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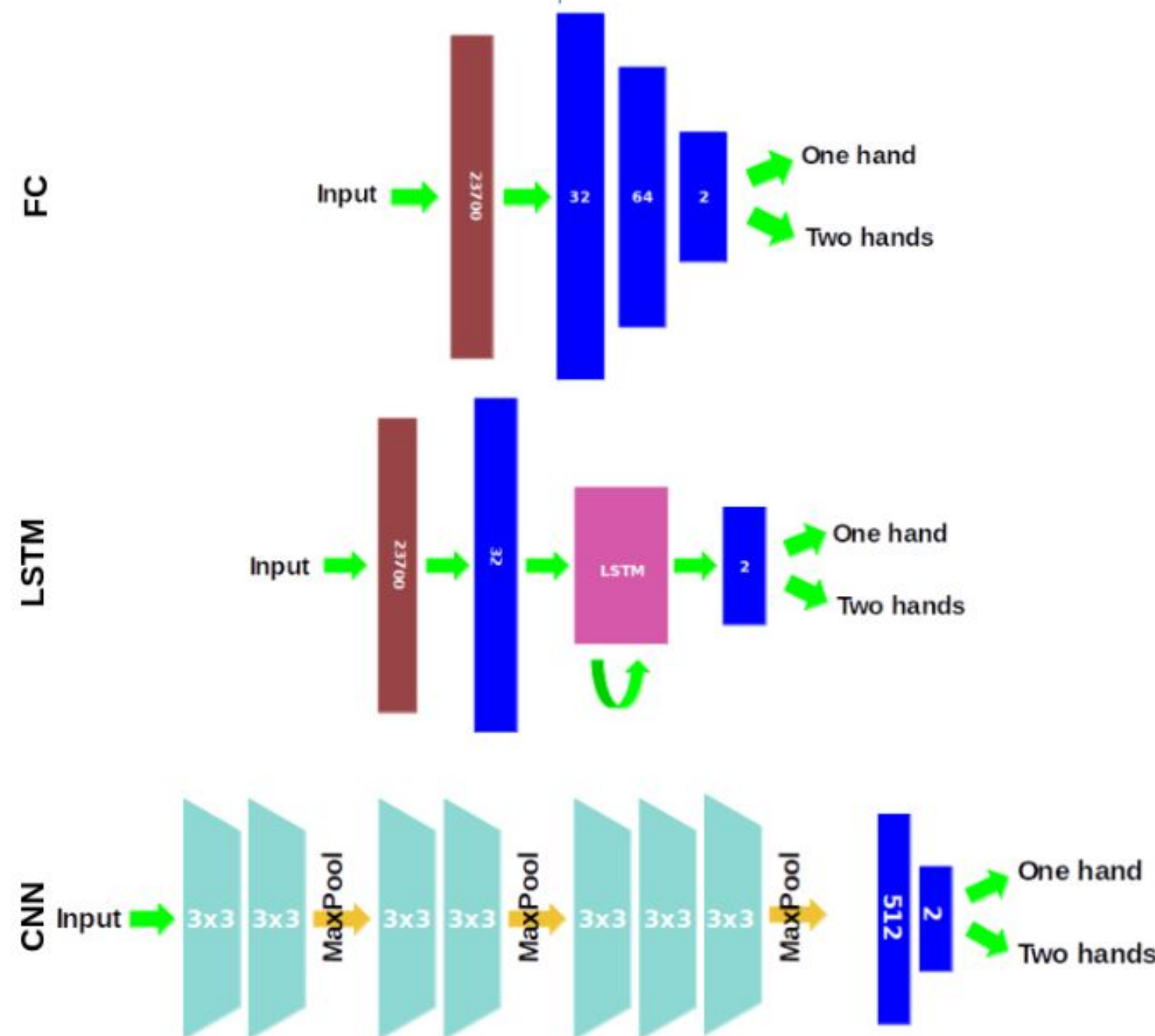
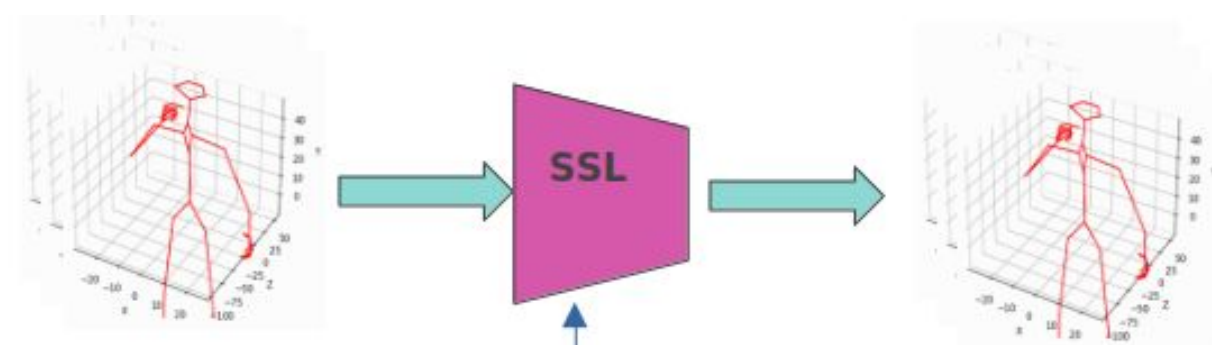
THE PROBLEM AND OBJECTIVE

SIGN LANGUAGE RECOGNITION

1. The problem:

- **Automatic gesture recognition** is important for non-verbal communication, especially **sign language**.
- Can **self-supervised learning** improve recognition performances ?

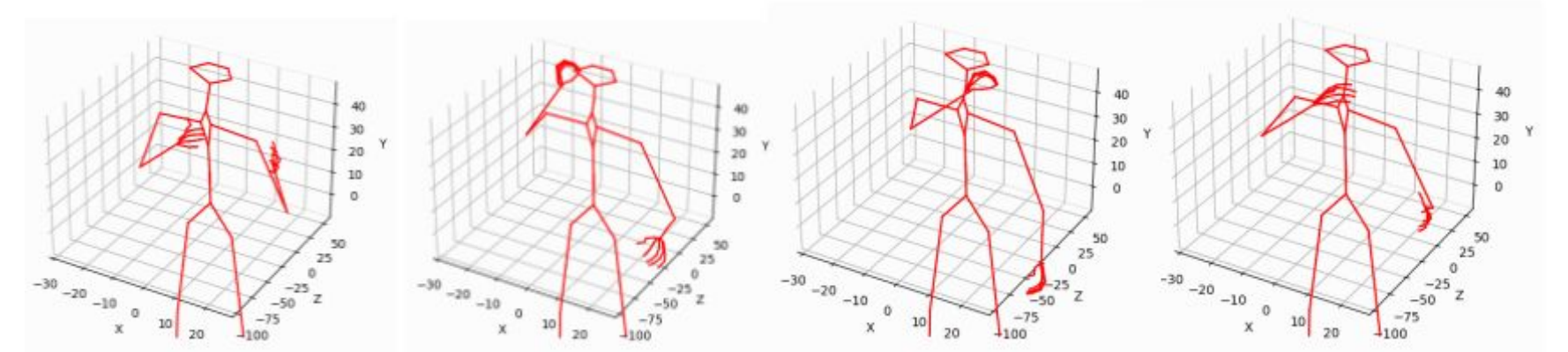
2. The objective: To **classify** gestures (**signs**) given some input data (**moving 3D skeletons**).



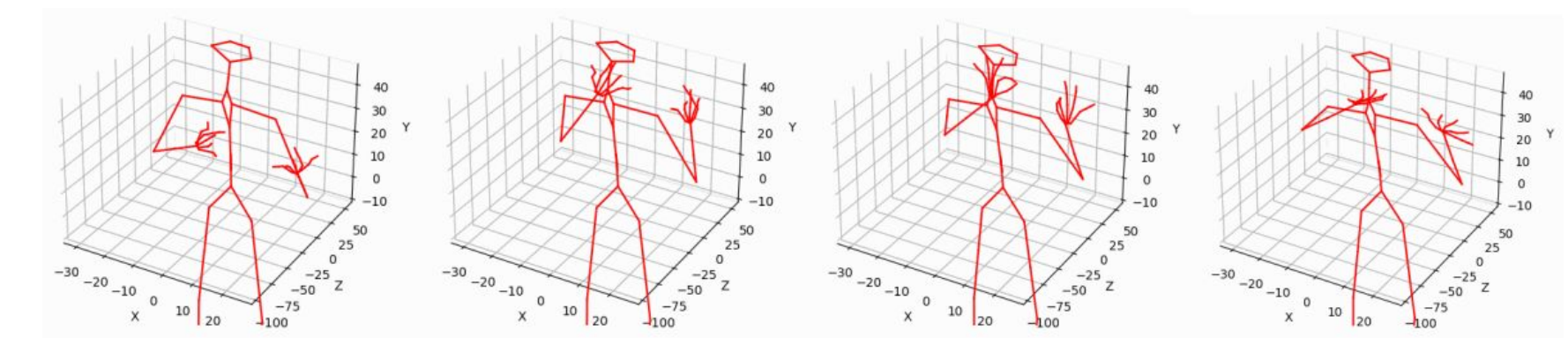
RESULTS AND TAKEAWAYS

SELF-SUPERVISED LEARNING PUT TO THE TEST

1. **Self-supervised learning leverages** small amount of **labeled data** for better results than supervised learning.
2. **Deep learning** methods are very powerful for **gesture recognition**.
3. **Limitations** :
 - Binary classification is an **'easy' task** on which simple models can excel. With **more data** and **more complex** labeling, we could provide **better insight**.
 - **Difficulties** to learn **two hands** signs.



One hand movement (label: Mono)



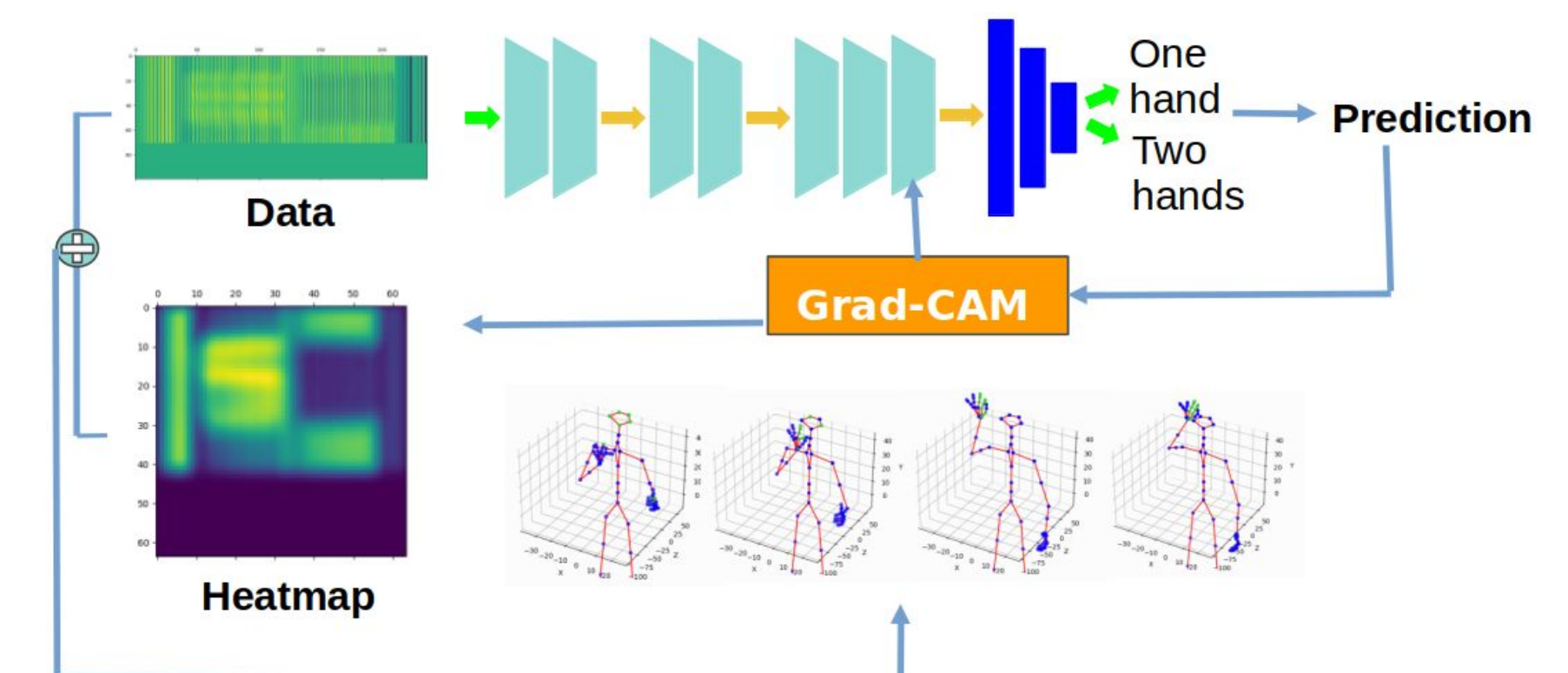
Two hands movement (label: Bi)

METHODOLOGY

A DIVERSITY OF DEEP LEARNING MODELS

1. Working on professional high-quality **motion capture data** provided by Mocaplab (appropriation & **visualization**).
2. Three **supervised learning** models : Fully connected, CNN and LSTM.

3. A **self-supervised learning** model.



Mocaplab Data One Hand vs Two Hands Gesture Classification with 100% of data		
Training Method	Data utilisation	Test Accuracy
Supervised FC	60% train, 10% validation, 30% test	97%
Supervised CNN	60% train, 10% validation, 30% test	100%
Supervised LSTM	60% train, 10% validation, 30% test	100%
Supervised CNN (10% of data)	5% train, 5% validation, 90% test	83%
Self supervised CNN	90% for unsupervised learning, 5% train, 5% validation	93%

Note : data used for unsupervised training is also used for testing

