

Image classification and detection with Imagenet using Transfer Learning

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Abbreviated abstract: We use transfer learning for image classification and detection to determine different types of animals in images and videos. We compare the results of two classification models: a model trained from scratch, without pre-trained weights, and a transfer learning model, with weights pre-trained on ImageNet. Then, we use the same dataset to train a YOLO object detection model. The results show a mAP of about 88% and AP over 80% for every class.

Related publications: (up to 2 references)

– Sato D., et al. Computational classification of animals for a highway detection system. *Braz J Vet Res Anim Sci.* 2021;58(special issue):e174951. <https://doi.org/10.11606/issn.1678-4456.bjvras.2021.174951>



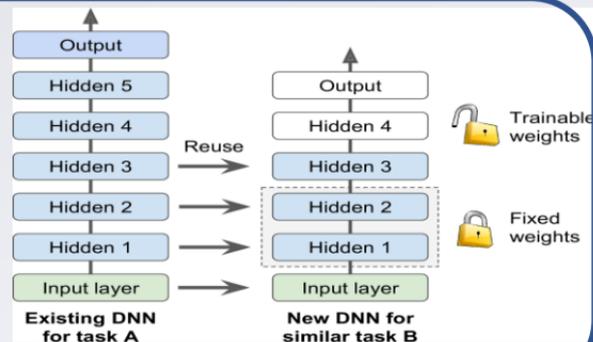
Motivation and approach

Motivation: The goal of this project was to create algorithms capable of **classifying** and **detecting** animals in images and videos; particularly in the case where only **limited data** is available.

Approach: Use transfer learning with CNN architecture and weights pre-trained on ImageNet for the classification task. Then use YoloV4 for object detection.

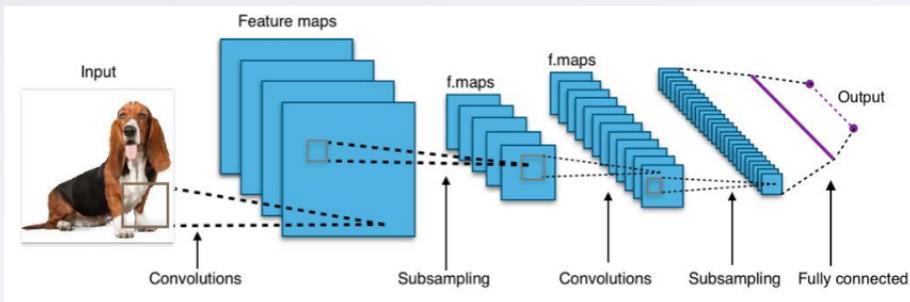
Transfer Learning is often beneficial when a limited amount of annotated data is available. Large annotated datasets, like **ImageNet**, can be used to pre-train state-of-the-art CNNs. Benefits:

- Faster training time
- Better performance of neural networks
- Don't need a lot of data



CNN are feed forward neural network architecture that have proven very effective in object detection and classification tasks. Their key features include:

- convolutional layers for feature mapping
- weight sharing for spatial coherence
- pooling and sub-sampling for dimensional reduction
- fully connected final layer for object classification

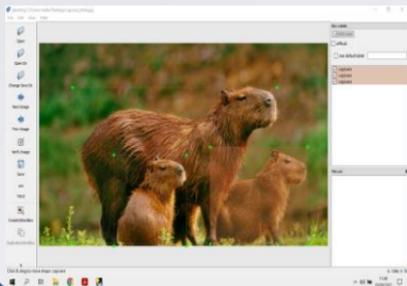


Method

Data Pre-Processing

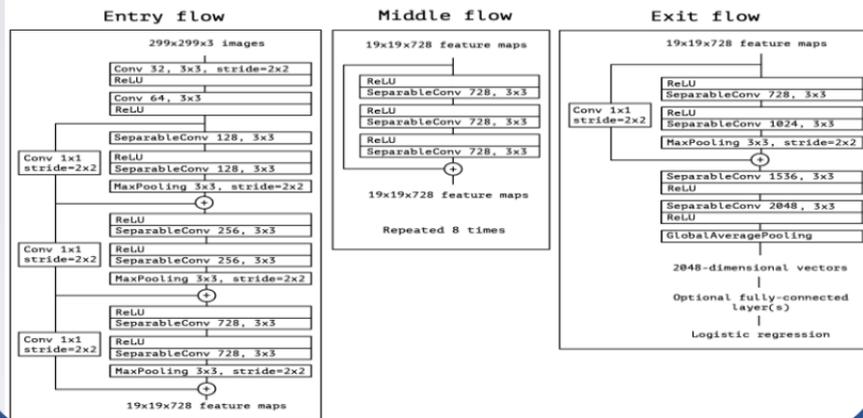


Data augmentation increase the number of available images for training using the initial data set as reference. It acts as a regularizer and helps reduce overfitting.

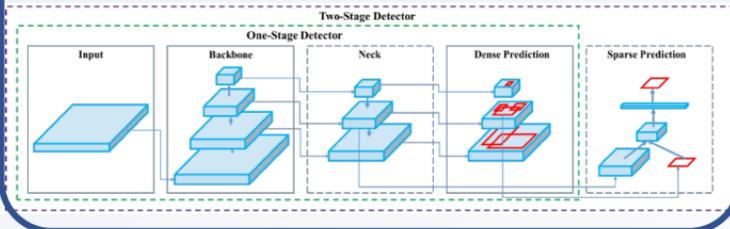


Images need to be **labelled** before we can use them for object detection. We added them using Labelling.

Classification Task with Xception

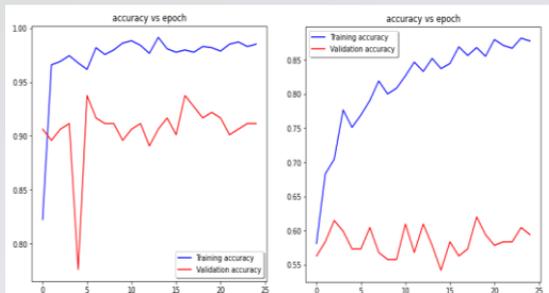


Object Detection with YoloV4



Results and Conclusions

Classification Task with Xception



Modelo 1

	Precisão	Recall	F1	Suporte
Equino	0.83	1.00	0.90	114
Capivara	1.00	0.82	0.90	135
Acurácia	0.91	0.91	0.90	249
Macro avg	0.91	0.91	0.90	249
Weighted avg	0.92	0.90	0.90	249

Modelo 2

	Precisão	Recall	F1	Suporte
Equino	0.00	0.00	0.00	123
Capivara	0.51	1.00	0.67	126
Acurácia	0.25	0.50	0.34	249
Macro avg	0.25	0.50	0.34	249
Weighted avg	0.26	0.51	0.34	249

The transfer learning in the classification task generated a superior model to the one trained from scratch.

Object Detection with YoloV4

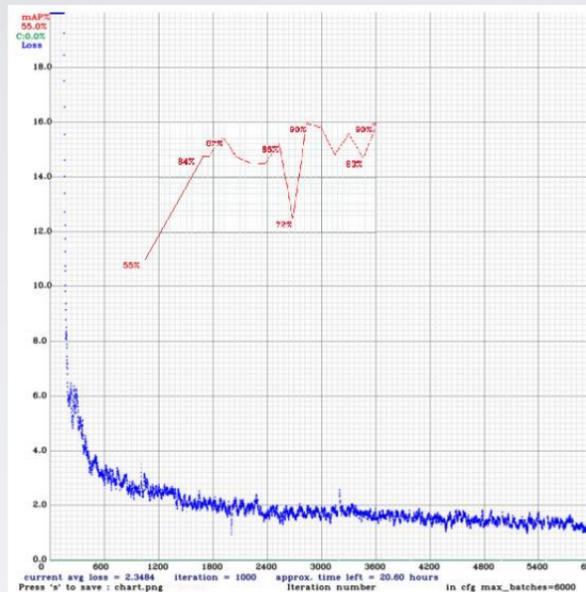
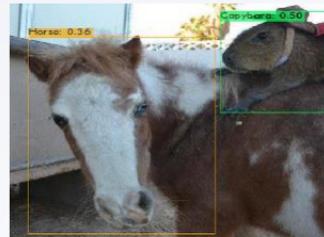


Tabela: Precisão média (AP) por classe

	1000	2000	3000	4000	5000	6000
Capivara	88.78%	91.39%	93.16%	92.11%	91.23%	91.74%
Equino	69.99%	81.13%	76.04%	82.47%	81.32%	81.41%
Cachorro	86.72%	94.01%	91.49%	90.37%	93.60%	93.81%

Conclusion

- The transfer learning allows for faster convergence and improved classification performance and generalizability.
- The detection algorithm achieved mAP of approximately 89% at the end of training and AP bigger than 81% for every class. The model also performed well in most video and image applications.
- Implementing more elaborate forms of data augmentation could lead to even better results.



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