



AI - powered Wearable Technology for Human Activity Monitoring

Outcome- A non-intrusive wearable device utilizing IMU sensors to monitor human activity through AI-based algorithms.

Impact - Can be utilized to monitor human activity, enabling the observation of gait patterns for early disease detection. Facilitates the performance monitoring of athletes, allows for long-term employee monitoring, and supports the analysis of individuals' psychomotor skills etc.

Team and Collaborators

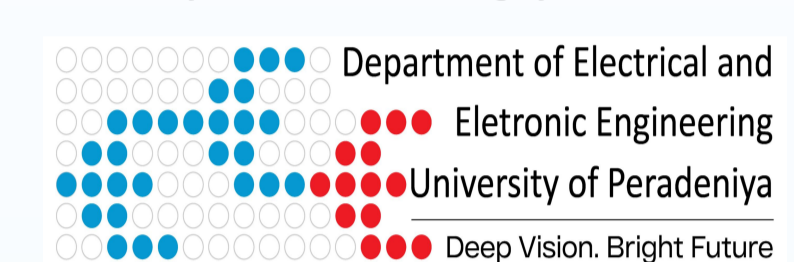
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Past Students

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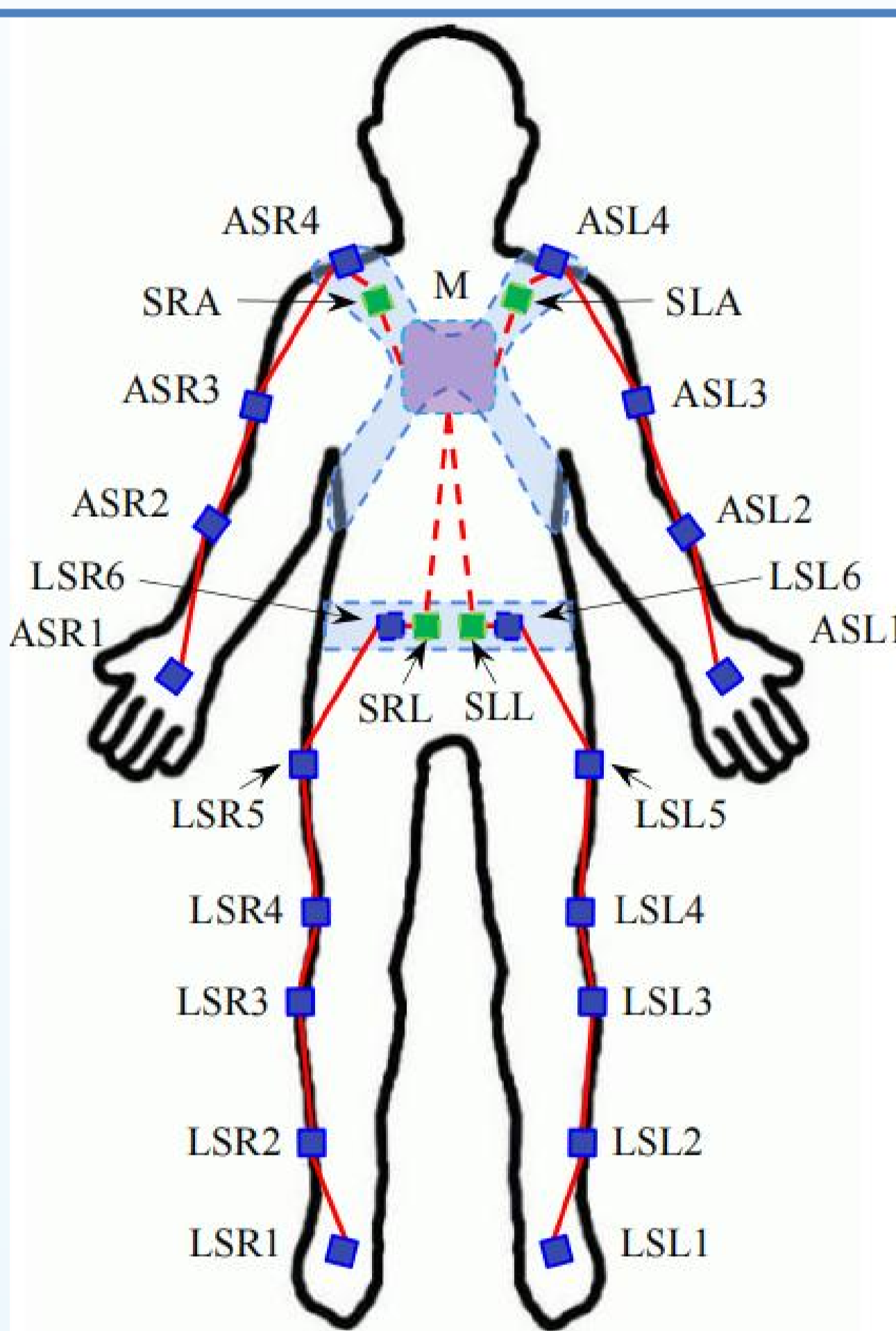
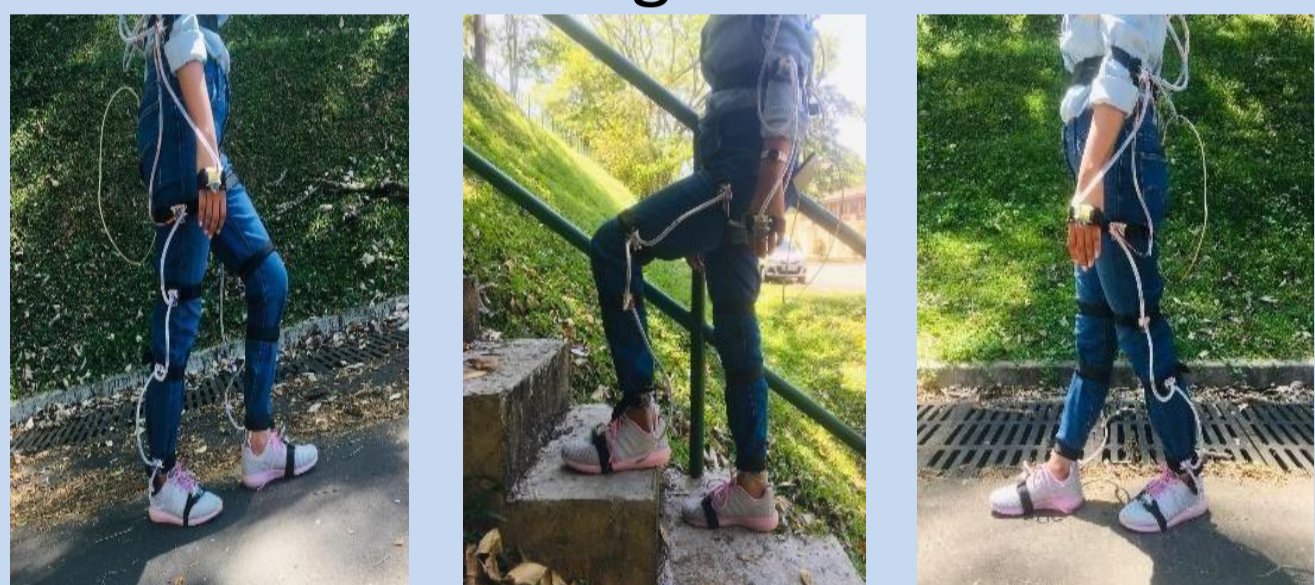
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For Gait and Hand Gestures Analysis

- 5 different terrains and 3 different shoe types
- 13 different hand gestures



Manufacturing Processes

Welding :5 individuals , 9 butt joint weldings per individual



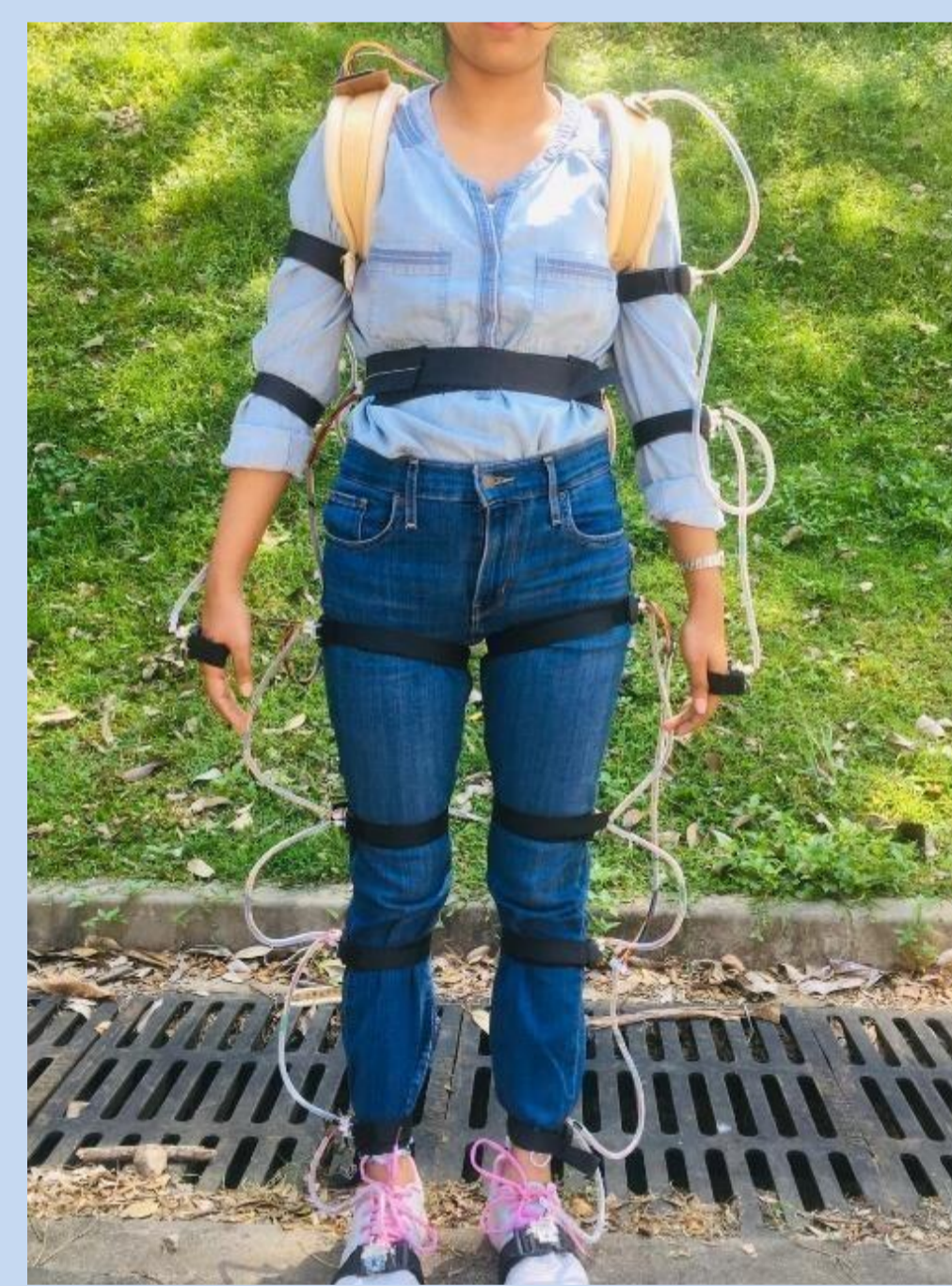
Marking Action Replication of Fabrics:



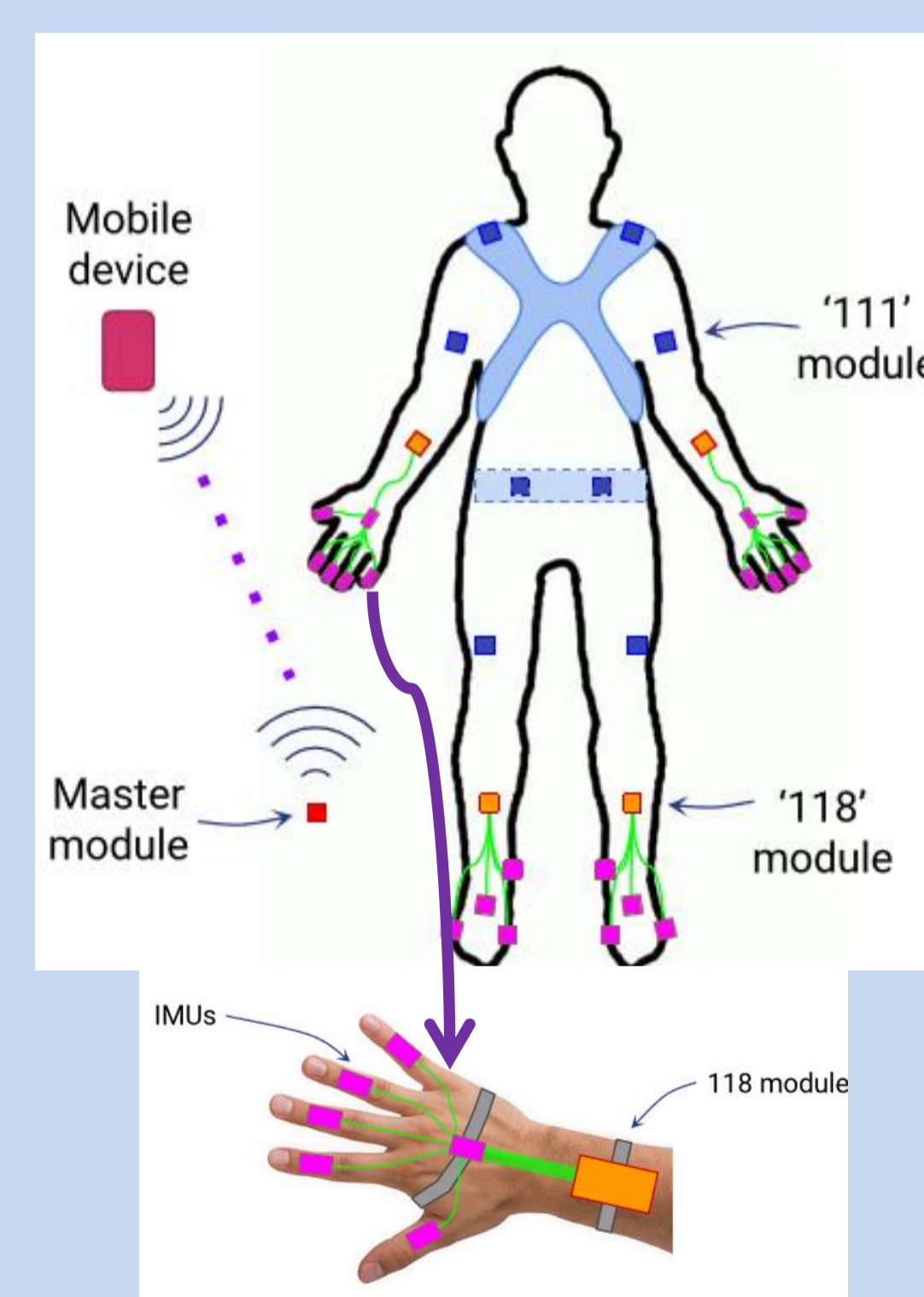
Why Wearables ??

- Wearables can be used directly at the location of activity **without needing controlled, lab-based environments**.
- Generally **more cost-effective** than video-based systems, which often involve expensive equipment.
- Utilize signal processing and AI techniques, **simplifying the analysis process** compared to complex computer vision algorithms required by video-based systems.
- Ensure privacy** by only recording activity signals, avoiding identifiable images and related privacy concerns of video-based monitoring.
- Support long-term monitoring**, unlike video-based systems that are limited in their ability to sustain continuous observation.
- Video-based methods often **require multiple cameras to capture every subtle movement**, while wearables do not face this issue.

Wired and Wireless Devices

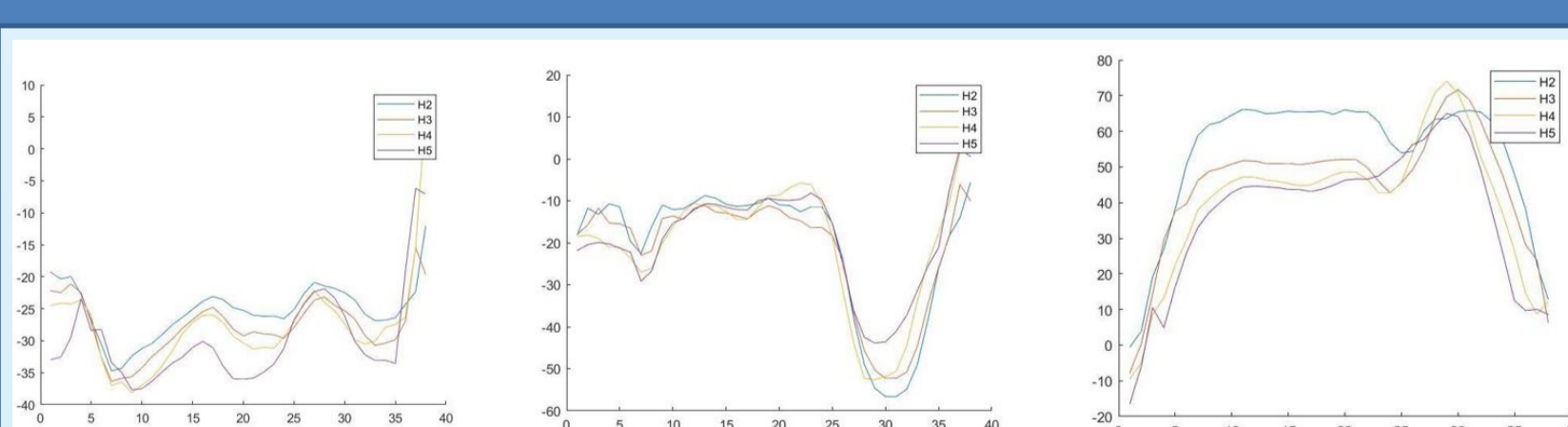


wired



wireless

Results



Gait Analysis for different shoe heights

Training Set	Validation Set	Action Recognition	
		Training	Validation
Person 1	Person 1	0.99	0.99
Person 1	Person 2	0.9841	0.1178
Person 1 + 2	Person 3	0.9854	0.5174
Person 1 + 2 + 3	Person 4	0.9861	0.5614
Person 1 + 2 + 3 + 4	Person 5	0.9911	0.5993

Training Set	Validation Set	Action Recognition	
		Training	Validation
Person 1	Person 1	0.99	0.99
Person 1	Person 2	0.9539	0.2544
Person 1 + 2	Person 3	0.9643	0.4339

S1	S2	S3	S4	S5	LR	KNN	RF	NB
					21.28	60.64	74.16	68.09
✓	✓			✓	62.92	61.80	68.54	75.53
		✓	✓	✓	71.28	75.53	84.04	84.05
			✓	✓	92.14	79.78	89.89	80.90

S1	S2	S3	S4	S5	LR	KNN	RF	NB
					68.18	56.06	54.55	54.85
✓	✓			✓	71.02	74.56	72.81	76.24
		✓	✓	✓				

Raw IMU Data

Data Pre-Processing

Filtering

Similarities

Classification

Distance Measures

Signal power (S1), Clustering measurement (S2), Kalman Filtering (S3), Distance Measures (S4) and PCA (S5)

Comparison

Classification using LSTM network

Research Publications: pre-print available at <https://arxiv.org/abs/2303.16468>

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