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An EMG-based Eating Behaviour Monitoring system with haptic feedback to promote mindful eating

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A R T I C L E I N F O

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Mindful eating
Mobile and wearable devices

A B S T R A C T

Mindless eating, or the lack of awareness of the food we are consuming, has been linked to health problems attributed to unhealthy eating behaviour, including obesity. Traditional approaches used to moderate eating behaviour often rely on inaccurate self-logging, manual observations or bulky equipment. Overall, there is a clear unmet clinical need to develop an intelligent and lightweight system which can automatically monitor eating behaviour and provide feedback. In this paper, we investigate: *i)* the development of an automated system for detecting eating behaviour using wearable Electromyography (*EMG*) sensors, and *ii)* the application of the proposed system combined with real-time wristband haptic feedback to facilitate mindful eating. For this, the collected data from 16 participants were used to develop an algorithm for detecting chewing and swallowing. We extracted 18 features from EMG which were presented to different classifiers, to develop a system enabling participants to self-moderate their chewing behaviour using haptic feedback. An additional experimental study was conducted with 20 further participants to evaluate the effectiveness of eating monitoring and haptic interface in promoting mindful eating. We used a standard validation scheme with a leave-one-participant-out to assess model performance using standard metrics (*F1-score*). The proposed algorithm automatically assessed eating behaviour accurately using the EMG-extracted features and a Support Vector Machine (SVM): *F1-Score* = 0.95 for chewing classification, and *F1-Score* = 0.87 for swallowing classification. The experimental study showed that participants exhibited a lower rate of chewing when haptic feedback was delivered in the form of wristband vibration, compared to a baseline and non-haptic condition ($F(2,38) = 58.243$, $p < .001$). These findings may have major implications for research in eating behaviour, providing key insights into the impact of automatic chewing detection and haptic feedback systems on moderating eating behaviour towards improving health outcomes.

1. Introduction

According to a report from the U.S. Department of Labour, the average person spends 1.18 h a day eating.[1] Oftentimes, during eating people may engage in additional concurrent activities such as working, driving, or reading. By engaging in concurrent activities, people become arguably less aware of the extent of time they devote to eating. This mindless eating – or the lack of awareness of the food we are consuming – has been linked to the obesity epidemic and other health problems attributed to unhealthy eating behavior [1,2]. For example, the speed of food consumption has been associated with increased Body Mass Index (BMI) [3], diabetes [4], and various eating disorders [5]. Hence, investigating eating behaviour interventions may have wide ranging implications including weight management and eating disorder treatment.

Self-reporting and reflection are often considered important

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[1] https://www.bls.gov/news.release/archives/atus_06282018.htm.

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activities to facilitate behaviour change [6]. Such activities can help maintain a state of 'mindful' eating, which is important to counter automatic eating and environmental influences [2] and facilitate reflection upon behaviour change goals. Current studies looking into eating speed often rely on participant self-monitoring or manual observation in experimental settings. Alternative approaches to studying eating speed have made use of a *mandometer*, an electronic scale measuring the weight of food over time, to estimate intake rate [5]. Although such tools provide an objective measure of eating speed, they do not provide sufficient and detailed evaluation of eating processes such as chewing and swallowing.

The focus of this work is therefore twofold: *i)* Study 1 focuses on the development of an automated system for detecting eating behaviour (chewing and swallowing) using Electromyography (EMG) signals; *ii)* Study 2 aims to investigate the feasibility of using haptic feedback using a smart wristband to facilitate mindful eating using the detection technique developed in Study 1.

2. Related works

2.1. Links between eating rate and health

Previous studies have investigated the effect of eating rate on food intake quantity through controlled experiments. For example, *Kokkinos* et al. [7] conducted a study using timed eating period and food quantity to control eating speed, and measured hunger stimulating and inhibiting hormone levels in the blood. They reported higher concentration of hunger reducing hormones after a slower meal and hypothesised that this might indicate eating rate could be related to overconsumption of calories. Similarly, *Zhu and Hollis* [8] investigated the effect of controlled chewing thoroughness (chew count) and found that increased chewing thoroughness was associated with reduced eating rate and food palatability. *Zandian* et al. [5] compared linear eaters (people who eat at a constant rate) and decelerated eaters (people who slow down during the meal) during eating sessions with intake speeds where feedback was provided. They found that participants in the decelerated eating group demonstrated difficulty maintaining set eating speeds.

Various diverse health factors may be related to chewing rate, directly or indirectly. For instance, *Yamazaki* et al. [9] examined 6827 participants and concluded that masticatory performance and eating rate can be considered potential risk factors and are associated with diabetes. There have also been studies suggesting a link between eating rate and 'stress-eating'. *Adam and Epel* [10] reported that those who release a large amount of cortisol in response to stress consumed more calories following application of high stress tests. *Tasaka* et al. [11] built on these hypotheses, relating salivary cortisol levels to chewing rate after study sessions involving stress loading and chewing at different rates, reporting reduced cortisol levels after fast chewing. Collectively, these studies concluded that there may be an association between psychopathological stress responses and eating behaviour, and also that chewing faster might contribute to stress relief. Some other studies like [12] investigated the effects of the food masticatory in older people with different dental condition, where the eating behaviour in different people with natural and full denture via EMG signals were explored.

2.2. Limitations of current techniques in logging eating behaviour

The two main approaches for tracking eating are self-logging, and through manual observation (i.e. observations by human raters). Self-reported measures offer an easy approach to log diet for tracking eating disorders or weight management [6], or for large scale population studies of eating behavior [13]. However, such measures are intrinsically subjective and might be unreliable or prone to bias [14]. For instance, in a large study of 4808 participants to compare self-reported and clinically measured height and weight, *Spencer* et al. [15] reported overestimated height and underestimated weight. Similar effects were shown in other studies [16], and such bias was also observed during reliability assessments of eating disorder screening questionnaires [17]. The main limitation of manual observation-based studies is time and resource demands, which restricts the amount of recorded data one can analyse. In any large-scale study, the collection of high-quality data is time consuming and requires considerable resources. For example, *Bajic* [18] conducted a study of the effects of music on eating amongst 103 participants, which involved manual analysis of approximately 52 h of video footage. Other studies overcome similar issues through strict experimental protocols to simplify recorded data [8]. Some automated solutions exist, such as using a *mandometer*, or automated systems of eating behaviours. However, these approaches are relatively restricted in purpose and are immobile, thus limiting their applicability in practical settings.

2.3. Using mobile technology to promote healthy eating

Over the last few years many studies highlighted advantages of mobile technologies in promoting healthy eating, i.e. the ability of mobile devices to provide users with an easily accessible platform which enables convenient recording of data regarding eating behaviours, and receiving relevant feedback about their dietary choices (see [19]). Notable examples include an image-based mobile food recording system, which uses before-after photographs of foods and beverages consumed by users [20]. Such technology has also been sought to help in managing specific diseases where dietary monitoring plays a key role (such as in diabetes care where eating habits are monitored in combination with physical activity to help patients manage their blood glucose levels) [21].

Recently, the concept of mindful eating has been proposed as a technique to help regulate eating behavior [1]. Mindfulness is the psychological process of bringing one's attention to experiences occurring in the present moment. Since eating is generally considered as a type of automatic behaviour, we tend to consume food without conscious consideration. By helping people maintain a state of mindfulness during eating and more consciously examining hunger and satiation, individuals may be able to better "override" automatic eating behaviours. However, in order to effectively monitor eating behaviours, most existing studies rely on users manually entering details about their food consumption which requires considerable effort and could be prone to bias and participant error. Hence, for a behavioural change system to be effective, a monitoring technique would need to be employed to allow real-time monitoring of eating rate.

Mobile technologies have been proposed as a low-cost way to measure eating rate [22]. *Jasper* et al. [23] implemented an automated system for monitoring bite rate based upon hand motion captured by a wrist worn gyroscope which was been evaluated under controlled and real-life conditions. They reported that feedback reduced the number of bites, but that this resulted in compensatory behaviour permitting increased intake [16]. Some technologies like computer vision has also been implemented for dietary and eating behaviour assessments where some focused on processing the meals picture [24,25] for monitoring the consumed calories and some other are focused on the motion recognition of body for eating behaviour analysis [26]. Among other technologies, some studies are also acoustic sensors like *laryngophone* for food intake recognition [27,28].

The use of automated EMG-based eating detection for the monitoring of eating rate is another viable alternative [29–31] as EMG signals are considered as gold standard for chewing and swallowing logging [32]. Prior EMG studies approach the detection of eating rate through the detection of chewing activities, by using signal thresholds to identify periods of signal activity which denote rhythmic chewing events. Chewing is typically represented in EMG signals of the masticatory muscles by a burst of signal amplitude, occurring in a rhythmic sequence throughout the course of eating. The onset and termination of muscle activity is generally determined through the use of a predefined threshold; identifying onset and termination as the points at which the signal crosses the given threshold value. However, this approach has been found to be an unreliable approach, prone to false positives [33]. In addition, EMG signal activity of many facial muscle groups may be sensitive to inter-muscular cross-talk, where the detected activity might not be associated with underlying chewing aspects that we want to be characterising.

3. Methods

In this section, we present the methodology for both studies. We first discussed the data collection procedure, participant selection, feature extraction and classifications in subsection 3.1. Also, the development and implementation of the real-time chewing detection model, data processing as well as the experimental protocols for the second study are discussed in subsection 3.2.

3.1. Study 1: automated detection of eating behaviour using EMG

In this study, we developed an algorithm aiming to provide accurate and robust detection of chewing and swallowing events using EMG signals.

3.1.1. Data collection

The data collection system consisted of custom hardware and software paired with a physiological sensor device and a standard laptop computer. Participants were mounted with standard surface electrode sensors *(#H124SG, Covidien, Ireland*) connected to a Bluetooth enabled EMG measurement and transmitter unit (*Shimmer 3, Shimmer Sensing, Ireland*). All data was collected with a sampling frequency of 1024 Hz. Chewing and swallowing activities were monitored using EMG signals. For mastication, the two primary masticatory muscles groups are the ‘masseter muscles’ and the ‘temporalis muscles’ used predominantly to control the elevation of the mandible [29]. In the context of EMG, *Criswell and Cram* [34] demonstrate the similarity of the signals from the two sites during chewing; describing mastication as the predominant action identifiable from the masseter muscles, and “assistance in chewing” as an important action of the temporalis. The masseter has also been described as easy to identify and reliable, which is a valid consideration for the purpose of reproducibility of this work [35]. In the meanwhile, the *Suprahyoid* muscles, while also related to mandible motion (jaw opening), are heavily associated with the elevation of the larynx and the oral, pharyngeal, and esophageal stages of swallowing and as such have been suggested as potential muscles that could be used

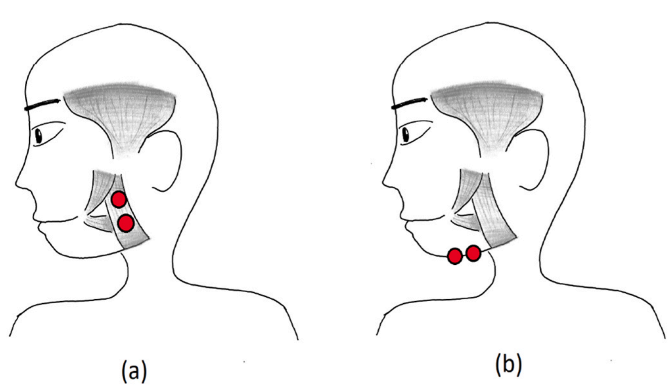

Fig. 1. Surface electrode placement positions for EMG measurement of the (a) Masseter muscles, and (b) Suprahyoid muscles, based on [30].

to detect swallowing activities with EMG [34]. Fig. 1 shows the approximate position of electrode placement in this study.

The data collection software (see Fig. 2 for a flowchart) was

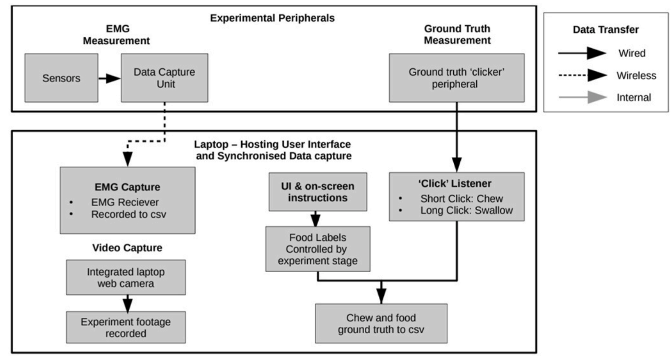

Fig. 2. A flowchart summarizing experimental data collection system.

developed using the C#.Net platform and the *Shimmer* API.[2] Participants were able to self-report individual chews and swallows by performing a short click or long-hold of a ‘clicker’ device respectively. All data was recorded concurrently and was synchronised. Video footages of the participants were captured to complement ground truth recording via the ‘clicker’. In addition, the software also served to guide participants through the data collection, providing textual and verbal instructions. Approval for the data collection procedures was granted by University of Kent Faculty of Sciences Research Ethics Advisory Group for Human Participants (Ref No 0721718).

3.1.2. Participants

For this study, on a par with other prior studies [32,36,37] we recruited 16 participants from a research University (details not provided to protect participants’ anonymity). Participants were selected to include a range of physical attributes (age, gender, height, and weight). Overall, the age of participants was between 18 and 40. Nine of the participants were female. Seven were considered to be overweight.

(BMI >25) and one was considered slightly underweight (BMI = 18.1). Participants were provided with a range of food items to consume. We selected five different food types which were representative of the textures and viscosities found in different food categories [30,33]; apple, jam sandwich, pizza, yoghurt, and water. Participants were each asked to consume 18 portions of each food item, over the two iterations of the experimental procedure and the various meal sections. Each solid food item was cut into small standard bite-size portions [32], approximately 2.5 cm square in the case of pizza and sandwiches, and apple slices 2 cm by 2.5 cm. Yoghurt was provided in a small container along with a 5 ml spoon. A portion of yoghurt was defined as a single spoonful. Unlimited water was provided, and a portion was described to participants as a small mouthful.

Participants were asked to follow on-screen instructions guiding them through the experimental procedure: 5 min of baseline measurement, 5 min speaking aloud, head motion, and consumption of a small meal. Head motion was also carried out at times while eating to simulate normal movement during eating. Inclusion of reading and head motion was to permit training of classifiers which are robust to unrelated activity. Fig. 3 shows the detailed protocol used in the study. Following completion, the sensors were removed from the participants, replaced, and the procedure was repeated. This process was followed to mitigate effects where minor changes in sensor placement might adversely impact the quality of data recorded. Each participant recorded two data sets, however for 3 of these participants only one dataset was considered viable due to hardware faults, and one participant elected not to return to take part in a session. Overall, a total of 28 datasets were collected, each comprising approximately 20 min of EMG data recorded during a combination of activities and food consumption. We processed 384 min

[2] https://github.com/openmhealth/shimmer.

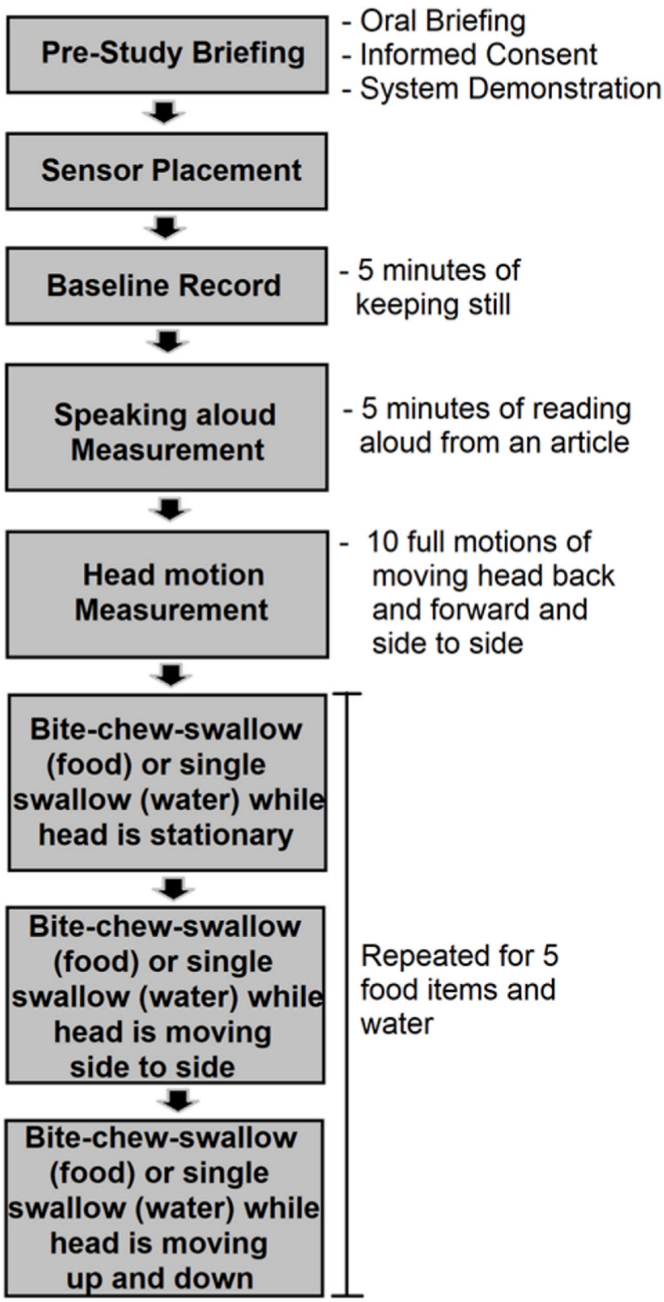

Fig. 3. The detailed protocol used to collect data for study 1.

of data from 16 participants. This includes 5 min of sitting still and 5 min of speech which were collected during each session. The remainder of the data consisted of participants consuming a small meal. During eating, a total 16,237 eating, 14,180 chews and 2057 swallows were recorded. The food types and associated labels (chewing and swallowing) are summarized in Table 1.

3.1.3. Data processing and feature extraction

The data was filtered and processed to eliminate noise and movement artefacts. Specifically, a unidirectional Butterworth bandpass filter was applied to the EMG signal with a low cut-off frequency at 20 Hz and a high cut-off frequency at 500 Hz (with cut-off order 5). The signal was then rectified using a full wave digital rectifier and normalised such that values lay within the 0–1 range. Each dataset was collected with self-reported ground truth labels (See Table 1). Whilst this gave a good indication of individual chew and swallow events, it was only an approximate indicator of the signal activity ground truth and did not guarantee the identification of uniform and predictable onset and termination times. To correct this, the ground truth for each dataset underwent automatic and manual review to ensure fidelity. Firstly, automatic correction of chewing event onset and termination was applied, using threshold-based activity detection (based on the EMG of the masseter muscle). Accurate ground truth timings could then be identified, where periods of potential EMG activity intersect or lay within close temporal proximity to ground truth timestamps and were used to correct ground truth. The same process was repeated for swallow ground truth correction, using submental activity. However, as these muscles also exhibited some activity during chewing, manual review of swallow EMG activity and video footage was used to confirm swallow ground truth onset and termination. The threshold value (*thr*) for this was determined using the suggest by *Abbink* et al. [38] and *Li* et al. [39] for EMG detection:

$$thr = \mu_0 + j^*\delta_0 \tag{1}$$

where μ_0 is the mean of the baseline, δ_0 is the standard deviation of the baseline, and $j = 5$.

Given that swallowing typically spans a longer period of time compared to chewing, we decided to treat this as binary classification problems: *i)* chewing classification - where all activities (including non-eating activities) were considered NA apart from chewing; ii) swallowing classification - where all activities were considered NA apart from swallowing. We down sampled the EMG signal by a factor of 10 and computed features using a sliding, overlapping Hamming window, which we set to 0.5 s (512 samples) for chewing and 1.625 s (1664 samples) for swallowing (see section 4.1 for more information).

Summarizing our data pre-processing approach: EMG signals were originally recorded with a sampling rate of 1024Hz, then filtered with a Butterworth band-pass filter with a range of 20Hz–500Hz. Subsequently, the signals were resampled using a sliding, overlapping Hamming window set to 0.5 s (512 samples) for chewing and 1.625 s (1664) samples for swallowing. Finally, the features were extracted for those signal segments (respectively).

Features were extracted from the two signal channels and the sample was labelled according to a period of inactivity (NA), or a chew (C) or a swallow (S) event. A total of 18 features were extracted across two channels of EMG and used in the classification models based on previous literature [31,40,41] (See section 7 for a detailed algorithmic definition of the features)

3.1.4. Classification of chewing and swallowing

We used different classifiers to assess binary differentiation of chewing and swallowing events: Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Decision Tree (DT), and Extra Trees meta estimator (ET). The statistical models' performance was assessed on a random selection of 25% of participants (4 participants). Furthermore, a leave-one-participant-out evaluation technique was employed, where in each run we trained the model using the samples from the *k*-1 participants and testing on the outed participants. The hyper-parameters of the classifiers were tuned using k-fold cross validation (k = 3) with grid search. Analysis of the Support Vector Classifier (SVC) revealed that a

Table 1
The number of eating events recorded for each food type (N = 16).

Type of Food	Class label		
	Chew	**Swallow**	Total
Apple	3595	369	3964
Sandwich	4282	376	4658
Pizza	6073	395	6468
Yoghurt	230	330	560
Water	0	587	587
Total	14,180	2057	16,237

SVC with a linear kernel was optimal for the classification of chews and swallows, and was able to perform generalised classification using data from unknown individuals as discussed in section 4.1. The model performance was assessed using *Precision*, *Recall*, and the *F1-score* (See Eq. (2)) which are widely used in binary class classification settings. We have used the following standard definitions for these performance metrics.

$$Precision = \frac{Tp}{Tp + Fp} \tag{2}$$

$$Recall = \frac{Tp}{Tp + Fn}$$

$$F1 = \frac{2 \times Presicion \times Recall}{Presicion + Recall},$$

where Tp = true positive, Fp = false positive, and Fn = false negative.

There was considerable imbalance in the class labels in the final training and testing sets, towards the inactive class. Class imbalance in the test sets was also liable to cause anomalous results during testing. The problem with class imbalanced data is that a statistical learner may fail to generalize sufficiently well, indicating the majority class as the dominating output. Therefore, there are different strategies to tackle statistical learning problems with class imbalanced data to overcome this limitation. The simplest approach which can provide a baseline performance is to undersample the majority class(es) so that all classes are equally represented in the dataset. Moreover, we can explore different thresholds within classifiers, e.g. adjusting the thresholds of probabilistic outputs so that the output of the classifier takes into consideration of class dominance and is adjusted accordingly. Therefore, we have reported findings using all data, and subsequently also undersampled the data with the aid of *RandomUnderSampling* library with the resampling strategy of '*majority*' to ensure that we provide a balanced dataset to the classifier.

3.2. Study 2: real-time haptic feedback for mindful eating

In Study 2, an experimental study was conducted to investigate the effectiveness of our proposed haptic feedback system. To achieve this, we first adapted the eating detection algorithm from Study 1 to work in real time. Then, a mobile application was developed integrating this real time algorithm and haptic feedback using a smart wristband; the entire process from feature extraction from the EMG signals, classification of the signals using the pre-trained classifier, and providing feedback to the wristbands was all conducted in real time.

3.2.1. Development of real time chewing detection algorithm

subsection 3.1 focused on the post-hoc classification of swallowing and chewing activity after data had been collected and pre-processed. The feedback system developed in Study 2 required real-time, or near real-time, detection of chewing events which could then be used to extrapolate information regarding chewing rate and providing feedback. The same dataset used in section 3.1 was used in the training and testing of the live chewing detection algorithm. Since we are interested in the chewing activity, only the EMG channel corresponding to the masseter muscle was used. This helped minimise participant's exposure to unfamiliar sensors on their face which were potential distractors for the feedback study.

We computed features processing each successive non-overlapping 0.5-s signal segment, extracting: the mean of the signal for each segment, the standard deviation, maximum amplitude, root mean square value, integrated EMG, mean frequency, and mean frequency band power (see section 7 for more info). The features were normalised using reference voluntary contractions to determine the appropriate maximal amplitude expected during eating. The reference amplitude was obtained during a short period of calibration (through eating one piece of each of the available foods) for each participant, during which the reference values were calculated. Afterwards, each entry in the final feature array was labelled as either occurring during a burst of EMG activity related to chewing behaviour (C) or as inactivity or unrelated activity (NA). A linear SVM based model was then trained using the available data. As for the hyper-parameters, a penalty value (parameter of C in SVM classifiers) of 5 (through cross validation grid search) and a squared hinge loss function was used. Considering the quadratic, $O(n^2)$, training time complexity of our SVC classifiers on the Big-O chart, the training time of the regression model via all the features was recorded as 11.87 s. For testing purposes, leave-one-participant-out approach was used. To compensate for class imbalances, the test sets were re-sampled at testing, down-sampling the majority classes to match the minority. The model was then evaluated based on the *F1-Score*, Precision and Recall (similarly to study1). Given the run-time complexity of SVC classifiers which mathematically defined as $O(k*d)$ [42], where k and d are defined as the number of support vectors and dimensionality of the data (i.e. number of features), respectively, the run-time of the model with linear kernel and penalty value of 5 was measured as 1.9 ms. The runtime of the feature extractor to extract the 18 features was measured as 1 ms. Thus, the overall runtime of the model for chewing classification was measured as 500ms + 1.9ms + 1ms ≅ 500 ms.

3.2.2. Implementation of the real-time chewing detection and haptic feedback system

The system consists of a Bluetooth enabled EMG signal capture device (*Shimmer 3*) connected to standard surface electrodes *(#H124SG, Covidien, Ireland*) axed across the masseter muscles on the dominant side of the user. To demonstrate the application's capacity in a mobile context, the measured signal was streamed live via Bluetooth to a smartphone (Samsung Galaxy S6) running Android version 3.0. The smartphone receives the signal via a custom application and acts as a local intermediary between the signal capture device and remote classier, and also handles user feedback regarding chewing rate.

Fig. 4 provides an overview of the chewing detection, monitoring, and feedback system. A laptop (*Dell, Inspiron 75,594*) connected to the mobile device via Bluetooth connection acted as a remote server with custom software handling signal processing and classification. It calculated chewing rate information, permitted live monitoring and returned live chewing rate information to the phone for feedback. Feedback was delivered via a Microsoft Band device (*Microsoft Band 2*).

3.2.3. Signal processing and classification software

A custom application hosted on the laptop server was developed to process and classify the incoming data. The application was developed using *Python 2.7* and *TKinter*, with matplotlib modules used for the purpose of providing a graphical user interface and visualising the live signal. The Linear SVM was implemented using the *Sci-kit learn* python library. Chewing bursts were estimated using a voting filter over a small window (of 8 samples), to reduce the probability of unexpected and individually occurring false positives.

The classification model was designed to return a positive prediction for all samples classified as occurring during an EMG chew burst. This enabled the system to determine the chewing events, which is defined as the period occurring between the onset and termination of positive predictions. Upon the termination of each detected chewing event, the predicted label, timestamps of the onset and termination of the event as well as the time duration of each event were logged on an output file. The chewing rate was then calculated based on the onset and termination timestamps of each detected chewing event (calculated as the number of chews per second) using Eq. (3):

$$CR = \frac{1}{n}\sum_{i=0}^{L} f(chew_{event}) \tag{3}$$

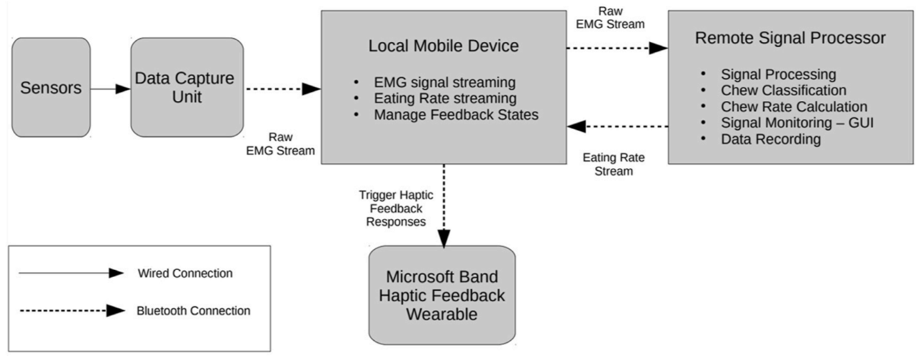

Fig. 4. Overview of the chewing detection and Haptic Feedback system developed in this study.

$$f(x) = \begin{cases} 1 & \text{if } x_{onset} \geq (t-n) \text{ and } x_{term} \geq t \\ 0 & \text{otherwise} \end{cases}$$

Giving the average number of chews per second over the last n seconds, where $chew_{event}$ is a chewing event occurring during the session, L is the number of chewing events observed during the session, x_{onset} is the starting time of chewing event x, x_{term} is the termination point of chewing event x, t is the current time, and $n = 5$. As the approximate duration of chewing events has been identified as 0.5 s in our earlier experiments, it was possible to measure chewing rate over the last 5 s with the timings of approximately 5 chews. This was deemed to provide acceptable accuracy for chewing rate calculation while attempting to minimise the time error for feedback response.

3.2.4. Haptic feedback system

Whilst biofeedback systems often make use of visual or audio feedback, visual feedback was disregarded for this study as it would require special attention while eating. Audible feedback on the other hand would be overtly obvious to other individuals in social scenarios. Therefore, in this study, we explored the use of haptic feedback. Haptic feedback is able to provide relatively covert feedback that would not demand special attention whilst still acting to draw the attention of the users back to their eating behaviour. The Microsoft band was configured to provide four different patterns of vibrations based on a normalised eating rate (between 0.0 and 1.0): *i)* No haptic pulses (representing a 'low' eating rate of around 0.0–0.3), *ii)* Periodic individual haptic pulses (representing a 'moderate' eating rate of around 0.3–0.6), *iii)* Periodic double haptic pulses (representing a 'high' eating rate of around 0.6–0.8), and *iv)* High intensity double haptic pulses (representing a '*very high*' eating rate of around 0.8–1.0).

3.2.5. Experimental study

A within-participant study was carried out to determine the effects of real-time feedback provided by our system on short-term eating behaviour. Each participant was asked to participate in three different conditions where *i)* in the control condition, they were asked to eat normally, *ii)* in the none-feedback condition, they were asked to self-moderate their eating rate, and *iii)* in the haptic feedback system, they were asked to self-moderate their eating rate using our proposed haptic system. The hypothesis of our experiment study is as follows: *i)* the haptic feedback system would result in a reduced chewing rate in comparison to the none feedback and control conditions and *ii)* the haptic feedback system would provide participants with more awareness in regard to the self-moderation of the eating rate in comparison to the none feedback and control conditions. Approval for the experimental procedures was granted by the University of Kent Faculty of Sciences Research Ethics Advisory Group for Human Participants (Ref No 0721718).

3.2.5.1. Participants. 20 additional participants were recruited from a research university (details of the University are not provided to protect participants' anonymity) (aged 18–50, 10 female) [32]. Only healthy participants were recruited with no dietary restrictions to the foods provided for the study. Consent was obtained to record anonymised sensor data and survey responses as well as to the record audios of the interview. The majority of participants (13) were within a healthy weight range according to their BMI, whilst 3 were found to be slightly underweight (BMI less than 18.5), and 4 were found to be overweight (BMI greater than or equal to 25).

3.2.5.2. Materials. The system specified in the previous section was used during the course of this study. Participants had adhesive electrode sensors axed over their masseter muscles, following the placement procedure outlined in Fig. 1, and were equipped with a Microsoft Band 2 for the study duration. The smartphone and remote processing laptop, which were included as part of this system, were placed nearby, but out of line of sight of the participants. The food selection was duplicated from previous data collection methodology involved in the development of chewing classification algorithms (section 3).

3.2.5.3. Study process. Each participant took part in a single study session consisting of three phases: a control phase involving unrestricted normal eating, and two treatment phases involving self-moderation of the eating rate, with and without feedback. At the beginning of the session, participants were equipped with the sensing equipment. Participants were then presented with food allotted to them for the experiment and asked if they would like to make any substitutions or reductions (participants ate the same type of food for all conditions which they participated in). Afterwards, the food was divided into three portions for each phrase of the study. Participants took part in the three phases of eating, completely consuming one portion of food during each phase. In the first phrase (the control condition), participants were asked to eat the food normally. This phrase served both to help assess the normal eating performance of each participant and allowed our software to be calibrated. Following this, participants were asked to self-moderate their eating rate based on two conditions:

- Self-moderation eating without Haptic Feedback condition (No-Feedback): In this condition, participants were asked to attempt to moderate their eating rate, trying to estimate their normal eating speed and slow down while eating the provided food portion; it is done by estimating their normal eating rate they usually eat in a normal situation (low-stress), and then trying so moderate their eating rate to that level.
- Self-moderated eating, with haptic feedback (Feedback): In this condition, participants were asked to moderate their eating behaviour with the help of our haptic feedback system. A brief training session was carried out at the beginning of this phase in which the

chewing rate haptic feedback system was then demonstrated to them.

The order in which participants took part in the Feedback and No-Feedback conditions were randomized to help reduce the order effects. Fig. 5 provides a visual summary of the study process.

3.2.5.4. Outcome measures. The outcome measures consisted mainly of measures related to the chewing behaviour (i.e. chewing rate) and the self-awareness of participants regarding their eating activity.

3.2.5.4.1. Chewing behaviour. During each meal phase, information was recorded in real time including the onset and termination of each individual eating event. A number of variables were extracted that were hypothesised as potentially affected by feedback, including: chewing rate across the entire eating phase, repeated measures of chewing rate across an eating sequence, the duration of detected events, and the period between detected events.

The live chewing rate was calculated and recorded using Eq. (3). However, this rate was sensitive to pauses between mouthfuls of food and as such was not used as an accurate indicator of chewing rate whilst eating across the entire meal phase. Instead, during data analysis, substantial gaps between chewing events were considered an indication of a pause following completion of a chewing sequence, or mouthful of food. During such a pause, a participant would swallow food and take in another portion for processing. Based on this, an adjusted chewing rate could be calculated to compensate for such pauses, by attenuating periods between chewing events which exceeded a given threshold. In this way, corrected values were found for chew event onset, *corrected_on*, and termination, *corrected_off* (see Eqs. (4)–(6). Simultaneously, this process could be used to identify the onset of chewing sequences, *seq_on*, and termination times of chewing sequences, *seq_off*. The chewing rate over the entirety of a session, *CR_overall*, was given as the average number of chews per second, and calculated as:

$$CR\_overall = \frac{1}{L}\left(corrected\_off_L - corrected\_on_L\right) \tag{4}$$

where L was the number of observed chews, $corrected\_off_L$ was the time in seconds at the termination of the last observed chew and $corrected\_on_L$ was the time is seconds at the onset of the first observed chew. Additional measures of eating were derived from the detected eating events. These measures included: average duration of chewing events, average period between chewing events, average duration of chewing sequences, average period between chewing sequences, and average number of chews per chewing sequence. Average duration of chewing events, *chew_dur*, was determined by the following equation:

$$chew\_dur = \frac{1}{L}\sum_{i=0}^{L}\left(chew\_off_i - chew\_on_i\right) \tag{5}$$

The average period between chewing events, *chew_gap*, was determined by the following equation:

$$chew\_gap = \frac{1}{L}\sum_{i=0}^{L}\left(corrected\_on_i - corrected\_off_{i-1}\right) \tag{6}$$

Following identification of chewing sequences based on a threshold for identifying significant gaps between chewing events, as discussed previously, the duration of and period between chewing sequences could be calculated. For instance, given the identification of chewing sequence onset (*seq_on*) and chewing sequence termination (*seq_off*), the average duration of eating sequences, *seq_dur*, and average period between chewing sequences, *seq_gap*, per meal could be calculated. Our hypothesis was that there would be significant differences between the six measures used to evaluate the chewing behaviour of participants, with the haptic feedback system significantly reducing the *chewing rate* and *chewing event* per *sequence* and increasing the *chewing sequence duration*, *chewing event duration*, *time between chewing event* and *time between chewing sequence* in comparison to the control and no-feedback groups.

3.2.5.4.2. Self-awareness in the eating activity. A short survey was administered after each phase of the study to gauge the participants' self-awareness of their eating activity and awareness of the food being consumed during that phase. The concept of 'mindfulness' of one's eating activity has been suggested as an important factor in supporting eating behaviour change and countering automated eating behaviour as a result of environmental factors [2,43]. In order to measure such effects, previous studies [1] had employed surveys such as the "*Kentucky Inventory of Mindfulness*" to capture participants' degree of mindfulness in day-to-day life [44], and the "Three Factor Eating Questionnaire" to identify participants' dietary restraint, disinhibition and hunger in a general context [45]. Whilst these give a general context of participant mindfulness and eating behaviour, they do not provide details regarding participant mindfulness or eating behaviour in regard to a particular task, or during said task. Based on these questionnaires, a custom questionnaire was developed which consisted of 23 statements regarding participants' self-awareness of eating, rated on a 5-point Likert-scale from 'strongly disagree' to 'strongly agree'. The statements were selected in an attempt to provide insights into participant awareness of their environment, eating behaviour, eating speed and their overall self-awareness. Participants were asked to consider a normal eating scenario and compare their experience with the recently

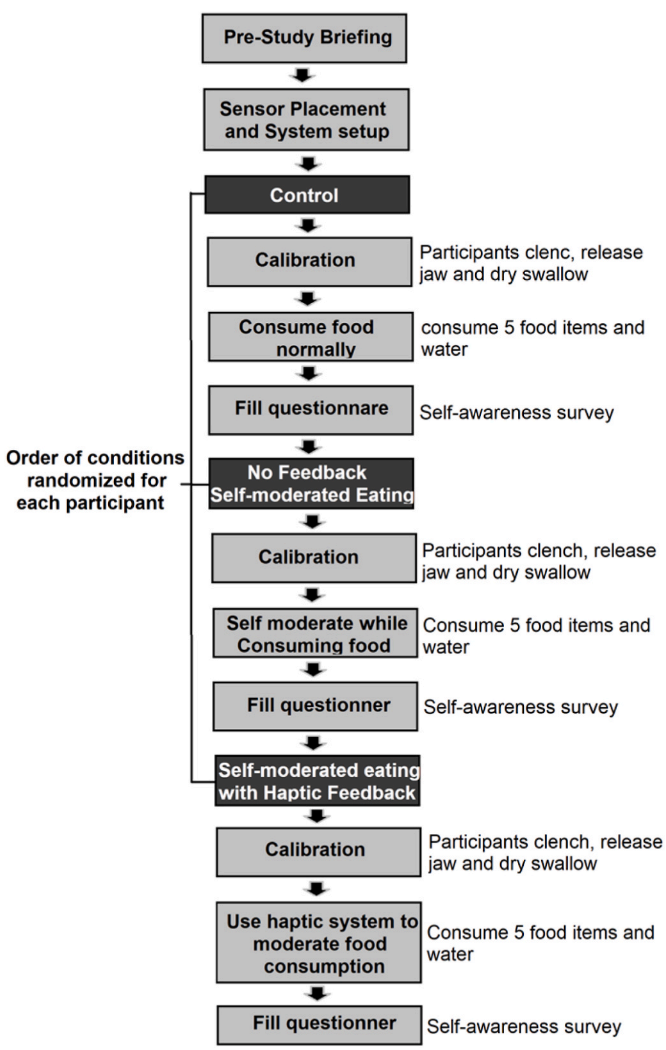

Fig. 5. Overview of the chewing detection and Haptic Feedback system developed in this study.

completed eating phase, and then provide their responses on a Likert scale survey. The survey responses were numerically categorised, between 1 = "strongly disagree" and 5 = "strongly agree". For each item, an awareness score was defined as an average of all responses for statements related to that factor. Overall, our hypothesis was that there would be significant differences between the self-awareness measures within the groups, with the Haptic feedback condition allowing users to focus more on their *food, eating activity* and *eating speed* and less on *the environment* in comparison to the control and no-feedback groups.

3.2.5.5. Data analysis. Repeated measures of Analysis of Variance (ANOVA) were carried out to investigate the differences between the 6 measures used to evaluate the chewing behaviour of participants (Chewing sequence duration, Chewing event duration, Time between the chewing event, Time between the chewing sequence and the Number of chewing events per sequence) between the control, No-Feedback and Feedback conditions. Prior to conducting ANOVA, normality was tested using the Shapiro-Wilk test of normality and sphericity was tested using Mauchly's Test of sphericity. Where sphericity was violated, the *Greenhouse-Geisser* correction for violations of sphericity. The same procedure was also used to analyse the measures for self-awareness in the eating activity. For measures which were found to be significant after carrying out the repeated measure ANOVAs, Bonferroni adjusted post-hoc tests were then used to determine the statistical differences between conditions. The IBM SPSS statistic software (version 25) was used to carry out the statistical analysis.

4. Results

In this section, we first introduce the results and findings of the first study for classification of chewing and swallowing at subsection 4.1. The results of the second study are presented in subsection 4.2 where the real-time haptic feedback system and its effectiveness in mindful eating is discussed.

4.1. Study 1: automated detection of eating behaviour using EMG

In this study, we implemented different classification models to provide accurate and robust classifications of chewing and swallowing events using EMG signals. The performance of the different models, as measured by F1-score are presented in Table 2 which suggests that SVC outperforms the other classifiers. This confirms that SVC with linear kernel is better suited for binary classification, which is linearly separable. Also due to the higher complexity of the DNN-based networks, and better performance of the conventional classifiers with limited datasets, DNN-based classifiers (e.g. LSTM) are not considered in this study [46].

Table 3 shows the results for the leave-one-participant-out evaluation. *F1-score* for the evaluation of the model with each test case is shown in Table 4. Overall, there was a low standard deviation between test cases for the *F1-score* for both models, with a deviation of only 0.02 for the chewing classifier and 0.04 for the swallowing classifier. This low standard deviation of the *F1-scores* support the conclusion that the models and extracted features generalize well to entirely unknown participants who might have different eating behavior in terms of the eating/swallowing rate.

The confusion matrixes of the offline chewing and swallowing detection models, evaluated in leave-one-out manner are also presented in Fig. 6.

Table 2
Performance summary for the binary chew and swallowing for each classifier algorithm.

Class	SVC	LDA	DT	ET
Chewing (C)	**0.95**	0.90	0.87	0.89
Swallowing (S)	**0.87**	0.76	0.63	0.59

Table 3
Performance summary for the chewing and swallowing offline classifier based on the Leave One Out evaluation method.

Class	Precision	Recall	F1-score
Chewing (C)	0.95	0.95	0.95
Swallowing (S)	0.87	0.87	0.87

Table 4
F1-score for the leave-one-participant-out.

Test case Number	F1-score per Classifier model		Demographics		
	Chew	Swallow	Age Range	Gender	BMI
1	0.95	0.89	18–25	Female	25.00
2	0.96	0.88	26–35	Female	21.00
3	0.95	0.81	36–45	Male	24.30
4	0.96	0.86	26–35	Male	20.00
5	0.97	0.92	18–25	Female	25.50
6	0.92	0.94	26–35	Female	25.95
7	0.93	0.87	18–25	Female	25.97
8	0.94	0.86	18–25	Female	25.00
9	0.95	0.86	18–25	Female	22.28
10	0.94	0.83	18–25	Female	34.21
11	0.97	0.95	26–35	Male	27.00
12	0.97	0.80	18–25	Male	20.07
13	0.98	0.88	26–35	Male	18.08
14	0.94	0.82	26–35	Male	36.16
15	0.93	0.86	26–35	Male	20.32
16	0.91	0.91	18–25	Female	30.00
Average	0.95	0.87			
SD	0.02	0.04			

Furthermore, the variation in age, gender, and BMI value across the participants in Table 4 suggest that these factors have little impact on the detection and classification of EMG signals during eating. For chewing, no test cases reported an *F1-score* of under 0.91 and the high scoring cases for chewing prediction (with *F1-score* above 0.96) were found to be evenly distributed between high BMI and normal BMI. Window size evaluation was performed to investigate the effects of the window sizes on the F1-score on both chewing and swallowing detection models. The evaluation for the binary chew classification case (Fig. 7a) presents a rapidly increasing accuracy until 512 observations in length (0.5 s) for all algorithms, followed by a gradual decline with increasing window size. For swallowing detection, accuracy gradually increasing with much greater window sizes (Fig. 7b). The optimum window size was found to be 1664 observations (1.62 s) for the linear kernel SVC, however the optimum window size was less uniform in this case, and varied between algorithms.

Additionally, analyses of the performance of the linear SVM chew and swallow classifiers using the unbalanced dataset were carried out. We investigated the use of thresholding applied to the sample confidence scores to determine predicted labels based on the decision function confidence score.

From this Fig. 8, we can aim to determine a convenient trade-off (which can be subjectively set by the user). Here, we set that to be at

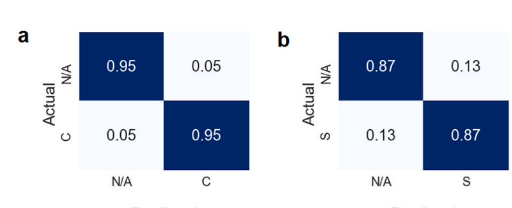

Fig. 6. Normalised Confusion Matrixes for Offline **a)** Chew and **b)** Swallow detection; N/A = Unrelated Activity, C= Chewing, S= Swallowing.

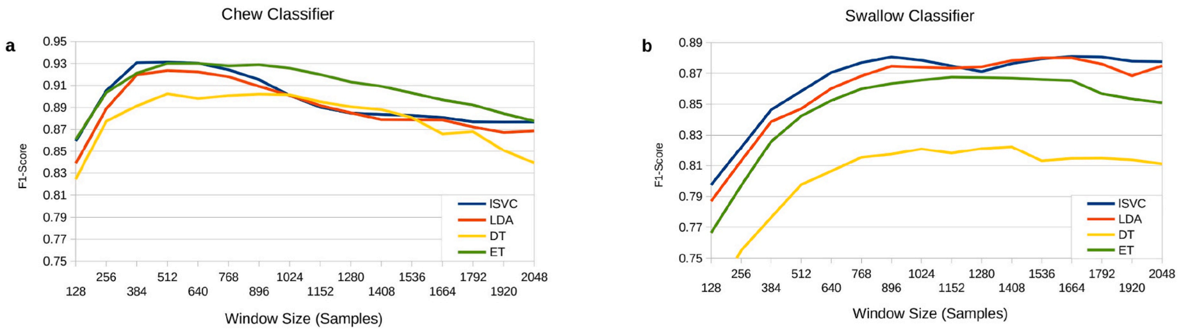

Fig. 7. Evaluation of sample window sizes for binary **a)** chew and **b)** swallow classifier models.

0.65 as a good compromise between good *Precision* and *Recall*, although this could be adjusted for specific applications (e.g. where *Precision* is the primary outcome of interest at the cost of worsening performance in terms of *Recall*). The confusion matrix based on this threshold approach was presented in Fig. 9.

4.2. Study 2: real-time haptic feedback for mindful eating

In Study 2, an experimental study was carried out to investigate the effectiveness of our proposed haptic feedback system. Table 5 shows the performance of the real-time chewing detection algorithm that was developed and integrated into the haptic feedback system used to conduct the user experiment, and Fig. 10 visualised the confusion matrix. Overall, for the classification of chewing activity in a real-time scenario from single channel EMG, the model resulted in an average *Recall*, *Precision* and *F1-Score* all of 0.92. Although these results demonstrate a small loss in performance from the model developed in the previous section, this loss was not substantial enough to suggest any detrimental impact resulting from the real-time approach to signal processing.

As for the results of the user experiment, Table 6 presents a summary of the differences between the measures used to assess chewing behavior (including details regarding chewing duration and time between chewing events and sequences etc.)

Overall, the repeated ANOVAs showed that there was a statistically significant difference between the 3 conditions with regards to Total chewing rate ($F(2,38) = 58.243$, $p < .001$), Chewing sequence duration ($F(2,38) = 31.696$, $p < .001$), Chewing event duration ($F(2,38) = 5.843$, $p = .006$), Time between chewing sequence ($F(1.3, 24.7) = 16.65$, $p < .001$), Time between chewing event ($F(2,38) = 66.01$, $p < .001$) and chew events per chewing sequence ($F(1.52,28.99) = 9.78$, $p = .001$). Post-hoc tests showed that there was a statistically significant difference between the (haptic) Feedback condition and the No (haptic) Feedback and control conditions.

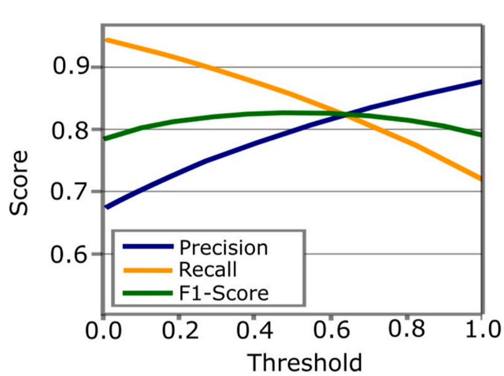

Fig. 8. The different scores (*Precision*, *Recall*, *F1-score*), as a function of different thresholds.

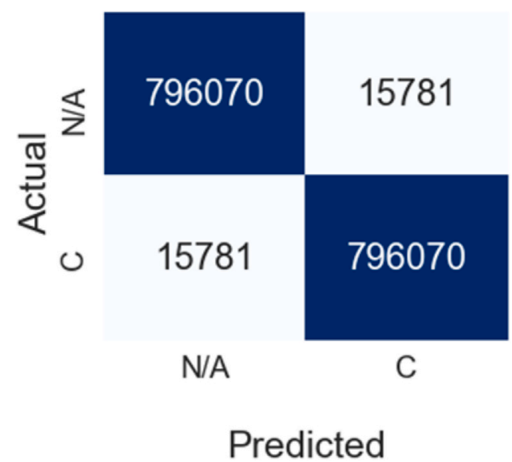

Fig. 9. Confusion matrix for offline chew classification (Threshold-based predictions).

Table 5
The average performance of the real-time chew classification model based on the Linear SVM algorithm. (Using leave-one-participant-out).

Class	Precision	Recall	F1-score
N/A	0.91	0.94	0.92
Chew	0.94	0.91	0.90

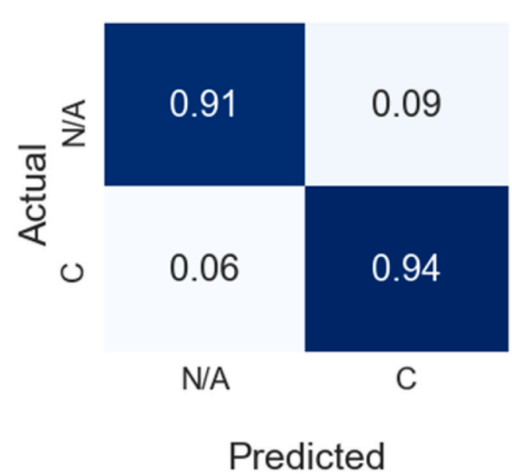

Fig. 10. Normalised Confusion Matrices (real time chewing classifier).

Table 6
A summary of the differences between the measures used to examine chewing behavior.

Measurement (Mean Value)	Condition		
	Control	No Feedback	Haptic Feedback
Total Chewing rate[a]	1.6 (SD = 0.32)	1.18 (SD = 0.34)	0.92 (SD = 0.35)
Chewing sequence duration[a]	4.84 (SD = 0.92)	5.48 (SD = 1.31)	7.64 (SD = 2.16)
Chewing event duration[a]	0.42 (SD = 0.07)	0.48 (SD = 0.11)	0.53 (SD = 0.15)
Time between Chewing event[a]	0.34 (SD = 0.16)	0.59 (SD = 0.23)	0.86 (SD = 0.45)
Time between Chewing sequence[a]	1.56 (SD = 0.65)	1.86 (SD = 0.60)	2.72 (SD = 1.31)
Number of chewing events per sequence[a]	6.50 (SD = 0.77)	5.39 (SD = 0.85)	6.03 (SD = 1.12)

[a] Indicates a statistically significant difference ($p < .001$).

The results showed that on average, the lowest observed chewing rate was found in the Feedback condition, (Mean = 0.92, SD = 0.35) which was significantly lower than the No-Feedback condition (M = 1.18, SD = 0.34) and the control condition (Mean = 1.6, SD = 0.32). Participants in the Feedback condition showed on average, the longest chewing duration when consuming their food in the Feedback condition (Mean = 7.64, SD = 2.16), which was significantly longer than the No-Feedback condition (Mean = 5.48, SD = 1.31) and the control condition (Mean = 4.84, SD = 0.92). On average, participants spent significantly more time chewing in the Feedback condition (Mean = 0.53, SD = 0.15) than the control condition (Mean = 0.42, SD = 0.07). However, there was not a significant difference in the average chewing event duration between the Feedback and No-Feedback condition and the No-feedback and control condition.

Participants in the haptic Feedback condition spent on average significantly more time between each chewing event (Mean = 0.86, SD = 0.45) than No-Feedback (Mean = 0.59, SD = 0.23) and control condition (Mean = 0.34, SD = 0.16). Similarly, on average participants spent significantly more time between each chewing sequence when provided in the Feedback condition (Mean = 2.72, SD = 1.31) than the No-Feedback condition (Mean = 1.86, SD = 0.60) and the control condition (Mean = 1.56, SD = 0.65). Finally, whilst participants in the control condition showed on average, a significantly higher number of chewing events per each chewing sequence (Mean = 6.5, SD = 0.77) than the No-Feedback condition (Mean = 5.39, SD = 0.85), there was not a significant difference in the number of chewing events per sequence in the Feedback and Non-Feedback and the Feedback and control conditions.

For the measures related to self-awareness, all factors were found to have a normal distribution. Post-hoc pairwise comparison indicated that there was a significant difference between the control condition and haptic Feedback condition in the participants' awareness in their environment ($p = .034$). For the factor of awareness with regards to their eating activity, the score of participants during the Feedback condition was found to be significantly higher than the control condition ($p = .008$). Finally, participants reported significantly higher awareness of their eating speed during both the Feedback condition and the No-Feedback condition than during the control period ($p < .001$). Fig. 11 shows a summary of the average score and standard deviation for each of the self-awareness factors measured in this study.

5. Discussion

The paper reported two studies; study 1 focused on the development of an algorithm to detect eating behaviour, whilst study 2 presented an experimental study looking into the use of haptic feedback to facilitate mindful eating. The results from study 1 showed that by using EMG signals of the masseter and submental muscles, our classifier algorithms based on a linear SVM, was capable of swallow detection with a *F1-score* of 87% and chew detection with a *F1-score* of 95%. In addition, the algorithm was shown to be robust and able to generalize well in a leave-one-participant-out evaluation scheme. This was achieved through the use of data from 16 participants over a wide range of BMI values, and including natural behaviour aspects such as head motion, reading aloud, etc. In the second study, we showed through an experiment with 20 participants that haptic feedback triggered by automatic eating behaviour detection, had a significant effect in supporting voluntary eating rate reduction; resulting in a significant difference in eating rate between treatment groups, with an average rate during feedback based moderation 46.9% slower than the no-feedback moderation. These studies demonstrated the use of eating driven real-time feedback for the purpose of behaviour change intervention through providing ongoing reminders of chewing moderation goals.

The first goal of this study was to develop automatic classification tools aimed towards automated chewing and swallowing detection based on EMG signals. Overall, we found that the models were robust, generalising well across different BMI and age range (see Tables 2–3). Compared to previous studies, the results of the study reported here were accurate in the presence of unrelated activities (e.g. reading, head

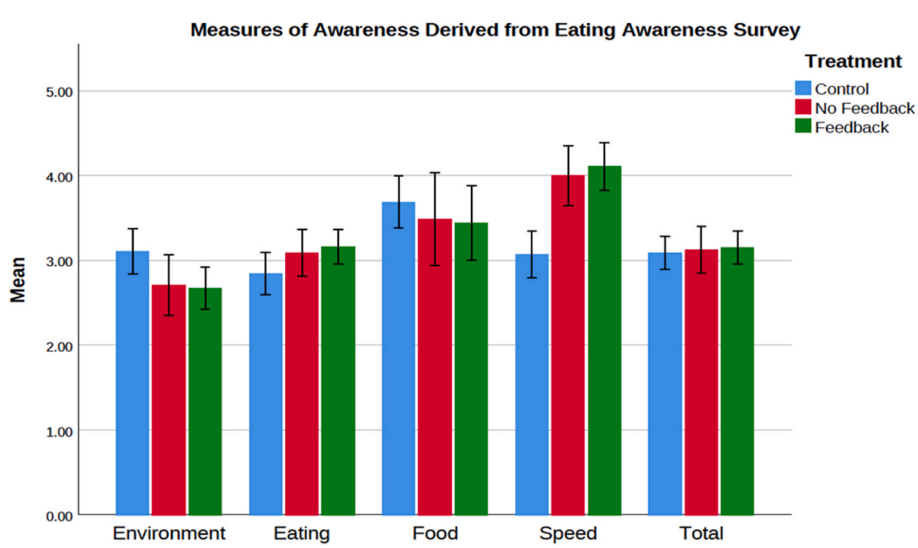

Fig. 11. The means score of each of the measures for self-awareness factors examined in this study.

motions, etc.). For instance, 'smart-glasses' based studies showed comparable performance for chewing detection using threshold-based algorithms [47,48]. Huang et al. [47] reported an accuracy of 96%, however they indicated a high degree of false positives associated with unexpected activity. Similarly*, Zhang and Amft* [48] reported chewing detection accuracy of approximately 94% for their algorithm in lab conditions, but only 80% accuracy in practical "free-living" settings (not under carefully controlled lab conditions). Our swallowing detection classifier resulted in an accuracy of 87% (*F1-score* = 0.87), which was lower than the accuracy of 93% reported by *Nahrstaedt* et al. [49] using a combined bioimpedance and EMG based algorithm. However, the higher performance in *Nahrstaedt* et al. [49] might be attributable to a number of factors, such as a limited subject pool, consisting of 9 subjects, two of whom were female (mean age 28.5), and seven male (mean age 27.4), with unspecified BMI differences. The study also involved experimentally controlled bolus size swallowed, and different sensor placement, across the sternohyoid muscle rather than submental muscles. Furthermore, the inclusion of both bioimpedance and EMG may add additional processing costs to the detection of swallowing activity, while the approach proposed in this study relies solely upon analysis of a single EMG channel.

Eating speed and chewing thoroughness have been suggested as factors impacting various aspects of physical health such as increasing the possibility of a high BMI or increasing the risk of developing eating disorders [50]. From the experiment, we found that participants exhibited a lower rate of chewing during self-moderation of eating than during the normal eating condition and were found to further reduce chewing rate through the use of haptic feedback. Overall, we found a significant increase in the period between chews in the feedback condition compared with the control, which was again larger in the haptic feedback condition. Interestingly, no statistically significant difference ($p = .39$) was found in the duration of chewing events between the no feedback and haptic feedback conditions. This suggests that although participants spent longer chewing each mouthful during moderation, particularly when supported by haptic feedback, the duration of individual chews remained relatively constant. The average number of chewing events occurring during each chewing sequence could be considered as an indication of chewing thoroughness. Like the chewing event duration, for this measure there were no significant differences. The average number of chews per chewing sequence remained relatively constant. Furthermore, the lack of change in the number of chews or duration of chewing events implies that the increase in average duration of chewing sequences, and chewing rate in general, may primarily be a function of the time between individual chews rather than other factors. However, we acknowledge that as one can imagine, in the haptic feedback mode, could have been as a result of reminding the participants to perform a mindful eating behaviour, which have also been happened by random feedback. Given that the answer of this question remined unknown in this study, we call the future studies to explore the effectiveness of a haptic feedback via a precise chewing detection mechanism versus a randomized or periodic haptic feedback.

In the experiment, participants' self-awareness was estimated from Likert scale type responses to a number of statements to estimate overall levels of mindfulness related to eating. Mindful eating has been suggested as a component of eating behaviour change [1,43,44] and it was hypothesised here that self-moderation and feedback would have an impact upon participants' self-awareness regarding eating. Our results only partially supported this hypothesis. No statistically significant difference was identified between the conditions for participant awareness scores focusing upon food ($p = .71$), or for total awareness ($p = .78$). It is interesting to note that the difference in the awareness was marginal between no feedback and haptic feedback group, while the eating speed between two groups differed significantly. This shows the utility of the haptic system in slowing down eating speed even when participants were not more 'mindful'. However, statistically significant differences were found for participant's self-awareness in relation to their environment, eating behaviour, and in regard to their focus upon eating speed ($p < .01$). Participants appeared to be more aware of their eating environment during the control condition. Whilst counter-balancing was applied between the No-Feedback and Feedback conditions to moderate any temporal effects, the control condition was always carried out prior to these. This was done to enable calibration of the system and for baseline measurement. As such, there is a potential that differences between control and treatment periods was the result of participants becoming familiar with the setting, and less self-aware regarding their environment. This may also explain the effect upon eating awareness and participant's awareness on their speed of eating. The scores for eating speed awareness were higher during the non-feedback and haptic feedback than the control, but did not differ significantly between one another.

The detection of various eating related features may be useful for providing valuable health-related feedback. In addition to visual evaluation of health (for instance through EMG for swallowing function monitoring), feedback regarding physiological processes and physical activity has been used for the treatment of certain health conditions. For example, biofeedback has been used to help an individual gain voluntary control of physiological processes to help treat conditions, as part of rehabilitation following a stroke [51], or for helping practice swallowing rehabilitation exercises in the treatment of swallowing disorders [52]. The technological approach we developed has the potential for other applications, for example, providing daily feedback regarding dietary intake goals based on automated detection of intake technique which has been used in conjunction with mobile based self-report of diet for weight change goals [53].

Previous studies had highlighted that the mobility and popularity of mobile devices, along with potential for personalised feedback and goal management, may facilitate tracking of dietary intake, exercise or weight management, and eating related interventions [22,53]. In particular, mobile phones could be particularly useful in automated systems for dietary tracking, eating monitoring, or for goal-based intervention or therapy, as a way to provide feedback, permit goal setting, and review of progress. Thus, the technology developed in this study could be particularly useful in weight change interventions: for providing feedback, encouraging the adoption of eating patterns and styles which have been associated with increased satiation and reduced intake [8], or for detecting adherence to a diet plan, using a model trained to detect specific foods. Such a system might help support clinical diet change for the treatment of obesity, or monitoring adherence to set diets prior to some surgeries or other treatment, sharing data regarding intake directly with medical staff. In regard to weight management, there are also implications of the system developed in this paper for the screening and monitoring of eating disorders during treatment. Traditionally, screening of eating disorders is carried out subjectively through clinical interviews and questionnaires. The classification models developed here, in conjunction with intake volume estimation and data sharing can be of considerable benefit to eating disorder treatment. Eating activity might be evaluated to identify patterns which are characteristic of eating disorders, such as periods of fasting, binging [54], or event related to eating speed [55]. Potentially, compensatory activities might also be detected, such as purging, based on facial muscle activity, or excessive exercise through the use of additional sensors (such as exercise tracking bands).

Finally, we have explored different classifiers to determine the best performing statistical model for the particular applications investigated herein. Due to space restrictions, we have only presented findings using the best performing classifier (linear SVM), which was consistently outperforming the competing classification approaches. We remark that although theoretical work in machine learning has demonstrated that more advanced SVM approaches (e.g., radial basis function SVM) often outperform standard SVM [56], they require a sufficiently large number of samples in order to robustly estimate the best performing hyper-parameters (SVM are known to be very sensitive in the choice of hyper-parameters). Therefore, because of the limited number of samples available to this study we had elected to only explore linear SVM. In addition, the sensors used in the current study are relatively intrusive as they are adhered to a person's face. This raises a question on the real-world application of the proposed technology to improve people's eating behaviour. However, there have been some significant advances in the development of flexible skin-like sensors, which are ultra-thin and non-invasive. Various studies have demonstrated the ability of such skin-like sensors in capturing high quality EMG signals [57–59]. These sensors are highly light-weighted and can be connected wireless to smartphones via standard Bluetooth technology, enabling the real-life monitoring of eating behaviour non-invasively.

6. Conclusion

We presented a system for automatically detecting eating behaviour in real time using EMG sensing. We demonstrated the use of a wearable haptic feedback device to help facilitate mindful eating. Overall, the work carried out in this study has major implications particularly for studying eating habits and improving our understanding of eating behaviour and the various influences upon eating choices such as food selection, intake volume, and intake speed. Automated eating detection systems may instead permit accurate collection of information with comparatively minimal processing. The methodology developed for the detection of eating speed could be extended to other forms of feedback regarding the users' eating rate (audio, visual, and haptic). The impact of different distraction types (television, music, or other stimuli), social meals, and portion sizes upon eating speed, or the effect of feedback or different stress conditions, might all be investigated using the system developed in this paper, with appropriate adaptation. Finally, eating speed might be investigated across demographic groups, to determine any particular associations between individuals with differing BMI, obesity, diabetes, or different eating disorders.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

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Appendix

This section presented the 18 extracted features from the EMG signals for both studies.

Table 8
18 Features extracted from EMG Signals

Feature name	Description	Method	Complementary
Mean Absolute Value (MAV)	Average of the absolute EMG signal across a signal segment.	$\mu = \frac{1}{N}\sum_{i=1}^{N}\lvert x_i\rvert$	x_i = The EMG signal sampled at time i N = The number of samples
Integrated EMG (IEMG)	Related to EMG signal firing point. Defined as the summation of the absolute EMG signal across an EMG segment	$IEMG = \sum_{i=1}^{N}\lvert x_i\rvert$	x_i = The EMG signal sampled at time i N = The number of samples
Variance (VAR)	Variance of EMG signal across a segment	$VAR = \frac{1}{N-1}\sum_{i=1}^{N}(x_i^2 - \overline{x})$	$\overline{x}$ = The mean of the segment x_i = The EMG signal sampled at time i N = The number of samples
Root Mean Square (RMS)	Square root of the average square of EMG amplitude across a segment	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2}$	x_i = The EMG signal sampled at time i N = The number of samples
Standard Deviation (SD)	Standard deviation () of the EMG signal across a given segment of EMG signal	$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \overline{x})^2}$	$\overline{x}$ = The mean of the segment x_i = The EMG signal sampled at time i N = The number of samples
Waveform Length (WL)	Cumulative length of EMG waveform over a signal segment	$\mathrm{WL} = \sum_{i=1}^{N-1}\lvert x_{i+1} - x_i\rvert$	x_i = The EMG signal sampled at time i N = The number of samples
Peak Amplitude	The peak amplitude across a given segment of the EMG signal	–	–
Myopulse Percentage Rate	Average Number of times that the absolute of the EMG signal exceeds *thr*.	$MYOP = \frac{1}{N}\sum_{i=1}^{N}[f(\lvert x_i\rvert)], f(x) = \begin{cases}1, & x \geq thr\\ 0, & x < thr\end{cases}$	x_i = The EMG signal sampled at time i N = The number of samples
Willison Amplitude (WAMP)	Sum of times the absolute EMG exceeds a given threshold *thr*	$WAMP = \frac{1}{N-1}\sum_{i=1}^{N}[f(\lvert x_i - x_{i+1}\rvert)],$ $f(x) = \begin{cases}1, & x \geq thr\\ 0, & x < thr\end{cases}$	x_i = The EMG signal sampled at time i N = The number of samples
Zero crossing (ZC)	Number of times EMG amplitude crosses zero amplitude	$ZC = \frac{1}{N-1}\sum_{i=1}^{N}[sgn((x_i \times x_{i+1}) \cap \lvert x_i - x_{i+1}\rvert) \geq thr]$	$sgn = \begin{cases}1, & x \geq thr\\ 0, & x < thr\end{cases}$ x_i = The EMG signal sampled at time i N = The number of samples *Thr* = Predefined crossing threshold
Slope Sign Change (SSC)	Count of the number of times the EMG signal slope changes across a signal segment	$\frac{1}{N-1}\sum_{i=1}^{N}[f((x_i - x_{i-1}) \times (x_i - x_{i+1}))]$	$f(x) = \begin{cases}1, & x \geq thr\\ 0, & x < thr\end{cases}$ x_i = The EMG signal sampled at time i N = The number of samples
Mean Frequency (MNF)	Average frequency	$\mathrm{MNF} = \frac{\sum_{j=1}^{M} f_j P_j}{\sum_{j=1}^{M} P_j}$	f_j = the frequency of the power spectrum at frequency j P_j = is the EMG power spectrum at frequency bin j M = The length of the frequency bin

(continued on next page)

Table 8 (*continued*)

Feature name	Description	Method	Complementary
Mean Power Spectrum (MNP)	Average power spectrum of the EMG signal sample	$MNP = \frac{1}{M}\sum_{j=1}^{M} P_j$	P_j = is the EMG power spectrum at frequency bin j M = The length of the frequency bin
Median Frequency (MDF)	Frequency at which the spectrum is divided into two regions of equal amplitude	$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j$	P_j = is the EMG power spectrum at frequency bin j M = The length of the whole frequency bin
Median Power Frequency (MPF)	Band power of the median frequency calculated using Fast Fourier Transform	–	–
Tp values	Defined as the normalised time point across a chewing cycle at which point P percent of the total cumulative EMG has occurred.	–	Calculated using the following steps. 1. Calculate cumulative sum across sample window 2. Normalised duration of sample 3. Tp is the normalised time at which P percent of the cumulative sum of the signal has occurred
Cycle Duration	Duration of a chew or swallow EMG activity cycle from onset to termination		
Cycles per sequence	Count of the number of chewing cycles within a given chewing sequence.	–	–

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