Sensor-Based Human Activity Recognition Using Deep Learning

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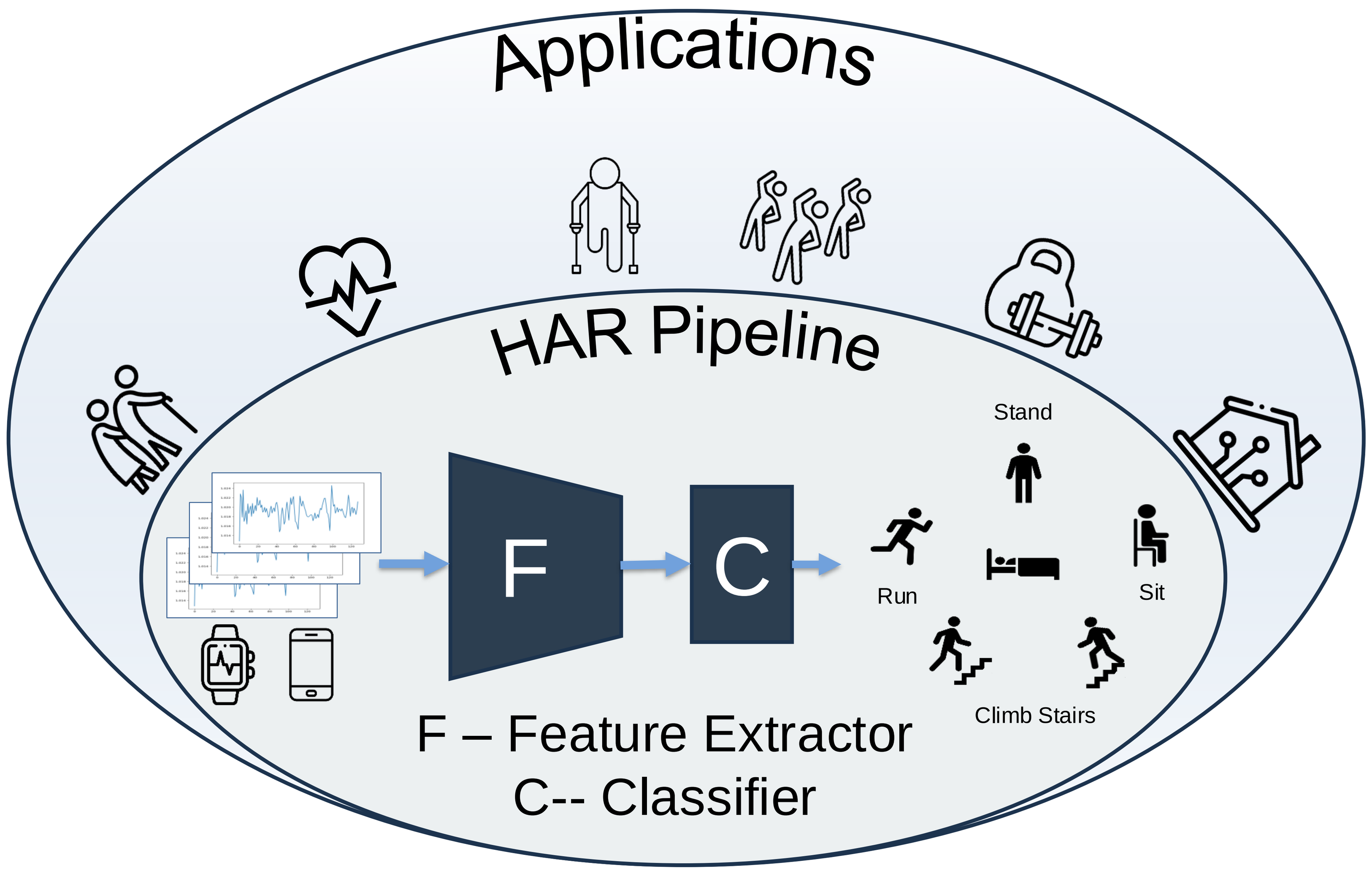
Motivation



- Applications: Elderly Care, Rehab, Well-being, Sports…
- However, there are still several gaps:
  - **Annotation: Providing ground truth is challenging [1].**
  - **Drop in classification performance due to several sources of variability:**
    - **Inter-Person: Differences in how the same activity is performed [2].**
    - **Sensor position: Sensor rotations and displacements [1].**

Ongoing Research

RQ1: Inter Person Variability

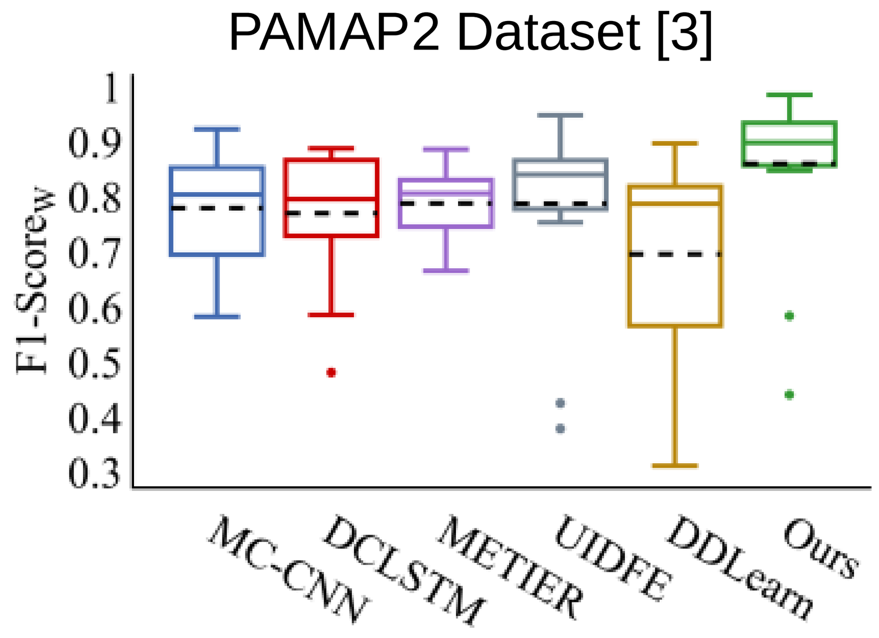
RQ1.1*: How can inter-person variability in performing the same activity be minimized to improve classification performance in HAR?*

Paper : Deep Adversarial Learning with Activity-Based User Discrimination Task for Human Activity Recognition [6].

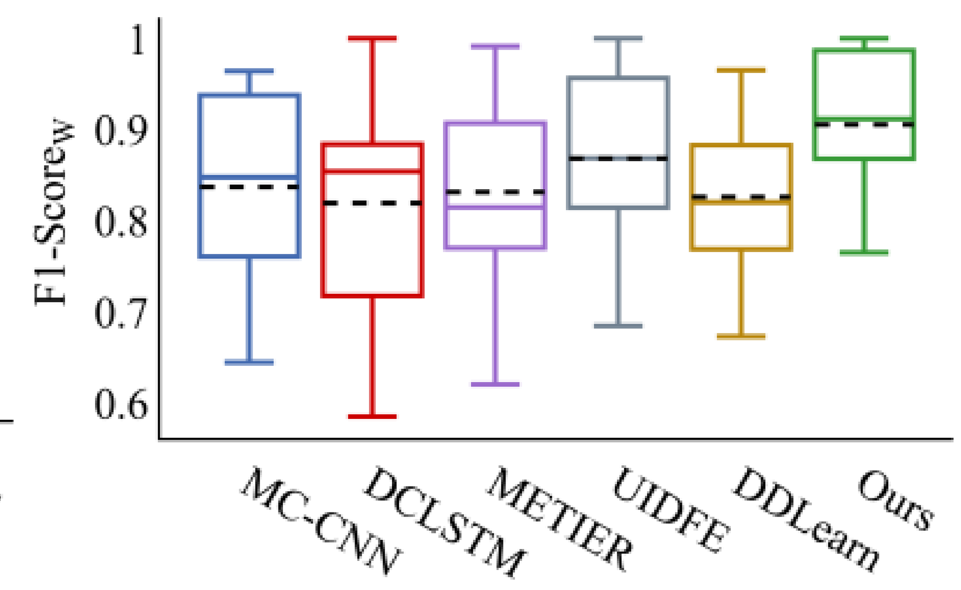
In this paper we proposed:

- A Deep Learning framework that **minimizes inter-person variability (IPV) and enhances performance** using adversarial learning.
- **A Performance comparison with SOTA adv. tasks.**

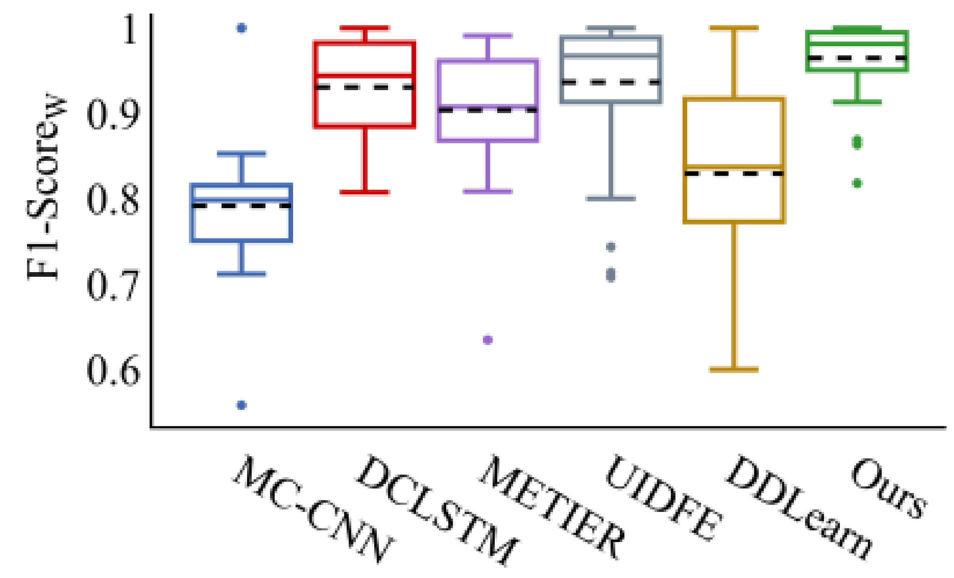
PAMAP2 Dataset [3]



MHEALTH Dataset [4]



REALDISP Dataset [5]



RQ2: Sensor Position

RQ2.1: *Are current sensor-based HAR methods invariant to rotations? What techniques can improve orientation invariance, and how do they impact classification performance?*
RQ2.2: *How do user-specific sensor orientations and inter-person variability interact to affect HAR model generalization?*

	Ideal		Self	
Models	Accuracy	F1-Score W	Accuracy	F1-Score W
CNN	0.783±0.111	0.751±0.139	0.512±0.369	0.486±0.370
CNN+LSTM	0.793±0.099	0.772±0.106	0.544±0.333	0.508±0.345
Attention	0.665±0.093	0.647±0.097	0.457±0.238	0.426±0.250
CNN+Aug	0.773±0.119	0.747±0.121	0.506±0.365	0.483±0.366
CNN+LSTM + Aug	0.813±0.103	0.781±0.131	0.536±0.352	0.507±0.358
Attention + Aug	0.527±0.078	0.510±0.077	0.408±0.162	0.379±0.170

Aug: Randomly rotate 10% of the data samples about X, Y, Z axes by increments of 20°, up to 180°.

- Dataset REALDISP [5]: Wearable IMU sensors.
  - Ideal: Sensor placed by an expert (consistent placement).
  - Self-Placement: Sensor placed by the user (less consistent placement).
- Training: Ideal data.
- Evaluation (Leave-One-Person Out Cross Validation):
  - Using ideal data (ideal column in the table).
  - Using self-placement data (self column in the table).

Future Steps

Compare these approaches with representation learning methods that explicitly address sensor placement variability, such as incorporating signal rotation into the learning process [7].

1.- T. Plötz, "If only we had more data!: Sensor-Based Human Activity Recognition in Challenging Scenarios," IEEE PerCom (2023)
2.- F. M. Calatrava-Nicolás and O. M. Mozos, "Light Residual Network for Human Activity Recognition using Wearable Sensor Data," in IEEE Sensors Letters (2023)
3.- A. Reiss and D. Stricker, "Introducing a New Benchmarked Dataset for Activity Monitoring" International Symposium on Wearable Computers (2012)
4.- Banos, Oresti, et al. "Design, implementation and validation of a novel open framework for agile development of mobile health applications." Biomedical engineering online (2015)
5.-Banos, T. Oresti, A. Mate, and Oliver, "REALDISP Activity Recognition Dataset," UCI Machine Learning Repository, 2014, DOI: https://doi.org/10.24432/C5GP6D.
6.- Calatrava-Nicolás, F. M., & Mozos, O. M. (2024). Deep Adversarial Learning with Activity-Based User Discrimination Task for Human Activity Recognition. *arXiv preprint arXiv:2410.12819*.
7.- Zhang, X., Teng, D., Chowdhury, R. R., Li, S., Hong, D., Gupta, R. K., & Shang, J. (2024). UniMTS: Unified Pre-training for Motion Time Series. arXiv preprint arXiv:2410.19818.

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