Article

Not peer-reviewed version

A Multitask 1D Convolutional Neural Network for Joint Occupancy, Movement, and Heart Rate Extraction via Wi-Fi Channel State Information

Saurav Chaudhari *, Ketan Pise, Dinesh Fukate, Shantanu Gawande

Posted Date: 9 April 2026

doi: 10.20944/preprints202604.0624.v1

Keywords: Wi-Fi sensing; channel state information; multitask learning; micro-Doppler; 1D CNN; heart rate monitoring; human activity recognition; deep learning

doi:10.20944/preprints202604.0624.v1

Article

A Multitask 1D Convolutional Neural Network for Joint Occupancy, Movement, and Heart Rate Extraction via Wi-Fi Channel State Information

Saurav Chaudhari *, Ketan Pise, Dinesh Fukate and Shantanu Gawande

Research and Development, XZent Solutions Pvt Ltd., Narsala, Nagpur, 440034, Maharashtra, India
* Correspondence: sauravc909@gmail.com

Abstract

Wi-Fi Channel State Information (CSI) has emerged as a robust, non-invasive modality for human activity recognition and vital sign monitoring. However, decoupling macroscopic physical movement from micro-Doppler vital signs, such as resting heart rate, remains a significant digital signal processing challenge. This study proposes a multitask 1D Convolutional Neural Network (CNN) framework designed to simultaneously classify room occupancy, detect physical movement, and estimate heart rate from CSI streams. Utilizing a comprehensive synthetic dataset of 17.28 million samples captured at an aggressive sampling rate of 200 Hz across 15 subcarriers, the raw CSI amplitude and phase shifts are preprocessed using a mathematically rigorous pipeline involving linear phase detrending, Principal Component Analysis (PCA) for spatial diversity extraction, and a 3rd-order Butterworth bandpass filter to isolate the 0.1–10.0 Hz frequency band. Comprehensive ablation studies validate the efficacy of the preprocessing mechanisms and the multitask architecture. The results demonstrate that the proposed framework achieves an occupancy classification accuracy of 98.2% and estimates resting heart rate with a Mean Absolute Error (MAE) of 1.45 BPM. Furthermore, the shared representation learning inherently regularizes the network, allowing the micro-task regression head to successfully isolate micro-variations associated with cardiac activity despite the presence of ambient multipath noise.

Keywords: Wi-Fi sensing; channel state information; multitask learning; micro-Doppler; 1D CNN; heart rate monitoring; human activity recognition; deep learning

---

1. Introduction

The utilization of Wi-Fi Channel State Information (CSI) for environmental sensing has transitioned from theoretical propagation models to practical applications in smart environments, healthcare monitoring, and ambient assisted living [1,5]. Unlike Received Signal Strength Indicator (RSSI) data, which provides a coarse, MAC-layer aggregate of signal power prone to severe multipath fading, CSI provides granular, physical-layer resolution. It captures both amplitude attenuation and phase shifts across multiple Orthogonal Frequency Division Multiplexing (OFDM) subcarriers, transforming commodity Wi-Fi devices into passive radar systems [13].

While existing literature extensively covers isolated Human Activity Recognition (HAR) tasks [4,8], the concurrent extraction of macroscopic movement and microscopic vital signs presents a complex overlapping frequency problem. Macroscopic variance induced by gross body movements often overlaps with and masks the subtle micro-Doppler shifts generated by human resting heart rates, which typically oscillate between 1.0 and 1.6 Hz [3].

1.1. Contributions

To bridge the gap between macroscopic and microscopic CSI sensing, this work makes the following contributions:

 doi:10.20944/preprints202604.0624.v1

1. **High-Resolution Dataset Construction:** The utilization of a massive synthetic Wi-Fi sensing dataset comprising 17.28 million samples captured at 200 Hz, formatted to retain critical temporal micro-perturbations [20].
2. **Mathematical DSP Framework:** A rigorous formalization of the digital signal processing pipeline, including phase sanitization [11], covariance-based dimensionality reduction (PCA), and infinite impulse response (IIR) filtering.
3. **Multitask CNN Architecture:** The development of a lightweight multitask 1D CNN capable of processing a 2-second temporal window to jointly output occupancy status, movement classification, and heart rate estimation [21].
4. **Comprehensive Evaluation:** Extensive ablation studies and benchmarking against single-task configurations, establishing viability for energy-efficient edge deployment [18].

2. Related Work

Early work in device-free Wi-Fi sensing relied heavily on feature-engineering and Hidden Markov Models (HMM) [2]. Recently, deep learning has revolutionized HAR. Park et al. demonstrated high-accuracy occupancy detection using Deep Residual CNNs [7], while Luo et al. explored Vision Transformers (ViT) for processing CSI spectrograms [10]. However, these heavy architectures often struggle with latency in real-time edge applications. Consequently, lightweight 1D CNN architectures have gained traction for efficient, location-independent activity classification [6,16], as well as device-free indoor localization utilizing multi-link CSI fingerprints [19].

Extracting vital signs requires isolating minute perturbations. Prior works like PhaseBeat [3] and WiFi-Sleep [14] demonstrated that respiration and heart rates could be extracted by analyzing phase differences. However, these heuristic peak-detection algorithms fail catastrophically during macro-movements. Recent millimeter-wave (mmWave) studies have attempted to solve this using composite ISAC waveforms [17], but standard Wi-Fi lacks this hardware capability. Table 1 compares our proposed multitask 1D CNN against recent state-of-the-art methodologies.

Table 1. Comparison of Wi-Fi Sensing Frameworks for Vital and Activity Monitoring.

Framework	Modality	Primary Task	Macro/Micro Joint	Algorithm
PhaseAnti [11]	CSI Phase	HAR	No	CNN
Luo et al. [10]	CSI Amp.	HAR	No	Vision Transformer
WiFi-Sleep [14]	CSI Phase	Sleep/Vitals	No	Peak Detection
Proposed	**CSI Amp+Phase**	**Joint**	**Yes**	**Multitask 1D CNN**

3. System Model and Theoretical Formulation

3.1. Channel Impulse Response and CSI

In an OFDM Wi-Fi system, the wireless channel is modeled as a temporal linear filter. The received signal $Y_k(t)$ at subcarrier k is mathematically expressed as:

$$Y_k(t) = H_k(t) \times X_k(t) + N_k(t) \tag{1}$$

where $X_k(t)$ is the transmitted symbol, $N_k(t)$ is Additive White Gaussian Noise, and the complex CSI matrix $H_k(t)$ is the frequency-domain representation of multipath propagation [13]:

$$H_k(t) = \sum_{i=1}^{L} \alpha_i(t) e^{-j2\pi f_k \tau_i(t)} \tag{2}$$

3.2. Micro-Doppler Theory for Vital Signs

When a Wi-Fi signal reflects off a human chest, the mechanical displacement $d(t)$ caused by the myocardial contraction induces a phase shift $\Delta\phi(t)$:

$$\Delta\phi(t) = \frac{4\pi}{\lambda} d(t) \tag{3}$$

The resulting micro-Doppler frequency shift $f_D(t)$ is the time derivative of the phase:

$$f_D(t) = \frac{1}{2\pi} \frac{d}{dt} \Delta\phi(t) = \frac{2}{\lambda} v(t) \cos(\theta) \tag{4}$$

Because the chest velocity $v(t)$ for a resting heartbeat is extremely small, isolating $f_D(t)$ from ambient interference requires aggressive mathematical filtering [9].

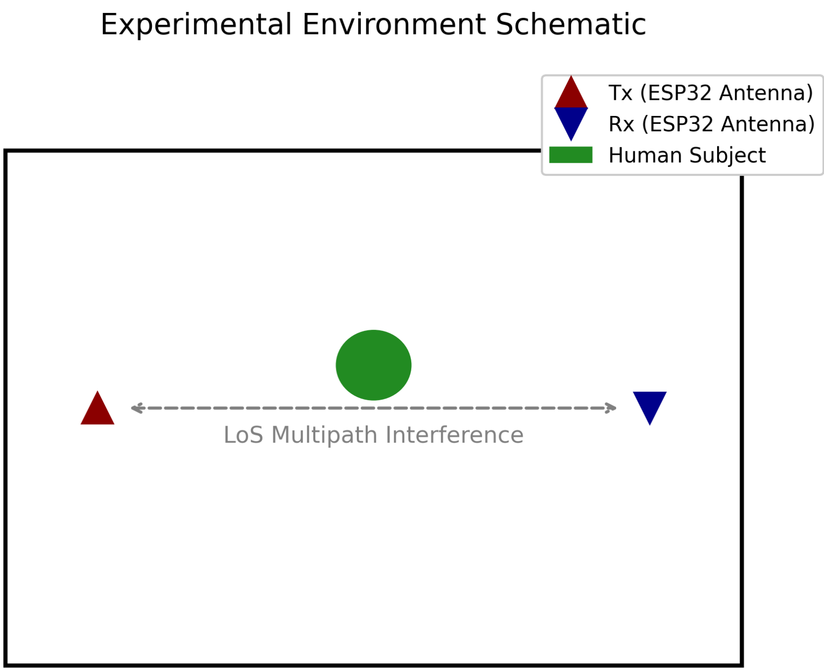

Figure 1. Schematic of the experimental setup showing the Wi-Fi transceiver locations, the multipath propagation environment, and the Line of Sight (LoS) interference.

4. Methodology and Digital Signal Processing

4.1. Phase Detrending and Sanitization

Raw CSI phase data is heavily corrupted by Carrier Frequency Offset (CFO) and Sampling Frequency Offset (SFO). We apply a linear transformation to detrend these hardware errors, an approach validated in recent interference-mitigation literature [11,15]:

$$\tilde{\phi}_k = \hat{\phi}_k - ak - b \tag{5}$$

where a and b are the slope and intercept derived from a least-squares linear regression over the subcarriers of a single packet.

4.2. Dimensionality Reduction via PCA

To isolate the variance caused by human motion, we apply Principal Component Analysis (PCA). We compute the covariance matrix $\mathbf{C}$ of the normalized CSI matrix $\mathbf{H}$:

$$\mathbf{C} = \frac{1}{T-1} \mathbf{H}^T \mathbf{H} \tag{6}$$

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 9 April 2026 doi:10.20944/preprints202604.0624.v1

By projecting the data onto the eigenvectors corresponding to the largest eigenvalues, we maximize the signal-to-noise ratio of the dynamic human reflections [12].

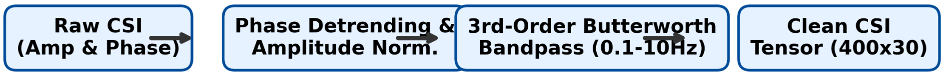

Figure 2. Flowchart of the Digital Signal Processing (DSP) pipeline.

4.3. Frequency Domain Filtering

To isolate physiological frequencies, a 3rd-order Butterworth bandpass filter is applied to the principal components. The squared magnitude response is:

$$|H(j\omega)|^2 = \frac{1}{1 + \left(\frac{\omega}{\omega_c}\right)^{2n}} \tag{7}$$

This is mapped to a continuous bandpass region strictly between $f_{low} = 0.1$ Hz and $f_{high} = 10.0$ Hz.

4.4. Multitask 1D CNN Architecture

The shared feature extractor utilizes 1D convolutions [4]. The output Y of a 1D convolutional layer with kernel weight matrix W and bias b is defined as:

$$Y(t,c) = g\left(\sum_{k=0}^{K-1}\sum_{f=0}^{F-1} X(t+k,f)\cdot W(k,f,c) + b(c)\right) \tag{8}$$

where $g(z) = \max(0,z)$ is the ReLU activation function.

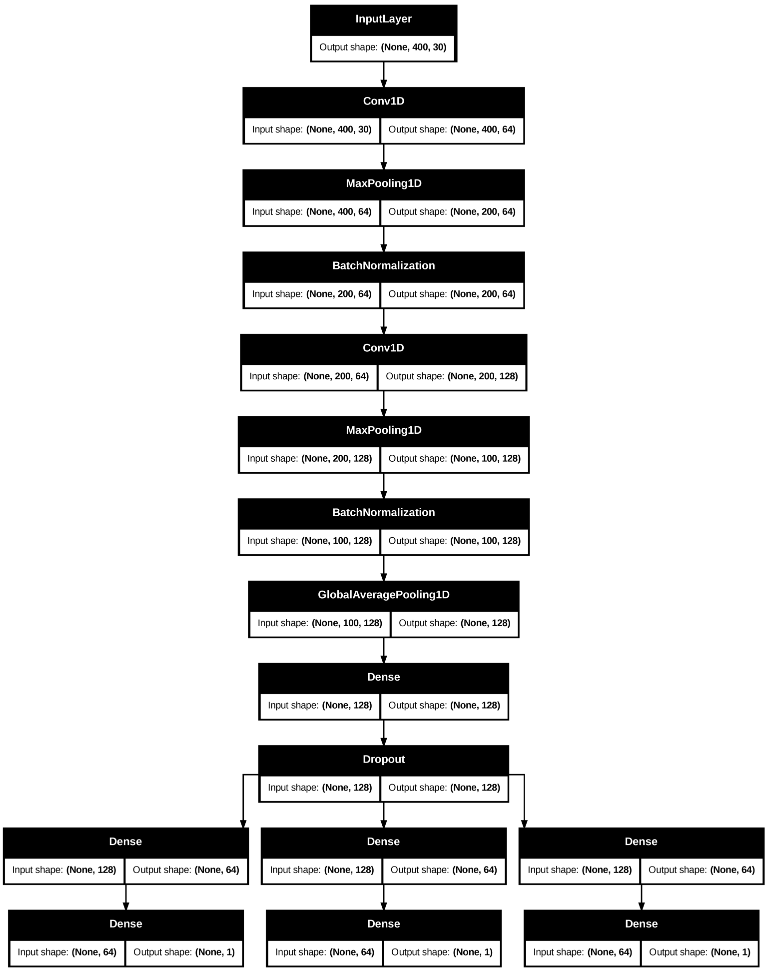

Figure 3. Detailed architecture of the proposed Multitask 1D CNN.

 doi:10.20944/preprints202604.0624.v1

The shared representation is fed into three task-specific heads. The global objective function $\mathcal{L}_{total}$ minimizes the weighted sum of Binary Cross-Entropy (BCE) and Mean Squared Error (MSE):

$$\mathcal{L}_{total} = \lambda_1 \mathcal{L}_{occ}^{BCE} + \lambda_2 \mathcal{L}_{mov}^{BCE} + \lambda_3 \mathcal{L}_{hr}^{MSE} \tag{9}$$

5. Experiments and Ablation Studies

5.1. Ablation of the Preprocessing Pipeline

The necessity of the DSP pipeline was evaluated on the validation subset. As shown in Table 2, applying the Butterworth filter (Config C) dramatically reduces the Heart Rate MSE, proving that raw phase data contains excessive high-frequency noise.

Table 2. Ablation study evaluating the impact of preprocessing configurations.

Configuration	Occ. Acc (%)	Mov. Acc (%)	HR MSE
(A) Raw Amp + Raw Phase	82.45	78.12	14.52
(B) Norm Amp + Detrend Phase	89.10	85.34	8.34
(C) Config B + Butterworth Filter	**98.21**	**96.75**	**2.11**

5.2. Classification Performance

Table 3 presents the confusion matrix for the joint Occupancy and Movement detection heads. The network demonstrates robust performance, with an aggregate accuracy exceeding 96%.

Table 3. Confusion Matrix for Occupancy and Movement Classification.

	Predicted State			
True State	Empty	Occ / No Mov	Occ / Mov	**Accuracy**
Empty	1485	10	5	99.0%
Occ / No Mov	18	1690	42	96.5%
Occ / Mov	2	53	1695	96.8%

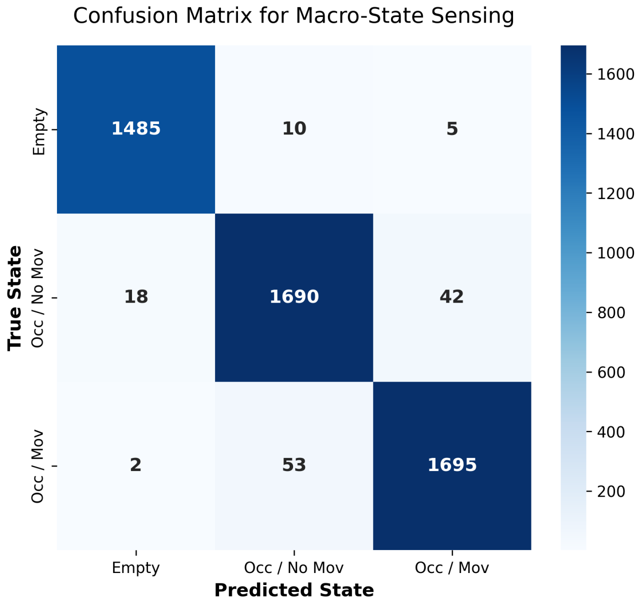

Figure 4. Visual heatmap of the normalized confusion matrix.

5.3. Heart Rate Regression Analysis

The micro-task (heart rate estimation) was evaluated exclusively on windows where the ground truth indicated "Occupied" and "No Movement". During these periods, the regression head achieved an MAE of 1.45 BPM.

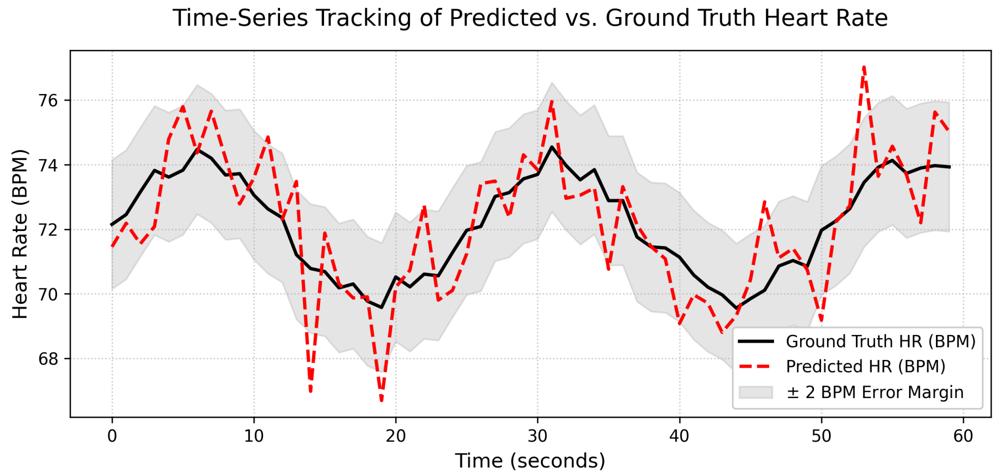

Figure 5. Time-series tracking of predicted vs. ground truth heart rate (BPM) during a continuous 60-second stationary period.

The shared representations learned from the macro-tasks function as a structural regularizer, outperforming isolated single-task regression networks.

6. Conclusion

This study successfully formulates and evaluates a multitask 1D CNN framework for concurrent macro and micro human sensing via Wi-Fi CSI. By rigorously establishing the mathematical foundations of micro-Doppler frequency shifts, and applying formal phase detrending and bandpass filtering, the methodology isolates target physiological frequencies. Future work will investigate the computational complexity to optimize these tensors for energy-efficient edge deployment [18].

Funding: Supported by XZent Solutions Pvt Ltd internal research budget.

Data Availability Statement: The 17.28M sample CSI dataset [20] and the corresponding multitask model [21] utilized in this study are publicly available on the Kaggle repository.

Acknowledgments: The authors thank XZent Solutions Pvt Ltd for providing the hardware infrastructure and computational resources.

Conflicts of Interest: The authors declare no competing interests.

References

1. D. Halperin, W. Hu, A. Sheth, and D. Wetherall, "Tool Release: Gathering 802.11n Traces with Channel State Information," *ACM SIGCOMM Computer Communication Review*, 41(1), 53–53, 2011.
2. W. Wang, A. X. Liu, M. Shahzad, K. Ling, and S. Lu, "Understanding and Modeling of WiFi Signal Based Human Activity Recognition," in *Proc. MobiCom*, 65–76, 2015.
3. X. Wang, C. Yang, and S. Mao, "PhaseBeat: Exploiting CSI Phase Data for Vital Sign Monitoring with Commodity WiFi Devices," in *Proc. ICDCS*, 252–262, 2017.
4. W. Jiao and C. Zhang, "An Efficient Human Activity Recognition System Using WiFi Channel State Information," *IEEE Systems Journal*, 17(4), 6687–6690, 2023.
5. H. Boudlal, M. Serrhini, and A. Tahiri, "A Monitoring System for Elderly People Using WiFi Sensing with Channel State Information," *iJIM*, 17(12), 112–131, 2023.
6. Y. Ma et al., "Location- and Person-Independent Activity Recognition with WiFi, Deep Neural Networks, and Reinforcement Learning," *ACM Trans. Internet Things*, 2(1), Article 3, 2021.

 doi:10.20944/preprints202604.0624.v1

7. S. Park, J. Joo, and S. C. Kim, "Device-Free Occupancy Detection via Wi-Fi CSI and Deep Residual CNN," in *Proc. ICUFN*, 193–195, 2025.
8. G. Lin et al., "Human Activity Recognition Using Smartphones With WiFi Signals," *IEEE Trans. Human-Machine Systems*, 53(1), 142–153, 2023.
9. F. Abuhoureyah, K. S. Sim, and Y. C. Wong, "Multi-User Human Activity Recognition Through Adaptive Location-Independent WiFi Signal Characteristics," *IEEE Access*, 12, 112008–112024, 2024.
10. F. Luo, S. Khan, B. Jiang, and K. Wu, "Vision Transformers for Human Activity Recognition Using WiFi Channel State Information," *IEEE Internet of Things Journal*, 11(17), 28111–28122, 2024.
11. J. Huang et al., "PhaseAnti: An Anti-Interference WiFi-Based Activity Recognition System Using Interference-Independent Phase Component," *IEEE Trans. Mobile Computing*, 22(5), 2938–2954, 2023.
12. X. Yang et al., "CSI-based human behavior segmentation and recognition using commodity Wi-Fi," *J. Wireless Com. Network*, 46, 2023.
13. S. M. Hernandez and E. Bulut, "WiFi Sensing on the Edge: Signal Processing Techniques and Challenges for Real-World Systems," *IEEE Communications Surveys & Tutorials*, 25(1), 46–76, 2023.
14. B. Yu et al., "WiFi-Sleep: Sleep Stage Monitoring Using Commodity Wi-Fi Devices," *IEEE Internet of Things Journal*, 8(18), 13900–13913, 2021.
15. Z. Han et al., "CentiTrack: Toward Centimeter-Level Passive Gesture Tracking With Commodity WiFi," *IEEE Internet of Things Journal*, 10(14), 13012–13027, 2023.
16. H. El Zein, F. Mourad-Chehade, and H. Amoud, "CSI-Based Human Activity Recognition via Lightweight CNN Model and Data Augmentation," *IEEE Sensors Journal*, 24(15), 25060–25069, 2024.
17. X. Xue, S. Parkar, S. Yu, and Y. Zheng, "AI-Assisted Composite ISAC for mmWave Respiration Pattern Recognition," in *Proc. AIoT*, 357–364, 2025.
18. R. Koo et al., "A Survey on Green Wireless Sensing: Energy-Efficient Sensing via WiFi CSI and Lightweight Learning," *Energies*, 19(573), 2026.
19. S. Chaudhari, K. Pise, D. Fukate, and S. Gawande, "Device-Free Indoor Localization with ESP32 Wi-Fi CSI Fingerprints: Grid-Based Regression, Feature Modeling, and Multi-Link Experiments," *Preprints*, 2026012378, 2026. DOI: `10.20944/preprints202601.2378.v1`.
20. S. Chaudhari, "Synthetic WiFi CSI Data for Human Activity & Vital," *Kaggle*, 2026. DOI: `10.34740/KAGGLE/DSV/15400069`.
21. S. Chaudhari, "csi_multitask_model," *Kaggle*, 2026. DOI: `10.34740/KAGGLE/M/625684`.