Can bite detection algorithms substitute manual video annotations in elderly people with and without Parkinson's disease? An experimental study

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ABSTRACT

Parkinson's disease, as a neurodegenerative disorder that affects movement, can significantly affect patients' nutrition, potentially leading to malnutrition and weight loss. Therefore, monitoring the eating behavior of Parkinsons' patients in real-time could better inform when interventions are needed to maintain or increase energy intake and improve the overall quality of life of patients, while reducing the disease severity. Traditional eating behavior analysis methods rely on self-reported measures, whose reliability is limited due to miss-reporting. This work aims to assess the ability of an automated algorithm to accurately idenitfy eating characteristics based on video inputs. Experimental results show the proposed deep learning-based algorithm achieves a near-perfect agreement (correlation coefficient 0.95) with manual annotation of bite instances, thus paving the way for the creation of automated eating behavior monitoring systems with the potential to be integrated with current clinical practice for improved Parkinson's disease assessment and handling.

CCS CONCEPTS

• **Applied computing → Consumer health**; • **Computing methodologies → Activity recognition and understanding**; *Neural networks*; • **Human-centered computing →** *Usability testing*.

KEYWORDS

Bite detection, Parkinson's disease, Video processing, Meal analysis

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1 INTRODUCTION

Parkinson´s disease (PD) is a neurological disease affecting about 1% of people above the age of 60 [21]. The development of the disease is slow, beginning with subtle symptoms that intensify as the disease progresses. Symptoms include both motor and non-motor symptoms (NMS) such as tremor, brady/hypokinesia, rigidity, sleep disorders and depression [10, 16]. Moreover, weight loss is common among PD patients, and associated with malnutrition and subsequent clinical issues, such as increased frailty [15], infections and lower quality of life [18]. Weight loss might also worsen other PD symptoms as a result of a greater cumulative dosage of levodopa per kilogram bodyweight [18]. Weight loss seen in PD patients could be the influence motor symptoms, dysphagia, constipation, and olfactory/taste impairments have on eating behavior, food intake and food selection [1, 2].

Based on the above, previous studies evaluated objective differences in energy intake during single meals amongst groups of healthy controls (HC) and PD patients, using traditional microstructural meal analysis. Such evaluations of the behavioral components of human food intake (e.g., eating rate and meal duration) have previously been developed to aid the understanding of basic mechanisms of human eating behavior and its patterns [14]. Lately, there has been an increasing interest in using these methods in obesity and eating disorder research to identify targets for intervention and to regulate energy intake [7]. One of the most widely evaluated parameters of single-meal eating behavior analysis is the number of mouthfuls (also referred to as bites) that individuals take during a meal [14]. This parameter has previously been associated with portion size of meals, and it has been proposed to be used as an alternative method for estimation of energy intake [5].

To collect such data on eating behavior, the traditional methods have been based on self-reported measures, which are relatively easy to use and low in cost. However, this comes with increased participant burden and limited reliability due to miss-reporting [22]. Another method to objectively measure eating behavior is the analysis of videos recorded during meals [9]. This method has several advantages when it comes to data collection, such as reduced participant burden, not requiring any wearable equipment and being appropriate to use in a range of settings, from laboratory to free-living [9]. However, large scale manual video analysis is time-consuming and requires trained personnel. Moreover, data collection is challenging without the participation of a researcher and eating while being observed might alter the participants eating behavior.

In our own research, linked to PD [8], using meal video analysis, we established that advanced-stage PD patients (ASPD), but not early-stage ones (ESPD), had significantly lower energy intake compared to healthy controls. In addition, we identified clinical features and eating behaviors that could assist in explaining these differences that were partly (≈86%) attributed to upper extremity tremor scores (PD motor symptom), increased subjectively reported eating problems, dysphagia, and taking fewer bites during the meal [8]. We then concluded that energy intake might be an important treatment target for PD patients with increased risk of weight loss, mirroring the suggestions from other studies [3, 20]. However, it should be noted that all the behavioral annotations for the meals were performed manually by trained researchers (as is traditional in the domain). In our report we noted that the required effort is a significant bottleneck for performing further larger scale studies that are needed to address different settings, internal and external validity, as well as the association of eating behavior parameters with disease severity and progress [8].

To overcome these limitations and improve the meal video analysis methodology, a deep learning-based algorithm to process meal videos and classify mouthfuls was developed in [11]. The Rapid Automatic Bite Detection (RABiD) algorithm showed almost perfect correlation with manual annotation for meal duration (correlation coefficient 0.99) and mouthfuls (correlation coefficient 0.94) on a healthy population [12]. In that effort, RABiD was trained on meal video recordings of healthy young women (mean age: 25.9 years), captured using a single camera facing the participant at an angle of 40°- 45°. This was done due to the availability of pre-existing meal videos, testing the usefulness of RABiD for such retrospective analysis. In that setting, the performance of the algorithm was found to be affected by the placement of the camera, since the side view can lead to occlusions in the algorithmically analyzed skeleton of the participant. Consequently, an algorithmic training on frontal recordings could improve algorithm performance even further.

The main goal of this study is to explore whether the RABiD algorithm can be used for automatic meal annotation in a population with PD, who might experience disturbed eating behaviors, due to motor symptomatology, as previously described [8], without any information and fidelity loss. In this context, we performed experiments, in which the RABiD algorithm was trained on only HC and on both HC and PD patients to assess the ability of the algorithm to accurately extract PD patients' eating behavior. Additionally, this study aims to evaluate whether the performance of RABiD can be improved by using frontal meal video recordings.

2 MATERIALS AND METHODS

2.1 Experimental design

The experimental design followed an iterative process, as shown in Fig. 1. Given a full dataset of 38 PD and 37 HC videos depicting individuals consuming a standardized meal under identical controlled conditions, a training dataset (TD1) was initially formed using 14 HC videos, while the experimental dataset (ED1) contained the rest 38 PD and 23 HC videos from the full dataset. TD1 was used for the training and internal performance evaluation of the RABiD_1 algorithm, while ED1 was employed for RABiD_1 testing and evaluation against the manual behavioral meal analysis. This procedure aims to show whether the RABiD algorithm trained only on healthy people can perform well and correctly identify the eating behavior of Parkinson's patients. Afterwards, a new training dataset (TD2) was formed using 16 PD and 24 HC videos, while the new experimental dataset (ED2) contained the rest 22 PD and 13 HC videos. As before, TD2 was used for RABiD_2 training and internal evaluation, while ED2 was employed for RABiD_2 testing and evaluation against the manual behavioral meal analysis. This approach aims to showcase how the performance of the algorithm is affected when trained on both HC and PD participants. The study was approved by the German ethical review board (EK 7502218) and data handling and analysis in Sweden was approved by the Swedish ethical review board (DNR: 2018/2425-31/2).

2.2 Participants and recruitment

Data from both PD and HC participants were used in the study. All PD patients were recruited from the in- and outpatient clinic of the Department of Neurology at the University Hospital of the Technical University Dresden (TUD), Germany. More details on the recruitment and the medical assessment of the participants

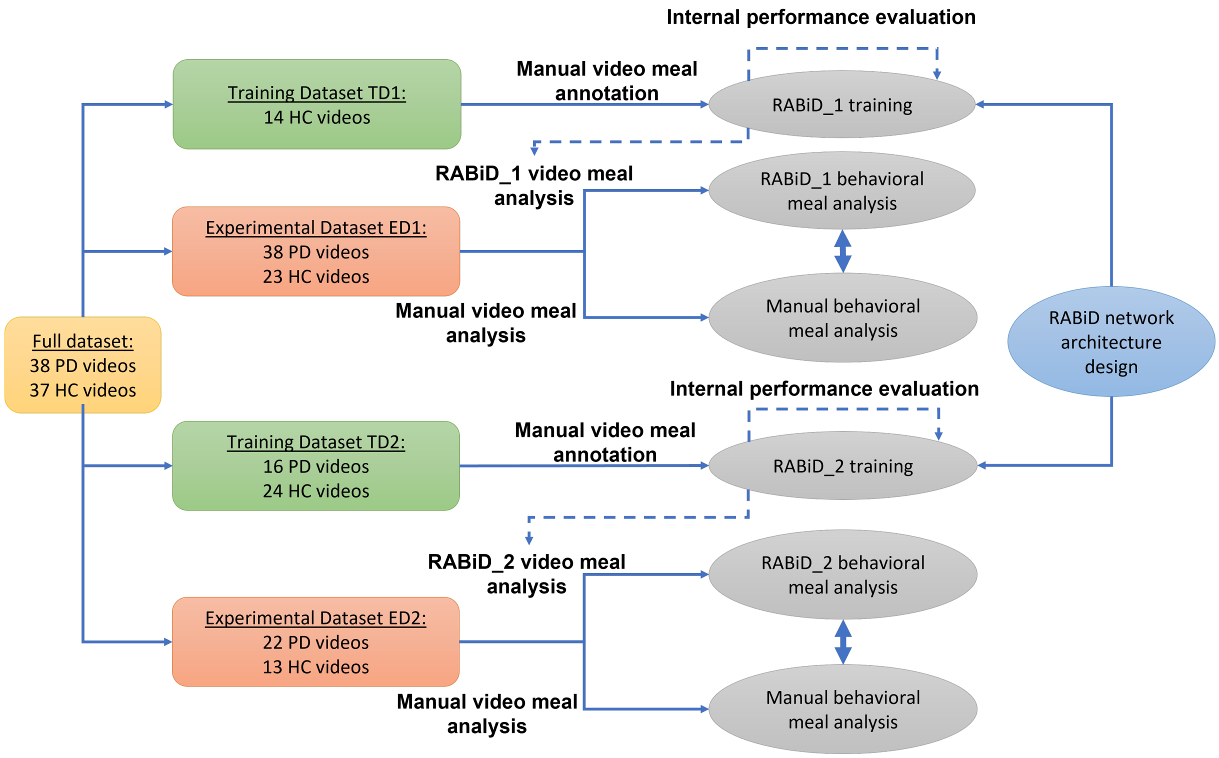


Figure 1: Schematic representation of the experimental design. The training dataset TD1 was used for the training, and internal performance evaluation of RABiD_1, while the experimental dataset ED1 was used for RABiD_1 meal analysis and comparison against manual video annotations. The same process was performed for a second iteration (RABiD_2) with different training and experimental datasets (TD2 and ED2).

is available in [8]. In short, the sole inclusion criterion was the presence of idiopathic PD in an early or advanced stage. The exclusion criteria included: (i) any other form of neurodegenerative disorder e.g., dementia, (ii) advanced PD treatment therapy (e.g., DBS, apomorphine/duodopa pump), (iii) any other issues or disease other than PD affecting eating behavior or nutritional status, or (iv) acute major depression. Out of the healthy controls, 14 were local health personnel (e.g., nurses and neurologists), 6 were partners of included PD patients and the remaining were recruited through promotion of the study (e.g., flyers). The clinical examination with regards to PD symptomatology and treatment, as well as height and weight measurements were performed prior to the experiment. Written informed consent was obtained from all participants before they took part in any study procedure.

Figure 2: Picture of the meal setting and the standardized lunch provided in the study.

2.3 Meal session procedure and video capturing

The meals were served to one participant at a time, during the usual German lunch hours (11:00-15:00) in a quiet room dedicated to the experiment at TUD, Germany. The participants were seated at a table with two video cameras (GoPro HERO 5, recording at 1920 x 1080 resolution with 30 frames per second), one of which placed to the participants' left and the other in front of them, at a distance of approximately 1 meter (see Fig. 2). Both the tray with food and the upper body of the participant were included in the cameras' field of view. The participants were also wearing two smartwatches (one on each wrist) to detect bite moments and upwards wrist micro-movements, as an attempt to objectively measure motoric details of the eating behavior (i.e., "plate-to-mouth" hand movement duration) [13]. The supervising researcher instructed the participants to start their meal at any point, after which the researcher turned

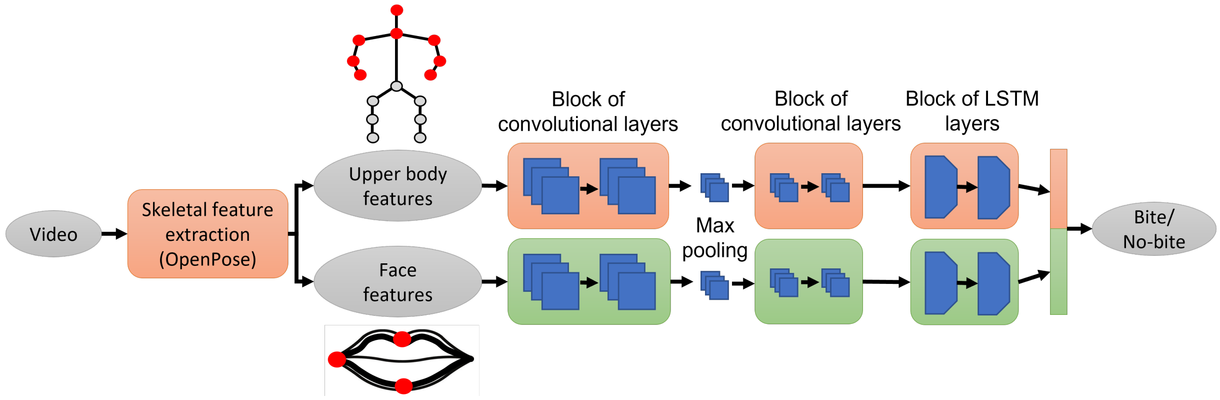


Figure 3: Schematic representation of the network architecture of RABiD. The relevant hand, nose and mouth features are depicted as red points.

	Healthy controls (n=13)	Parkinson patients (n=22)
Males/females, n	4/9	16/6
ESPD/ASPD, n	-	11/11
Age, years	64.60 (8.46)	61.70 (8.62)
Height, cm	1.67 (0.07)	1.76 (0.10)
Weight, kg	74.16 (11.76)	85.22 (15.90)
BMI, kg/m2	26.49 (3.34)	27.59 (5.0)

Table 1: Anthropometric characteristics of the participants in the study.

	Mean (SD)	Median (Q1 - Q3)
Manual annotation		
Healthy controls	51.7 (9.1)	51.0 (48.0 – 59.0)
Parkinson's patients	56.5 (17.9)	55.0 (45.5 – 65.5)
Total	54.7 (15.2)	53.0 (47.0 – 61.5)
RABiD_2 analysis		
Healthy controls	52.1 (9.8)	51.0 (47.0 – 62.0)
Parkinson's patients	58.6 (18.8)	56.0 (47.3 – 71.3)
Total	56.2 (16.2)	55.0 (47.0 – 62.5)

Table 2: Number of mouthfuls recorded by the manual annotator and the RABiD_2 algorithm.

on the cameras and left the room, waiting to be notified when the participants had finished their meal. Thus, the participants were alone in the room while eating with no access to other activities, such as smartphone use or reading material.

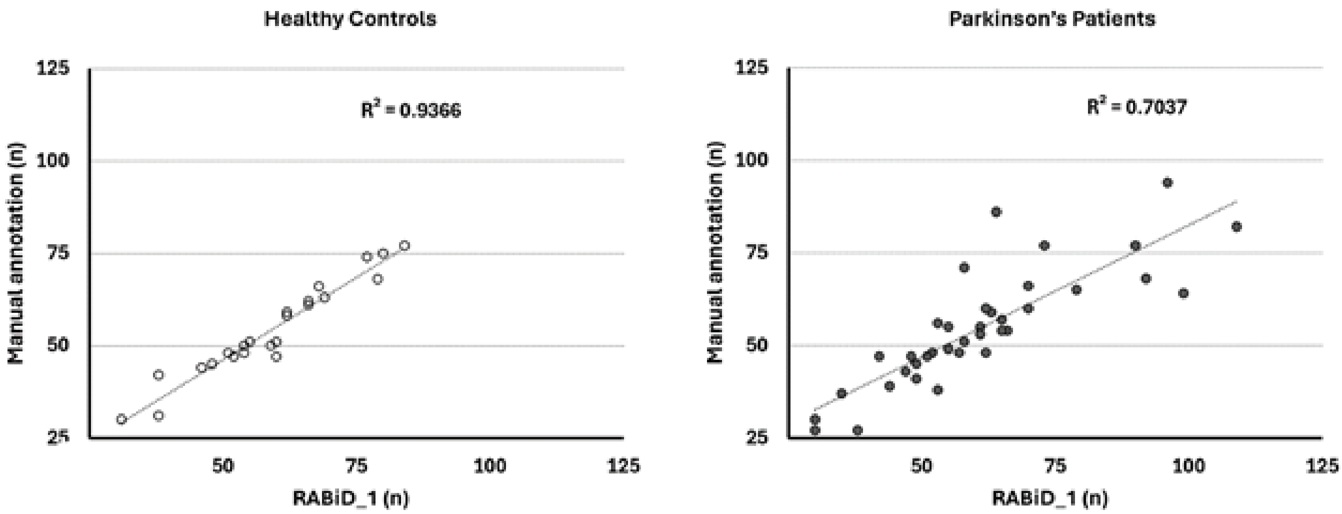
2.4 Data handling and manual video annotation

The video files were initially saved locally in the Go Pro cameras, before being shared with the Swedish researchers through encrypted peer-to-peer connections. The videos were then synchronized (frontal and side view) and annotated in the Observer XT software (version 12.5) to analyze the relative timing of each mouthful taken by the participants during their meal. A mouthful was defined as the moment the food entered the mouth of an individual. All the meals were annotated by the same trained researcher to minimize the risk of intra-annotator errors. The annotators had synchronous access to both video feeds to ensure full visibility of the subject movements. To achieve objective evaluation, no video content was shared with the algorithm developers at CERTH, as the RABiD training and analysis was performed locally in Karolinska Institutet.

2.5 Design of RABiD algorithm

The RABiD algorithm aims to automatically detect bite instances through the processing of visual features, overcoming the need for human annotators. The same network architecture (see Fig. 3) was utilized for both trained versions of RABiD (i.e., RABiD_1 and RABiD_2). The system initially employs OpenPose [4, 19] to extract body and face features from each video frame. Afterwards, only the most relevant features are aggregated and fed to a two-stream deep network. The first stream receives a temporal sequence of upper body features and specifically the nose and hand joint coordinates and the distances between each pair of them, while the second stream takes as input a temporal sequence of face features and specifically the middle points of the upper and lower lips, the point where the lips converge (i.e., corner of mouth) and the distances between these points.

RABiD was designed based on the supposition that the hand and mouth movements are the most significant motor indicators of bite instances. RABiD applies the same processing of the input features in its two streams. It initially employs blocks of convolutional layers to compute spatiotemporal interactions between neighboring features, while it downsamples the feature space to



(a) (b)

Figure 4: Scatterplots displaying the number of mouthfuls recorded by the RABiD_1 algorithm on the x-axis and manual annotation on the y-axis, for healthy controls on the left and Parkinson's patients on the right.

improve robustness through pooling operations. Afterwards, long short-term memory (LSTM) units are responsible for modelling long-term temporal dependencies in the feature sequences. Finally, the computed features from the two streams are concatenated, thus combining the information from the hands, head, and mouth to achieve more accurate and robust bite detection results.

2.6 Automatic meal analysis

The full-length meal videos were fed as input to RABiD one video at time with no special preparation. RABiD was used to detect the exact time frames during which bite instances occur by employing an overlapping window of 2 seconds with a step of 1 frame. This resulted in a bite probability for each video frame and a continuous signal of bite detection probabilities. Since the output of RABiD was a continuous signal, post-processing was required to detect exact locations of bite instances and remove false alarms. Initially, a n-th order median filter was applied to smooth the signal and remove small and abrupt changes in probabilities that could be attributed to misclassifications. The order of the median filter was set to $n = 40$ to achieve heavy smoothing. Afterwards, the mean m_p and standard deviation s_p of the signal were computed and the probabilities below the threshold of $m_p + s_p$ were zeroed. Finally, all local maxima (i.e., peaks) of the signal were identified and considered as candidate bite instances. These candidate bite instances were further processed by discarding the ones with a width smaller than a threshold T_w, set equal to 22 frames, thus requiring an actual bite instance to have a duration of around 1 second. In addition, the distance between candidate bite instances was computed and for those instances with distance smaller than a threshold T_s, the one with the highest probability was preserved. The threshold T_s was defined to be equal to 50 frames based on the assumption that under normal circumstances a person cannot receive two bites in less than 2 seconds time difference. The remaining candidate bite instances were the output of the RABiD algorithm and they were considered as actual bite instances.

3 RESULTS

3.1 Participant characteristics

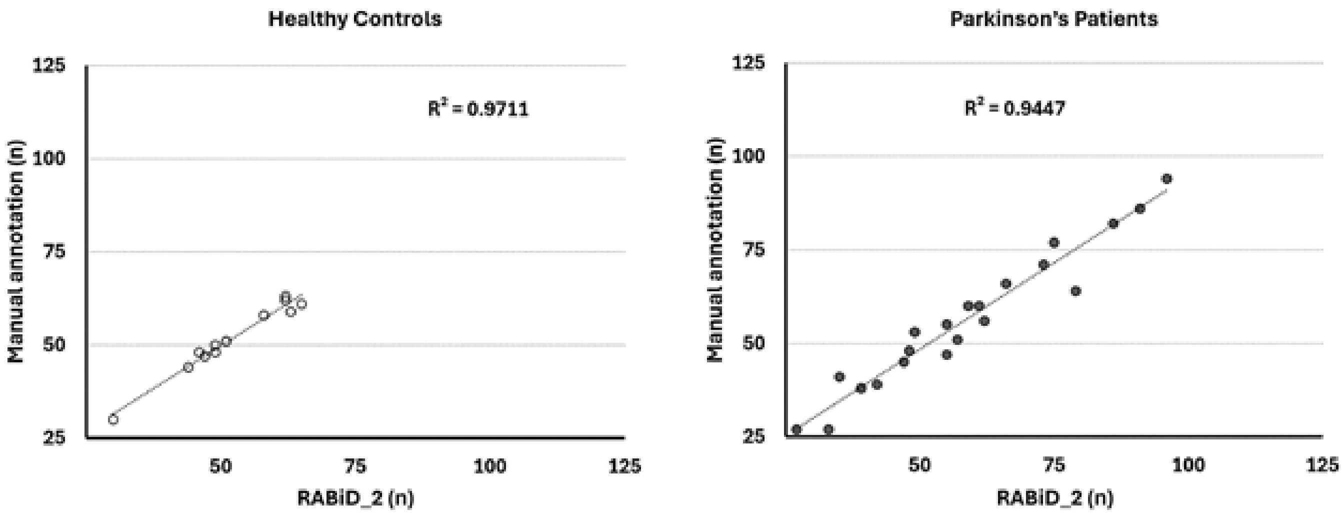
The full dataset consists of a total of 75 individuals, 38 of which are PD patients and the rest 37 are healthy controls. The anthropometric characteristics of the participants are shown in Table 1.

3.2 Manual vs. RABiD_2 number of mouthfuls

For the entire group (Parkinson's patients and healthy controls), the mean difference and standard deviation (SD) between the number of mouthfuls recorded with manual annotations and the RABiD_2 algorithm was 1.51 (± 3.74), as shown in Table 2. For subgroups, the mean difference and standard deviation (SD) between the number of mouthfuls recorded with manual annotations and the RABiD_2 algorithm was 0.38 (± 1.76) for healthy controls and 2.18 (± 4.4) for Parkinson's patients.

3.3 RABiD_1 performance

There was a high positive correlation between number of mouthfuls measured by the human annotator and RABiD_1 (R: 0.873, CI: 0.796 – 0.922, p-value: <0.001), showing a near-perfect agreement between the two methods, as shown in Fig. 4. There was a discrepancy between groups, with a very high positive correlation in the healthy control subgroup (R: 0.968, CI: 0.924 – 0.986, p-value: <0.001) and a high correlation in the Parkinson's subgroup (R: 0.839, CI: 0.709 – 0.914, p-value: <0.001).



(a) (b)

Figure 5: Scatterplots displaying the number of mouthfuls recorded by the RABiD_2 algorithm on the x-axis and manual annotation on the y-axis, for healthy controls on the left and Parkinson's patients on the right.

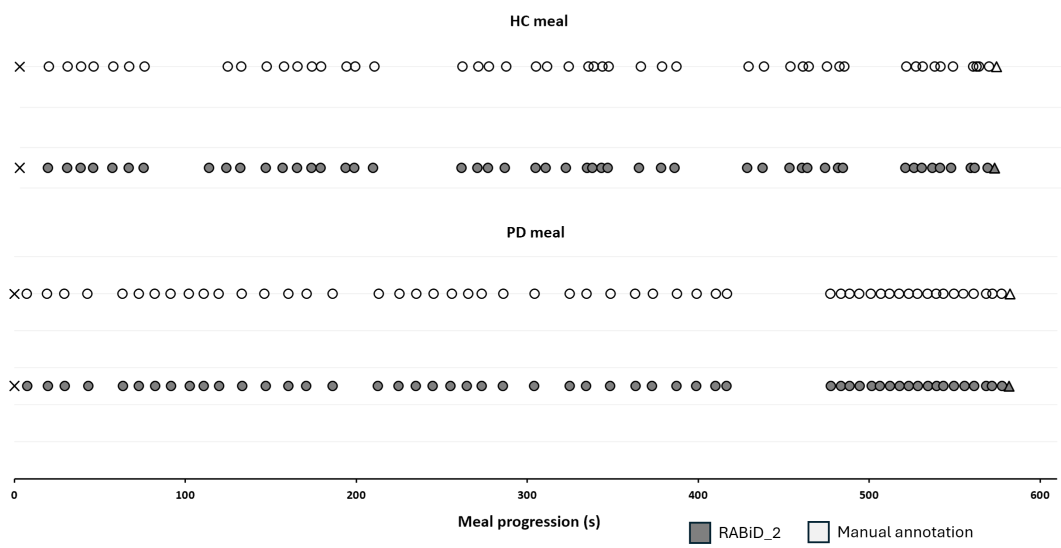


Figure 6: Temporal distribution of mouthfuls across a HC meal (top of the figure) and a PD meal (bottom of the figure). Manual annotations appear in white, while RABiD_2 analysis in grey.

3.4 RABiD_2 performance

There was a very high positive correlation between number of mouthfuls measured by the human annotator and RABiD_2 (R: 0.973, CI: 0.948 – 0.987, p-value: <0.001), showing a near-perfect agreement between the two methods, Fig. 5. The very high positive correlation was maintained in both the healthy control subgroup (R: 0.985, CI: 0.951 – 0.996, p-value: <0.001) and the Parkinson's subgroup (R: 0.972, CI: 0.932 – 0.989, p-value: <0.001).

The temporal distribution of mouthfuls was also highly correlated between RABiD_2 and the manual annotations, enabling a more granular analysis of the eating behavior for each participant. Fig. 6 displays the temporal distribution of mouthfuls in a meal of a healthy control and one of a Parkinson's patient, analyzed by manual annotation and the RABiD_2 algorithm, showcasing the bite-to-bite agreement between the manual and the RABiD_2 annotations. Similarly, the compatibility between the extracted micro-behavioral meal measures between RABiD_2 and the manually

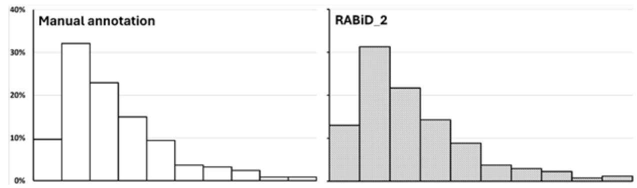


Figure 7: Distributions of mouthful intervals during a meal, with the intervals displayed as bins on the x-axis, and the percentage of intervals that fall within each bin expressed as percentages on the y-axis.

annotated videos is showcased in Fig. 7, displaying the distribution of the intra-mouthful periods between consecutive mouthfuls based on duration (s) in a histogram. Here, the duration between mouthfuls (mouthful interval) is calculated as $n_t - (n-1)_t$, where n is the current mouthful and n_t represents the time of the current mouthful. These analyses are typically used to identify micro-structural eating behaviors, such as bite interval and inter-bite interval behaviors.

4 DISCUSSION

Weight loss in PD patients has a negative impact on the severity of the disease, the quality of life, as well as on mortality [17]. Finding strategies to maintain or increase energy intake in PD patients is therefore important. This study shows that the RABiD system, which in this study showed near-perfect agreement (correlation coefficient 0.95) with manual annotation of mouthfuls, can be used to automatically analyze the number of mouthfuls individuals with PD take during meals in clinical settings, with minimal interference and burden on the patient. This paves the way for the creation, not in the long future, of eating characteristic monitoring systems that can be integrated with current clinical practice, as potential markers of disease progression, but also as important markers of patient nutritional and eating behavioral measures. In parallel, such automatic measures can be the targets for motoric training sessions, in order to empower patients, increasing their real world functional capabilities and their overall independence in real life.

The RABiD system has important benefits. Foremost, in contrary to manual annotations, the system allows for large-scale video analysis of meal videos at a relatively low cost and without the need of trained personnel. This feature is vital to support the performance of larger studies with more participants in the future, including repeated experimental meal occurrences per individual, in similar or differentiated settings. Secondly, the system is non-invasive to the patient. No sensors or other equipment interfering with the patient is needed. The only equipment needed is a video camera which can be disguised in order not to disturb the patient and to minimize the risk of altering the eating behavior of the patient. Additionally, the system objectively measures number of mouthfuls taken during the meal. Objective measures are preferable over self-reported data since self-reported estimates of energy intake are often poor [6]. For groups with potential cognitive impairments, such as individuals with PD, self-reporting of energy intake is extra challenging.

In PD patients, the system could in future studies be used to objectively assess and monitor changes in eating behavior throughout the course of the disease. This can be useful in improving the knowledge on how the disease, and its progression, affects eating behavior and energy intake, and to provide targeted assistance and tools before a severe weight loss occurs. Additionally, there is potential for the system to be used to assess and monitor eating behaviors in populations with other diseases or disorders affecting eating behaviors, for instance various types of eating disorders.

5 CONCLUSIONS

This work evaluated the ability of the deep-learning based algorithm, called RABiD, to accurately identify bite instances in videos of people consuming meals. The experimental results revealed the high correlation between RABiD results and the manual annotations, showcasing the ability of an automated system to replace tedious manual annotation procedures. Moreover, RABiD was found to be easily adapted to different eating behaviors, managing to perform accurately on both HC and PD participants, especially if trained on samples from different population groups.

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REFERENCES

[1] RA Abbott, M Cox, H Markus, and A Tomkins. 1992. Diet, body size and micronutrient status in Parkinson's disease. *European journal of clinical nutrition* 46, 12 (1992), 879–884.

[2] Elsy Athlin, Astrid Norberg, Karin Axelsson, Agnetha Möller, and Göran Nordströ. 1989. Aberrant eating behavior in elderly parkinsonian patients with and without dementia: Analysis of video-recorded meals. *Research in nursing & health* 12, 1 (1989), 41–51.

[3] Michela Barichella, Emanuele Cereda, Erica Cassani, Giovanna Pinelli, Laura Iorio, Valentina Ferri, Giulia Privitera, Marianna Pasqua, Angela Valentino, Fatemeh Monajemi, et al. 2017. Dietary habits and neurological features of Parkinson's disease patients: implications for practice. *Clinical nutrition* 36, 4 (2017), 1054–1061.

[4] Zhe Cao, Tomas Simon, Shih-En Wei, and Yaser Sheikh. 2017. Realtime multi-person 2d pose estimation using part affinity fields. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 7291–7299.

[5] Paige M Cunningham, Liane S Roe, Kathleen L Keller, Anouk EM Hendriks-Hartensveld, and Barbara J Rolls. 2023. Eating rate and bite size were related to food intake across meals varying in portion size: a randomized crossover trial in adults. *Appetite* 180 (2023), 106330.

[6] Nikhil V Dhurandhar, Dale Schoeller, Andrew W Brown, Steven B Heymsfield, Diana Thomas, Thorkild IA Sørensen, John R Speakman, Madeline Jeansonne, and David B Allison. 2015. Energy balance measurement: when something is not better than nothing. *International journal of obesity* 39, 7 (2015), 1109–1113.

[7] Petter Fagerberg, Evangelia Charmandari, Christos Diou, Rachel Heimeier, Youla Karavidopoulou, Penio Kassari, Evangelia Koukoula, Irini Lekka, Nicos Maglaveras, Christos Maramis, et al. 2021. Fast eating is associated with increased BMI among high-school students. *Nutrients* 13, 3 (2021), 880.

[8] Petter Fagerberg, Lisa Klingelhoefer, Matteo Bottai, Billy Langlet, Konstantinos Kyritsis, Eva Rotter, Heinz Reichmann, Björn Falkenburger, Anastasios Delopoulos, and Ioannis Ioakimidis. 2020. Lower Energy Intake among Advanced vs. Early Parkinson's Disease Patients and Healthy Controls in a Clinical Lunch Setting: A Cross-Sectional Study. *Nutrients* 12, 7 (2020), 2109.

[9] Ioannis Ioakimidis, Modjtaba Zandian, Lisa Eriksson-Marklund, Cecilia Bergh, Anastasios Grigoriadis, and Per Södersten. 2011. Description of chewing and food intake over the course of a meal. *Physiology & behavior* 104, 5 (2011), 761–769.

[10] Joseph Jankovic. 2008. Parkinson's disease: clinical features and diagnosis. *Journal of neurology, neurosurgery & psychiatry* 79, 4 (2008), 368–376.

[11] Dimitrios Konstantinidis, Kosmas Dimitropoulos, Ioannis Ioakimidis, Billy Langlet, and Petros Daras. 2019. A deep network for automatic video-based food bite detection. In *Computer Vision Systems: 12th International Conference, ICVS 2019, Thessaloniki, Greece, September 23–25, 2019, Proceedings 12*. Springer International Publishing, 586–595.

[12] Dimitrios Konstantinidis, Kosmas Dimitropoulos, Billy Langlet, Petros Daras, and Ioannis Ioakimidis. 2020. Validation of a deep learning system for the full automation of bite and meal duration analysis of experimental meal videos. *Nutrients* 12, 1 (2020), 209.

[13] Konstantinos Kyritsis, Petter Fagerberg, Ioannis Ioakimidis, K Ray Chaudhuri, Heinz Reichmann, Lisa Klingelhoefer, and Anastasios Delopoulos. 2021. Assessment of real life eating difficulties in Parkinson's disease patients by measuring plate to mouth movement elongation with inertial sensors. *Scientific reports* 11, 1 (2021), 1632.

[14] Billy Langlet, Mona Tang Bach, Dorothy Odegi, Petter Fagerberg, and Ioannis Ioakimidis. 2018. The effect of food unit sizes and meal serving occasions on eating behaviour characteristics: Within person randomised crossover studies on healthy women. *Nutrients* 10, 7 (2018), 880.

[15] Birgitta Lorefält, Göran Toss, and A-K Granérus. 2007. Bone mass in elderly patients with Parkinson's disease. *Acta Neurologica Scandinavica* 116, 4 (2007), 248–254.

[16] Ronald B Postuma, Daniela Berg, Matthew Stern, Werner Poewe, C Warren Olanow, Wolfgang Oertel, José Obeso, Kenneth Marek, Irene Litvan, Anthony E Lang, et al. 2015. MDS clinical diagnostic criteria for Parkinson's disease. *Movement disorders* 30, 12 (2015), 1591–1601.

[17] Jagdish C Sharma and Anna Lewis. 2017. Weight in Parkinson's disease: phenotypical significance. *International review of neurobiology* 134 (2017), 891–919.

[18] Jagdish C Sharma and Michael Vassallo. 2014. Prognostic significance of weight changes in Parkinson's disease: the Park–weight phenotype. *Neurodegenerative disease management* 4, 4 (2014), 309–316.

[19] Tomas Simon, Hanbyul Joo, Iain Matthews, and Yaser Sheikh. 2017. Hand keypoint detection in single images using multiview bootstrapping. In *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*. 1145–1153.

[20] Michael J Toth, Paul S Fishman, and Eric T Poehlman. 1997. Free-living daily energy expenditure in patients with Parkinson's disease. *Neurology* 48, 1 (1997), 88–91.

[21] Ole-Bjørn Tysnes and Anette Storstein. 2017. Epidemiology of Parkinson's disease. *Journal of neural transmission* 124 (2017), 901–905.

[22] Helena Wehling and Joanne Lusher. 2019. People with a body mass index $\gg$ 30 under-report their dietary intake: A systematic review. *Journal of health psychology* 24, 14 (2019), 2042–2059.

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