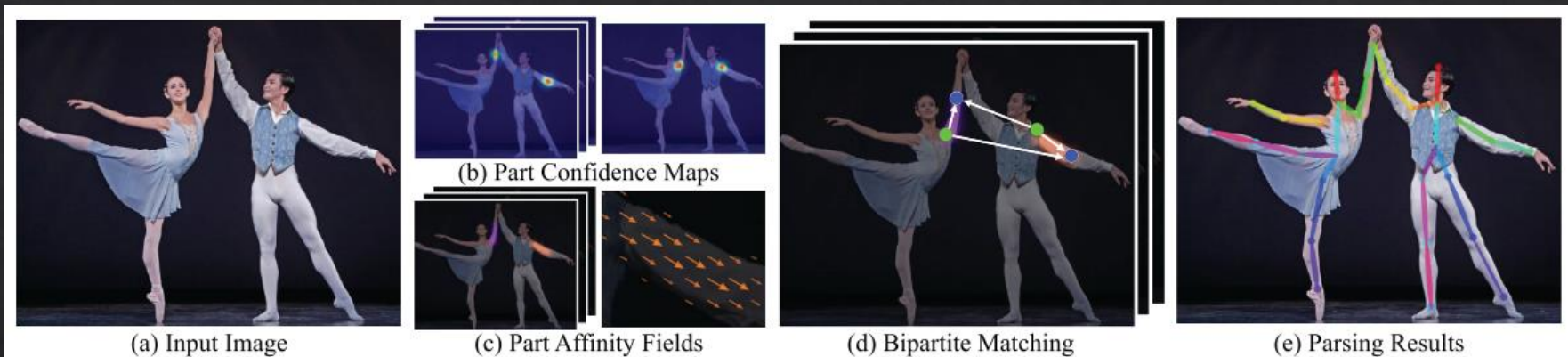


Figure 2. Overall pipeline. Our method takes the entire image as the input for a two-branch CNN to jointly predict confidence maps for body part detection, shown in (b), and part affinity fields for parts association, shown in (c). The parsing step performs a set of bipartite matchings to associate body parts candidates (d). We finally assemble them into full body poses for all people in the image (e).

Part Affinity Fields



$$L_c(p) = \begin{cases} v & \text{if } p \text{ on line } c \\ 0 & \text{otherwise} \end{cases}$$



$$v = \frac{x_{j2} - x_{j1}}{\|x_{j2} - x_{j1}\|_2}$$

Multiple Monkey Pose Estimation

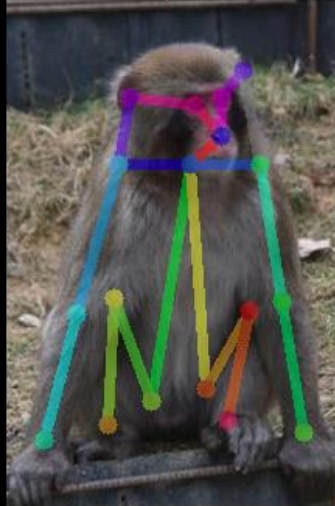
- Model capable of detecting monkey body features and posture
- No restrictions on the number of monkey subjects in the image
- It should work with different monkey behaviors
 - Sniffing, grooming, eating, crawling, etc.
- Robust against collusion and social interactions
- No environment restrictions, useful “In the wild”
 - Not limited to laboratory environments



MacaquePose Dataset

Total number of monkeys	16393
Total number of images	13083

17 Body Features



Occlusion Information

- Nose ●
- Right ear ●
- Left ear ●
- Right eye ●
- Left eye ●
- Right shoulder ●
- Left shoulder ●
- Right elbow ●
- Left elbow ●
- Right wrist ●
- Left wrist ●
- Right hip ●
- Left hip ●
- Right knee ●
- Left knee ●
- Right ankle ●
- Left ankle ●

Segmentation masks

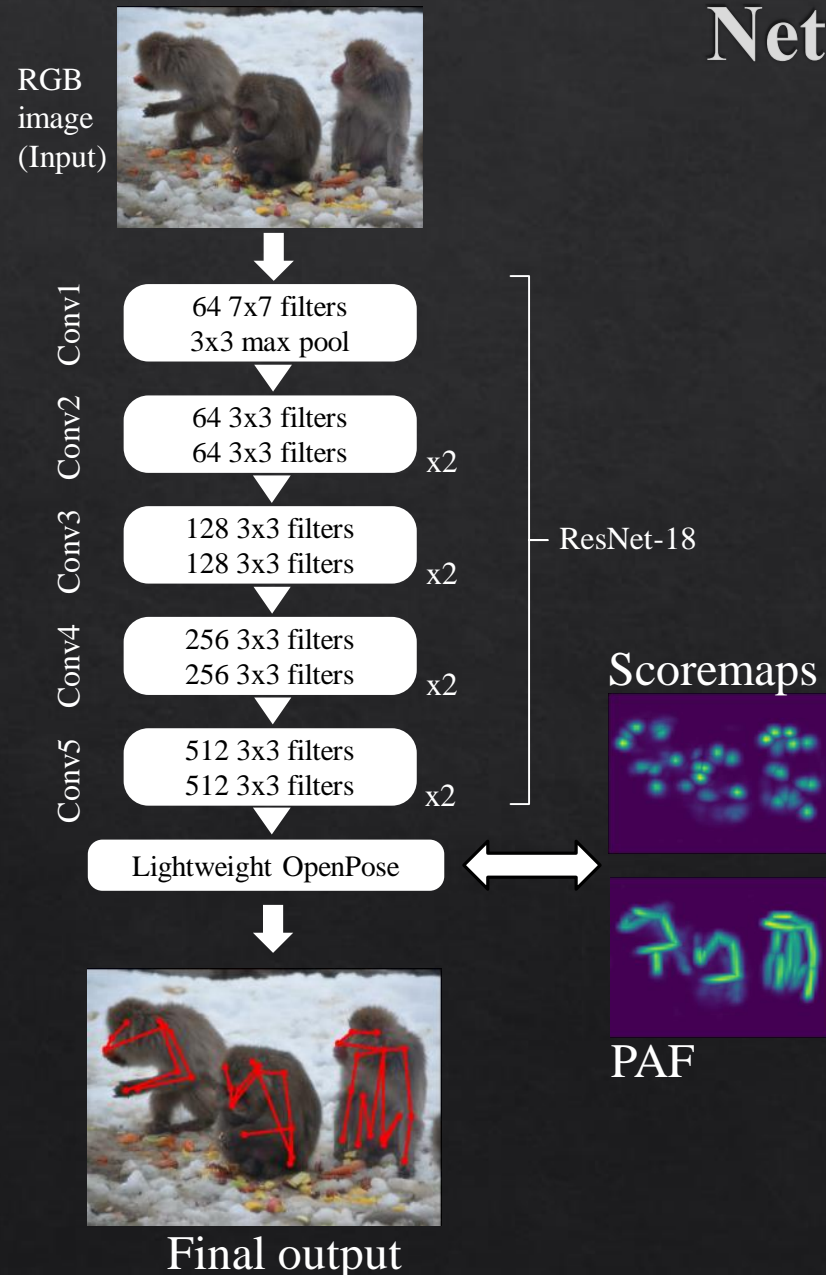


Original OpenPose applied to monkey images

- In a few cases OpenPose is able to detect monkey features.
- The confidence maps show that the network is able to detect some body features, but with low confidence.



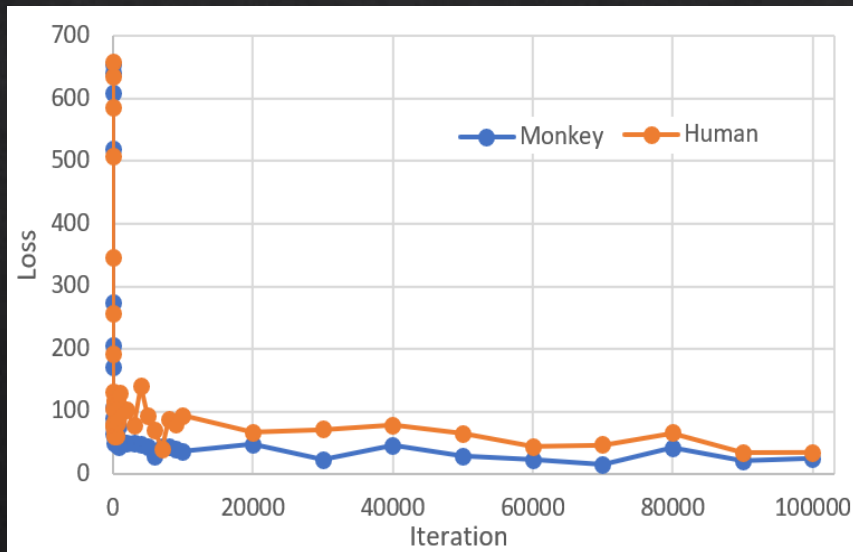
Network Architecture



- Images resized to 640 pixels, on height or width.
- ResNet18 allows the network to be lightweight
- Lightweight implementation of OpenPose
- TensorFlow Framework
- Hyperpose an open-source implementation of OpenPose from Tensorlayer
- The network was exported to the ONNX for real-time run

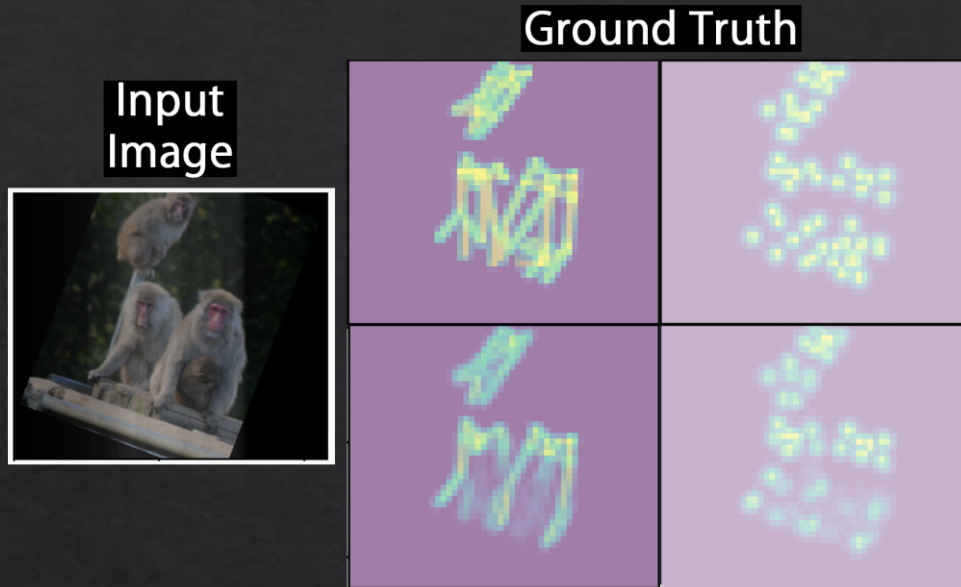
Training

	Train	Val	Total
Images	12265	818	13083
Images %	93.75 %	6.25 %	
Monkeys	15373	1020	16393
Monkeys %	93.77 %	6.22 %	



- The model is trained on a Nvidia GeForce GTX TITAN X
- The model is trained for 100,000 iterations
- The required time to train the network is approximately 24 hours
- Loss significantly decreased during the first 10,000 iterations
- Afterward, the Loss keeps dropping at a slower but steady rate
- The graph also shows a comparison against the same network trained with the human MSCOCO 2017 dataset

Results



- Predicted score maps and PAF reassemble the ground-truth
- AP was used as a metric
- Monkey model evaluated on 757 images from the evaluation set
- Human model evaluated on 1831 images from the evaluation set
- Original OpenPose results included in table

Prediction					
Network	Dataset	Ap^{50}	Ap^{75}	Ap^M	Ap^L
Lightweight Openpose + ResNet18	Monkey Dataset	80.8	37.3	37.3	42.8
Lightweight Openpose + ResNet18	MSCOC O 2017	38.0	6.9	12.8	15.7
Original OpenPose	MSCOC O 2016	83.4	66.4	55.1	68.1

Visual Inspection Success cases



- Unseen images from the dev set
- The sampled images display various activities that include
 - Eating
 - Playing
 - Jumping
 - Crawling
 - Standing
- The backgrounds are rich and varied
 - Natural sceneries
 - Plants and trees
 - City with a sea view

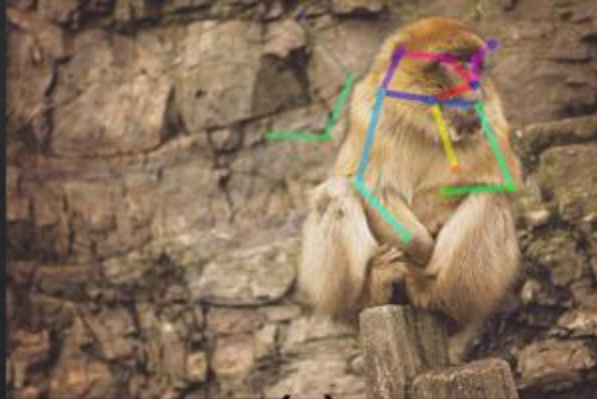
Visual Inspection Failure cases



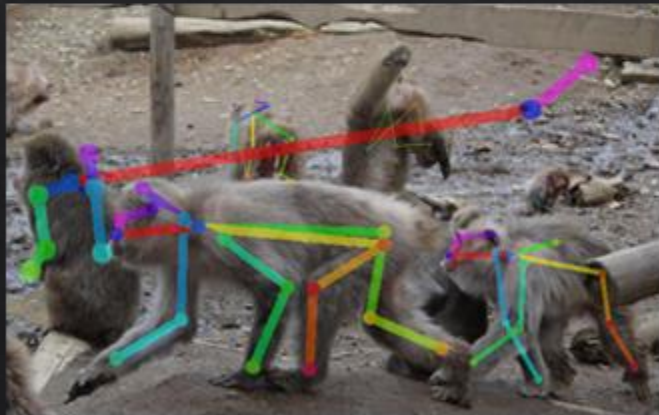
(a)



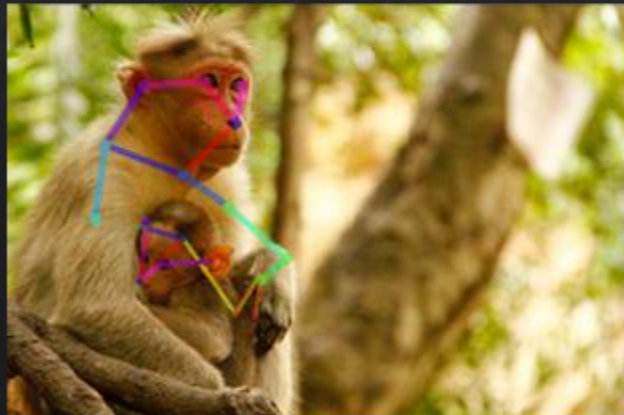
(b)



(c)



(d)

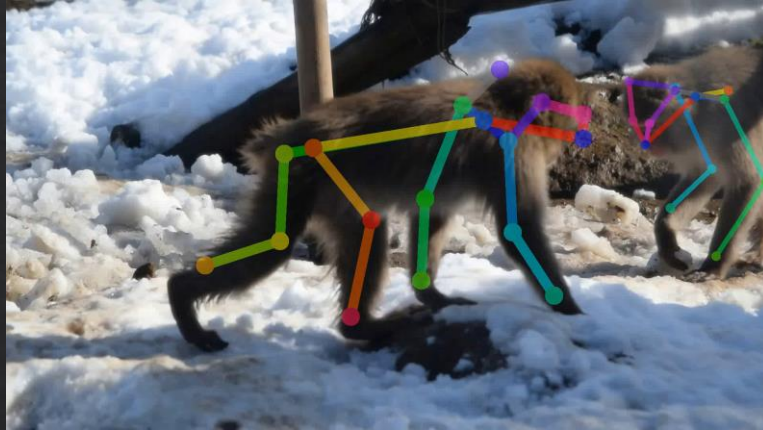


(e)

- a) Some body parts are not detected
- b) A monkey is not detected
- Body parts detected in the background
 - c) Independent
 - d) Attached to a monkey
- e) Mixed body features

Unsen videos

Sniffing



Mating



Grooming



Gathering



Conclusion

- Trained OpenPose neural network using the MacaquePose monkey dataset.
- The trained model is capable of detecting monkey body features and generating PAF on unseen images.
- The final output is the monkey's posture; there are no restrictions on the number of monkey subjects in the image.
 - It is robust against collusion and social interaction
 - It works on challenging backgrounds.
- The model was exported to the ONNX format allowing the model to run in real-time.
- Better results could be achieved
 - Using information from contiguous frames on videos or tracking the subjects.
 - Using a deeper network and transfer learning.

Thank you

REFERENCES

- M. A. Nashaat, H. Oraby, L. B. Peña, S. Dominiak, M. E. Larkum, and R. N. S. Sachdev, “Pixying Behavior: A Versatile Real-Time and Post Hoc Automated Optical Tracking Method for Freely Moving and Head Fixed Animals,” *Eneuro*, vol. 4, no. 1, p. ENEURO.0245-16.2017, 2017.
- Z. Cao, T. Simon, S. E. Wei, and Y. Sheikh, “Realtime multi-person 2D pose estimation using part affinity fields,” *Proc. - 30th IEEE Conf. Comput. Vis. Pattern Recognition, CVPR 2017*, vol. 2017-Janua, pp. 1302–1310, 2017.
- T. Nakamura *et al.*, “A markerless 3D computerized motion capture system incorporating a skeleton model for monkeys,” *PLoS One*, vol. 11, no. 11, pp. 1–18, 2016.
- P. Bala, B. Eisenreich, S. B. M. Yoo, B. Hayden, H. S. Park, and J. Zimmermann, “OpenMonkeyStudio: Automated Markerless Pose Estimation in Freely Moving Macaques,” *Nat. Commun.*, no. 2020, pp. 1–12, 2020.
- R. Labuguen, V. Gaurav, and S. Blanco Negrete, “Monkey Features Location Identification Using Convolutional Neural Networks,” *28th Annu. Conf. Japanese Neural Netw. Soc.*, pp. 28–30, 2018.
- R. Labuguen, D. K. Bardeloza, S. Blanco Negrete, J. Matsumoto, I. Kenichi, and T. Shibata, “Primate Markerless Pose Estimation and Movement Analysis Using DeepLabCut.”
- R. Labuguen *et al.*, “MacaquePose: A novel ‘in the wild’ macaque monkey pose dataset for markerless motion capture,” *bioRxiv*, p. 2020.07.30.229989, 2020.
- A. Mathis *et al.*, “DeepLabCut: markerless pose estimation of user-defined body parts with deep learning,” *Nat. Neurosci.*, vol. 21, no. 9, pp. 1281–1289, 2018.
- A. Sanakoyeu, V. Khalidov, M. S. McCarthy, A. Vedaldi, and N. Neverova, “Transferring Dense Pose to Proximal Animal Classes,” *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 5232–5241, 2020.
- I. F. Rodriguez *et al.*, “Multiple animals tracking in video using part affinity fields,” *Work. Vis. Obs. Anal. Vertebr. insect Behav. Proc. 24th Int. Conf. Pattern Recognit. (ICPR), Beijing, China*, pp. 20–24, 2018.
- H. Dong *et al.*, “TensorLayer : A Versatile Library for Efficient Deep Learning,” no. 1, pp. 1–4.
- D. Osokin, “Real-time 2D multi-person pose estimation on CPU: Lightweight OpenPose,” *ICPRAM 2019 - Proc. 8th Int. Conf. Pattern Recognit. Appl. Methods*, pp. 744–748, 2019.
- T. Y. Lin *et al.*, “Microsoft COCO: Common objects in context,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 8693 LNCS, no. PART 5, pp. 740–755, 2014.

