Sensing technology for detecting food intake - a systematic literature review

W.B. KONING, University of Twente, The Netherlands

Accurately monitoring dietary food intake is an important aspect in researching the relation of food intake with health outcomes. The methods currently available to monitor dietary intake are fairly inaccurate and often based on self-report. Sensing technology can play a crucial role in creating methods that are reliable in detecting when, what, or how much food intake is measured.

This study is a systematic literature review of papers that published on sensing technology with the intended use of measuring one of the dimensions of food intake(when, what and how much). Out of a total of 521 papers selected for screening, 51 papers were reviewed in full-text. 32 studies reported relevant findings. The review shows an overview of sensing principles, locations and eating phases studied as well as their relation to the different food intake dimensions.

The results indicate that the event detection of when a person eats is the most studied food intake dimension. Smartwatches worn on the extremities were the most common sensor type used, and camera modules also occurred frequently. Ingestion was the eating phase measured most to detect when a person eats and oral processing was the most commonly measured to detect what a person eats. Artificial and controlled settings are most utilized measurement settings, although comparison with previous literature shows a shift towards less artificial controlled studies and more towards natural settings and free environments.

Additional Key Words and Phrases: Sensing technology, Food intake, Systematic review

1 INTRODUCTION

Nowadays a lot of health sciences are researching the link between health-factors and food intake. For example, a study focused on weight management looks at diets to find that the impact of nutrient balance may play a more important role in weight management than caloric balance[11]. Other studies find strong associations that poor eating habits and lower quality diet have an impact on food cravings[1]. Dietary intake has been found to play an important role in the development of physical and mental functional impairments in elderly[24] and food intake has also been associated with oral health outcomes, where families resorting to cheaper and unhealthier foods were associated with worse oral health[25]. An accurate overview of food intake is crucial for studies that relate food with health outcomes.

Dietary intake monitoring is commonly used to track food intake, with self-reporting being the most used tool[8], however, there are some negative aspects of manually reporting food intake and there are several reasons why food diaries may be inaccurate. A combination of several studies has shown on average a 30% underreporting of nutritional intake in adults with energy intake being underestimated by approximately 15% [41]. Self-reporting requires quite a bit of effort and diary protocols that stretch over longer periods will typically see commitment to the protocol go down over time, and with that also the accuracy of the entries[46]. Eating habits can also be an issue, with people having more eating moments throughout the day having more trouble accurately reporting their consumption[45] and people struggling with obesity have been acknowledged to have a bias towards under-reporting their food intake[43].

There have been studies that try to address the problem of misreporting in dietary intake measurements, and several tools have been developed to minimize reporting errors[8, 45]. There are web and smartphone applications that assist the user in logging their food-diary by presenting a pre-existing database of listed foods in which the user can search and choose. Other applications allow for digital imagery assistance to identify foods that can be used to list entries is the food diary[8, 14, 32]. Although these solutions help eliminate user bias towards calorie and nutrient intake, they are still mainly based on self-report and require constant input from the people using them.

Technology that can automate the detection of food intake could help eliminate the user biases that currently exist in dietary reporting. Some sensing technologies in development look promising with respect to automatic detection of when a person eats, such as smartwatches that detect eating behavior based on wrist gestures[10]. Another example is automatic chewing detection, where the chewing motion of the jaw is detected using a headphone and reported as a parameter of food consumption [5]. Other technologies aim to detect what people eat, for example, by trying to accurately classify food types or nutrient compositions from imagery using deep learning models[39]. There exists a lot of literature on these types of technologies that report on a specific part of monitoring dietary intake with a specific measurement design. Some of them report good performance but still only paint part of the picture when it comes to completely automating food intake monitoring. A comprehensive overview describing these types of sensing technologies along with the type of measurement approach used could be helpful to create meaningful connections between these different technologies.

This research aims to obtain a broad and complete overview of the sensing technologies used to detect food intake. The goal is to provide a basis of relevant information that allows for the analysis of the current state of sensing technologies to detect food intake. Relevant information includes the type of sensing that is performed, details on sensor types and placement, and information regarding the measurements of the study. To reach this goal, the following research question was formulated: What insights can be derived from obtaining a comprehensive overview of sensing technologies for detecting food intake?

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2 RELATED WORK

The starting point for this research is a systematic literature review done in 2020 on sensing technologies for detecting food intake[19]. This systematic review retrieved 2633 articles that were published within the time frame of 2005 and 2020 and after screening and thorough assessment resulted in 186 articles that met the inclusion criteria and 264 total studies with relevant measures of food intake included. This led to a large overview of the technologies that were used for detecting food intake in which at least one of the three food intake dimensions(when, what, how much) was measured, with the use of sensing technology where the technology was also validated.

The methodology used in this systematic literature review resulted in a quick and appropriate way to select relevant papers and led to insightful results. The review showed a significant increase in papers published on sensing technology in the few years leading up to 2020, and with a few years that have passed, it seems likely that more meaningful results are to be found. Therefore, this research will use the methodology of the review to create a newer version of this review and to see how the field of sensing technology has changed in this time.

Some highlights of this review include the setting in which the studies were performed. A total of 159 studies were done in artificial and just 51 in natural setting, which is about 76% artificial. A total of 54% environments were controlled, 27% semi-controlled and 19% free. The review showed that 70% of the studies reported on the when, 20% what and 10% how much food intake dimensions.

When taking a look at sensing principles, the review presents sound as the most used sensing principle in 68 instances and mentions that it is also most common in combinations. Motion is used most in measuring when a person eats. Locations used for the sensors were spread pretty evenly with ear, external, extremities and neck all ranging between 46-51 out of 264 total. A combination of sensing locations occurred in 24 studies.

Ingestion and oral processing were the most common easting phases studied, with a combined total of 69% Swallowing or a combination of eating phases made up for most of the rest of the studies with a combined total of 30%.

3 METHODOLOGY

3.1 Literature search

The electronic database Scopus is used to search for relevant papers documenting on sensing technologies to detect food intake. A search string previously constructed and used by Haarman et al[19] is utilized to find papers that have keywords mentioned in three categories: keywords that mention the dimensions of food intake that were measured(When, What and how much), words that are linked to the use of sensing technology and lastly words that are related to the description of performance to find papers that have validated the use of sensing technology. All papers must have at least 1 specific term in all of the three categories to be selected as relevant for this literature review.

3.2 study selection

The resulting papers were selected eligible for full-text reading based on the following criteria: (1) Sensing technology was used for measuring at least one of the three dimensions of food intake (When, what, how much). (2) Sensing technology was intended for use in a real-life setting. (3) Description of technical performance and validation procedure was included. (4) Full-length English archival publication must be available. To further narrow the scope of the selection, studies that contain the following criteria were excluded: (1) The target group includes infants or animals. (2) Sensing technology was solely based on smartphone usage for self-report. (3) Intended use of sensing technology was diagnostics (e.g. medical or clinical use), characterization of food properties (e.g. food texture or oral processing characteristics), or screening of food (e.g. safety reasons). This selection was based on reading the titles and abstracts of the papers from the literature search, when title and abstract were not enough to determine deselection, they were included in the full-text reading.

3.3 data extraction

Data extraction of the selected papers was done in a systematic way, where all papers were assessed and relevant information was categorically listed in a large table. The structure of the table is based on the table from the study previously done on this subject[19] to allow for the making of connections and comparisons to the results from 2005-2020. Table categories are listed and elaborated below.

Year, Author, Title, Reference number: Information about the paper itself, referencing details.

Sensing principle, Sensor type, Sensor Details, Number of sensors: Information related to the sensing technology used. The type of sensor used alongside the principles linked to that sensor. For example, accelerometers and gyroscope sensors are commonly used to track motion, camera modules capturing images for vision, and microphone sensors for sound. Details about specific product types are noted alongside the number of sensors.

Sensing location, Location details: The location of the sensor was differentiated in different areas of the body where the sensors could be worn, such as the face, ear, neck, torso, extremities or external if not worn directly on the person. Within those areas specific location details such as the anatomical or spatial positions were included based on the authors description.

Eating phases: For the decomposition of the eating phases, the dietary activity model presented by Schiboni in 2018 is used[42], This model describes six eating phases as follows: (1) preparation (food preparation before the actual meal starts); (2) ingestion (fetch the food, bring food to the mouth, bite); (3) oral processing (chewing sequence, liquid transport); (4) swallowing (liquid and/or solid swallow); (5) digestion (gastric mobility, cardiac response, glucose composition, body weight, thermogenesis); (6) conclusion (cleaning, weighing the left-over food). In case of multiple eating phases being jointly assessed, the label combination was given.

Dimensions, Sub-dimensions: The three dimensions of food intake are when, what and how much a person eats. These are listed alongside the sub-dimension that relate to the main food intake dimension but give a more precise meaning. examples of sub-dimension

when would be intake gestures, bites/sips, chews, swallows or other event detections. Sub-dimension *what* would be identifying type of food or type of beverages. Sub-dimension *how much* relates to the recognition of the amount of food or beverage, volume and/or the amount of nutrients in the food that was eaten.

Measures of food intake, Measurement details, Type of food: Measures of food-intake are listed in the table as the specific measure that the paper reports on within sub-dimensions of food intake. E.g. several studies can report on the *events* sub-dimension, when some are eating recognition measures and others could be drinking recognition. Measurement details were noted as the measurement that the data was analyzed by. some were distinguishing between 20 foods, others were measuring food-related events to non-food related events. next to those details, the type of food used was also noted.

Measurement setting, Number of participants, Performance: Measurement setting relates to the location where the data was gathered. The setting could either be artificial or natural. Artificial was when the eating data was gathered in a research facility created for the measurement. Natural was when the environment is part of a real-life setting. The measurement setting also reports on the degree in which the data gathering is controlled. This was set to 'controlled' when all steps were pre-determined. 'semi-controlled' when partly the steps were determined, but there was room for own behavior of the participant. 'free' when the measurement protocol did not restrict the participant in their behavior during the data gathering. The number of participants that took part in the study is noted as well as the performance reported in the study. Different studies reported their performance in a lot of different ways. Some reported error margins, other in accuracy or F-1 scores. The performance reported in this review is in the form written by the authors of the paper.

3.4 Data analysis

The data that resulted from the extraction were analyzed and formatted in smaller tables to help gain a visualization and interpretation of the results. This resulted in tables that have similar form of the previously done study. Tables report on the number of studies done per setting, the relation of food intake dimension versus sensing principle, sensing location and eating phases. Sensing principles versus sensing location and eating phase versus sensing location and sensing principle.

4 RESULTS

The literature search yielded 1873 unique papers for the period of 2020-2025. Due to a limited time frame 521 papers from the years 2022 and 2025 were selected for screening based on title and abstract. This resulted in 91 papers found to be eligible for full-text reading. Due to time constraints only 51 of these papers were reviewed in full. Of these 51 papers, 26 papers were included, and 25 articles did not meet the criteria for inclusion. Reasons for exclusion are mentioned in figure 1. Some papers reported on multiple food intake measures, and they were treated as separate entries in this review.

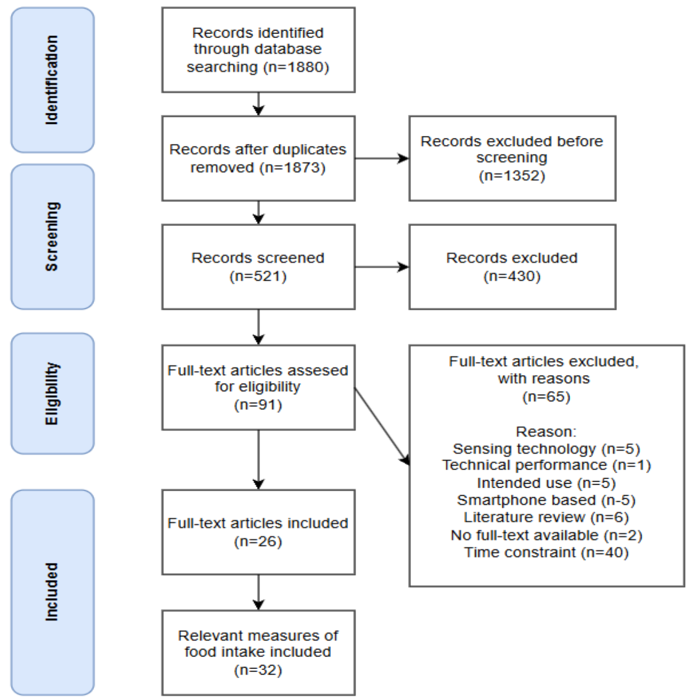

Fig. 1. Flow diagram for the scoping review process

Table 1. Number of studies per setting

Setting	Controlled	Semi-controlled	free
Artificial	12	7	-
Natural	3	2	8

A full list of papers that were included in this review is listed in Appendix A

Table 1 shows the setting in which the studies were conducted. A total of 32 studies were identified, 19 of which were done in an artificial setting. The artificial setting was either a controlled (12/19) or semi-controlled (7/19) environment. 13 studies were conducted in a natural setting with (8/13) in a free environment, (3/13) controlled and (2/13) in semi-controlled environments.

4.1 Food intake dimensions

When taking a look at the dimension of food intake, It can be clearly seen that most studies were done in the *when* dimension with (18/32). interestingly the amount studies relating to *what* are quite high with half the amount of *when* (9/32), considering most of these studies used some form of event detection(*when*) system before classifying the food types. less was reported on the *How much* food intake dimension (5/32). Some differences that can be noted is that *when* and *what* food dimensions typically reported performance base on accuracy or F1-score, while *how much* food intake dimension studies reported performance based on error margins.

Table 2. Sensing principles used for the three main aspects of food intake, when, what, and how much.

Sensing Principle	Food intake dimension			
	When	What	How much	Total
Conductance	2	-	2	4
Motion	11	3	1	15
Object labelling	-	-	-	-
Pressure	-	-	-	-
Sound	-	3	-	3
Spectral analysis	-	-	-	-
Strain	-	1	-	1
Vision	1	2	1	4
Combination	4	-	1	5
Total	18	9	5	32

Table 3. Sensing locations used for the three main aspects of food intake, when, what, and how much.

Location	Food intake dimension			
	When	What	How much	Total
Ear	2	3	-	5
External	2	1	1	4
Extremities	8	1	2	11
Face	4	1	1	6
Intra oral	-	-	-	-
Neck	1	3	1	5
Torso	-	-	-	-
Combination	1	-	-	1
Total	18	9	5	32

4.2 Sensing principle

The sensing principles used, as shown in Table 2, were mainly *motion* and *vision*. The five entries listed as *combination* all used both *motion* and *vision* as well, adding up to (24/32) studies done on these two sensing principles. The studies seem to suggest that *sound* and *strain* are the unique sensing principles solely used for sensing *what* food intake can be measured.

4.3 Sensing Location

Table 3 depicts the location placement of the sensors in the reported studies. Most sensor locations used body-worn sensors (27/32), of the sensors that were not body-worn (3/4) were cameras. The combination used a smartwatch on the wrist combined with an externally placed camera. Apart from the dominant use of smartwatches containing accelerometer + gyroscope sensors worn on the wrist (9/32), there seems to be quite an even spread of other sensor location setups.

4.4 Eating phase

Different eating phases were used for different aspects of food intake. It can be seen in Table 4 that *ingestion* and *oral processing* were the most important phases examined. With *ingestion* being the main contributing phase for detecting *when* food intake was registered and *oral processing* for monitoring the *what* food intake dimension.

Table 4. Eating phases used for the three main aspects of food intake, when, what, and how much.

Eating phase	Food intake dimension			
	When	What	How much	Total
Preparation	-	2	1	3
Ingestion	12	1	2	15
Oral processing	4	6	1	11
Swallowing	1	-	1	2
Digestion	-	-	-	-
Combination	1	-	-	1
Total	18	9	5	32

4.5 Sensing principle versus location

Table 5 shows us the sensing principles used in relation to the location of the sensors. Six sensors were located in the *face* area, with (4/6) being a *combination*. These were all setups combining motion-type sensors on the temple of the glasses combined with a camera towards the front taking pictures while eating. *Motion* is the most often used sensing principle and is also measured using sensors in most locations. Interestingly *neck* is the location that is most versatile in the principle it can measure, but it is not used for measuring *motion*.

4.6 Eating phase versus location

In Table 6 the relationship between eating phase and sensing location is displayed. The sensors worn on the *extremities* were solely used for the *ingestion* phase, these sensors captured the pickup of food and the gesture of bringing it to the mouth. Sensors located in the *ear* area all used headphones in the *oral processing* eating phase. A difference that can be noted in Table 5 is that they use the *sound* of eating and the *motion* of the jaw muscles when chewing.

4.7 Eating phase versus Sensing principle

Table 7 shows the eating phase together with the sensing principle. Several principles are used in the *ingestion* and *oral processing* phases. *Preparation* phase only uses camera modules to sense *vision*, with cameras placed externally or in the neck area(Table 6). The eating phase swallowing is also only measured with one sensing principle being *conductance* with sensors placed in the neck area. The *combination/combination* study used *motion* and *vision* in both *ingestion* and *oral processing* phases.

5 CONCLUSION AND DISCUSSION

5.1 Key findings

In 59% of the studies on sensing technology for the detection of food intake, the system was tested in an artificial setting, and 47% of all studies were conducted in a controlled environment. The food intake dimension that is studied the most is when people eat, taking up 56% of the total number of studies. The most commonly used sensing principle was motion, occurring in fifteen studies on its own as well as in five of the studied that had combined sensing principles, which means that it is measured in 63% of all studies. When it comes to sensor locations, apart from five instances where cameras were

Table 5. Sensing principles versus the location used.

Sensing principle	Location								
	Ear	External	Extremities	Face	Intra-oral	Neck	Torso	Combination	Total
Conductance	-	-	2	-	-	2	-	-	4
Motion	3	1	9	2	-	-	-	-	15
Object Labeling	-	-	-	-	-	-	-	-	-
Pressure	-	-	-	-	-	-	-	-	-
Sound	2	-	-	-	-	1	-	-	3
Spectral analysis	-	-	-	-	-	-	-	-	-
Strain	-	-	-	-	-	1	-	-	1
Vision	-	3	-	-	-	1	-	-	4
Combination	-	-	-	4	-	-	-	1	5
Total	5	4	11	6	-	5	-	1	32

Table 6. Eating phases versus the location used.

Eating phase	Location								
	Ear	External	Extremities	Face	Intra-oral	Neck	Torso	Combination	Total
Preparation	-	2	-	-	-	1	-	-	3
Ingestion	-	2	11	1	-	-	-	1	15
Oral Processing	5	-	-	4	-	2	-	-	11
Swallowing	-	-	-	-	-	2	-	-	2
Digestion	-	-	-	-	-	-	-	-	-
Combination	-	-	-	1	-	-	-	-	1
Total	5	4	11	6	-	5	-	1	32

Table 7. Eating phases versus the principles used.

Eating phase	Sensing principle									
	Conductance	Motion	Object labeling	Pressure	Sound	Spectral analysis	Strain	Vision	Combination	Total
Preparation	-	-	-	-	-	-	-	3	-	3
Ingestion	2	10	-	-	-	-	-	1	2	15
Oral Processing	-	5	-	-	3	-	1	-	2	11
Swallowing	2	-	-	-	-	-	-	-	-	2
Digestion	-	-	-	-	-	-	-	-	-	-
Combination	-	-	-	-	-	-	-	-	1	1
Total	4	15	-	-	3	-	1	4	5	32

placed externally, all sensors were body-worn(27/32). Smartwatches worn on the extremities were the most common, occurring in ten studies. Apart from smartwatches, the use of cameras was also quite frequent. nine instances of which five were located externally, one in the neck area and three attached to glasses pointing forward. When looking at the eating phase in which the technology is used, ingestion is the most common(15/32), followed by oral processing(11/32). Oral processing was the most studied eating phase to measure what a person eats.

5.2 Comparison with related work

When compared to the review previously done by Haarman et al.[19]. Some interesting differences can be found. Firstly the setting in which the studies were done. The previous review reported 76% of studies in artificial setting, this review has seen a decrease in artificial and an increase in more natural settings with 59% being artificial. This review also showed a slight shift towards more free environments and less controlled. The previous review reported 54% controlled, 27% semi-controlled and 19% free environments. this study 47%, 28%, and 25%, respectively.

There has also been a shift in the food intake dimensions measured. Previously studies showed a 70% when, 20% what, and 10% how much ratio. This review has seen an increase in measurements reporting on what (28%) and how much (16%) a person eats. When is still the most used food intake dimension with 56%, but a notable change nonetheless. a possible explanation for this could be that advances in AI and machine learning models have opened the door to more accurately predict food types and food composition[35, 40], making it more attractive for experiments.

Another interesting difference to mention was the use of sound as a sensing principle, with the previous review indicating that sound was the most used principle along with other literature mentioning its popularity[37], while this review only found a few instances. The use of motion is still the most used principle in detecting when a person eats. This is not strange since most of the wearables on the market contain accelerometer and gyroscope sensors that track the users motion[38], making data collection fairly easy. There are also a lot of datasets publicly available with this type of data that are being used to train eating detection models[44, 47].

When comparing sensing locations, the review done in 2020 reported sensing locations ear, external, extremities and neck all between 17-19% of total, while this review shows a dominant use of extremities as a sensing location with 34%. This change can possibly be attributed to the rising popularity of smartwatch technology, Swapping a normal watch with a smartwatch is an easy switch to integrate this technology into life without much intrusion[37], contrary to wearing sensors attached to glasses[12] which are eye-catching. They have been used in almost all cases when extremities were the chosen sensing location.

Ingestion and oral processing seem to be the most studies eating phases in both reviews, increasing in this review from 69% to 81% of total phases studied.

5.3 Limitations

This review addresses just a selection of papers published on this subject over the last few years and therefore only represents a part of the entire sensing technology field used in detecting food intake. 51 papers out of the years 2022 and 2025 were assessed in full-text for this review. Due to time constraints a part of the papers published from these years as well as all the papers from the years in between were not used in the analysis. This review compares the results with a study previously done with the same methodology, but consists of considerably less papers making it difficult to weigh the importance of these comparisons.

5.4 Future work

A number of studies that fit the criteria for full-text analysis as well as a number of papers published in other years were excluded from this review due to time-constraints. Increasing the total amount of studies included in this review, could enrich the findings and would make the results more representative of the entire field.

There were papers that reported on systems that used sensing technology to detect multiple food intake dimensions e.g. *when* and *what* or *when* and *how much*. In this review, we entered them as separate entries in the tables. However, to paint a more complete picture of what sensing technology might hold for automating dietary intake monitoring, it would be interesting to look at systems that report on multiple of these food intake dimensions together.

5.5 Conclusion

This research resulted in a comprehensive overview of the sensing technologies used to detect food intake. The information of 26 papers reporting on 32 studies allowed for the creation of tables that display relevant information about the current state of the field of sensing technology for detecting food intake. These tables allowed for comparison with the literature review conducted in 2020 and indicate some changes in the field.

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A INCLUDED PAPERS

Table 8. Overview of papers included in this review

Author	Title	Year
Asmiza Selamat, N.; Hamid Md Ali, S.; Ghadafi Ismail, A.; Anom Ahmad, S.; Nisa'Minhad, K.	Novel Chewing Cycle Approach for Peak Detection Algorithm of Chew Count Estimation	2025 [2]
Avramoni, D.; Virlan, R.; Prodan, L.; Iovanovici, A.	Detection of Pill Intake Associated Gestures using Smart Wearables and Machine Learning	2022 [3]
Baldi, I.; Lanera, C.; Bhuyan, M. J.; Berchialla, P.; Vedovelli, L.; Gregori, D.	Classifying Food Items During an Eating Occasion: A Machine Learning Approach with Slope Dynamics for Windowed Kinetic Data	2025 [4]
Bao, C.; Li, Q.; Tian, F.; Zang, Q.; Hong, F.	ChewSense: Real-Time Detection of Chewing Counts and Food Types with Reverse Signals from Headphones	2025 [5]
Bell, B. M.; Alam, R.; Mondol, A. S.; Ma, M.; Emi, I. A.; Preum, S. M.; de la Haye, K.; Stankovic, J. A.; Lach, J.; Spruijt-Metz, D.	Validity and Feasibility of the Monitoring and Modeling Family Eating Dynamics System to Automatically Detect In-field Family Eating Behavior: Observational Study	2022 [6]
Bi, S.; Kotz, D.	Eating detection with a head-mounted video camera	2022 [7]
Chiang, H. C.; Wu, Y. H.; Li, G. H.; Shirmohammadi, S.; Hsu, C. H.	PALM: Personalized Active Learning for mmWave-Based Activity Recognition	2025 [9]
Chung, Y. M.; Nikooienejad, A.; Zhang, B.	Automatic Eating Behavior Detection from Wrist Motion Sensor Using Bayesian, Gradient Boosting, and Topological Persistence Methods	2022 [10]
Doulah, A.; Ghosh, T.; Hossain, D.; Marden, T.; Parton, J. M.; Higgins, J. A.; McCrory, M. A.; Sazonov, E.	Energy intake estimation using a novel wearable sensor and food images in a laboratory (pseudo-free-living) meal setting: quantification and contribution of sources of error	2022 [13]
Gao, Z.; Yuan, X.; Lei, J.; Guo, H.; Marinello, F.; Guerrini, L.; Carraro, A.	A vision-based dietary survey and assessment system for college students in China	2025[15]
Ghosh, T.; Sazonov, E.	A Comparative Study of Deep Learning Algorithms for Detecting Food Intake	2022 [16]
Goldstein, S. P.; Hoover, A.; Thomas, J. G.	Combining passive eating monitoring and ecological momentary assessment to characterize dietary lapses from a lifestyle modification intervention	2022 [17]
Guan, J.; Wang, J.; Niu, W.; Peng, Z.; Wang, S.; Liu, Z.; Zhou, G.; Ren, B.	Towards Recognizing Food Types for Unseen Subjects	2025 [18]
Heydarian, H.; Adam, M. T. P.; Burrows, T. L.; Rollo, M. E.	Exploring Score-Level and Decision-Level Fusion of Inertial and Video Data for Intake Gesture Detection	2025 [20]
Hong, W.; Lee, J.; Lee, W. G.	A finger-perimetric tactile sensor for analyzing the gripping force by chopsticks towards personalized dietary monitoring	2022 [21]
Hossain, K.; Ghosh, T.; Sazonov, E.	Development of Cloud-based Infrastructure for Real Time Analysis of Wearable Sensor Signal	2022 [22]
Hussain, G.; Al-Rimy, B. A. S.; Hussain, S.; Albarrak, A. M.; Qasem, S. N.; Ali, Z.	Smart Piezoelectric-Based Wearable System for Calorie Intake Estimation Using Machine Learning	2022 [23]
Khan, M. I.; Acharya, B.; Chaurasiya, R. K.	Hybrid BiLSTM-HMM based event detection and classification system for food intake recognition	2022 [26]
Khan, M. I.; Acharya, B.; Chaurasiya, R. K.	iHearken: Chewing sound signal analysis based food intake recognition system using Bi-LSTM softmax network	2022 [27]
Khan, M. T.; Ghaffarzadegan, S.; Feng, Z.; Hasan, T.	A Fabric-based Inexpensive Wearable Neckband for Accurate and Reliable Dietary Activity Monitoring	2022 [28]
Liang, F.; Hernandez, R.; Sheng, W.	A Collaborative Elderly Care System using a Companion Robot and a Wearable Device	2022 [29]
Lutze, R.	Practicality of Automatic Monitoring Sufficient Fluid Intake for Older People	2022 [30]
Malvuccio, C.; Kamavuako, E. N.	The Effect of EMG Features on the Classification of Swallowing Events and the Estimation of Fluid Intake Volume	2022 [31]
Mekruksavanich, S.; Jantawong, P.; Hnoohom, N.; Jitpattanakul, A.	Deep Learning Networks for Eating and Drinking Recognition based on Smartwatch Sensors	2022 [33]
Mekruksavanich, S.; Jantawong, P.; Jitpattanakul, A.	Smartwatch-based Eating Detection and Cutlery Classification using a Deep Residual Network with Squeeze-and-Excitation Module	2022 [34]
Morshed, M. B.; Haresamudram, H. K.; Bandaru, D.; Abowd, G. D.; Ploetz, T.	A Personalized Approach for Developing a Snacking Detection System using Earbuds in a Semi-Naturalistic Setting	2022 [36]