## Projet 6 : Parcours Machine Learning Classez des images à l'aide d'algorithmes de Deep Learning





Septembre 2023 Clara Yaïche Étudiante en alternance NXP - OpenClassrooms Parcours Machine Learning

## La problématique

Classification multi-classe

approche supervisée

Vision par ordinateur





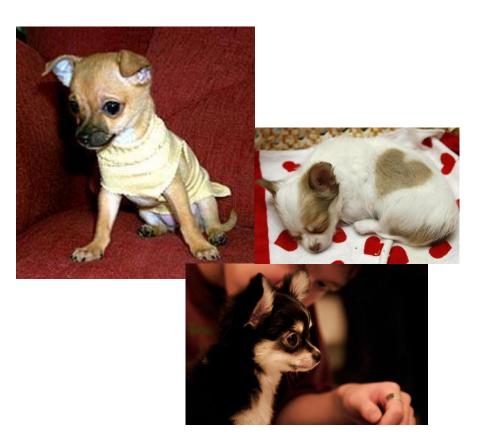




## **Sommaire**

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  - 1. Standford Dog dataset
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  - 3. Data augmentation
- II. Le choix du modèle
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  - 1. Métriques et comparaison des résultats
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#### **Standford Dog dataset**



20 580 images couleur

120 races de chiens

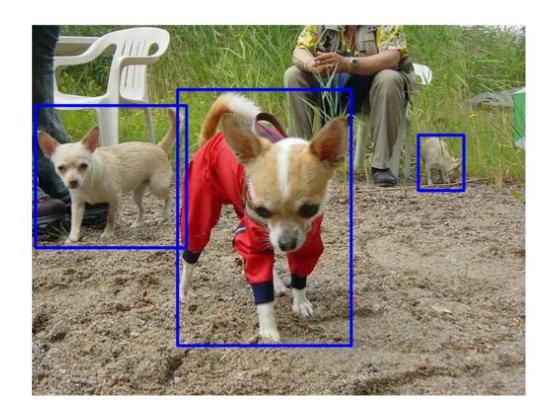
148 à 252 images par race

159 en moyenne

100 à 2562 px de hauteur

97 à 3 264 px de largeur

#### **Prétraitements des images**



#### **Prétraitements des images**

Original dimension from extract, target dim 50176px



56959 px



7571 px



Open CV resize function





crop image from center but let margin if possible







#### **Data augmentation**













miroir zoom rotation translation

changement de contraste

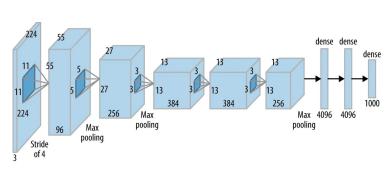
x 10 images

6 000 à 60 000 dans le set d'entrainement

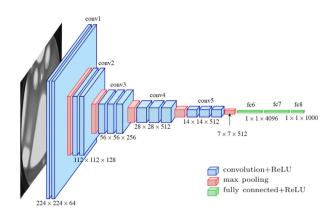
## Le choix du modèle

#### Le choix du modèle

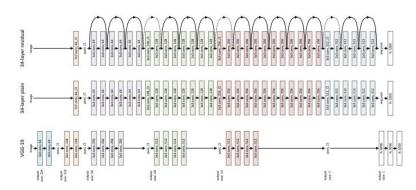
#### État de l'art : l'intérêt des couches convolutives



AlexNet, 2012



VGGNet 2014



ResNEt, 2015

#### Le choix du modèle Filter concatenation **Transfer Learning: Xception, 2014** 5x5 convolutions 3x3 convolutions 1x1 convolutions 1x1 convolutions 1x1 convolutions 1x1 convolutions 3x3 max pooling Middle flow Exit flow Entry flow Previous layer 299x299x3 images 19x19x728 feature maps 19x19x728 feature maps Conv 32, 3x3, stride=2x2 ReLU ReLU SeparableConv 728, 3x3 SeparableConv 728, 3x3 Conv 64, 3x3 ReLU Conv 1x1 SeparableConv 728, 3x3 stride=2x2 SeparableConv 1024, 3x3 SeparableConv 128, 3x3 MaxPooling 3x3, stride=2x2 SeparableConv 728, 3x3 Conv 1x1 stride=2x2 SeparableConv 128, 3x3 SeparableConv 1536, 3x3 MaxPooling 3x3, stride=2x2 19x19x728 feature maps SeparableConv 2048, 3x3 Repeated 8 times SeparableConv 256, 3x3 GlobalAveragePooling Conv 1x1 stride=2x2 SeparableConv 256, 3x3 2048-dimensional vectors MaxPooling 3x3, stride=2x2 Optional fully-connected layer(s) SeparableConv 728, 3x3 Logistic regression Conv 1x1 stride=2x2 SeparableConv 728, 3x3 MaxPooling 3x3, stride=2x2 19x19x728 feature maps

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Ø 25 days ago	12.7s	20230827_1	(2, 2)	256		True	64	(224, 224, 3)	categorical	['accuracy']	10	150	adam	10	200
Ø 25 days ago	13.3s	20230827_1	(2, 2)	256	-	True	64	(224, 224, 3)	categorical	['accuracy']	10	40	adam	10	200
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## **Evaluation**

#### **Entrainement et évaluation**

métriques et comparaison des résultats

Séparation : train/validation / test sets

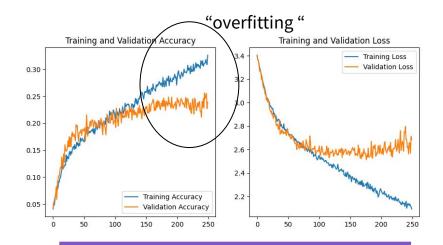
Métrique : accuracy

nombre de prédictions correctes sur le nombre de prédictions totales

Loss:

erreur d'entropie croisée catégorielle (categorical crossentropy)

Optimizer: Adam

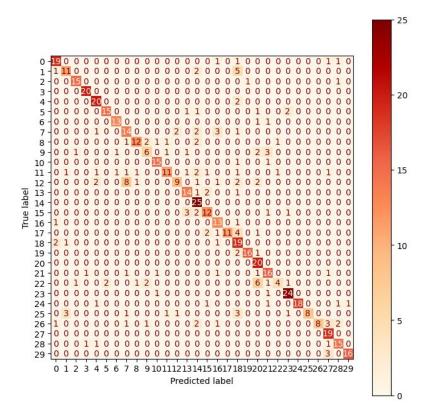


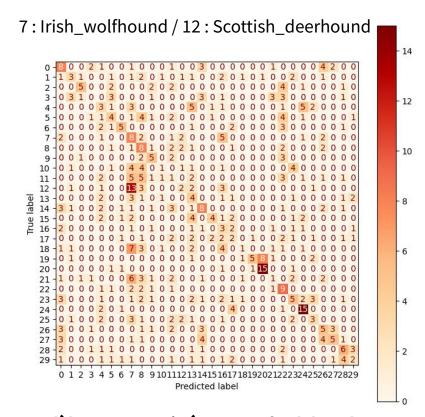
**Transfert learning / CNN** 

0.73 / 0.25 accuracy
1.42 / 2.62 loss

#### **Entrainement et évaluation**

#### Erreurs et pistes d'amélioration





Modèle CNN entrainé sur Stanford dog dataset

Modèle par "transfer learning"

#### **Entrainement et évaluation**

#### Erreurs et pistes d'amélioration

#### Scottish\_deerhound wrongly classified



Irish\_wolfhound



Irish\_wolfhound



Sealyham\_terrier



## How to Tell the Difference Between the Scottish Deerhound & Irish Wolfhound

source: https://www.akc.org/expert-advice/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound/lifestyle/difference-between-irish-wolfhound-scottish-deerhound-lifestyle/difference-between-irish-wolfhound-scottish-deerhound-lifestyle/difference-between-irish-wolfhound-scottish-deerhound-lifestyle/difference-between-irish-deerhound-lifesty

Irish wolfhound wrongly classified





Scottish\_deerhound



cairn



# **Autres pistes**