



## Design of an intelligent multi-sensor medical device for the detection of low mobility

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## Context and Objectives

In the context of chronic pain management, there is a need for a secure, autonomous, non-invasive wearable device able to collect sedentary data and monitor patients daily.

1. Detect and quantify sedentary and physical activity levels for patients with chronic pain.
2. Patient surveillance and evaluation of medical intervention efficiency.
3. Detailed result interpretation based on quantitative data.
4. Provide a learning tool that can be used to detect similar physiological patterns, characteristic behaviour or bio-markers from different subjects.

## Methods and Materials

- Physical activity detection and data collection:

- Activity detection using an Inertial Measurement Unit (IMU)

- Data processing and analysis:

- An ARM-based (Cortex-M family) Micro-controller processes data and runs them through an embedded deep learning model for activity classification.

- Data transmission:

- The model output is transmitted to a sink using a low energy module. *i.e Bluetooth Low Energy (BLE), LoRa*

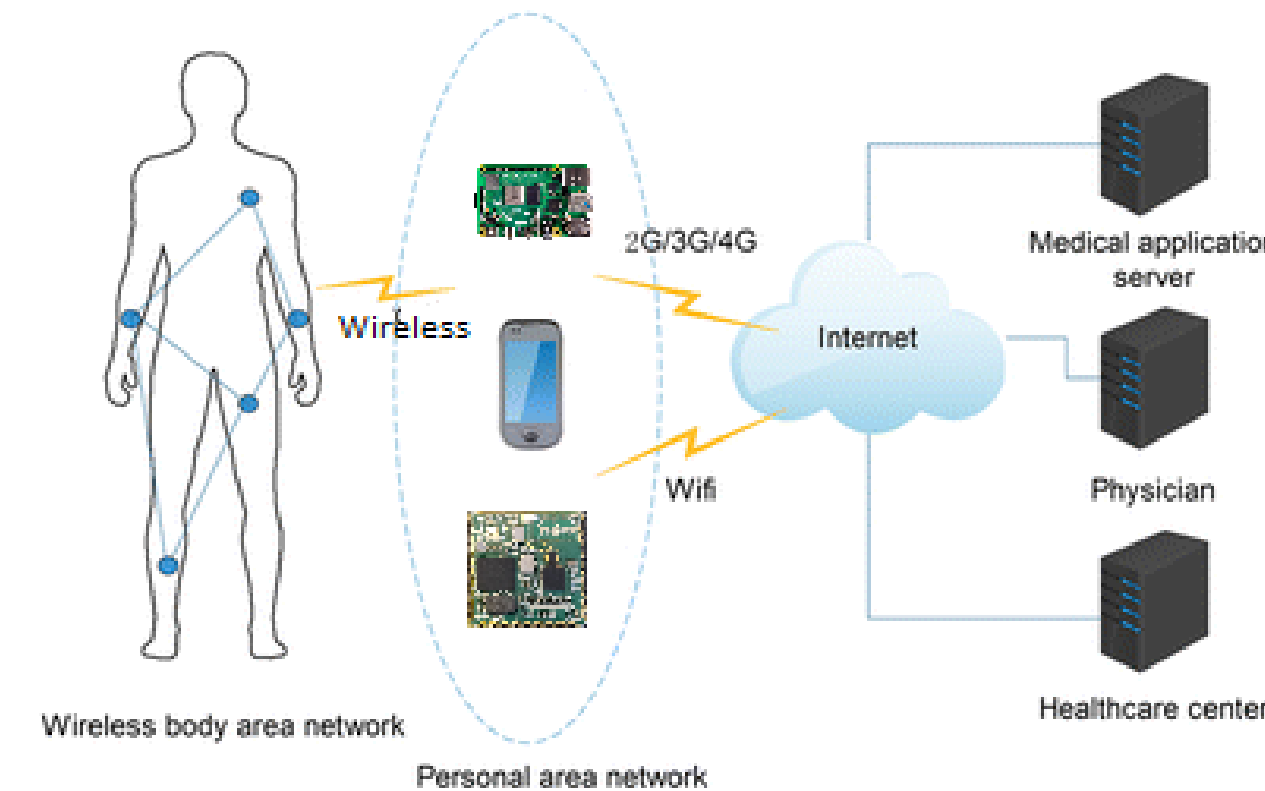


Figure 1: Body Area Network

## Deep learning

The first model was built using a public dataset of data collected on smartphone with different subjects [1]

- Characteristics:

- Multiple sensor data (Accelerometer, Gyroscope and Magnetometer)
- Multiple positions (pockets, belt, upper-arm and wrist)
- Collected at a frequency of 50Hz

- Feature Engineering and Extraction:

- Data preparation and train-test split (80% - 20 % respectively)
- Model training and accuracy evaluation using a DCNN Model (Deep Convolutional Neural Network). [2]

- Deployment:

- Model conversion to a C++ library using TensflowLite [3]
- Inference run directly on Micro-controller

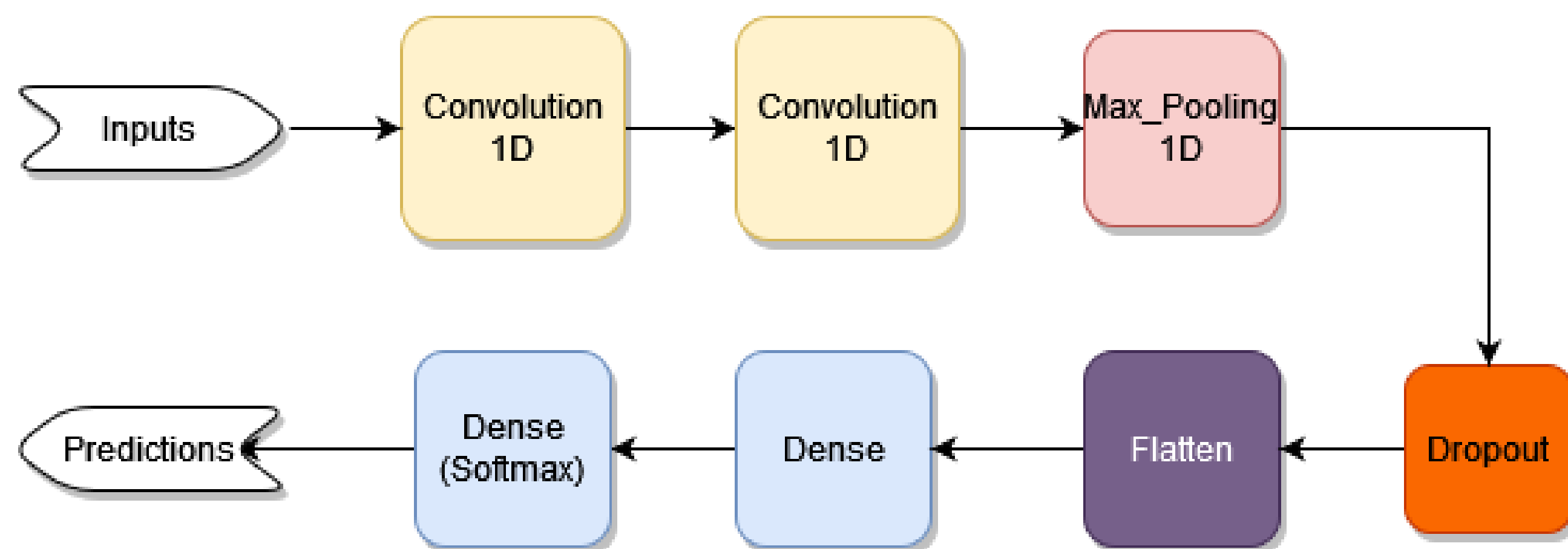


Figure 2: Model structure

## Results: Model Features

- Feature selection:

Acc(x,y,z)	Acc	Gyr(x,y,z)	Gyr	Results
•	•	•	•	X
•	•	•	•	X
•	•	•	•	✓

Table 1: Feature selection

\*The use of magnetometer data in combination with accelerometer based data does not necessarily improve classification accuracy.

- Model performance on a single position:

Position	Pockets	Belt	Upper-arm	Wrist
Accuracy	98.8%	95.7%	90.3%	94.6%

Table 2: Model accuracy on different positions

## Results: Model Evaluation

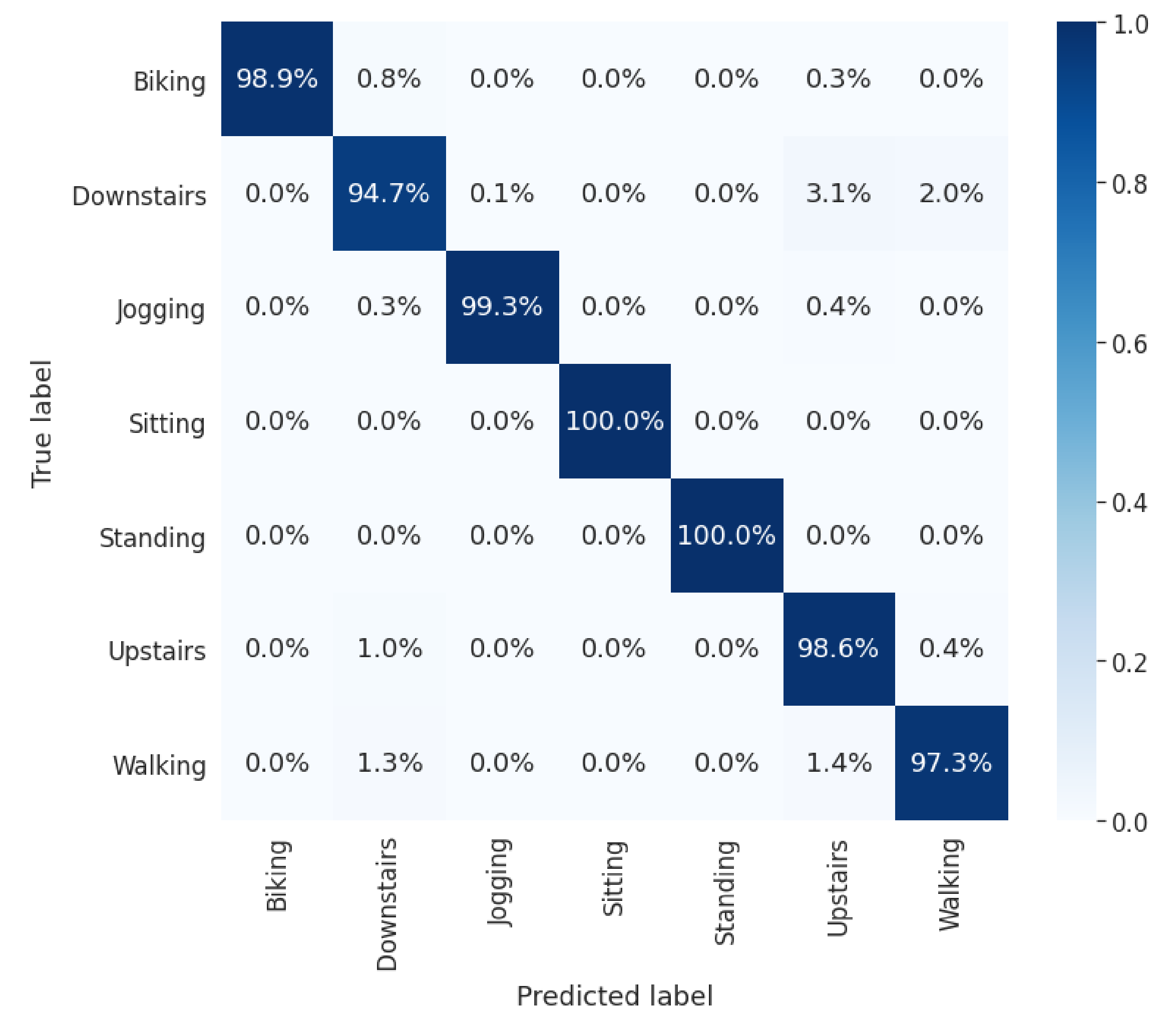


Figure 3: Inferences on test data

## Data Collection

After a successful inference run using the model generated from public dataset, we conducted multiple data acquisition sessions on different participants performing complex daily activities.

- Data Collected:

- Accelerometer data on 3 positions (Belt, Wrist and ankle)
- High-Resolution video, Optical Motion data (Qualisys Track Manager)

## Conclusion

- We proved that deep-learning algorithms can be used for human activity recognition even on resource constrained embedded systems with good accuracy.
- Power consumption reduction by 10% using Embedded-AI versus Remote AI
- Creation of a custom dataset with complex gestures and multiple nodes, this dataset will be used in future studies.
- Future Work:
  - Defining an energy consumption model.
  - Generating a deep learning model with our data.
  - Use of distributed DCNN model on multiple sensors forming a BAN (Body Area Network)
  - Designing and building a custom device with optimized memory and energy consumption

## References

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- [4] M. Muaaz, A. Chelli, A. A. Abdelgawwad, A. C. Mallofré, and M. Pätzold, "Wiwehar: Multimodal human activity recognition using wi-fi and wearable sensing modalities," *IEEE Access*, vol. 8, pp. 164453–164470, 2020.