



INSTITUT
POLYTECHNIQUE
DE PARIS

FINAL TERM PRESENTATION

DEEP LEARNING BASED METHOD FOR AUTOMATIC HUMAN POSE UNDERSTANDING

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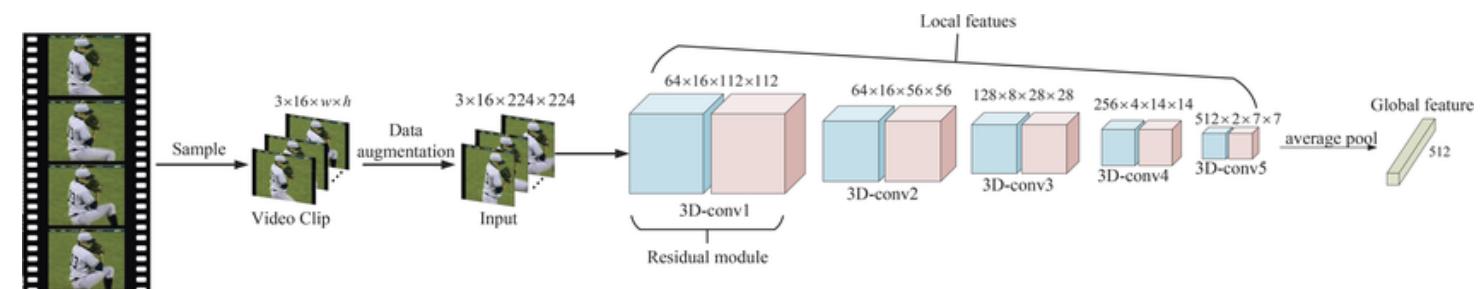
OBJECTIVES

AUTOMATIC ACTION RECOGNITION

1. To build basic action recognition with the use of Deep Learning based computer vision method.
2. To evaluate the capability of the developed method on the common datasets
3. To apply the method on the real life setting
4. Use image or keypoints for action recognition

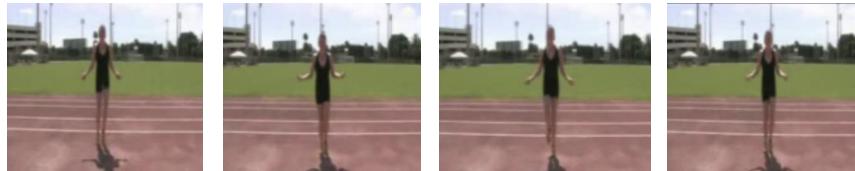


(b) stretching leg



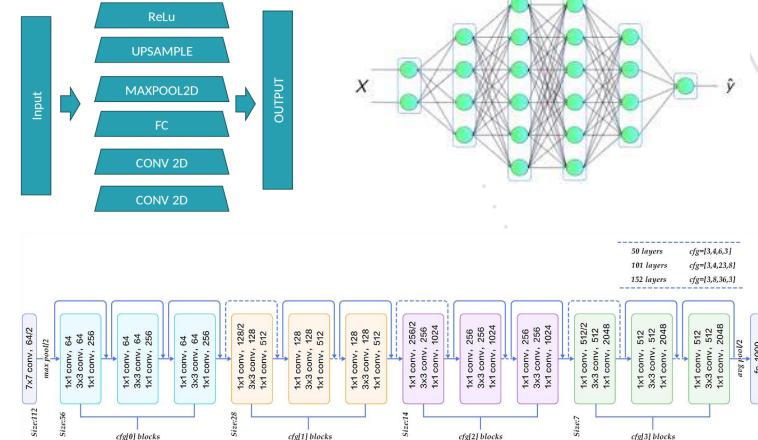
PIPELINE

Data loader

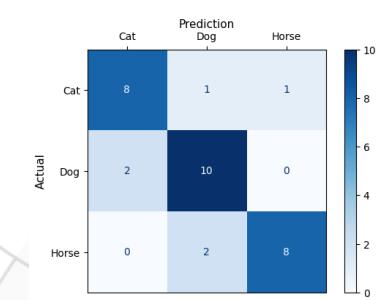


(b) stretching leg

Model



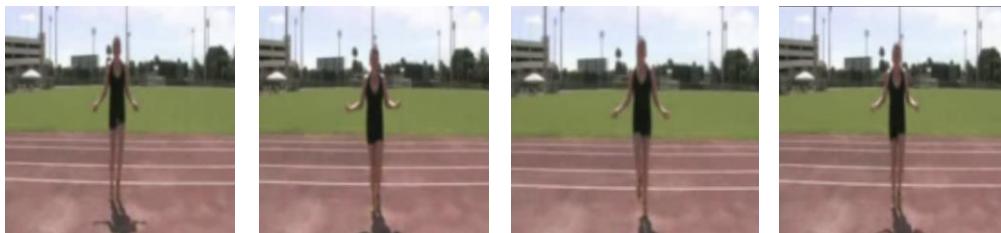
Output



Data Loader – Activity Net and UCF 101

UCF 101

- Data pre-processing :
 - Statistic : 13 320 videos & 101 labels
 - Input : frames (16/video)
 - Output : class labels + frames



```
=====
Début de l'extraction des frames pour l'action : JumpRope
Dossier de destination : /home/amine_tsp/DL2026/Datasets/UCF101/mes_frames_video
Terminé ! Toutes les images sont générées.
=====
```

ActivityNet

Json file (video url, timecode, label)

- Download videos (95% corrupted videos).
- -> ~1000 number of videos, 200 classes
- Croping videos
- Data augmentation
- Data splitting (training, testing, validation)
- Framing clips



(b) stretching leg

Model : Fully Connected

Image 224x224

Frames : 16

Color : 'RGB'

Shape : [3, 16, 224, 224]

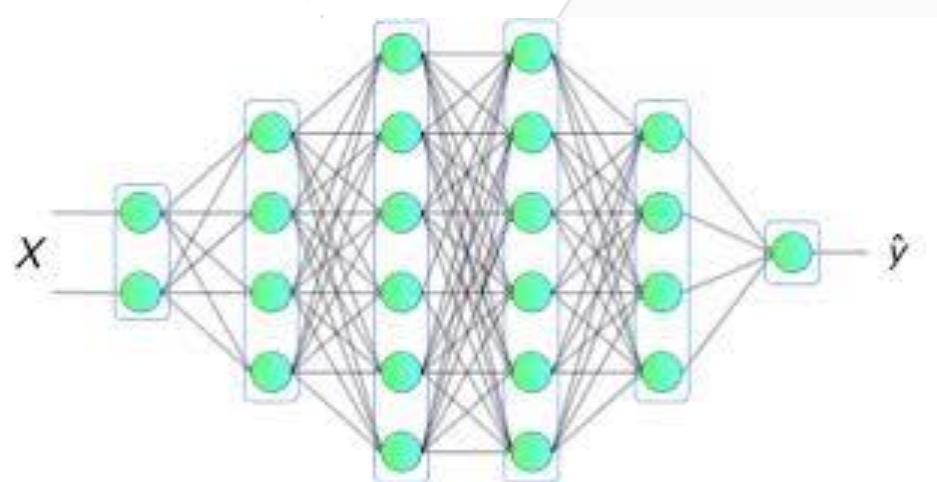
InputNode = $3 \times 16 \times 224 \times 224$
= 2 408 448

OutputNode : 101

```
class FC(nn.Module):
    def __init__(self,inputNode=561,hiddenNode = 256, outputNode=1):
        super(FC, self).__init__()
        #Define Hyperparameters
        self.inputLayerSize = inputNode
        self.outputLayerSize = outputNode
        self.hiddenLayerSize = hiddenNode

        self.relu = nn.ReLU()

        # weights
        self.Linear1 = nn.Linear(self.inputLayerSize, self.hiddenLayerSize)
        self.Linear2 = nn.Linear(self.hiddenLayerSize, self.outputLayerSize)
```



Model : CNN+LSTM

Image 224x224

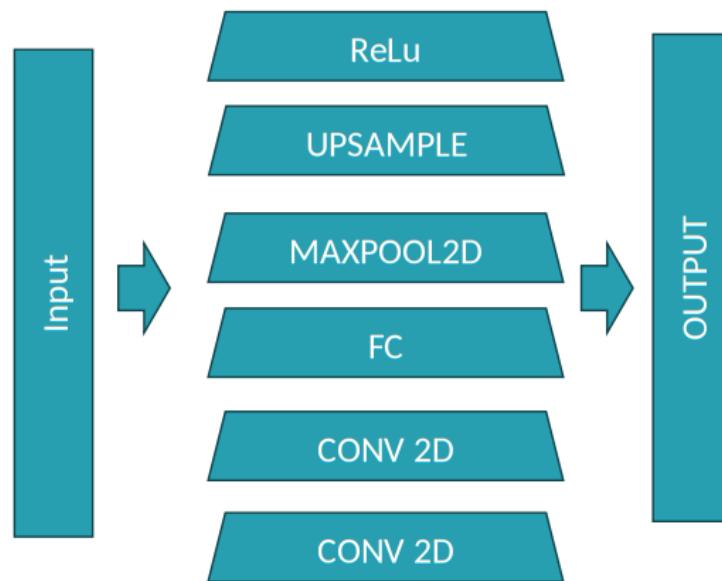
Frames : 16

Color : 'RGB'

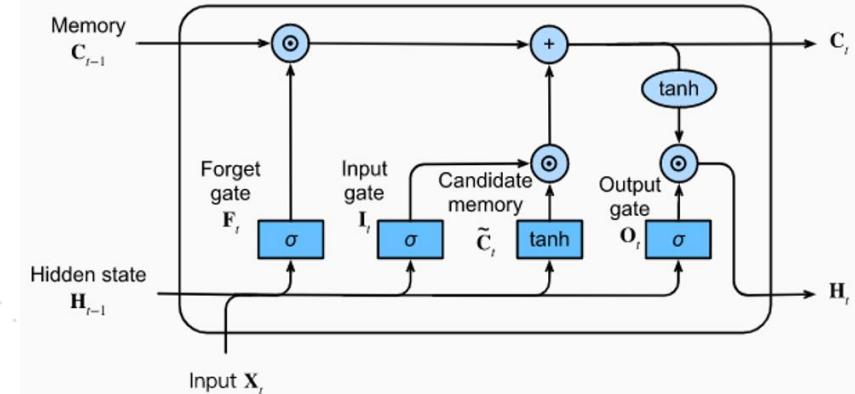
Shape : [3, 16, 224, 224]

**InputNode = $3 * 16 * 224 * 224$
 $= 2\ 408\ 448$**

OutputNode : 101



CNN



LSTM (RNN)

Model : ResNet50+LSTM

Pre-trained ResNet50 on CIFAR-10

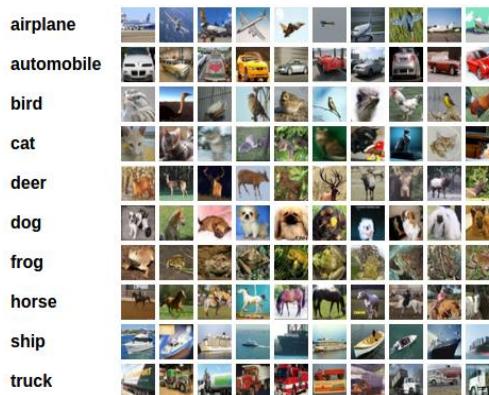
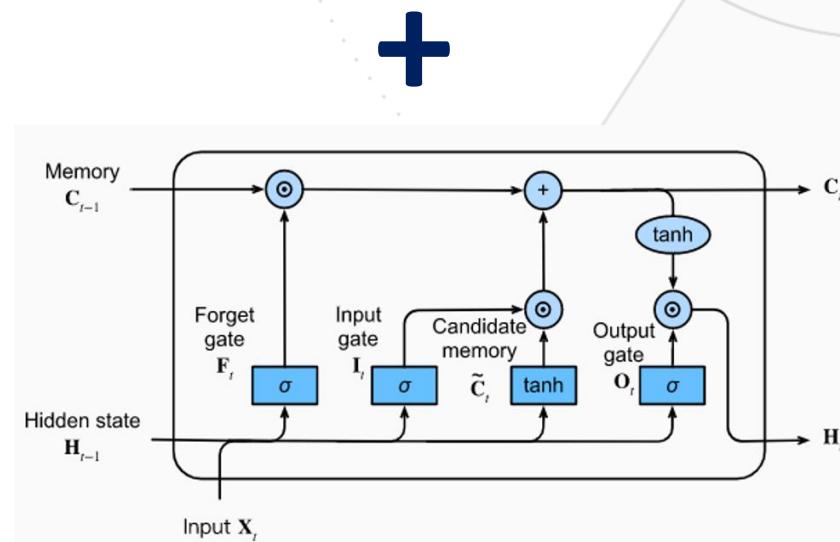
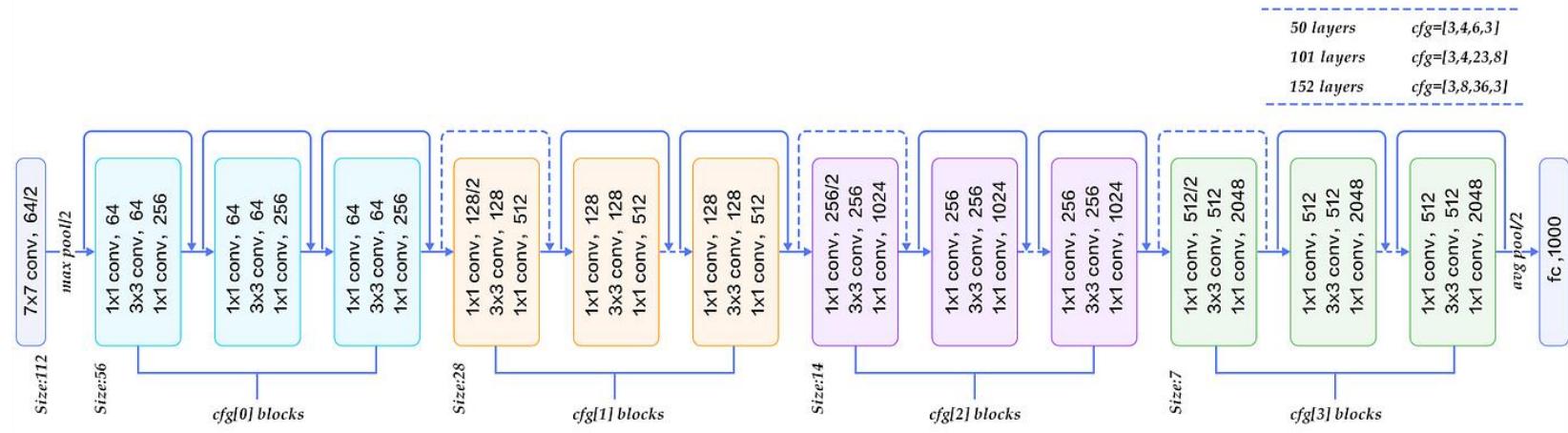


Image 224x224
Frames : 16
Color : 'RGB'
Shape : [3, 16, 224, 224]
InputNode = $3 \times 16 \times 224 \times 224$
 $= 2\,408\,448$
OutputNode : 101



Model : ResNet3D-18

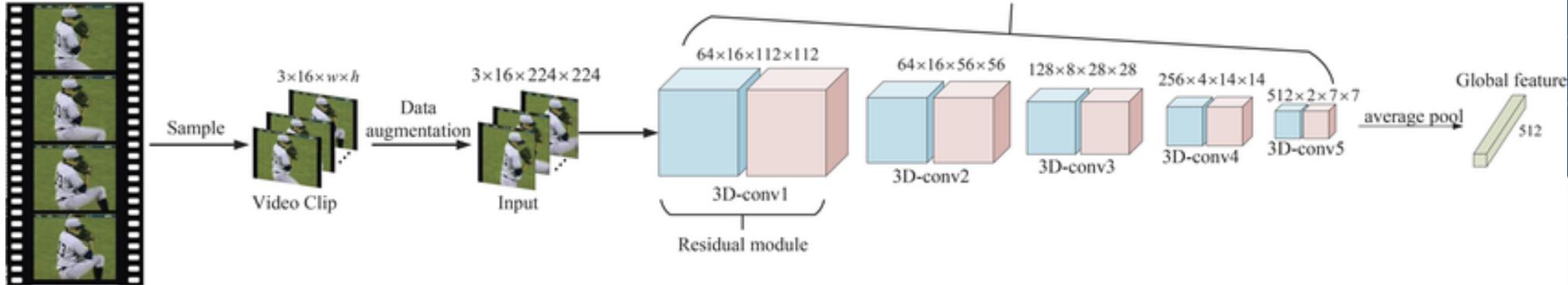


Image: 224×224

Frames: 16

Colors: 'RGB'

Shape: [3, 16, 224, 224]

InputNode = $3 * 16 * 224 * 224$
= 2 408 448

OutputNode : 101

Pre-trained on Kinetics-400



(c) shaking hands

Quantitative evaluation

Accuracy

Accuracy measures the absolute correct prediction of the model

$$\text{Accuracy} = \frac{\text{Correct predictions}}{\text{All predictions}}$$

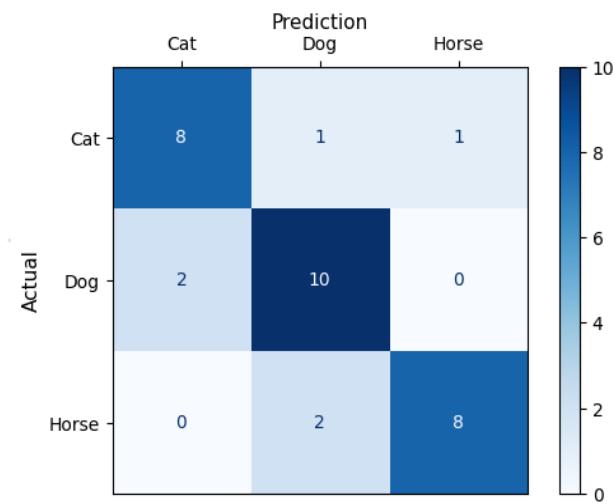
F1score

F1 score takes into account the label distribution

$$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$$

Confusion matrix

Compare the prediction with their true label



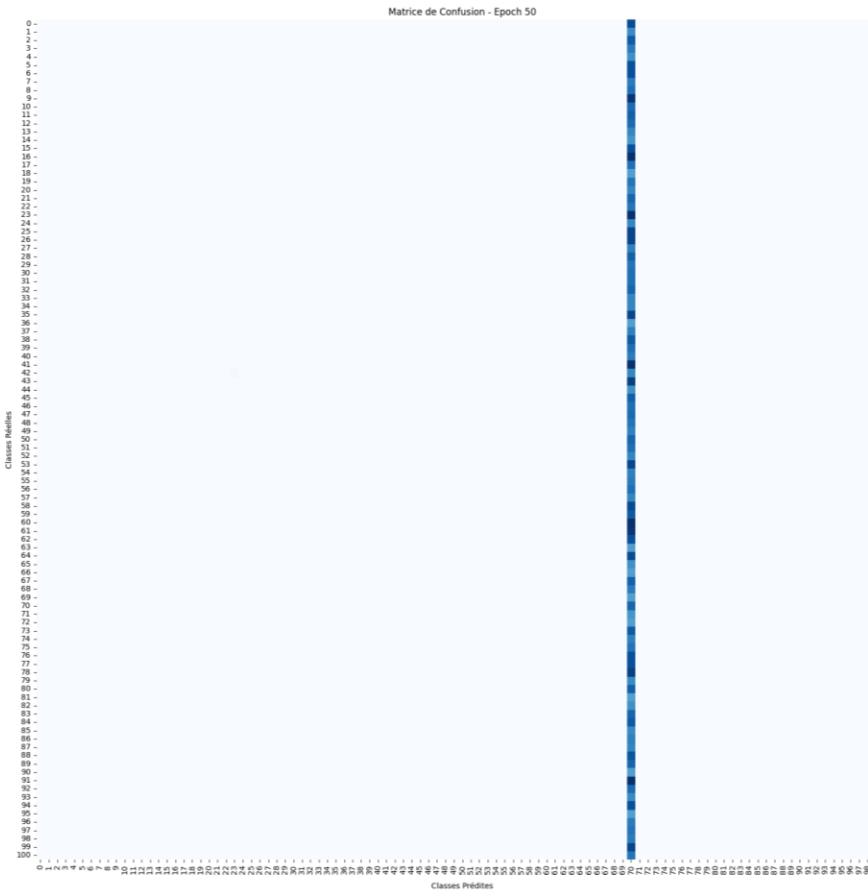
Quantitative Comparisons

- The best methods are the ResNet3D, with accuracy score of 79,67% and F1 score of 0,7895
- FC doesn't do well bc of complexity of the model and data
- CNN+LSTM worked better than FC bc it takes into account the image information (text, color etc) and the time information
- ResNet50 and ResNet3D worked even better given that they have been pre-trained on other datasets

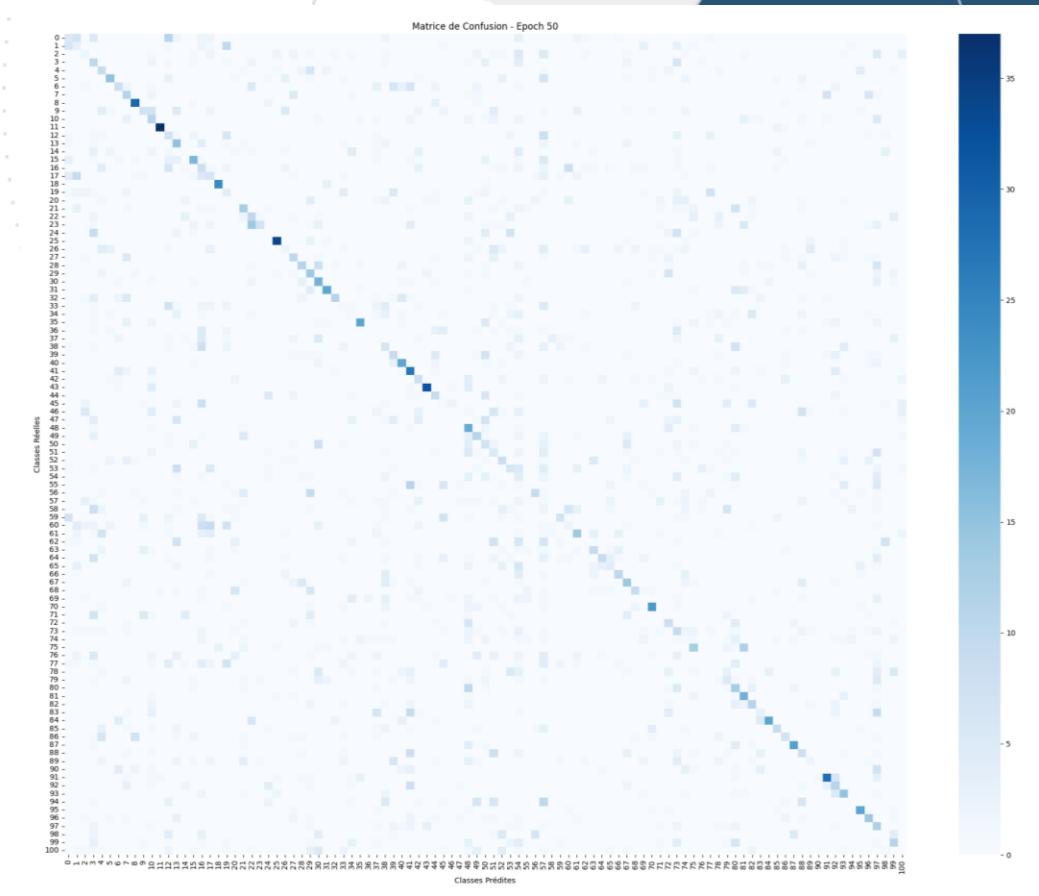
Methods	UCF 101	
	Accuracy	F1 score
Fully connected	1.14%	0.0002
CNN + LSTM	25.67%	0.2379
ResNet50 + LSTM	72.38%	0.7072
ResNet3D	79.67 %	0.7895

Result 1 : confusion matrix for each model (1/2)

Fully Connected

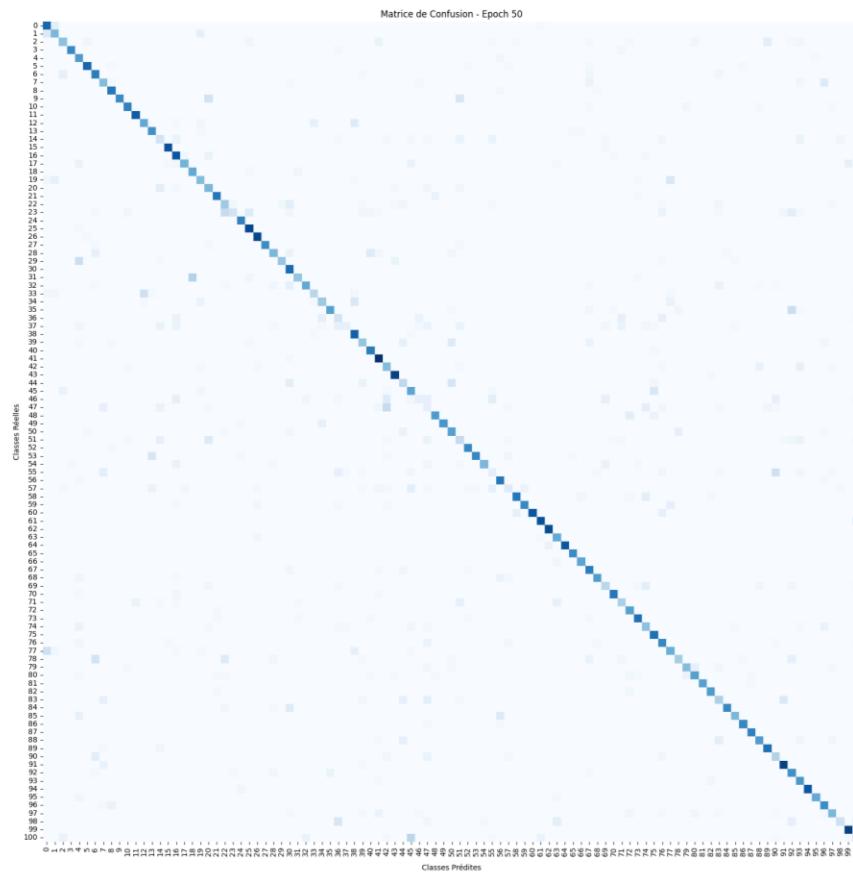


CNN + LSTM

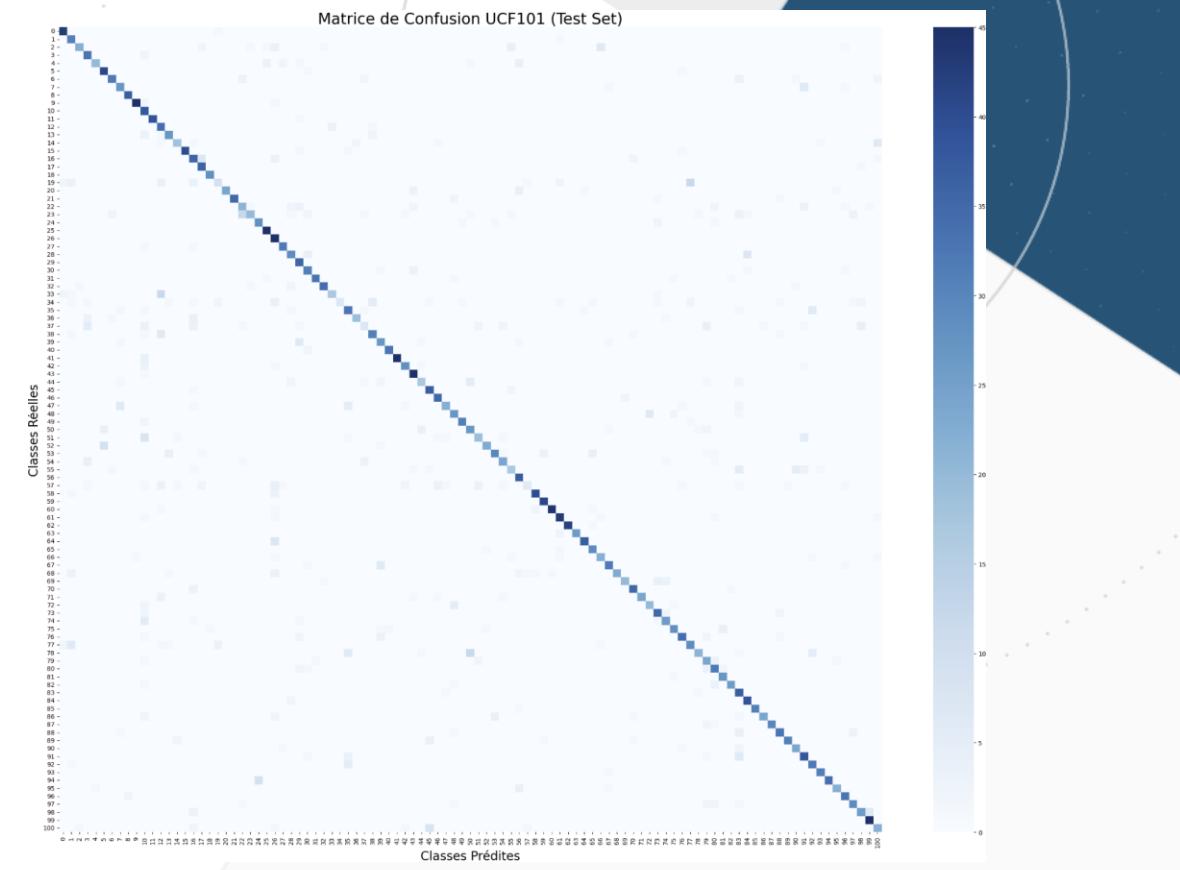


Result 1 : confusion matrix for each model (2/2)

ResNet50 + LSTM



ResNet3D-18





Label : Basketball

Result – Predict single video

Vidéo analysée : v_Basketball_g01_c01		
RANG	CLASSE	CONFIANCE
1	Punch	1.23%
2	PlayingCello	1.21%
3	ShavingBeard	1.19%
4	PlayingGuitar	1.19%
5	CricketShot	1.18%

FC

Vidéo analysée : v_Basketball_g01_c01		
RANG	CLASSE	CONFIANCE
1	TennisSwing	98.68%
2	Basketball	1.04%
3	BasketballDunk	0.15%
4	FieldHockeyPenalty	0.05%
5	VolleyballSpiking	0.02%

ResNet3D-18

RANG	CLASSE	CONFIANCE
1	Fencing	36.68%
2	FloorGymnastics	28.83%
3	Kayaking	27.59%
4	Rafting	4.41%
5	WalkingWithDog	1.26%

CNN + LSTM

RANG	CLASSE	CONFIANCE
1	Basketball	99.59%
2	SoccerJuggling	0.23%
3	VolleyballSpiking	0.06%
4	TennisSwing	0.04%
5	BodyWeightSquats	0.01%

ResNet50 + LSTM

Live result with ResNet50 + LSTM



Summary

Whole project successfully implemented the basic deep learning models for action recognitions.

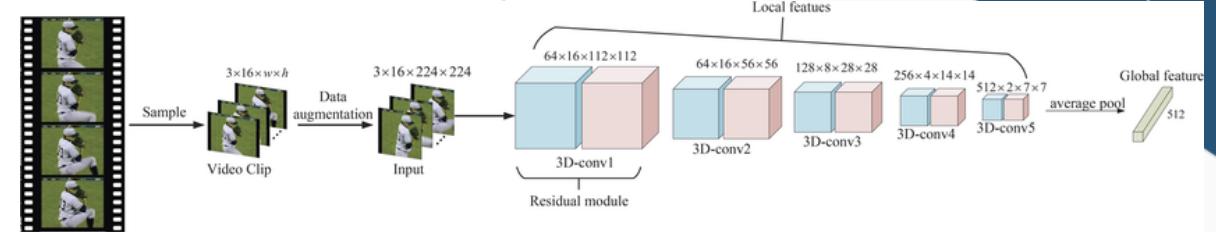
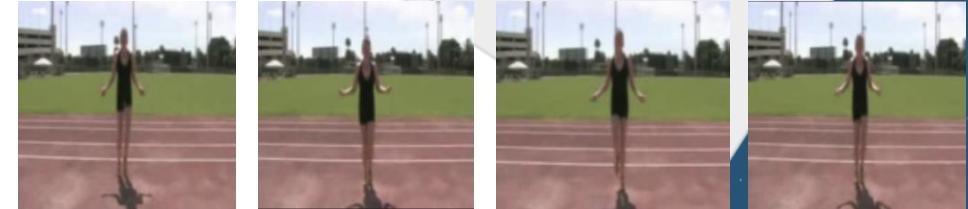
Four methods are implemented (FC, CNN + LSTM, Resnet + LSTM, and Resnet3D-18)

The best methods are Resnet3D, mainly that it is pretrained in relevant dataset (Kinetics-400)

Live inference shows the ability of the methods to do prediction.

To improve:

1. To use bigger methods, such as transformer
2. To use keypoints as the inputs (openpose)
3. To enhance the inference (Two Stream Fusion with 2 buffers pixels+keypoints)



Methods	UCF 101	
	Accuracy	F1 score
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ResNet3D	79.67 %	0.7895



What did we learn and challenges

Topics:

Keypoint prediction
Action recognition

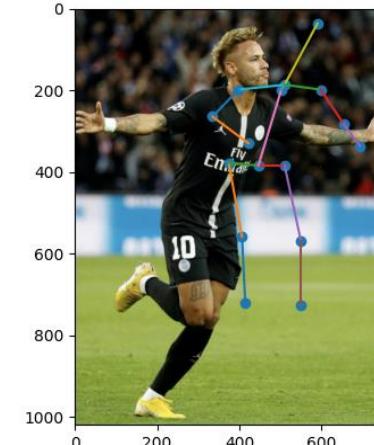
Methods:

FC, CNN+LSTM, RESNET50+LSTM, RESNET3D,
Openpose (keypoints)

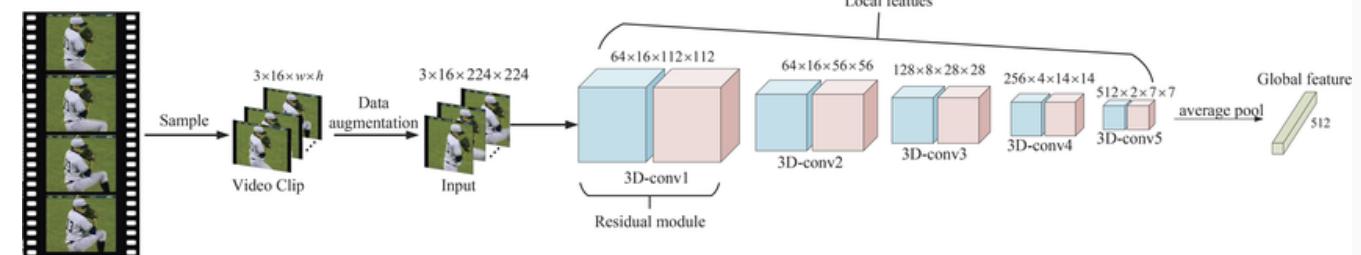
Code management: Access SSH server, install libraries, environments, GPU management

Challenges :

- Code management (beginning)
- Understand last year code (beginning)
- Modelling
- Technical limitations



(b) stretching leg



ANY QUESTIONS ?





THANK YOU

- **DJEDDOU Kaïs**
- **MAUREL Alexandre**
- **JEAN-MARIE Matisse**
- **KEMPF Louis**