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CSIWatch: Detecting Eating Activity Using CSI Data From a Smartwatch Worn on the Non-Dominant hand

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***Abstract*—Smartwatches equipped with multimodal sensors are capable of detecting and classifying various human activities, including eating behavior. To facilitate the detection of eating behavior, researchers often instruct participants to wear a smartwatch on their dominant hand, ensuring that motion signals associated with eating are effectively captured. However, this practice of wearing a watch on the dominant hand may feel unnatural to many individuals, as smartwatches are typically worn on the non-dominant hand. To address this usability limitation, in this paper, we demonstrate that it is possible to detect the eating behavior even when the watch is worn on the *non-dominant* hand. We have developed a system – *CSIWatch* – that runs on a wrist worn device. CSIWatch captures Wi-Fi channel state information (CSI) data, leverages movement-induced perturbations observed in that data, and uses machine learning techniques to detect the eating behavior. In a small user study, we demonstrate that CSIWatch can detect eating in various scenarios, even when the watch is worn on the non-dominant hand. Using a Support Vector Machine classifier with a polynomial kernel, the system achieved F1-scores of up to 80%. This system is a step towards removing the long-standing constraint of wearing a smartwatch on the dominant hand to detect eating behavior.**

***Index Terms*—Wi-Fi CSI, Single Antenna System, ESP32-S, Smartwatch, Non-Dominant hand.**

I. INTRODUCTION

Eating detection has been a long-standing topic of interest in the mobile and ubiquitous computing research community. While prior studies have explored diverse methods and devices for identifying eating activities [4], our work specifically focuses on using wrist-worn devices like smartwatches to detect the eating behavior. Indeed, most automated eating detection systems use a wrist-worn device to detect eating behavior because the smartwatch is always *on* the person and can continuously detect eating [4]. Existing wrist-based eating detection approaches primarily rely on inertial sensor data from smartwatches to identify eating moments [22]. This approach presents a major challenge because it requires the user to wear the device on their *dominant* hand to enable accurate detection of hand movements during eating. People, however, typically do not wear smartwatches on their dominant hand [2]. In this work, we demonstrate that wrist-worn devices worn on the *non-dominant* hand can detect eating activities. We developed CSIWatch, a system that leverages Channel State Information (CSI) signals from a wrist-worn device worn on the non-dominant hand for eating detection. This design enables effective detection of eating activities without imposing the constraint of wearing the device on the dominant hand.

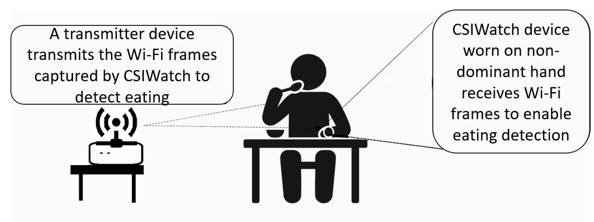


Fig. 1: The CSIWatch system worn on the non-dominant hand utilizes the perturbations caused to the Wi-Fi signal when a person is eating. Due to physical constraints, the dominant hand performing the eating activity is in close proximity to the CSIWatch system, allowing it to capture the CSI data changes.

The CSIWatch system is designed around a wrist-worn device. The core intuition behind our current design is that hand movements during eating induce perturbations in the Radio Frequency (RF) signal. Because the CSIWatch device is positioned close to the eating area, it can effectively capture these signal variations, enabling reliable detection of eating activities [18]. In our prototype implementation, we use a low-cost (less than $5 USD per device), single-antenna microcontroller – the ESP32-S from Espressif Systems [9] – as the wrist-worn device. This microcontroller is securely strapped to the user's non-dominant wrist to mimic a smartwatch. The ESP32-S continuously receives and processes the Wi-Fi frames. CSIWatch uses this data to determine eating moments. In addition to the wrist-worn device, a second device continuously transmits the Wi-Fi frames; *This second device can be a smartphone carried by the user*, providing flexibility in deployment, as presented in Figure 1. For experimental consistency, our current prototype also utilizes an ESP32-S microcontroller as the second device.

Eating is a complex human activity characterized by diverse movements and contextual variations. Consequently, CSIWatch must address several challenges to function as a practical and reliable eating detection system. First, individuals may eat while positioning their non-dominant hand in a variety of positions; thus, the system must accurately detect eating behavior regardless of the hand's location. Second, users may not always sit in pre-defined positions to consume a meal. CSIWatch should detect the eating activity irrespective of user's location. Finally, the eating process comprises alternating periods of hand-to-mouth movements and non-eating actions. The system must be robust to non-eating activities and maintain high accuracy in identifying eating gestures.

In this work, we address these challenges while developing a system capable of detecting eating under diverse conditions. The primary **contributions** of this work are:

- We developed CSIWatch, a system that uses CSI data to detect the eating activity. We present the design of the system in the paper.
- We demonstrate for the first time that a system worn on the *non-dominant hand* can automatically and unobtrusively detect eating moments using the CSI data. We present the spectrogram of the captured signals to visually demonstrate the changes in RF signal during eating activities.
- Using machine learning techniques, we preliminarily demonstrate the possibility of detecting eating with an F1-score of up to 80% using Support Vector Machine classifier.

Overall, automating the eating detection process has been a concern for researchers in various domains, and CSIWatch demonstrates the possibility of tracking the eating activity naturally and continuously using a smartwatch that (unlike prior approaches) is not worn on the dominant hand.

II. Background and Related Work

Eating is a complex activity characterized by multiple physiological and behavioral changes, and no single sensing modality can comprehensively capture all aspects of eating behavior [1]. Therefore, it is essential to clearly specify which characteristics of eating CSIWatch aims to capture. A clear operational definition of "eating" is necessary to establish the system's scope and evaluation criteria. In this work, we define eating as *the hand transitions from a resting state to the food plate to pick up a food item, transfers the item to the mouth, and then returns to rest*. This definition deliberately imposes no temporal constraints – that is, it does not restrict the duration of any phase within the sequence. Moreover, it remains agnostic to the eating modality, accommodating various hand movements and utensil types (e.g., using hands, forks, chopsticks, or spoons).

While the eating activity can be detected in several ways, in this work, we specifically focus on using the CSI data captured from a wearable device to detect eating. Wi-Fi CSI captures the characteristics of a wireless communication channel, describing how signals propagate from a transmitter to a receiver while being influenced by the surrounding environment. In this section, we primarily focus on related works in two aspects: (a) understanding various automatic eating detection approaches, and (b) detecting human activities using CSI data. To visualize the CSI pattern when a person performed eating and non-eating activities while seated between a transmitter and receiver, we collected data from two scenarios, one where the person sat idle between the transmitter-receiver pair (Figure 2 (a)), and other when the person was eating while seated between the transmitter-receiver pair (Figure 2 (b)). The figure presents the temporal variation of the 114 observed subcarriers under these two conditions. From the figure, we anecdotally observe that there is much more variations in the CSI subcarriers when a person is eating, as compared to the data collected when the person is not eating.

A. Automatic eating detection approaches

Automatic eating detection using wearables or infrastructure devices has long been a goal of the mobile health community [23]. Over the years, researchers have proposed diverse eating activity monitoring techniques, with the majority of wearable-based eating detection systems utilizing smartwatches [4]. Paradoxically, despite the natural tendency for individuals to wear smartwatches on the non-dominant hand, studies on smartwatch-based eating detection frequently require participants to wear the device on the *dominant* hand to more effectively capture hand movements associated with eating behaviors [22]. We address that shortcoming in this paper.

Orthogonal to smartwatches, researchers have also used head-based wearables to detect eating behavior [5], [27]. It is noteworthy that in all these systems the users wear devices that they might not seem natural. BiteSense [7] leverages IMU data from earable devices. However, a limitation of such approach is that wearing earable devices during eating is not a common practice. Eyeglasses are a natural wearable for many individuals (of course, people who do not wear eyeglasses might comment against eyeglasses being natural!). Researchers have investigated using various sensors integrated into eyeglasses for eating detection, including cameras [3], [26]. Cameras, in the eyeglass form factor or any other wearable form factor [6], [20], can capture eating moments, but raise significant privacy concerns (no one wants a video record from the breakfast table after a long night). These concerns highlight the need for privacy-preserving eating detection approaches – Wi-Fi based sensing being one such approach. These concerns highlight the need for privacy preserving eating detection approaches – Wi-Fi based sensing being one such approach.

Jain et al. recently demonstrated that it is indeed possible to detect the eating activity using a low-cost, single-antenna Wi-Fi device [14]. This was a major shift from exiting approaches that focus on using multiple antenna MIMO systems for detecting eating using the CSI signal [15]. While multi-antenna configurations offer enhanced detection capabilities, integrating them into a compact wrist-worn device poses significant design challenges. Moreover, such systems are typically costly; in contrast, a single-antenna microcontroller provides a low-cost yet effective alternative for reliable eating detection. However, Jain et al.'s work required users to be seated in specific locations, a constraint that we have removed with CSIWatch.

B. Human activity detection using CSI

While CSI obtained from USRP devices offers a powerful means to track human activities, but such systems are often prohibitively expensive, sometimes costing tens of thousands of dollars [10]. The use of CSI for human activity recognition (HAR) gained prominence with the introduction of tools capable of extracting CSI data from the now-discontinued Intel 5300 Wi-Fi card [12]. Researchers used this device for tasks like shopping activity monitoring [24], person identification [25],

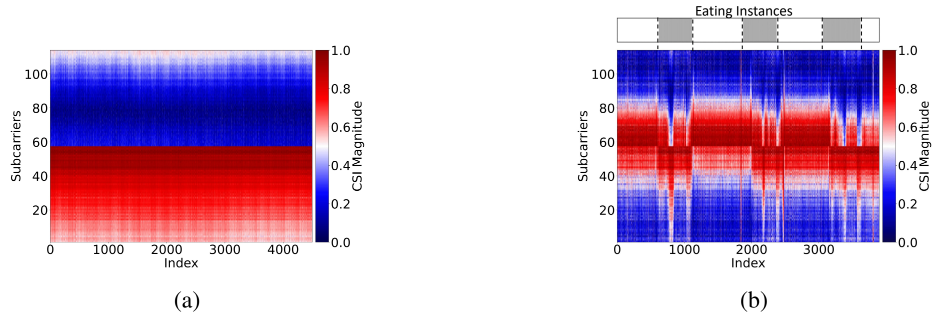


Fig. 2: Time-based variation of normalized CSI data from 114 subcarriers captured by the CSIWatch system in two scenarios: (a) the person is sitting idle, and (b) the person is performing an eating activity. The ground truth bar indicates eating moments.

or finger tracking [21]. The Intel 5300 and USRP platforms commonly used in HAR research capture CSI data via multi-antenna configurations. Although effective, these systems are costly and impose space constraints, making them unsuitable for small form-factor wearables. Whether a low-cost, single-antenna system can achieve comparable performance remains an open question until now.

In addition to single-device setups, researchers have explored multi-device setups for HAR studies. Work such as DensePose utilize data from multiple Intel 5300 and develop a deep learning model to detect the human poses [11]. Similarly, Cominelli et al. used the CSI data from multiple routers for HAR [8]. While multi-router setups are promising, placement of these devices introduces unwanted constraints, and economic and processing cost. In comparison, a low-cost, single-antenna device is more practical for widespread deployment.

III. System Design

CSIWatch uses a smartwatch or similar wrist-worn device worn naturally on the non-dominant hand of an individual who wishes to monitor their eating habits, including when they consumed a meal, and how many hand-to-mouth gestures occur during each eating activity as a proxy for how much the person ate. This wrist-worn device implements the IEEE 802.11 b/g/n Wi-Fi stack, captures Wi-Fi packets to extract the CSI data and has sufficient processing power to run a lightweight machine-learning model. In addition to the wrist-worn device, another device is necessary in the environment to transmit these Wi-Fi packets [13]. As noted above, this device could be a user's smartphone or a Wi-Fi access point at home.

In our current implementation, both these devices are mimicked by the single-antenna ESP32-S microcontrollers from Espressif Systems [9]. Although currently we use the bare microcontroller, in the future, we plan to develop a functional smartwatch designed around an ESP32-S device that one can wear on their wrist for daily life activity monitoring. Similarly, we will develop the transmitter on a smartphone so that the system can capture eating information throughout the day.

In the current setting, the two microcontrollers operate in complementary network configurations – the wrist-worn device acts like an access point device to which the station connects using the IEEE 802.11 protocol. Subsequently, in this manuscript, we refer to the wrist-worn device as 'AP' device and the other device as 'STA'. While the AP is worn on the wrist of the user, the user is not expected to perform any action with the non-dominant hand to facilitate the detection of eating. The STA device continuously transmits Wi-Fi frames.

The AP module of CSIWatch captures the Wi-Fi frames and extracts the CSI data transmitted by the STA at 100 frames per second (the same rate that Wi-Fi access points send beacon frames). The devices operate on a 40 MHz channel, utilizing 114 subcarriers to extract the raw in-phase (I) and quadrature (Q) samples. In our current prototype, the collected CSI data is then transferred to a laptop via a serial communication interface for machine learning-based eating inference. In future work, we plan to run machine learning-based classifiers on the watch.

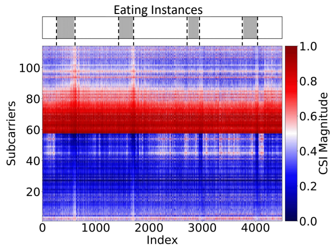
The machine learning module composes the data into windows of size n seconds (currently we use $n = 0.5$ seconds with 50% overlap between subsequent windows). Each n-second window has data from 114 subcarriers. For every subcarrier, CSIWatch extracts four features – mean, median, standard deviation, and slope – for the window of length n seconds by utilizing the amplitude computed from the collected CSI data. Thus, we obtain a feature vector of length $114 \times 4 = 456$ per window. The feature vector is then passed onto a machine learning model to determine whether that window contains an eating activity. We experimented with various classifiers (both shallow and deep learning) like Support Vector Machine (SVM) (Polynomial, RBF, Sigmoid), XGBoost, and MLP (Multi-Layer Perceptron) to determine the model's eating detection accuracy.

IV. Methodology and Preliminary Results

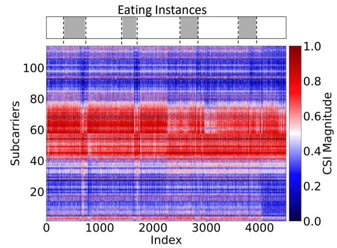
We next discuss the methodology adopted to evaluate CSIWatch, and then report the preliminary results.

A. Dataset

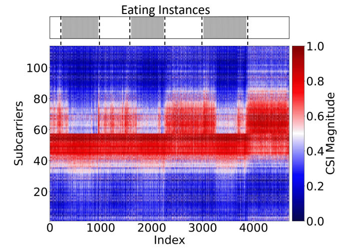
To determine the possibility of detecting eating moments using the CSIWatch system, we collected data from 9 eating episodes. These episodes were performed in a controlled setting when a participant consumes a plate of rice (4 instances), bread (1 instance) or noodles (4 instances) while sitting on a chair in front of a table. This setup is similar to Jain et al.'s data collection process [14]. We emphasize, however, that unlike Jain et al. where devices are placed in specific, pre-determined positions, CSIWatch does not require specific device placement.



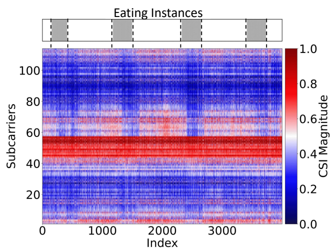
(a) Wrist-worn device above table, transmitter above table on dominant side, eating in between



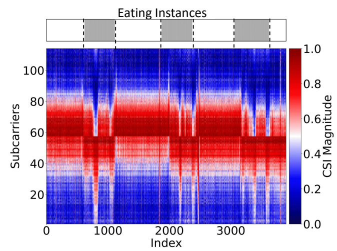
(b) Wrist-worn device above table, transmitter above table on non-dominant side, eating not in between



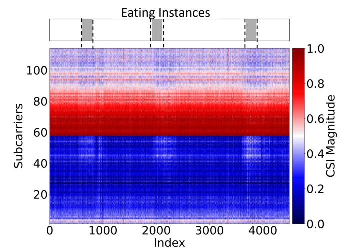
(c) Wrist-worn device above table, transmitter below table on dominant side, eating in between



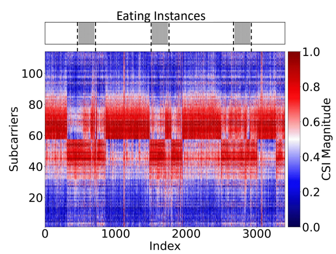
(d) Wrist-worn device above table, transmitter below table on non-dominant side, eating not in between



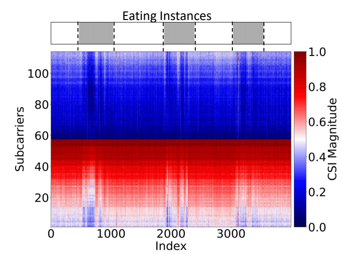
(e) Wrist-worn device below table, transmitter above table on dominant side, eating in between



(f) Wrist-worn device below table, transmitter above table on non-dominant side, eating not in between



(g) Wrist-worn device below table, transmitter below table on dominant side, eating in between



(h) Wrist-worn device below table, transmitter below table on non-dominant side, eating not in between

Fig. 3: Visualizing the time-based variation of the 114 sub carriers when the wrist-worn device and the transmitting device are placed at various positions during an eating episode using normalized CSI values for each subcarrier.

In this work, users were free to position their non-dominant hand as they wished, and likewise, there were no placement restrictions for the STA. Indeed, we empirically demonstrate in Figure 3 that eating induces distinct CSI perturbations, even when the two devices are in different positions. Specifically, we experimented with various positions of the AP (non-dominant hand) e.g., above the table, below the table while the dominant hand performed various activities. For normalizing the CSI data, we first applied a logarithmic transformation with an offset to stabilize variance and reduce skewness. The transformed values were then scaled to the range [0,1], ensuring comparability across subcarriers. We also experimented with placing the STA near the dominant hand, away from dominant hand, and also above and below the table. Figure 4 depicts examples of the CSI changes from all 8 possible positions of the dominant hand, non-dominant hand, and station in our experiments.

The AP is connected to a laptop via a serial peripheral. All data from the AP was transferred to this connected laptop for visualization purposes as well as for performing the machine learning tasks. In addition to processing the CSI data, the

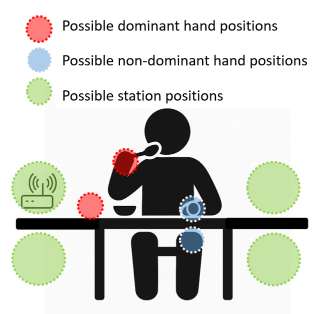


Fig. 4: Various conditions under which data was collected to determine the feasibility of realizing CSIWatch.

laptop also executes a script that captures and timestamps a video feed via its camera. In our study, the laptop is placed in front of the person such that it captures the video of the person while they consume their meal. This video data was used to mark the ground truth for eating moments in the data. Overall, there are 284 seconds of eating moments in our dataset

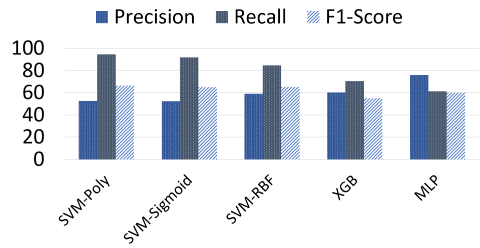


Fig. 5: Leave-One-Person-Out Cross-Validation of CSIWatch for eating detection

and 1336 seconds of non-eating moments. The 284 seconds of eating moments captured 77 hand-to-mouth eating gestures.

In the current dataset, there are at least 120 seconds of data from each of the scenarios depicted in Figure 4. In Figure 3, the spectrogram for the 8 possible eating positions are presented. The x-axis in the figure represents the index of Wi-Fi frame (analogous to time), while the y-axis represents the CSI data for the 114 subcarriers. The CSI data for each subcarrier is normalized using min-max normalization technique, and thus all CSI data is in the range 0 to 1. In each of these 8 scenarios, there are moments when a person is eating and when they are either at rest or performing other activities – the eating moments are represented by the gray rectangle on top of each figure. From the figures, it is evident that there is perturbation in the RF channel in every mentioned scenario. As expected, the observed perturbation was higher when the non-dominant hand was near the dominant hand performing the eating activity (e.g., Figure 3 (a), as compared to less obvious perturbations when AP and STA are below the table, while the dominant hand performs the eating activity (Figure 3 (h)).

B. Evaluation Strategy and Metric

To determine the possibility of detecting the eating moments, we performed a leave one episode out cross validation. We used F1-score as the evaluation metric for our approach. The F1-score provides a harmonic mean between precision and recall, balancing out the outcome without favoring one among precision and recall over the other. In this work, we report the F1-score for eating activity computed every 5 seconds.

C. Initial Findings

We experimented with multiple machine learning techniques and identified that Support Vector Machine classifier with kernel Polynomial provided the best performance in detecting the eating activity. The results of various classifiers are shown in Figure 5. Based on our evaluation, we observed that we could detect eating using a Support Vector Machine classifier with Polynomial kernel with a F1-score of 66.55%. Although the dataset size is small, it still demonstrates that the direction of using the data from a wrist-worn device worn to detect eating is promising. Among the eight cases that we demonstrated in Fig 4, we observed that CSIWatch achieved the highest performance when the watch was worn on the non-dominant hand and kept above the table, while the receiver device was kept on the dominant hand side below table and eating occurred in between the two devices. Indeed in this case, we could achieve an F1-score of 80% in detecting all the eating instances in the episode. Orthogonally, the system only achieved a F1-score of 57.14% when the watch was worn on the non-dominant hand and kept below the table; the STA device was kept above the table, and eating occurred in between the two devices. Table I presents the performance of CSIWatch when the devices were placed at different positions. Overall, this study shows promise in the approach.

TABLE I: Performance of the Support Vector Machine classifier with Polynomial Kernel for different positions.

Position Description	Precision	Recall	F1-score
AP above table, STA below table on dominant side, eating in between	68.75%	95.65%	80%
AP below table, STA above table on non-dominant side, eating not in between	70.58%	75%	72.72%
AP above table, STA above table on dominant side, eating in between	56.75%	100%	72.41%
AP above table, STA below table on non-dominant side, eating not in between	51.35%	100%	67.85%
AP above table, STA above table on non-dominant side, eating not in between	48.64%	100%	65.45%
AP below table, STA below table on dominant side, eating in between	48.14%	81.25%	60.46%
AP below table, STA below table on non-dominant side, eating not in between	42.85%	100%	60%
AP below table, STA above table on dominant side, eating in between	40%	100%	57.14%

V. Discussion and Future Work

In this paper, we present the idea of developing a wrist-worn wearable device that is worn naturally (i.e., on the non-dominant hand) and can yet detect the eating behavior of an individual. Currently, we have performed a preliminary proof of concept. There are several aspects of CSIWatch that needs improvement in order to make it a robust eating detection system.

Robustness to eating behavior and environmental factors: We have currently collected data in a static environment. The data has been collected from a small number of participants. As an obvious next step, we will increase the corpus of data, collected from a diverse set of participants and in more uncontrolled environments. Similar to other data collection approaches in the past [14], we will collect more data to determine the robustness of CSIWatch. One might wonder if the position of the devices will affect the eating detection performance. We believe that as the AP is on the person, the eating activity will occur in different Fresnel Zones (an ellipse between the transmitter and receiver) that will create changes in the CSI. As the eating activity occurs in the Fresnel Zone, it should not be affected by other noise in the environment [19].

Improving performance: Currently, we are relying on the CSI data captured by the wrist-worn device on the non-dominant hand. Smartwatches, in general, are embedded with a number of sensors. In future, we can explore opportunistically using data from other sensors like cameras [20], or audio sensors [16] to improve the eating detection quality. Furthermore, as no additional sensor is turned on while capturing CSI data (assuming Wi-Fi is always on in smartphones), this system can help in turning on more robust sensing modalities (like earables [7], [17]) when it predicts the start of an eating activity.

Additionally, the current system uses a shallow learning pipeline for eating detection. With the popularity of deep learning techniques, such as ones used in DensePose [11], an obvious question arises whether deep learning techniques can help improve performance of the CSIWatch system. Currently, with the small dataset, it might not be possible to determine the true potential of deep learning techniques. Indeed, our initial assessment of deep learning approaches on our dataset did not demonstrate promising results. In future, with a larger dataset, we will evaluate the performance of deep learning techniques.

VI. Conclusion

In this paper, we present CSIWatch, a prototype system based on wrist-worn wearable device for eating detection. CSIWatch removes the traditional constraint of wearing a wrist-worn device on the *dominant* hand to detect the eating behavior. Through a small user study, we demonstrate the possibility of CSIWatch detecting the eating behavior in several diverse conditions. Overall, we observed that CSIWatch could detect eating gestures with a F1-score of up to 80%, which reinforces the claim that the system is capable of detecting eating activity despite being placed on the non-dominant hand. CSIWatch's ability to operate on the *non-dominant* hand will enable development of a more natural eating detection system.

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References

[1] Oliver Amft and Gerhard Troster. On-body sensing solutions for automatic dietary monitoring. *IEEE Pervasive Computing*, 8(2), 2009.

[2] BeatXP. Which hand is best for smartwatch? https://www.beatxp.com/blog/which-hand-is-best-for-smartwatch/, 2025. [Accessed: 2025-10-24].

[3] Abdelkareem Bedri et al. Fitbyte: Automatic diet monitoring in unconstrained situations using multimodal sensing on eyeglasses. In *Conference on Human Factors in Computing Systems (CHI)*, 2020.

[4] Brooke M Bell et al. Automatic, wearable-based, in-field eating detection approaches for public health research: a scoping review. *NPJ Digital Medicine*, 3(1):38, 2020.

[5] Shengjie Bi et al. Auracle: Detecting eating episodes with an ear-mounted sensor. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT)*, 2(3):1–27, 2018.

[6] Daniel Castro et al. Predicting daily activities from egocentric images using deep learning. In *ACM International Symposium on Wearable Computers*, pages 75–82, 2015.

[7] Garvit Chugh, Indrajeet Ghosh, Sandip Chakraborty, and Suchetana Chakraborty. Bitesense: Earable-based inertial sensing for eating behaviour assessment. In *2025 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 2025.

[8] Marco Cominelli, Francesco Gringoli, and Francesco Restuccia. Exposing the CSI: A systematic investigation of CSI-based Wi-Fi sensing capabilities and limitations. In *International Conference on Pervasive Computing and Communications (PerCom)*, pages 81–90. IEEE, 2023.

[9] Espressif Systems. ESP32-S Series, 2025. https://www.espressif.com/en/products/modules [Accessed: 2025-10-27].

[10] Ettus Research. USRP Software Defined Radio Products. https://www.ettus.com/products/, 2025. [Accessed: 2025-11-30].

[11] Jiaqi Geng, Dong Huang, and Fernando De la Torre. Densepose from Wi-Fi. *arXiv preprint arXiv:2301.00250*, 2022.

[12] Daniel Halperin, Wenjun Hu, Anmol Sheth, and David Wetherall. Tool release: gathering 802.11n traces with channel state information. *SIGCOMM Computer Communications Review*, 41(1):53, 2011.

[13] Steven M Hernandez and Eyuphan Bulut. Lightweight and standalone IoT based WiFi sensing for active repositioning and mobility. In *International Symposium on "A World of Wireless, Mobile and Multimedia Networks"(WoWMoM)*, pages 277–286. IEEE, 2020.

[14] Shreyans Jain, Yash Bhisikar, Surjya Ghosh, Timothy J Pierson, and Sougata Sen. Sanddune: Single antenna device for detecting user's natural eating habits. In *IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops)*. IEEE, 2025.

[15] Zhenzhe Lin, Yucheng Xie, Xiaonan Guo, Yanzhi Ren, Yingying Chen, and Chen Wang. Wieat: Fine-grained device-free eating monitoring leveraging Wi-Fi signals. In *International Conference on Computer Communications and Networks (ICCCN)*, pages 1–9. IEEE, 2020.

[16] Mark Mirtchouk, Christopher Merck, and Samantha Kleinberg. Automated estimation of food type and amount consumed from body-worn audio and motion sensors. In *ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp)*, pages 451–462, 2016.

[17] Alessandro Montanari, Ashok Thangarajan, Khaldoon Al-Naimi, Andrea Ferlini, Yang Liu, Ananta Narayanan Balaji, and Fahim Kawsar. Omnibuds: A sensory earable platform for advanced bio-sensing and on-device machine learning. *arXiv preprint arXiv:2410.04775*, 2024.

[18] Timothy J Pierson, Travis Peters, Ronald Peterson, and David Kotz. Closetalker: Secure, short-range ad hoc wireless communication. In *Proceedings of the International Conference on Mobile Systems, Applications, and Services (MobiSys)*, pages 340–352. ACM, 2019.

[19] Timothy J Pierson, Travis Peters, Ronald Peterson, and David Kotz. Proximity detection with single-antenna IoT devices. In *International Conference on Mobile Computing and Networking (MobiCom)*, 2019.

[20] Sougata Sen, Vigneshwaran Subbaraju, Archan Misra, Rajesh Krishna Balan, and Youngki Lee. The case for smartwatch-based diet monitoring. In *International Conference on Pervasive Computing and Communication Workshops (PerCom workshops)*, pages 585–590. IEEE, 2015.

[21] Sheng Tan and Jie Yang. Wifinger: Leveraging commodity WiFi for fine-grained finger gesture recognition. In *International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, 2016.

[22] Edison Thomaz, Irfan Essa, and Gregory D Abowd. A practical approach for recognizing eating moments with wrist-mounted inertial sensing. In *International Conference on Ubiquitous Computing (UbiComp)*, 2015.

[23] Tri Vu, Feng Lin, Nabil Alshurafa, and Wenyao Xu. Wearable food intake monitoring technologies: A comprehensive review. *Computers*, 6(1):4, 2017.

[24] Yunze Zeng, Parth H Pathak, and Prasant Mohapatra. Analyzing shopper's behavior through WiFi signals. In *Proceedings of the Workshop on Physical Analytics*, 2015.

[25] Yunze Zeng, Parth H Pathak, and Prasant Mohapatra. WiWho: WiFi-based person identification in smart spaces. In *International Conference on Information Processing in Sensor Networks (IPSN)*. IEEE, 2016.

[26] Rui Zhang and Oliver Amft. Monitoring chewing and eating in free-living using smart eyeglasses. *IEEE Journal of Biomedical and Health Informatics*, 22(1):23–32, 2017.

[27] Shibo Zhang, Yuqi Zhao, Dzung Tri Nguyen, Runsheng Xu, Sougata Sen, Josiah Hester, and Nabil Alshurafa. Necksense: A multi-sensor necklace for detecting eating activities in free-living conditions. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT)*, 4(2):1–26, 2020.