Meeting 3

LM-RTA · LIGHTWEIGHT MODELS FOR REAL-TIME APPLICATIONS

REAL-TIME SMARTWATCH SENSOR INTELLIGENCE: HOW DATA QUALITY AFFECTS HUMAN ACTIVITY RECOGNITION

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1 · Data structure

2 · Timestamps

3 · Gaps

MAIN RESEARCH MATRIX

ID	Anomaly type	How to simulate in the signal	Detection method	Preproce-ssing / correction	CWT impact	CNN-based HAR impact	Evaluation metrics
E0	Clean signal (baseline)	Use original sensor data without artificial corruption	Data quality audit; channel completeness and timestamp checks	No correction	Reference Morlet scalograms	Baseline performance of DenseNet121	Macro-F1, Accuracy, per-class Recall, latency
E1	Missing data	Remove 1–20% of samples or continuous segments (3–9 s) from one channel	Missing-value detection, gap analysis	Linear / spline interpolation; exclude unrecoverable windows	Discontinuities and missing time-frequency information	Reduced recognition accuracy, particularly for short and transitional activities	MAE, RMSE, RCME, SSIM, Macro-F1, Recall
E2	Outliers and spikes	Add isolated extreme values or 1–5 short impulses per window	Hampel Filter, Modified Z-Score (MAD), IQR	Median Filter; replace detected outliers	Artificial high-energy coefficients across multiple scales	CNN may interpret spikes as genuine movement patterns, increasing misclassification	MAE, RMSE, RCME, SSIM, Macro-F1, Recall

E3	High-frequency noise	Add Gaussian noise at SNR levels: 30, 20, 10 and 0 dB	Signal statistics, PSD analysis; Modified Z-Score (MAD) for extreme deviations	Butterworth Low-Pass Filter; Savitzky–Golay Filter	Increased energy at small scales and reduced contrast of relevant patterns	Reduced sensitivity to activity-specific features and lower Macro-F1	RMSE, SNR, RCME, SSIM, Macro-F1
E4	Drift and baseline shift	Add a slowly changing trend or a sudden constant offset	EWMA, CUSUM, Bayesian Change Point Detection	Detrending, baseline correction; EMA as an optional smoothing baseline	Distorted low-frequency coefficients and changed scalogram intensity	CNN may learn biased patterns and confuse activities with similar movement characteristics	MAE, RMSE, RCME, SSIM, Macro-F1, Recall
E5	Sampling and timing errors	Introduce irregular sampling intervals, duplicate timestamps or shift gyroscope data relative to accelerometer data	Timestamp analysis, sampling-interval statistics, cross-correlation	Resampling, time alignment and channel synchronisation	Distorted temporal localisation of frequency components	Misaligned sensor features may reduce recognition of dynamic activities and transitions	RCME, SSIM, Macro-F1, per-class Recall, latency

E6	Sensor bias and scaling	Add a constant offset or multiply one axis by 0.8–1.2	Modified Z-Score (MAD), IQR, EWMA; baseline and range analysis	Bias correction, sensor calibration, normalisation	Changes in coefficient magnitudes and relative scalogram intensity	Sensitivity to amplitude differences may reduce generalisation across participants	MAE, RMSE, RCME, SSIM, Macro-F1
E7	Multi-axis data loss / Sensor channel dropout	Remove 10–50% of samples from two or more sensor axes, either simultaneously or independently	Missing-value detection, channel completeness analysis, Mahalanobis Distance, Robust PCA	Channel-wise interpolation, multichannel reconstruction, or exclusion of unreliable windows	Missing time-frequency information and distorted energy distribution across axis-specific scalograms	Reduced recognition accuracy due to incomplete movement information, especially when several correlated channels are affected	MAE, RMSE, RCME, SSIM, Macro-F1, per-class Recall, valid-window ratio
E8	Activity label errors	Randomly change 1–10% of activity labels while keeping sensor signals unchanged	Label consistency analysis, manual annotation review	Label correction or exclusion of uncertain samples	No direct effect: the signal and CWT scalogram remain unchanged	CNN learns incorrect input-label associations, reducing classification performance	Macro-F1, Accuracy, per-class Precision, Recall, Confusion Matrix

E9	Activity boundary errors	Shift activity transitions by 10–50 samples	Transition detection, temporal label consistency	Boundary-aware windowing; exclude ambiguous boundary windows	Scalograms contain patterns from two or more activities	CNN receives mixed-activity examples with potentially incorrect labels	Macro-F1, per-class Recall, Confusion Matrix
E10	Sensor / transmission failures	Remove blocks of 10–100 samples; simulate interruptions in one or several channels	Missing-value detection, gap analysis, channel completeness checks; Mahalanobis Distance for multichannel inconsistencies	Interpolation where reliable; exclude incomplete windows when reconstruction is unreliable	Incomplete or distorted scalograms with missing time-frequency information	Unreliable predictions or failure to recognise activities in incomplete windows	MAE, RMSE (reconstructed segments), RCME, SSIM, Macro-F1, Recall, valid-window ratio

APPROACHES IN THE LITERATURE

Approach	Used (times)	Papers
Time-frequency image (mostly CWT) + deep network (mostly 2D CNN)	7	[1]-[7]
Wavelet layer inside a 1D network (mostly 1D CNN)	9	[8]-[16]
Run on a device or built in hardware (FPGA)	3	[9], [15], [17]
Tested with missing data	4	[10], [18]-[20]
Wavelet denoising, wavelet features, choice of wavelet	3	[21]-[23]

Gaps (according to the review):

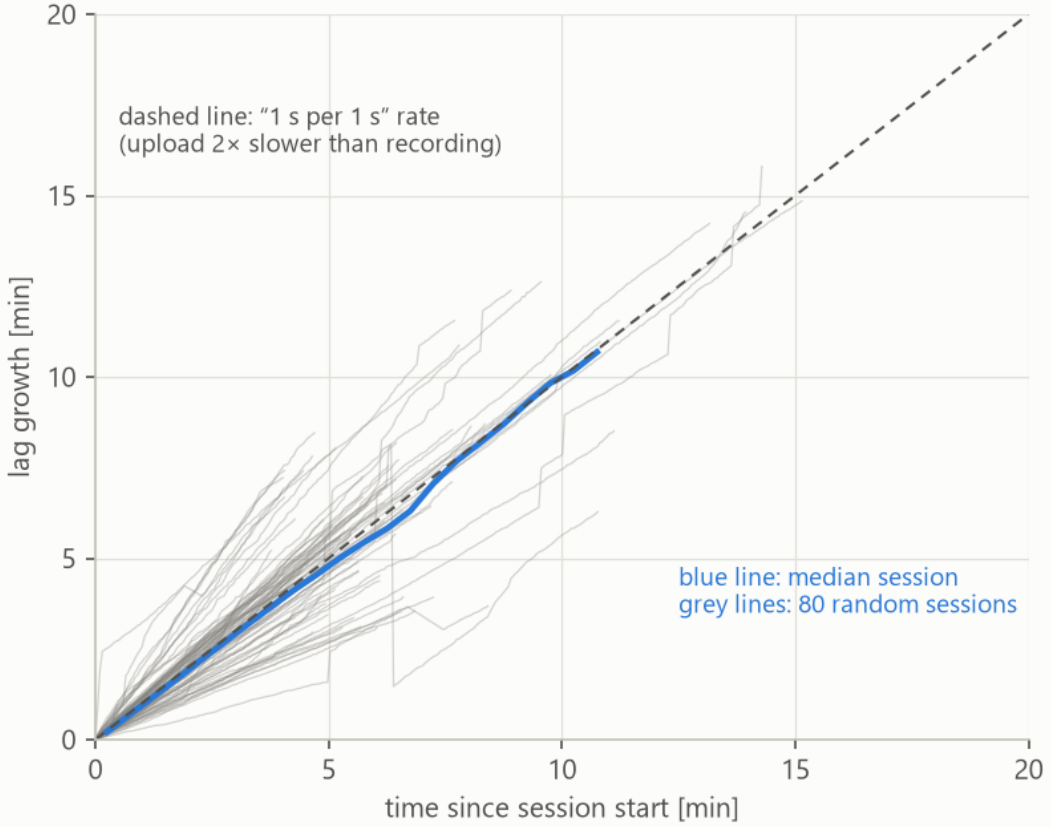
- No paper measured CWT + CNN on a smartwatch.
- No paper tested CWT + CNN with missing data.
- Few papers test on a subject-wise split.

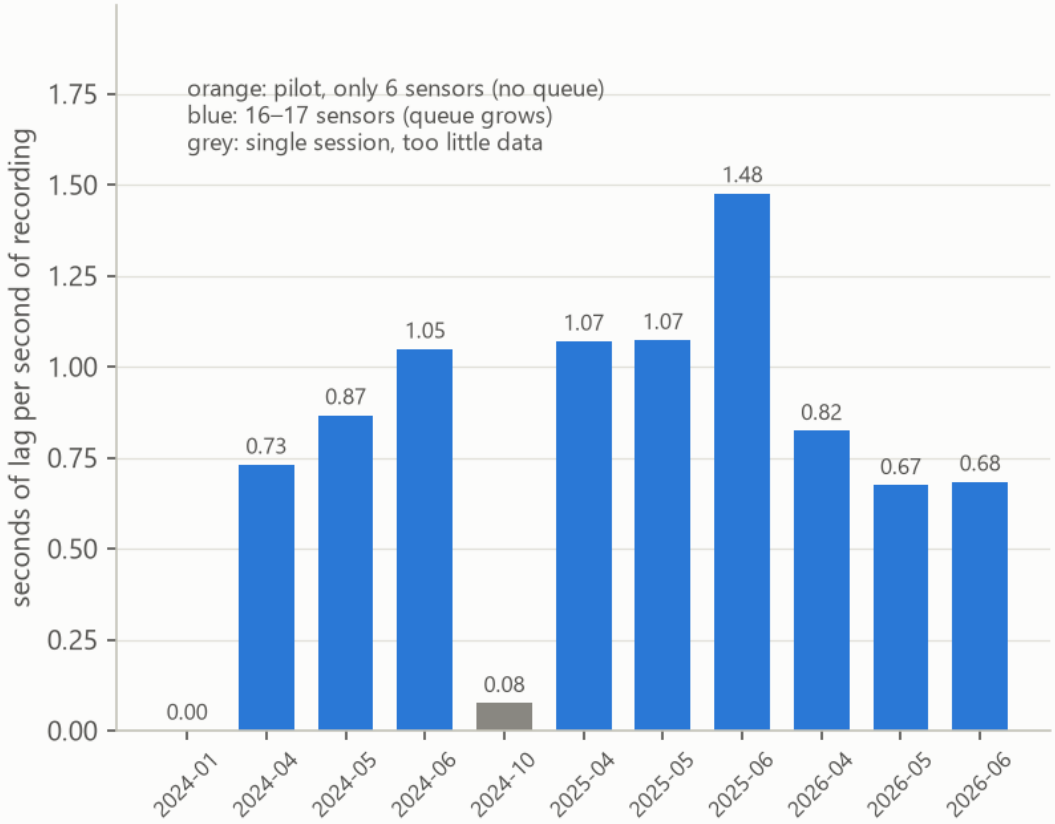
[1] Vuong et al., Sensors 2023 - [2] Nedorubova et al., arXiv 2021 - [3] Ahmed et al., Sensors 2024 - [4] Rahimi Taghanaki et al., IEEE THMS 2023 - [5] Tavakkoli et al., JAISE 2023 - [6] Xia et al., IEEE INDIN 2025 - [7] Sakai et al., IEEE Access 2025 - [8] Zhao et al., ISWC 2022 - [9] Sengupta et al., ISCAS 2022 - [10] Liu et al., arXiv 2024 - [11] Dahou et al., IEEE IoT J 2023 - [12] Yao et al., IEEE TIM 2025 - [13] Wieland & Pankratius, IEEE Sensors J 2025 - [14] Li et al., IEEE TAI 2025 - [15] Sengupta et al., IEEE TCAS-I 2025 - [16] Prabhu et al., arXiv 2026 - [17] Gurung et al., arXiv 2026 - [18] Xaviar et al., arXiv 2023 - [19] Liu et al., IJCAI 2025 - [20] Mamun et al., EMBC 2022 - [21] Zhang et al., Sci. Rep. 2025 - [22] Syed et al., Sensors 2021 - [23] Nematallah & Rajan, Sensors 2024

Paper	What was done	Methods	What is new	Result
[1] Vuong 2023, Sensors	HAR on 5 datasets	CWT image + CNN	Picks CWT settings automatically	F1 2-9 points higher than the same network without CWT
[4] Rahimi Taghanaki 2023, IEEE THMS	HAR with fewer labels	Two networks: CWT image and raw signal	Pre-training without labels	F1 0.83-0.93; transfers to other datasets
[13] Wieland 2025, IEEE Sensors J.	Wavelet add-on for existing HAR models	Wavelet layer + attention	Pre-trained add-on	Macro-F1 up to 0.29 higher; authors say it is fast enough for a smartwatch
[17] Gurung 2026, arXiv	HAR on a phone and a microcontroller	Small network with STFT spectrogram input	Speed, memory and energy measured on device	CWT gives similar F1 to STFT but needs 7-18× more computation
[10] Liu 2024, arXiv	HAR with noisy and missing data	Wavelets split the signal into frequency bands	Wavelets help separate noise from movement	F1 0.60-0.67 with 50% of sensors missing (best baseline 0.38-0.48)
[18] Xaviar 2023, arXiv	HAR with missing data	One network fills the gaps, another recognizes activity	Realistic way to simulate gaps	12-18% higher accuracy than 2 robust baselines; linear interpolation gets worse as gaps get longer

The watch cannot keep up with uploading: the lag grows during a session

Left: growth of the delay until a frame reaches the server, since the session start. Right: seconds of delay added per second of recording.





Source: MotionSensors database dump of 2 Nov 2026 (accelerometer and gyroscope; activities Stand, Sit, Stand-sit, Walk; 597 subjects).

WHAT DATA DID WE ANALYSE?

483 917	597	4	6
sensor records	participants	activities	sensor types

Selection criteria

- 3-second windows – 100 Hz – 300 readings per sensor record
- Activities: Stand, Sit, Stand-sit, Walk
- Sensors: Accelerometer X/Y/Z and Gyroscope X/Y/Z