Pulse-Fi: A Low-Cost System for Accurate Heart Rate Monitoring Using Wi-Fi Channel State Information

Pranay Kocheta[1], Nayan Sanjay Bhatia[2], Katia Obraczka[2]
[1]Independent, Boston, Massachusetts, USA
pranayko021@gmail.com
[2]University of California, Santa Cruz, Santa Cruz, California, USA
{nbhatia3, obraczka}@ucsc.edu

***Abstract*—Non-intrusive monitoring of vital signs has become increasingly important in various healthcare settings. In this paper, we present Pulse-Fi, a novel low-cost system that uses Wi-Fi Channel State Information (CSI) and machine learning to accurately monitor heart rate. Pulse-Fi operates using low-cost commodity devices, making it more accessible and cost-effective. It uses a signal processing pipeline to process CSI data fed into a custom low-compute Long Short-Term Memory (LSTM) neural network model. We evaluated Pulse-Fi using two datasets: one that we collected locally using ESP32 devices named ESP-HR-CSI Dataset and another containing recordings of 118 participants using the Raspberry Pi 4B called EHealth, making it the most comprehensive data set of its kind. Our results show that Pulse-Fi can effectively estimate heart rate from CSI signals with comparable or better accuracy than hardware with multiple antenna systems, which can be expensive.**

***Index Terms*—Heart Rate Monitoring, Channel State Information, Wi-Fi Sensing, Deep Learning**

I. Introduction

Non-intrusive monitoring of vital signs such as heart rate is critical to improving elderly care and early health intervention [1]. Long-term care and healthcare institutions increasingly need systematic continuous accuracy that is easy to deploy. Wi-Fi signals offer unique advantages: they penetrate walls, are ubiquitous indoors, and avoid camera-based privacy concerns. By analyzing Channel State Information (CSI), which captures signal propagation characteristics, subtle heartbeat movements can be detected [2], [3].

Wi-Fi infrastructure for heart rate detection should ideally satisfy the following requirements:

- **Universality** is a challenge due to hardware and firmware limitations of many Wi-Fi chipsets, restricting compatibility and accessibility; hence open-source tools like Nexmon CSI and ESP-32 help address this.
- **Robustness** to diverse environments is important, as CSI signals often degrade in real-world settings with noise and distance, making standard methods less effective.
- **Thorough testing** across diverse scenarios and participants to ensure generalization in medical contexts.
- **Low computational cost** is necessary for widespread low-cost deployment, especially in everyday devices.

Pulse-Fi fulfills these requirements by: (1) using commodity, low-cost devices, making it more accessible and cost-effective, AND (2) including a signal processing pipeline to process CSI data which is then fed into a custom low-compute Long Short-Term Memory (LSTM) neural network model. The contributions of this paper can be summarized as follows:

- We describe Pulse-Fi's design and architecture including: (1) Pulse-Fi's CSI data processing pipeline and (2) Pulse-Fi's compact LSTM model whose low computing requirements make it feasible to deploy in resource-constrained devices such as ESP32 and Raspberry Pi platforms, enabling real-time, continuous monitoring at settings other than hospitals and specialized clinics.
- We evaluate Pulse-Fi using two datasets: (1) One CSI dataset was collected using ESP32 devices with seven participants in a semi-controlled indoor environment across varying distances (2) The other CSI dataset uses 118 participants in 17 positions/activities, making it the most comprehensive dataset of its kind.
- We show that Pulse-Fi can achieve high accuracy and low Mean Absolute Error (MAE) levels using only amplitude information from single-antenna systems outperforming State Of The Art (SOTA) approaches that need multi-antenna devices to provide phase difference information.

The remainder of the paper is organized as follows: In Section II, we provide an overview of the related work. Section III provides an overview of Pulse-Fi, while Sections IV and V describe Pulse-Fi's functional components in detail and Pulse-Fi's CSI processing and heart-rate estimation, respectively. Section VI outlines the experimental methodology we use to evaluate Pulse-Fi. Section VII and VIII present results of our experiments and summarizes our findings, highlighting key insights. Finally, Section IX concludes the paper.

II. Related Work

Heart rate monitoring techniques can be broadly categorized into contact and non-contact based sensing. Contact-based sensing include Electrocardiogram (ECG), Photoplethysmography (PPG), and Polysomnography (PSG) and are common in clinics for their accuracy. They require multiple specialized sensors and therefore are costly. Alternative techniques (chest straps, pulse oximeters, smartwatches) suffer from long-term discomfort, specialized design needs, and high costs. Non-contact approacehes that are camera-based such as remote photoplethysmography (rPPG) and thermal imaging estimate vital signs without contact but require expensive equipment and raise privacy concerns, and are sensitive to lighting and skin tone variations [4], [5].

More recent non-contact approaches have used wireless signals as they propagate in the environment to monitor heart rate. In particular, Channel State Information (CSI) telemetry captures environmental conditions through the phase and amplitude of different subcarriers, which mitigates the effects against scattering, fading, and power delays [2]. Although CSI-based vital sign monitoring has shown great potential, current state-of-the-art systems have several limitations. Many rely on discontinued, specialized hardware such as Intel 5300 NICs to extract phase-difference information for accurate monitoring [6]–[10]. Many existing approaches [1], [3], [6], [7], [10] have been developed and evaluated using data from a single individual or a small homogeneous group. Other limitations include no variation in subject posture/position or the amount of time over which data needs to be collected (temporal duration) [6]–[11]. Despite recent advancements in machine learning (ML) and its proven effectiveness in signal processing tasks, there has been limited exploration of ML techniques for heart-rate monitoring [2]. Some more recent efforts [6], [10] use convolution neural networks (CNNs) to adapt to environment dynamics however they are computationally expensive [12]. The work presented in [13], uses the CSI dataset EHealth, which is one of the datasets that we use to evaluate Pulse-Fi. To our knowledge, EHealth is the only dataset with a substantial number and diversity of participants. The accuracy results presented in [13] show inconsistencies in various positions / activities with errors as high as 6.74 bpm. The results in [13] used data from 59 participants, while the current data set has 118.

III. Pulse-Fi: System Overview

Pulse-Fi's goal is to provide a low-cost, accessible end-to-end solution to non-intrusive, continuous heart rate monitoring using Wi-Fi Channel State Information. Fig 1 illustrates Pulse-Fi's system architecture which consists of three main components: data collection using commodity Wi-Fi devices, a CSI signal processing pipeline, and a custom lightweight Long Short Term Memory neural network for heart rate estimation. Pulse-Fi's design prioritizes accessibility and real world usability while maintaining high accuracy.

A. CSI Processing Pipeline

Pulse-Fi's CSI processing pipeline is designed to isolate and extract subtle CSI variations caused by heartbeats while removing environmental noise and interference. The pipeline consists of five stages: 1. Amplitude conversion. 2. Stationary noise removal. 3. Pulse extraction. 4. Pulse Shaping. 5. Segmentation and normalization. PulseFi's stages are described in detail in Section IV.

B. LSTM Network

PulseFi's heart rate estimation uses an LSTM neural network because it has been shown to handle sequential and variable-length data, making it effective for inputs with different durations [14]. It has relatively low compute cost and offers robustness to external noise [15].

IV. CSI Data Processing

As shown in Figure 1, Pulse-Fi's CSI data processing component consists of several steps to improve CSI signal quality and extract features for heart rate estimation. These steps aim at isolating the subtle variations in the CSI signal that correspond to changes caused by heart rate.

1) Amplitude Conversion: Raw CSI data (Fig 2) contains magnitude and phase information. We extract the amplitude portion of the CSI since variation in amplitude of the signal are directly related to physical movements caused by heartbeats. We chose not to use phase information as Pulse-Fi employs low-cost, single-antenna devices and thus does not have access to phase difference information.

2) Stationary Noise Removal: Raw CSI data typically include different forms of noise caused by hardware imperfections, noise from the environment, etc. To remove them, we eliminate the signal's Direct Current component. [16].

3) Pulse Extraction: One key challenge in measuring heart rate from CSI data is to isolate the rhythmic beating of the heart from various other biological and environmental factors. To address that, we use a third-order (empirically determined) Butterworth bandpass filter [17] set to 0.8 - 2.17 Hz (corresponding to 48-130 BPM). This gives sufficient frequency separation while remaining computationally efficient with no passband rippling that could introduce artifacts.

4) Pulse Shaping: To further improve the signal and reduce high-frequency noise while preserving important features, we applied a Savitzky-Golay filter [18]. This filter performs local polynomial regression on a series of values, providing smoothing that is very effective at maintaining the shape of physiological signals. In our current implementation, we use a window length of 15 and a polynomial order of 3, which were empirically derived to balancing noise reduction with signal preservation. Data post processing can be seen in Fig 2.

5) Data Segmentation and Normalization: To prepare data for Pulse-Fi's LSTM heart rate estimator, we segment the CSI into overlapping windows of fixed packet length. For example, with a window size of 100, the first window is packets 1–100, the next is 2–101, etc. The temporal duration of each window is calculated as the window size in seconds multiplied by the sampling rate.

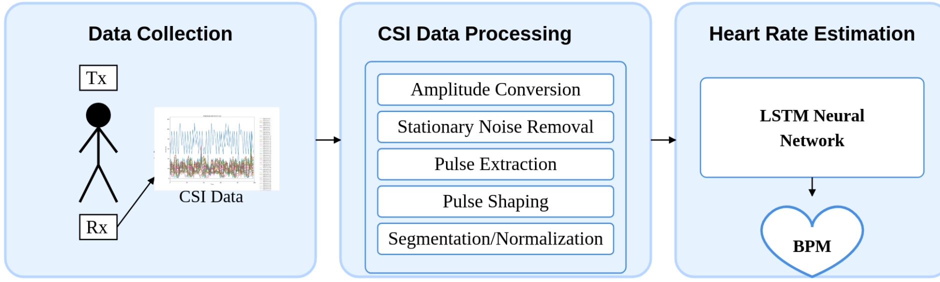

Fig. 1. Pulse-Fi System Architecture

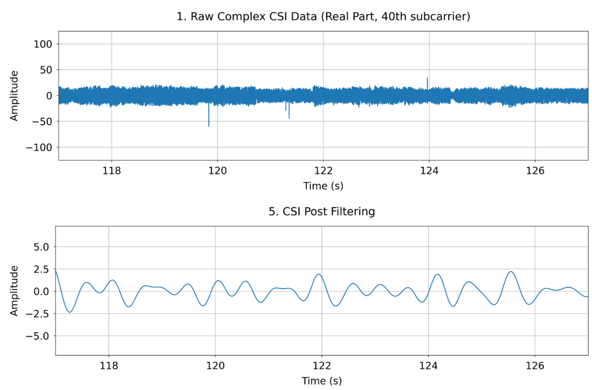

Fig. 2. CSI data before and after filtering

V. Heart Rate Estimation

Processed CSI data are fed to Pulse-Fi's heart rate estimation module, which uses an LSTM neural network to continuously estimate heart rate. As discussed previously, models based on LSTM are well suited for tasks such as continuous heart rate estimation because they can find long-term dependencies in time-series data [14], [15].

1) Pulse-Fi's LSTM Architecture: LSTMs extract the characteristics of long- and short-term data set using *memory cells* and *gates*. Memory cells store dependencies, such as short-term spikes (e.g., increased heart rate during running) and long-term trends (e.g., resting heart rate).

After the LSTM layer extracts the important features from the wireless signal, the dense layer summarizes it and estimates the BPM. After training, the model outputs a vector indicating relevant features. A higher numerical value indicates relevance in predicting heart rate. A negative number means the particular feature is irrelevant and an activation function (ReLU in our case) discards them.

2) Model Training: We train our model using the ADAM optimizer [19], known to handle large data sets and high-dimensional parameter spaces effectively by combining momentum with adaptive learning rates. We empirically set the learning rate to 0.001, balancing convergence speed and stability, resulting in stable training and validation losses, indicating successful convergence. Our loss function is Mean Squared Error (MSE), which heavily penalizes larger errors. We use early stopping (Patience 10) and halve the learning rate if validation loss does not improve to prevent overfitting.

Pulse-Fi's LSTM models are trained with a 64-16-20% split between train, validation, and test, ensuring generalization by shuffling. The accuracy of heart rate estimation is evaluated using MAE (average error) and MAPE (scale-independent percentage error), with additional analysis on the percent of estimations under 1.5 BPM error.

VI. CSI Data Collection

We evaluate Pulse-Fi using two different datasets. The first, the ESP-HR-CSI dataset, was collected locally using two ESP32's, each with a single antenna. For the second dataset, we use the EHealth dataset [20] which was collected by researchers in Brazil using a Raspberry Pi with a single antenna. We describe these datasets in more detail below.

A. ESP-HR-CSI Dataset

We collected the ESP-HR-CSI dataset from seven participants (5 male, 2 female) in a room of a public indoor library. It was collected using two ESP32 devices, one as the transmitter and the other as the receiver. The sampling rate is 80Hz, with a 20 MHz bandwidth with 64 subcarriers positioned at different distances. Each participant was measured at distances of 1, 2 and 3 m for 5 minutes each. The participants sat in a chair between the devices and wore a pulse oximeter on their finger to collect ground-truth information as seen in Fig. 4.

B. E-Health Dataset

The E-Health dataset [20] contains CSI collected from 118 participants (88 men, 30 women) in a controlled indoor environment measuring 3m x 4m (Fig 4). The setup consists of a router set in the 5GHz band at 80MHz bandwidth as a transmitter, a laptop as receiver and a single-antenna Raspberry Pi 4B with NEXMON firmware for CSI data collection (234 subcarriers). Participants wore a Samsung Galaxy Watch 4 for the ground truth.

Each participant performed 17 standardized positions or activities, with each position held for 60 seconds.

VII. Results

1) ESP-HR-CSI Data Performance: We use the ESP-HR-CSI dataset to evaluate the model on two factors: transmitter–receiver distance and the LSTM window size. Our

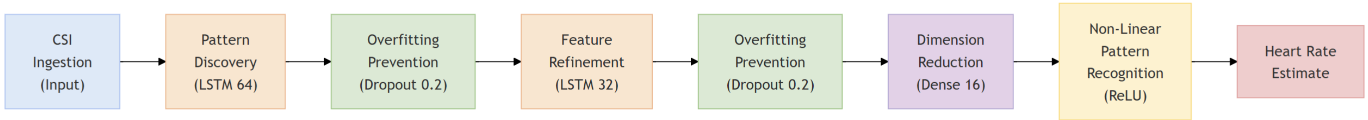

Fig. 3. Heart Rate LSTM Architecture

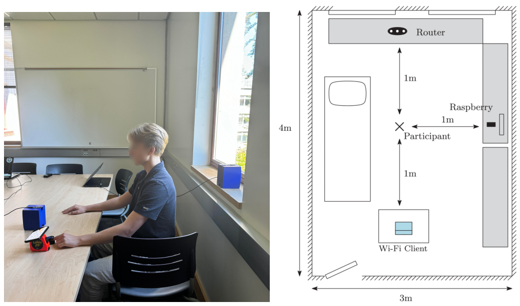

Fig. 4. ESP-HR-CSI (left) and eHealth (right) Dataset Collection Setup

system's top performance is reached at 30-second windows where the MAE is 0.459 and the MAPE is 99.45. Table II summaries the results comparing PulseFi's performance against that of previous approaches. When comparing performance at different distances, Pulse-Fi can stay relatively consistent with a MAE of 0.429 at 1m, 0.482 at 2m, and 0.488 at 3m, a range of only 0.059 between 1m and 3m with 30's window. Past approaches have struggled to accurately detect heart rate at varying distances. Sun et al. [6] reported MAE of 0.80 at 1m, but the MAE doubled (1.75) at 3m distance. Similarly, in Khamis et al. [7], the MAE dropped from 1.14 at 1m to nearly 3 at 2.5m. Tsubota et al. [8] achieved 1 BPM error which equals to 98.5% MAPE at 1m distance. Their MAE dropped to 96% at 3m implying a BPM error of roughly 2.7. Measurements of percent of estimations under 1.5 BPM error can be found in Table I as $<$1.5(%).

TABLE I
PERFORMANCE COMPARISON ON ESP-HR-CSI AND EHEALTH DATA

Win (s)	ESP-HR-CSI			EHealth		
	MAE	MAPE	$<$1.5(%)	MAE	MAPE	$<$1.5(%)
1	1.17	98.55	70.9	6.1	94.18	16.68
5	0.51	99.38	96.1	0.78	99.23	87.85
10	0.55	99.33	96.5	0.35	99.64	98.94
15	0.51	99.376	96.0	0.2	99.81	99.62
20	0.53	99.36	95.7	0.24	99.77	99.45
25	0.51	99.34	96.5	0.17	99.83	99.61
30	0.46	99.45	96.8	0.14	99.87	99.69

2) EHealth Data Performance: We analyzed how different postures and data window sizes affect performance on the EHealth dataset. Table I shows the model MAE, MAPE, and percent of estimations under 1.5 BPM when tested using different window sizes. The best performance is achieved with a 30s window with a MAE of 0.14 and MAPE of 99.87. The performance at 20s window is also notable with a MAE of 0.20 BPM. When looking at how positions affected accuracy using a 20s window, the best position had an accuracy of 0.19, whereas the worst 0.22. The state of the art had errors ranging from as low as 0.07 BPM (Position 10) to as high as 6.74 BPM (Position 7 to 9). On average, [13] has an MAE of 2.72 BPM while our proposed method reduces it to just 0.20 BPM.

VIII. DISCUSSION

The results achieved show several key advantages of the Pulse-Fi system compared to existing approaches. First, the system shows robustness across both datasets. In the ESP-HR-CSI dataset, we achieved an MAE of 0.46 BPM with a 30-second window, and this accuracy was kept nearly consistent across 1, 2, and 3m, a task previous peak detection-based models struggled with. This shows the system's ability to handle the weaker amplitude and higher noise levels found at greater distances. This holds true for all window sizes larger than 1 second. On the larger and more diverse EHealth dataset, where with a 20s window, Pulsefi had a range of 0.03 across all positions, where the previous SOTA struggled with this, having an error range of 6.67 BPM. It should also be noted that the previous SOTA used a specific window setting for each position, whereas our approach uses one model for all positions. This significant decrease shows robust results across different positions and the system's noise handling abilities.

A key novelty of our work is to analyze how the size of the LSTM window affects performance. Our results show a clear trend: while very short windows (1s) yield relatively high error rates, performance improves dramatically with windows of 5s or longer. The probable reason for this is that there are no peaks (those caused by a heart beat) to detect in such a small window size. The LSTM requires temporal features which are more prevalent at higher window sizes. This relationship between window size and accuracy, as seen in Table I, has not been previously explored in CSI-based vital sign monitoring, giving possible direction for future system designs. We observed different patterns of diminishing returns between our datasets. The ESP-HR-CSI dataset shows optimal performance at 30s windows with slow improvements until then, except for the 5s window, which achieved the second best performance. EHealth showed a consistent improvement across all lengths. This can be explained by the limited number of subcarriers on the ESP, making 5 seconds of data enough to learn and generalize the trend, whereas the Raspberry Pi has more subcarriers, allowing the model to see marginal improvements.

Computationally, Pulse-Fi is remarkably efficient—the complete model requires only 500-600KB of storage, enabling

TABLE II
COMPARISON OF DIFFERENT HEART RATE ESTIMATION METHODS

Name	Parameters					MAE	MAPE (%)
	Method	Window (s)	Chip	Ant.	Part.		
Wang [9]	Peaks	Sliding	Intel 5300	3	4	1.19	95.5
Sun [6]	Peaks	12-20	Intel 5300	3	9	0.80	97.1
Zhang [3]	Peaks	30	Intel 5300	3	1	3.53	94.7
Khamis [7]	Peaks	20	Intel 5300	3	4	1.14	NA
Gouveia [13]	Peaks	Case specific	Raspberry Pi	1	59	2.72	NA
Liu [10]	CNN	50	TL-WDR 4300	2	1	0.60	98.58
Tsubota [8]	Peaks	NA	Intel 5300	3	NA	1.00	98.5
Pulse-Fi (ESP-HR-CSI)	**LSTM**	**5**	**ESP32**	**1**	**7**	**0.51**	**99.38**
Pulse-Fi (EHealth)	**LSTM**	**15**	**Raspberry Pi**	**1**	**118**	**0.20**	**99.81**

deployment on resource-constrained devices like ESP32 or Raspberry Pi for near real-time monitoring without specialized hardware. Our 1.5 BPM error threshold aligns with clinical standards (1-5% tolerance), with 96.84% of ESP-HR-CSI and 99.87% of EHealth measurements meeting this requirement using only commodity hardware.

Pulse-Fi outperforms existing methods in multiple metrics (Table II). Its MAE of 0.2 BPM improves on the state of the art peak detection [6] by 75% and recent deep learning methods [10] by 66.9%. Additionally, its 99.45% MAPE surpasses all compared methods, reflecting a more consistent accuracy across heart rate ranges, positions, and distances.

IX. CONCLUSION

This paper presented Pulse-Fi, a novel low-cost system that uses Channel State Information (CSI) to continuously and non-intrusively monitor heart rate. Pulse-Fi highlights that adequate accuracy can be achieved using low-cost, off-the-shelf commodity hardware amplitude information. Our experimental results using two distinct datasets demonstrate that Pulse-Fi's CSI processing pipeline, combined with its custom low-compute Long Short Term Memory (LSTM) neural network, is able to monitor heart rate accurately. We also show that Pulse-Fi yields heart monitoring accuracy comparable to or higher when compared with existing systems that employ more specialized hardware and/or require higher computational power.

ACKNOWLEDGMENT

The authors thank Célio Albuquerque and the contributors to the EHealth data set for allowing this work, and the shepherd and reviewers for their valuable feedback.

REFERENCES

[1] C. Chen, S. Ding, and J. Wang, "Digital health for aging populations," *Nature Medicine*, vol. 29, pp. 1623–1630, 2023.

[2] J. C. Soto, I. Galdino, E. Caballero, V. Ferreira, D. Muchaluat-Saade, and C. Albuquerque, "A survey on vital signs monitoring based on wi-fi csi data," *Computer Communications*, vol. 195, pp. 99–110, 2022.

[3] X. Zhang, Y. Gu, H. Yan, Y. Wang, M. Dong, K. Ota, F. Ren, and Y. Ji, "Wital: A cots wifi devices based vital signs monitoring system using nlos sensing model," *IEEE Transactions on Human-Machine Systems*, vol. 53, no. 3, p. 629–641, Jun. 2023. [Online]. Available: http://dx.doi.org/10.1109/THMS.2023.3264247

[4] B. Huang, S. Hu, Z. Liu *et al.*, "Challenges and prospects of visual contactless physiological monitoring in clinical study," *npj Digital Medicine*, vol. 6, p. 231, 2023.

[5] V. Vats, A. Nagori, P. Singh, R. Dutt, H. Bandhey, M. Wason, R. Lodha, and T. Sethi, "Early prediction of hemodynamic shock in pediatric intensive care units with deep learning on thermal videos," *Frontiers in Physiology*, vol. 13, p. 862411, 2022.

[6] J. Sun, X. Bian, and M. Li, "Non-contact heart rate monitoring method based on wi-fi csi signal," *Sensors*, vol. 24, no. 7, p. 2111, 2024.

[7] A. Khamis, C. T. Chou, B. Kusy, and W. Hu, "Cardiofi: Enabling heart rate monitoring on unmodified cots wifi devices," in *Proceedings of the 15th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, 2018, pp. 97–106.

[8] K. Tsubota, Y. Nagatsu, and H. Hashimoto, "Biometric information acquisition system using vmd in wi-fi channel status information," in *IECON 2021 – 47th Annual Conference of the IEEE Industrial Electronics Society*, 2021, pp. 1–6.

[9] X. Wang, C. Yang, and S. Mao, "On csi-based vital sign monitoring using commodity wifi," *ACM Transactions on Computing for Healthcare*, vol. 1, no. 3, p. 12, 2020.

[10] M. Liu, Z. Lin, P. Xiao, and W. Xiang, "Human biometric signals monitoring based on wifi channel state information using deep learning," 2022.

[11] H. Solgun, A. Ozcan, and O. Pinarer, "Real-time heart rate monitoring via wi-fi signal," in *2023 IEEE International Conference on Big Data (BigData)*, 2023, pp. 4973–4978.

[12] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M. A. Fadhel, M. Al-Amidie, and L. Farhan, "Review of deep learning: concepts, cnn architectures, challenges, applications, future directions," *Journal of big Data*, vol. 8, pp. 1–74, 2021.

[13] B. G. Gouveia, I. Galdino, E. Caballero, J. C. H. Soto, T. C. Ramos, R. Guerra, D. Muchaluat-Saade, and C. V. N. Albuquerque, "Parameter tuning for accurate heart rate measurement using wi-fi signals," in *2024 International Conference on Computing, Networking and Communications (ICNC)*, 2024, pp. 407–411.

[14] S. Shang, Q. Luo, J. Zhao, R. Xue, W. Sun, and N. Bao, "Lstm-cnn network for human activity recognition using wifi csi data," *Journal of Physics: Conference Series*, vol. 1883, no. 1, p. 012139, apr 2021. [Online]. Available: https://dx.doi.org/10.1088/1742-6596/1883/1/012139

[15] K. Krishna, D. Jain, S. V. Mehta, and S. Choudhary, "An lstm based system for prediction of human activities with durations," *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, vol. 1, no. 4, Jan. 2018. [Online]. Available: https://doi.org/10.1145/3161201

[16] G. Wang, Y. Zou, Z. Zhou, K. Wu, and L. M. Ni, "We can hear you with wi-fi!" in *Proceedings of the 20th annual international conference on Mobile computing and networking*, 2014, pp. 593–604.

[17] S. K. Jagtap and M. Uplane, "The impact of digital filtering to ecg analysis: Butterworth filter application," in *2012 International Conference on Communication, Information & Computing Technology (ICCICT)*. IEEE, 2012, pp. 1–6.

[18] R. W. Schafer, "What is a savitzky-golay filter?[lecture notes]," *IEEE Signal processing magazine*, vol. 28, no. 4, pp. 111–117, 2011.

[19] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," 2017. [Online]. Available: https://arxiv.org/abs/1412.6980

[20] I. Galdino, J. C. H. Soto, E. Caballero, V. Ferreira, T. C. Ramos, C. Albuquerque, and D. C. Muchaluat-Saade, "ehealth csi: A wi-fi csi dataset of human activities," *IEEE Access*, vol. 11, pp. 71 003–71 012, 2023.