

DOG BREED CLASSIFICATION USING NEURAL NETWORKS

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DATASET



Source :

<http://vision.stanford.edu/aditya86/ImageNetDogs/>



Total number of images : 20580 ~ 170 per breed



Number of breeds : 120



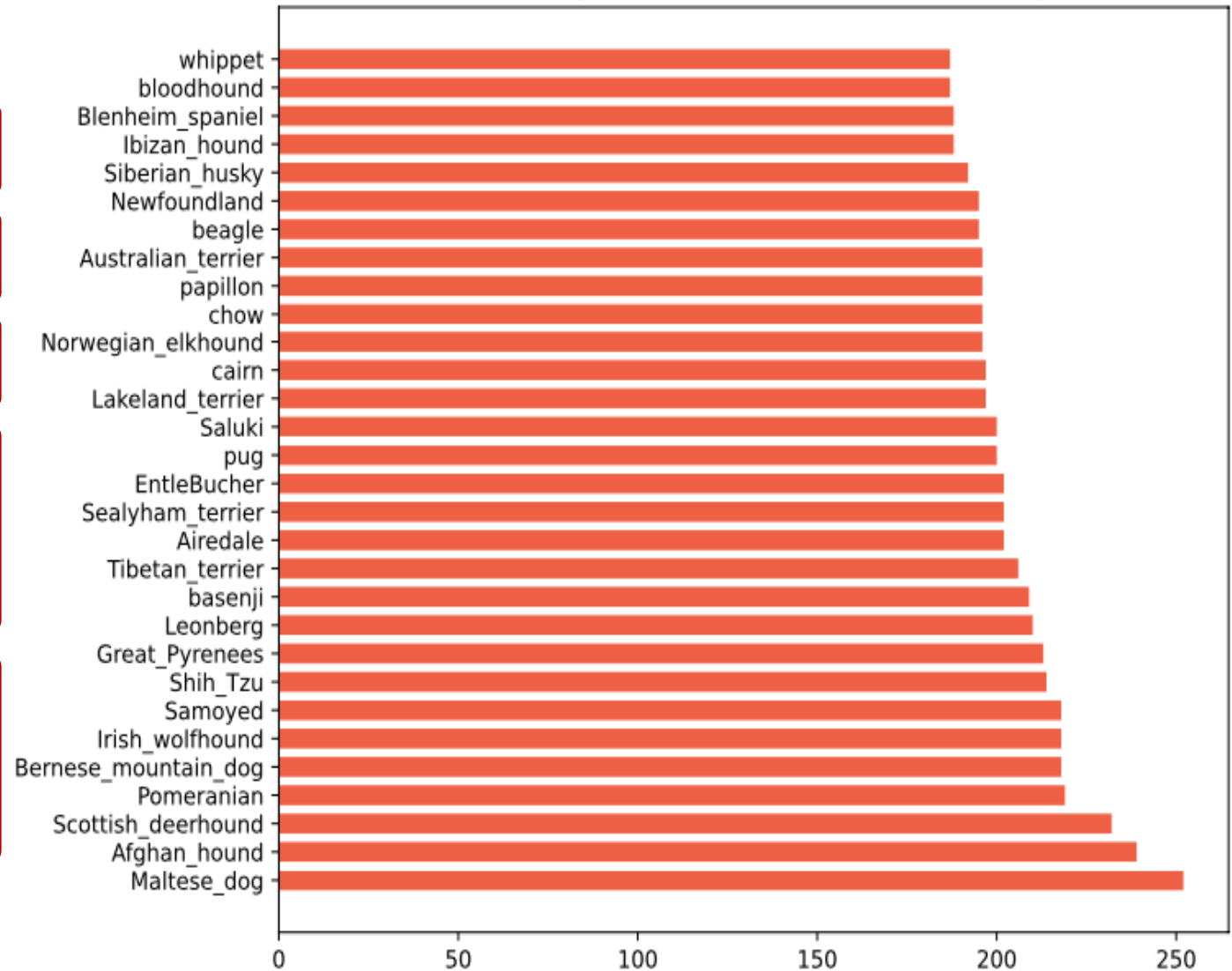
In the folder Images we have 120 folders containing each the images corresponding to one breed, while in the Annotation folder we have the information of the boundary boxes with the dog for each image.



Problem: Lot of classes and few data for each class

- Difficult to make accurate predictions
- Risk of overfitting
- Long time to train the model

Number of images of different breeds in descending order



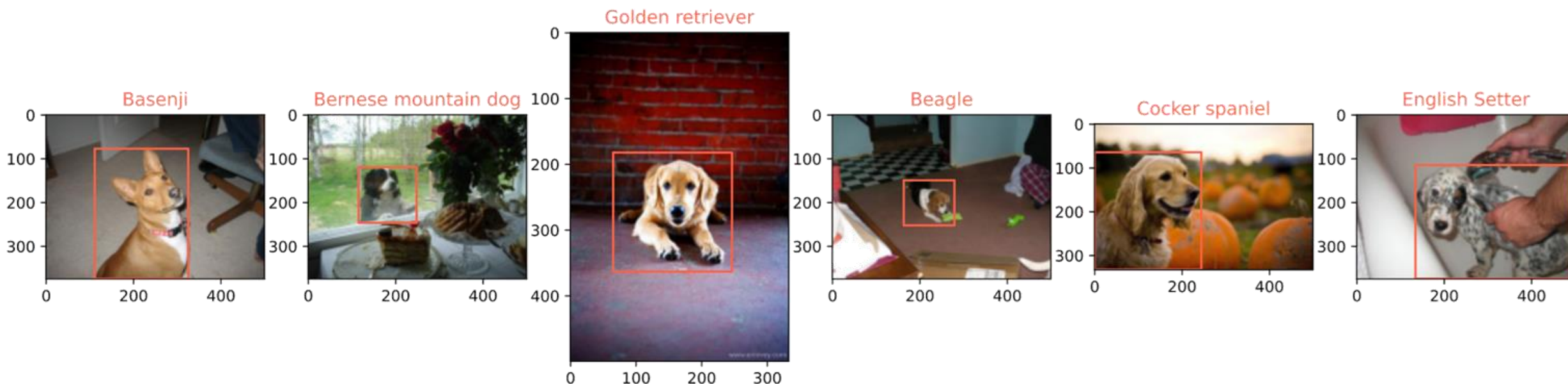
BOUNDARY BOXES

BOXES FROM ANNOTATIONS

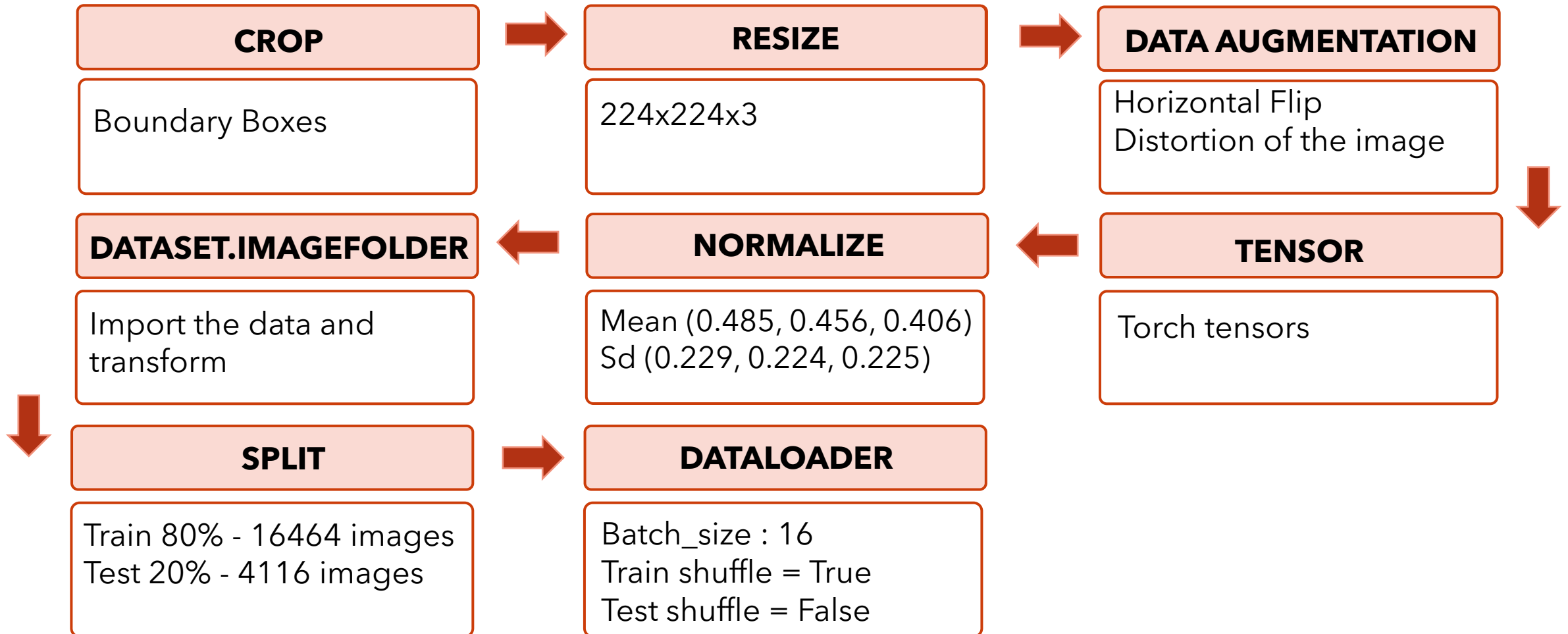
Extracting informations contained in the files of the folder Annotations to create the boxes where the dog is contained.

OBJECT DETECTION USING NEURAL NETWORKS

We used Faster R-CNN ResNet50 to detect objects in the images, that creates their own bounding boxes.

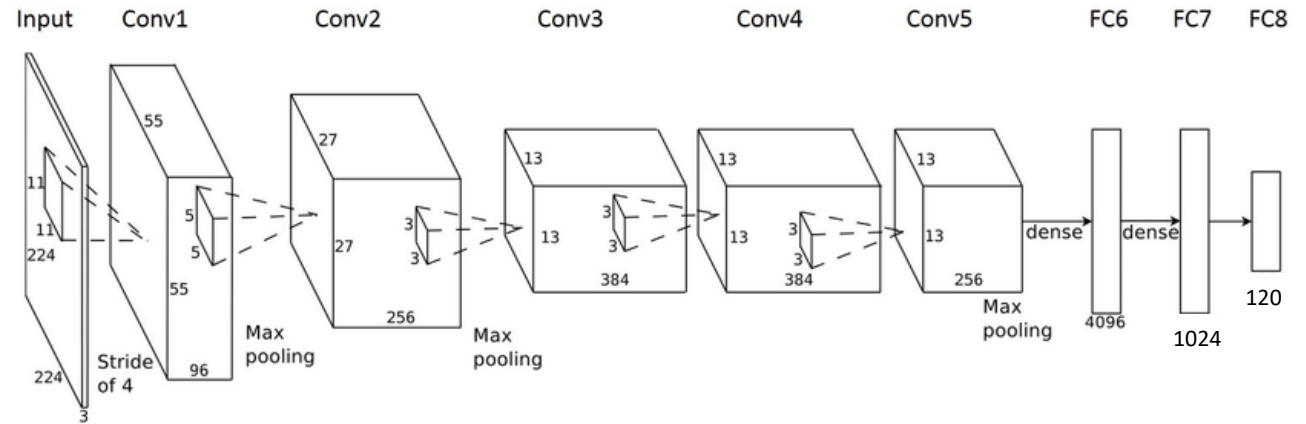


PREPARE THE DATA



AlexNet

- Model imported from **PyTorch**
- Changed the last 2 layers
- **Loss** : CrossEntropyLoss
- **Optimizer** : Stochastic Gradient Descent with learning rate 0.001
- Two implemetations:
 - **Not pretrained** : updated all the parameters
 - **Pretrained** : used as a fixed feature extractor, updated only the paramters of the last layer

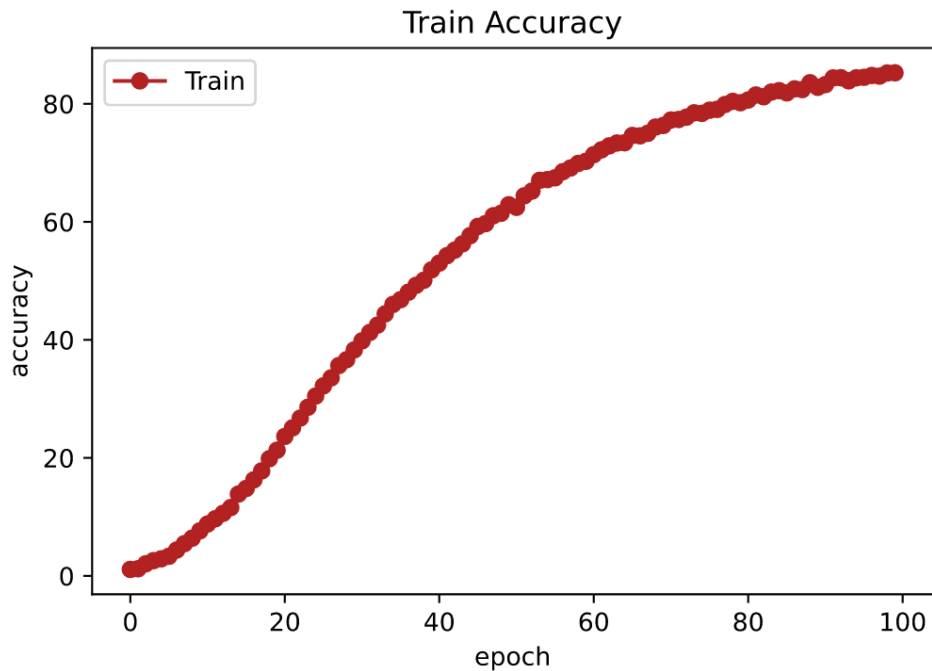


```
AlexNet(  
  (features): Sequential(  
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))  
    (1): ReLU(inplace=True)  
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)  
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))  
    (4): ReLU(inplace=True)  
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)  
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (7): ReLU(inplace=True)  
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (9): ReLU(inplace=True)  
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))  
    (11): ReLU(inplace=True)  
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)  
  )  
  (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))  
  (classifier): Sequential(  
    (0): Dropout(p=0.5, inplace=False)  
    (1): Linear(in_features=9216, out_features=4096, bias=True)  
    (2): ReLU(inplace=True)  
    (3): Dropout(p=0.5, inplace=False)  
    (4): Linear(in_features=4096, out_features=1024, bias=True)  
    (5): ReLU(inplace=True)  
    (6): Linear(in_features=1024, out_features=120, bias=True)  
  )  
)
```

AlexNet results

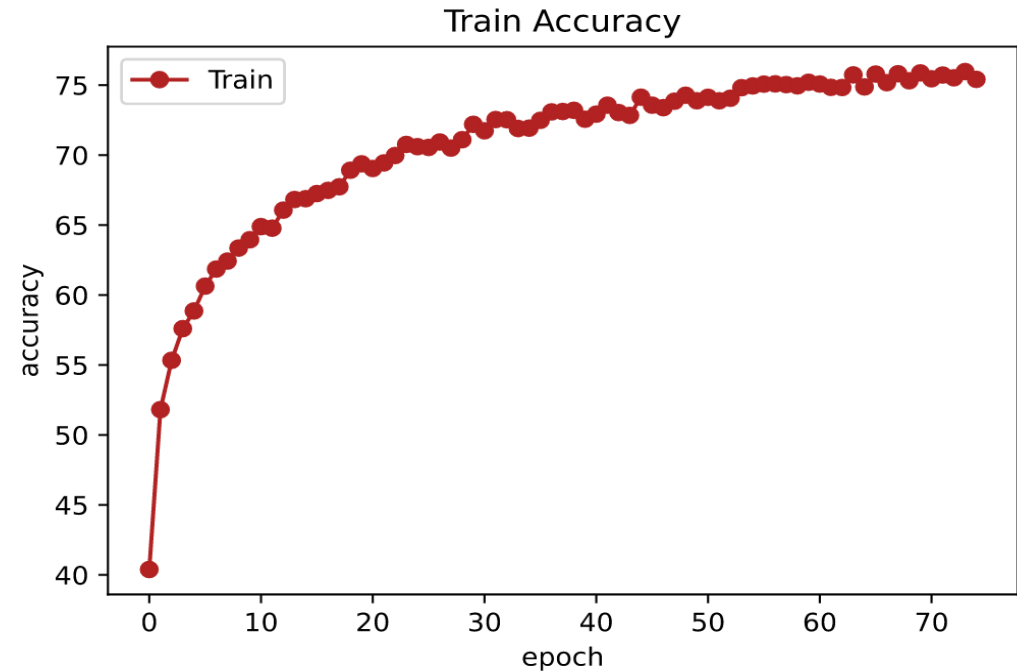
AlexNet not pretrained in 100 epochs reached an accuracy of:

- 85,25% on train set
- 85,59% on test set



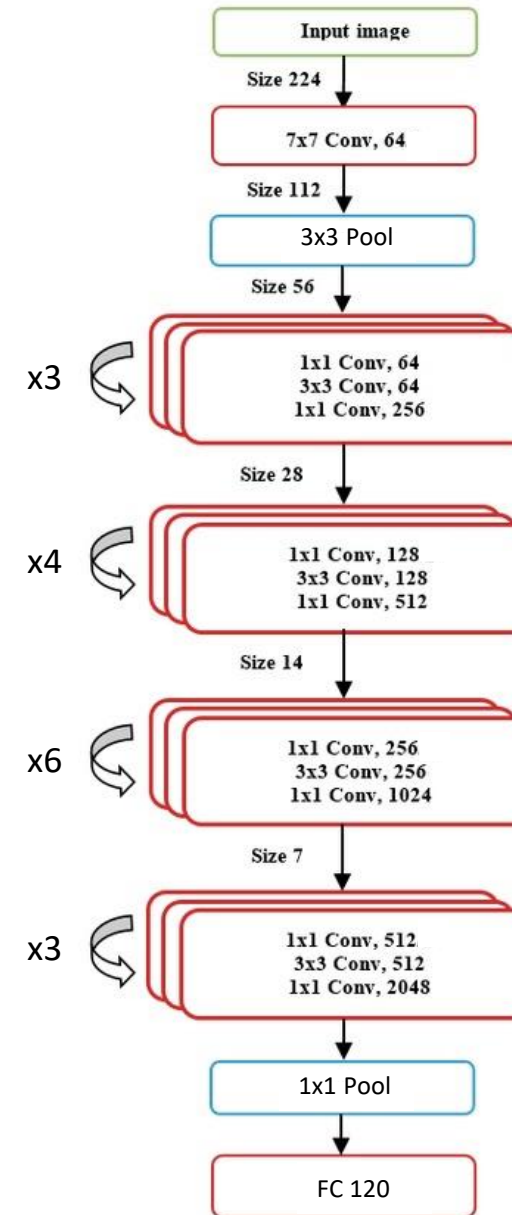
AlexNet pretrained as fixed feature extractor in 75 epochs reached an accuracy of:

- 75,41% on train set
- 82,09% on test set



ResNet50

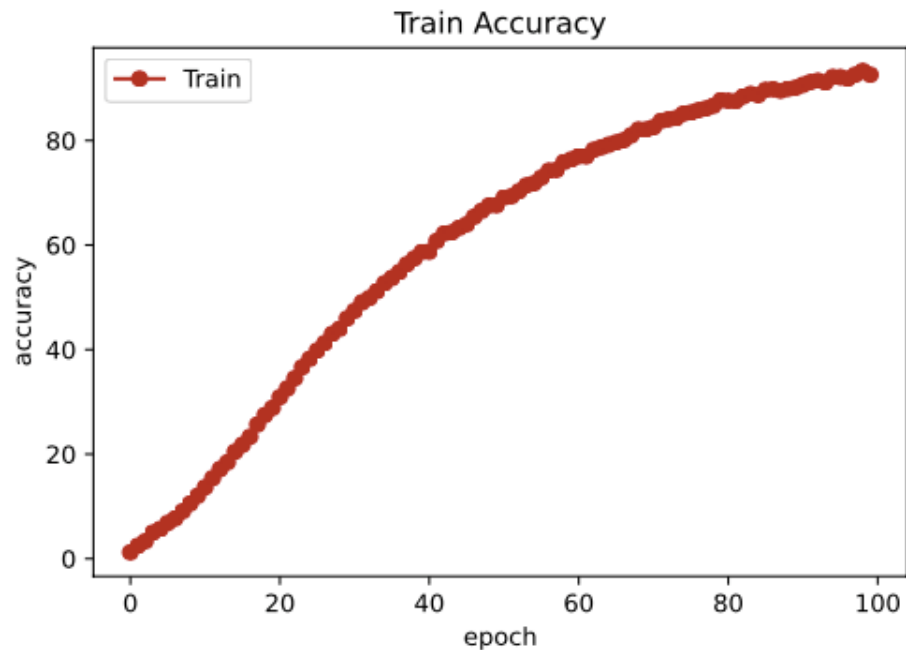
- Model imported from **PyTorch**
- Changed the last layer
- **Loss** : CrossEntropyLoss
- **Optimizer** : Stochastic Gradient Descent with learning rate 0.001
- Two implemetations:
 - **Not pretrained** : updated all the parameters
 - **Pretrained** : used as a fixed feature extractor, updated only the paramters of the last layer



ResNet50 results

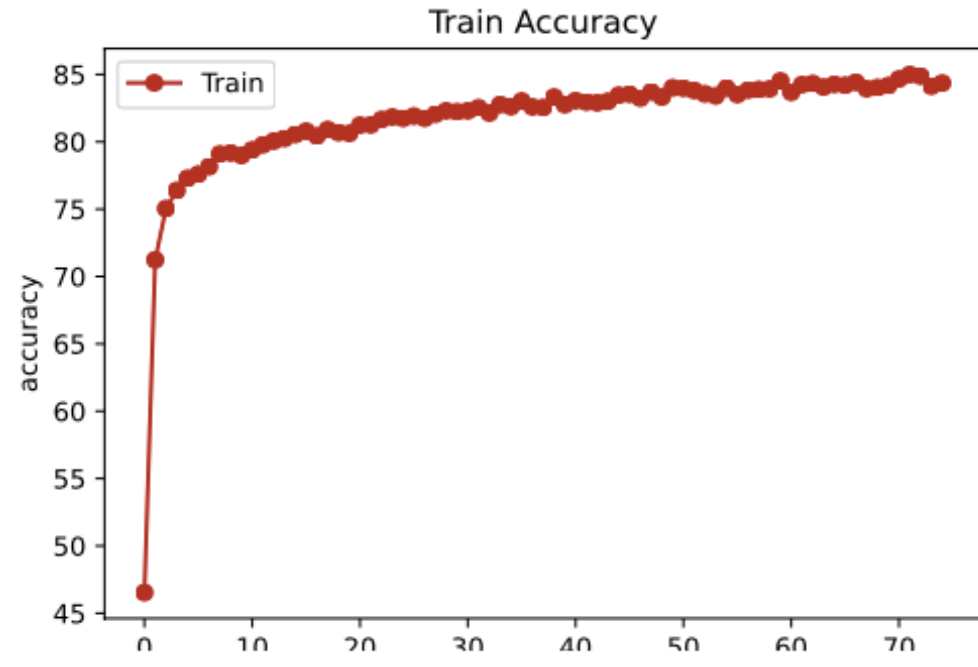
ResNet50 not pretrained in 100 epochs reached an accuracy of:

- 92.58% on train set
- 87,83% on test set



ResNet50 pretrained as fixed feature extractor in 75 epochs reached an accuracy of:

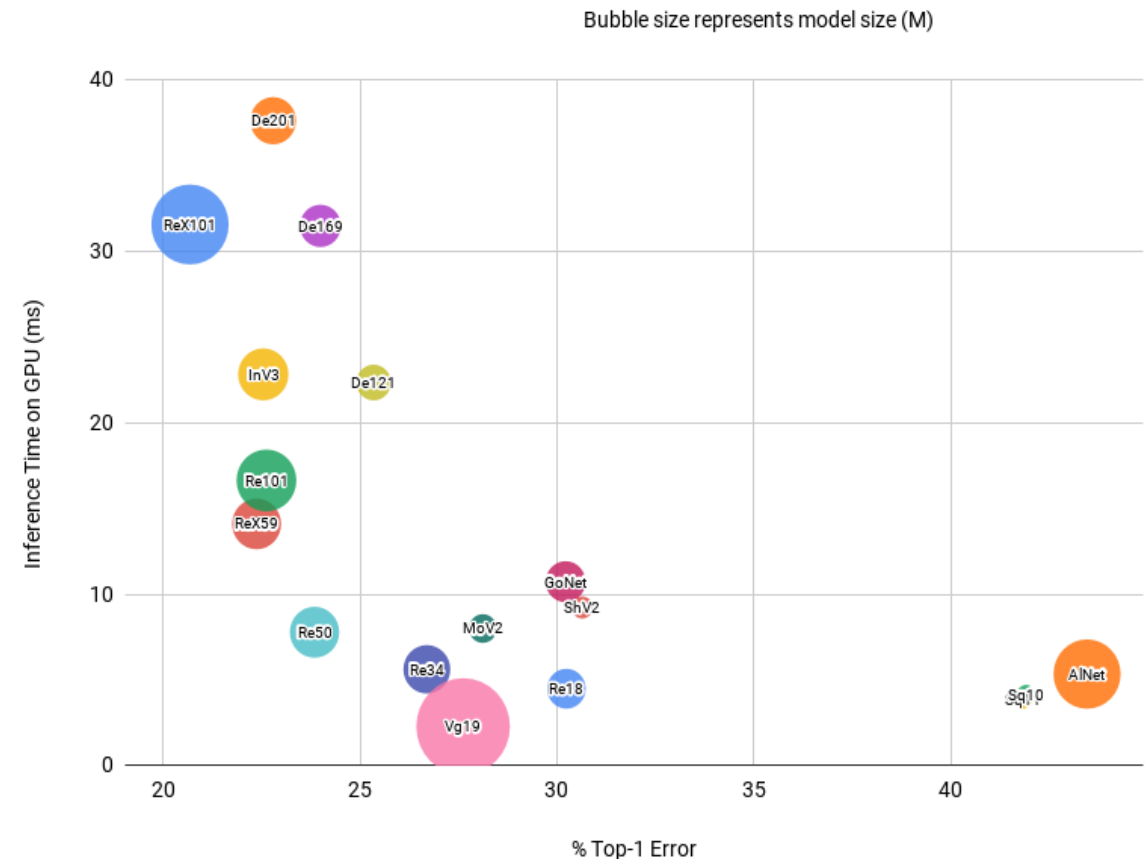
- 84,35% on train set
- 87,27% on test set



CONCLUSIONS

- **Differences between AlexNet and ResNet50:**
ResNet is a deeper model so the results are better than AlexNet.
- **Differences between pretrained and not pretrained:** thanks to the work done previously on ImageNet we can have a faster training of the model. ResNet50 pretrained obtains a train accuracy of 75% in only 3 epochs.
- **Possible ideas to improve the performances:**
 - Greater number of epochs for not pretrained models
 - Fine tuning for the pretrained models
 - Decrease batch size
 - Decrease learning rate

PRE-TRAINED MODEL COMPARISON



P R E D I C T I O N S

REAL BREED

**ALEXNET
NOT
PRETRAINED**

**ALEXNET
PRETRAINED**

**RESNET50
NOT
PRETRAINED**

**RESNET50
PRETRAINED**

MARGOT

BERNESE
MOUNTAIN
DOG



AFGHAN
HOUND



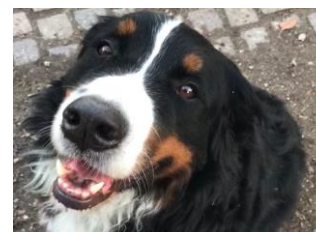
GORDON
SETTER



BORDER
COLLIE



BERNESE
MOUNTAIN
DOG ✓



KOBE

UNKNOWN



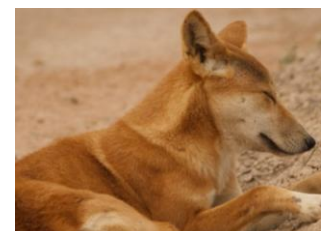
DHOLE



DHOLE



DINGO



KELPIE

