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Feature Selection Analysis of Chewing Activity Based on Contactless Food Intake Detection

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Abstract: This paper presents the feature selection methods for chewing activity detection. Chewing detection typically used for food intake monitoring applications. The work aims to analyze the effect of implementing optimum feature selection that can improve the accuracy of the chewing detection. The raw chewing data is collected using a proximity sensor. Pre-process procedures are implemented on the data using normalization and bandpass filters. The searching of a suitable combination of bandpass filter parameters such as lower cut-off frequency (Fc1) and steepness targeted for best accuracy was also included. The Fc1 was 0,5Hz, 1.0Hz and 1.2H, while the steepness varied from 0.75 to 0.9 with an interval of 0.5. By using the bandpass filter with the value of [1Hz, 5Hz] with a steepness of 0.8, the system's accuracy improves by 1.2% compared to the previous work, which uses [0.5Hz, 5Hz] with a steepness of 0.85. The accuracy of using all 40 extracted features is 98.5%. Two feature selection methods based on feature domain and feature ranking are analyzed. The features domain gives an accuracy of 95.8% using 10 features of the time domain, while the combination of time domain and frequency domain gives an accuracy of 98% with 13 features. Three feature ranking methods were used in this paper: minimum redundancy maximum relevance (MRMR), t-Test, and receiver operating characteristic (ROC). The analysis of the feature ranking method has the accuracy of 98.2%, 85.8%, and 98% for MRMR, t-Test, and ROC with 10 features, respectively. While the accuracy of using 20 features is 98.3%, 97.9%, and 98.3% for MRMR, t-Test, and ROC, respectively. It can be concluded that the feature selection method helps to reduce the number of features while giving a good accuracy.

Keywords: Chewing detection, feature selection, proximity sensor, temporalis muscle, food intake detection

1. Introduction

In assessing the dietary intake, several methods have been considered either based on food intake detection based[20] or food detection based[22]. The application of automatic food intake detection in daily life will help ease users count calorie intake and track the consumed food without requiring the systems to recognize the food. Food intake detection is the first stage in automatic food intake monitoring; it could be the most crucial stage as it will provide all the data

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required for further analysis. A typical eating process requires each individual to perform hand-to-mouth (HtM) movement, bite, chew, and swallow. Among those, chewing has a direct connection to food consumption compared to other activities. Chewing or mastication is crushing food by using teeth to make it into a smaller piece. Repetition of jaw movement with the cooperation of the masseter's muscle movement, the temporalis, the medial pterygoid, and the lateral pterygoid muscles during mastication produce a sequential pattern. Among the muscle movement that contributes to chewing activity, the temporalis muscle movement has captured researchers' attention in food intake monitoring or diet monitoring. Eventhough the movement of the temporalis muscle is small or less significant than other muscles. However, the muscle's position is suitable for the wearable device of the eyeglass. The use of eyeglass makes the sensor is less prominent.

Several sensor approaches such as piezoelectric, electromyography (EMG), and accelerometer had been proposed by previous research in detecting chewing based on temporalis muscle movement. The piezoelectric sensor had been used to capture the temporalis muscle movement by attaching the sensor to the temporalis muscle by using medical tape [7], while [13] attached the piezoelectric bend sensor to the temple of the eyeglass. The accelerometer is attached using a headband [24] and the eyeglass [10] in capturing the temporalis muscle movement. The EMG sensor was attached to the eyeglass using a different EMG electrode type, such as a dry electrode [26] and stainless steel dry electrode [25]. One of the disadvantages of using EMG and piezoelectric sensors is direct sensor attachment to the skin. The accelerometer does not require a direct attachment to the skin; it is, however, impacted by the noisy environment and active physical activities. Besides the intention of capturing a temporalis muscle movement, this study also aims to provide a sensor that does not require direct contact with the skin. Some of the researchers proposed a chewing detection system based on a non-contact sensor detection area by using a photoplethysmography (PPG) sensor [17], a photo sensor[23], a proximity sensor [5][27], and a doppler sonar sensor [14]. Most of the proposed non-contact sensor is based on jaw movement detection where physical activity would interrupt the signals. The previously discussed sensors that captured the temporalis muscle movement have the classifier performance of F1-score of 80%[26],91.5%[10], 94.2%[25], and 99.85% [7], while the non-contact-based detection gives an F1-score of 91.9% [5] and accuracy of 91.4% [14]. Both ranges of classifier performance are based on the laboratory environment. It was observed that the contact sensor provides a higher classifier performance in comparison to the non-contact-based sensor.

The capability of the systems in providing good accuracy is also affected by the methods used in processing the signals. The data undergo pre-processing, segmentation, feature extraction, feature selection, and classification in signal processing stages. This work will provide classification accuracy analysis based on parameter variation in pre-processing and feature selection of the signal processing. The signal pre-processing is the first process to work with the raw signals and function to improves the signal quality by eliminating unwanted signals such as DC component (due to fundamental frequency), powerline interface (due to power frequency of 50/60Hz), motion artifact, signal noise, frequency noise, and correcting the baseline drift. There are several pre-processing steps, such as normalization, detrend, smoothing, down-sample, and filtering. Depending on the application, characteristic, and desired signal output, the selected method could be single or combinations. While the feature selection method is optional, the researchers implemented the method if there are many features to be evaluated. It helps eliminate redundant features and reduce the total number of evaluated features, lowering the computational cost and time for evaluation. Some of the features selection methods implementation for chewing detection applications are forward features selection (FFS) [19][11][10], information gain; random forest (RF)[12], mutual information; minimum Redundancy, and Maximum Relevance (mRMR) [15], discriminatory information; fisher score (FS) [9], dimensionality reduction such as Principal Component Analysis (PCA)[2], sequential forward floating selection algorithm (SFFS) [1], and combination of mRMR and fisher score [10]. Researchers [4] and [3] use a combination of feature significance scores, the Benjamini-Yekutieli procedure, and the Recursive Feature Elimination (RFE) algorithm with a Lasso kernel to reduce the number of features from 700 to 40 features and 412 to 8 features, respectively.

This work is an extension of [21], where the previous work had introduced the new approach in chewing detection based on a contactless sensor. It also discussed the accuracy of varying the signal processing parameters such as varying k-fold and the upper-cut frequency bandpass filter. The results show that the systems can achieve an accuracy of 97.5% with the k-fold value of 10, lower, and upper cut-off frequency of 0.5Hz and 5Hz, respectively. The current work presented aims to provide the system's accuracy in terms of feature selection methods implementation to find good accuracy using fewer features. The analysis of the varying combination of steepness and lower cut-off frequency, Fc1 is done first to identify the highest accuracy that the system could be achieved.

2. Food Intake Detection System

This work used a temporalis muscle movement-based to capture the chewing activity during food intake. The developed system consists of a wearable sensor, the push button, and the microprocessor. The wearable sensor is designed using a proximity sensor of VCNL4040 attached to an eyeglass using 3D printed housing. The sensor is selected because it can capture the object's closeness within a short range of 20cm and fulfill the need for contactless detection. The pushbuttons function to provide the data labeling or ground truth for a validation process eating activity and chewing activity. The data transferred to a microprocessor (Arduino Uno board) using a sampling rate of 50Hz. Fig. 1 shows the implementation of a wearable sensor for capturing the temporalis muscle movement.

(a) (b) (c)

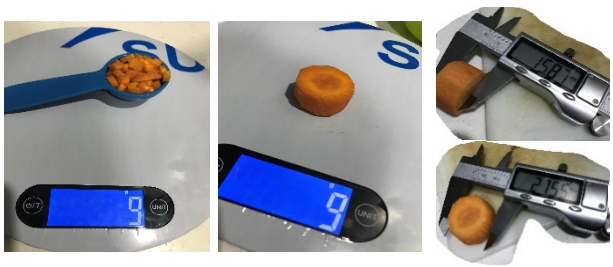
Fig. 1 - Chewing detection system: (a) the proximity sensor into the 3D printed housing; (b) attachment of wearable sensor to the eyeglass; (c) temporalis muscle position

3. Methodology

3.1 Data Collection

This study collecting a single subject with a repeated set of activities, with each set of data requires the subject to perform only eating and resting in the controlled environment. For eating activity, the subject requires to eat three test food with different hardness. The foods are banana, apple, and carrot, which represent food hardness of soft, medium, and hard, respectively, as used by [13]. A food portion based on one spoonful was used to eliminate inferences by food size and obtain comparable results. One spoonful measurement is obtained by cutting the test food as small as it can and placed into the measuring spoons. Then, the foods were weighed by using a food scale where it shows that one spoonful of small cut food represents nine grams. Each test food was cut into a cylindrical shape with the same thickness (±15mm), diameter (±27mm), and weight (9g). Fig. 2 shows the food test preparation.

The subject performed ten sets of the same sequence of activities that involved eating carrots for about 90s, eating a banana in 30s, eating an apple in 30s with 30s resting in between food intake, 15s resting during start, and after the last food taken. In short, the total time of 240s requires completing each set of data. The sequence for a set of activities is shown in Fig.3. E and R represent eating and resting, respectively. Additionally, while performing the activities, the subject must provide the ground truth for eating and chewing by labeling eating and chewing activities using pushbuttons. For each set of data, the chewing detection system will give three outputs: raw proximity signal, eating ground truth, and chewing ground truth; an example for all output is shown in Fig. 4. Next, the set of raw proximity signal data, eating ground truth, and chewing ground truth will be combined to form a dataset of the raw sensor signal and ground truth, respectively.



(a) (b) (c)

Fig. 2 - Test food portion preparation and measurement: (a) one spoonful of test food being weighted, a cylindrical test food being; (b) weight; (c) measure

Activity	R	E-Carrot	R	E-Banana	R	E-Apple	R
Time (s)	15	free	30	free	30	free	15

Fig. 3 - Activity sequence for each set of data

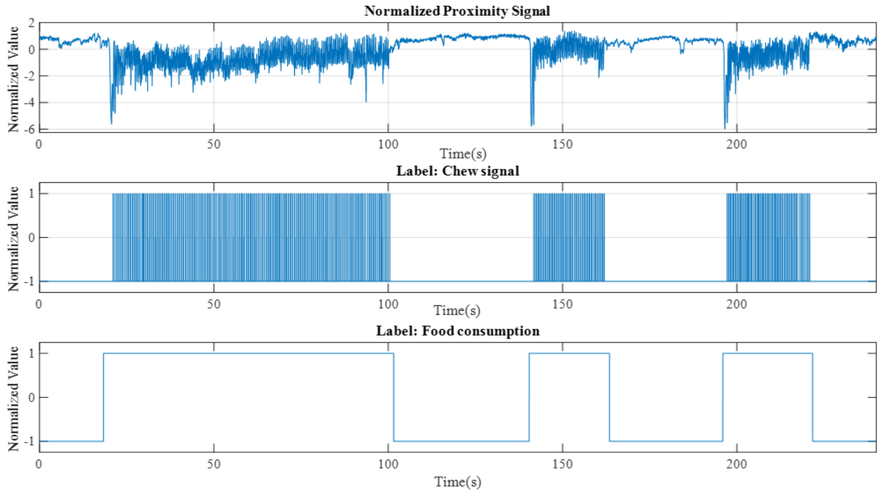


Fig. 4 - An example of chewing detection system output for a set of data

3.2 Signal Processing

The summary of the pre-processing method used is shown in Fig. 5.

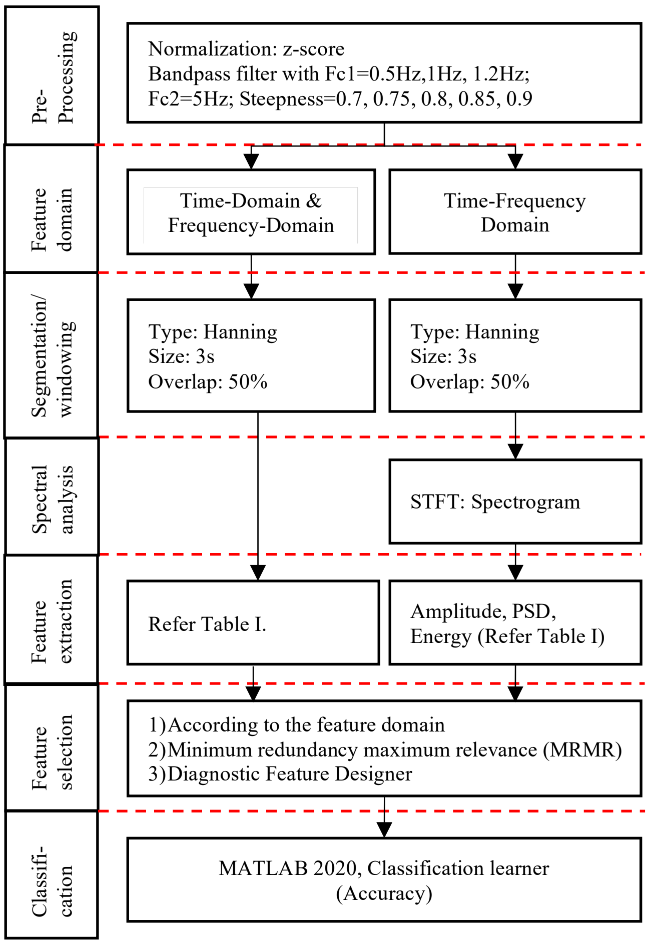


Fig. 5 - Signal processing pipeline

3.2.1 Data Pre-processing

This study uses the pre-processing method of normalization and filtering—the signal normalized by using z-score normalization as in (1) to eliminate amplitude variation, while the filter is to conserves only the chewing frequency data. In (1), X is sample data, $\bar{x}$ is the mean of the sample, and S is the standard deviation of the sample. Researchers have defined the chewing frequency in the range of 0.94 Hz to 2.17 Hz [18], 1.25 Hz to 2.5 Hz [19], and 0.5 Hz to 2.5 Hz [24]. Previous work in the same study [21] had presented the details of the hardware approach with analysis of the system accuracy according to vary the number of k-fold value, the upper cut-off frequency value of the bandpass filter in the range of 2.5Hz to 20 Hz using fix lower cut-off frequency value of 0.5Hz. The highest accuracy based on previous work is 97.3% using the pre-processing setting of 10 k-fold, bandpass filter of [0.5Hz, 5Hz] and defaults steepness of 0.85. This work is an extension of the study [21].

Previous work does not consider the lower cut-off frequency and steepness effect on the accuracy as it slightly less impactful compared to upper-cutoff frequency. Nevertheless, finding an optimal accuracy requires considering all of the factors. This paper includes three lower cut-off frequencies in the range of less than the stated frequency range of 0.5Hz, 1.0Hz, and 1.2Hz. While the steepness value of 0.70, 0.75, 0.80, 0.85 and 0.9 is used. 'Steepness' in the bandpass filter will determine the transition band of the filter is a scalar in the interval of 0.5 to 1. The filter response capable of achieving the ideal lowpass response as the steepness value increase. However, as it approaches '1', the filter length and the computational cost would also increase proportionally. This study will observe the suitable bandpass filter parameters setting of the chewing detection system. An example of the bandpass filter sample for a set of a pre-processed chewing signal is shown in Fig. 6.

$$z = \frac{x - \bar{x}}{S} \tag{1}$$

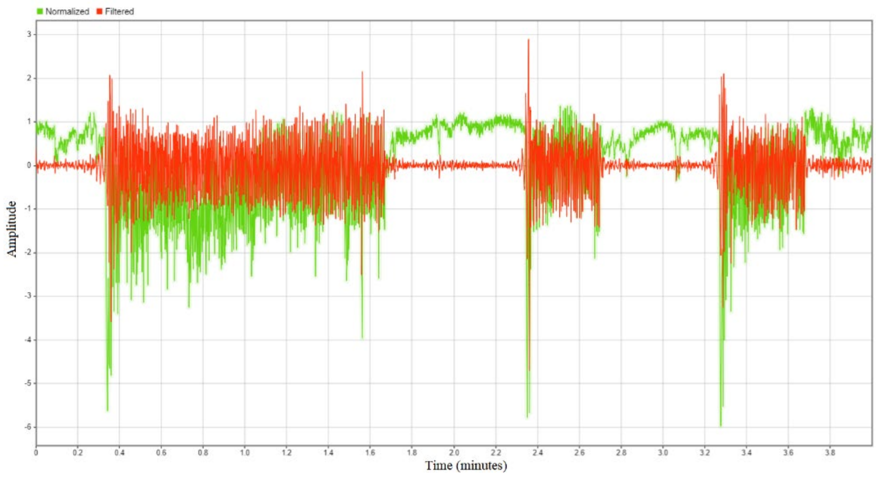


Fig. 6 - Example of a pre-processed proximity signal normalized and filter using a bandpass filter of [1, 5], steepness=0.8

3.2.2 Segmentation, Feature Extraction & Classification

The pre-processed signal needs to be segmented using an appropriate window type, size, and the number of overlaps before the extraction of the features. Two commonly used window type is the Hanning and Hamming. For window size, there is no standard size for chewing detection applications[20]. However, researchers had suggested several window size in the range of 3s to 30s, that are 3s [7], 4s [16], 5s[8][5], 15s[11] and 30s[19]. The data is segmented using a 3s window size with 50% overlapping using a Hanning window for this work.

The total of fourty features will be extracted from the time-domain (TD), frequency-domain (FD), and time-frequency domain (TFD). For TD and FD, the features could be directly extracted from the segmented data. While TFD is obtained based on the transformation of the time-domain data using Fast Fourier Transform (FFT), the process is called short-time Fourier transform (STFT). STFT could also be computed using a spectrogram to return the square magnitude values of STFT and power spectral density (PSD) for 0 to half of the sampling frequency. The equation to calculate PSD in the spectrogram is shown in (2). For full PSD, the PSD value obtained from the spectrogram must be multiplied by two except fundamental frequency as shown in (3). Where Fs is the Sampling frequency, S is the Magnitude of STFT (0 to Fs/2), W is the segmented window length (sample), Win is the type of window used with a defined length, PSD_{Full} is the Full power spectrum density value. The list of the features with the features number is shown in Table I, where all extracted features are based on researches of chewing and food intake detection applications that are [20][5][27][14], and[6]. The features numbers is a reference number that will represent the selected features in feature selection methods.

In this work, all set up for the classification process is the same as previous work, such as Classification Learner, labeling, the number of k-fold value with k=10, and the performance evaluation of the accuracy.

$$PSD = \frac{|S|^2}{U \times W \times Fs} \quad (2)$$

$$U = \frac{1}{W} \times \sum win^2$$

$$PSD_{full} = PSD \times 2\ (for\ 1\ to\ Fs/2) \quad (3)$$

Table 1 - List of the extracted features

Features Category	Features and its number	No. of Features
Time-domain (TD)	(1) Minimum; (2) Maximum; (3) Maximum-Minimum; (4) Root Mean Square, RMS; (5) Median; (6) Variance; (7) Standard Deviation, SD; (8) Skewness; (9) Kurtosis; (10) Interquartile range, Iqr.	10
Frequency-Domain (FD)	(11) Mean frequency; (12) Power bandwidth; (13) Median frequency.	3
Time-Frequency domain (TFD)	**PSD (9)**: (14) Minimum; (15) Maximum; (16) Mean; (17) Standard deviation; (19) Spectral entropy; (24) Spectral kurtosis; (38) Kurtosis; (39) Skewness; (40) Median. **Amplitude (2):** (36) Kurtosis; (37) Skewness. **Energy (15)**: (20) Sum; (21) Minimum; (22) Maximum; (23) Mean; Total energy in four bands of frequency-(25) Q1, (26)Q2, (27)Q3, (28)Q4; Energy for frequency in the range of chewing frequency of 1.3Hz to 3Hz – (29)1.3Hz, (30)1.6Hz, (31)1.9Hz, (32)2.1Hz, (33)2.4Hz, (34)2.7Hz and (35)3.0Hz) (23) Concentration measure, CM.	27

3.3 Feature Selection

This work analyzes several feature selection methods to reduce the number of evaluated features and still provide good accuracy, where the implementation is based on features domain and feature importance methods. In the features domain method, the features are selected based on its features domain of either TD, TF, and TFD. For feature importance methods, three types of rank feature ranking method of minimum redundancy maximum relevance (MRMR) algorithm, and diagnostic feature designer MATLAB application; t-Test and receiver operating characteristic curves (ROC). The MRMR is selected as it is one of the commonly used methods for feature selection. Feature ranking using diagnostic feature designer is selected due to ease of use as it is a readily available MATLAB application. In the applications, two types of classification ranking of t-test and ROC are used as it suits the problem of classifying two activities and related to accuracy evaluation, respectively.

4. Results & Discussion

The results are presented based on further analyzing the bandpass filter parameter setting of [21] to find optimal accuracy. Besides that, the addition of a feature selection method will provide information on the possibility of reducing evaluated features and identifying them accordingly.

4.1 Classification Accuracy Based on The Variation of A Bandpass Filter Parameter

Previous work on the same study had used the bandpass filter of [0.5Hz, 5Hz] using a default steepness of 0.85, gives an accuracy of 97.3%, which will be used as the baseline. Each of the steepness values of 0.7, 0.75, 0.8, 0.85, and 0.9 pair with a lower cut-off frequency of 0.5Hz, 1.0Hz, and 1.2Hz. All features will be extracted according to the parameters' value, and accuracy is obtained using the Classification Learner. The accuracy of the chewing detection systems based on the combination of different Fc1 and steepness values is shown in Table 2. The results of the combination of bandpass filter parameters are shown in Fig. 7. By observing the pattern of the results, 0.5Hz gives the lowest accuracy, which in the range of 97% compared to others Fc1. The combination between 1Hz and 1.2Hz with a variation of steepness value gives comparable results, as most of them are around 98%. The combination of Fc1 of 1Hz and steepness of 0.8 had given the highest accuracy of 98.5%. Comparing the result to the previous work by changing the Fc1 from 0.5 Hz to 1Hz while maintaining other parameters gives an accuracy of 98%, which improves the accuracy by 0.7%. Next, changing the bandpass filter's steepness from 0.85 to 0.8 gives an accuracy of 98.5%. Overall, this work had improved the accuracy compared to the previous study by 1.2% by changing the bandpass filter parameter value. Additionally, the support vector machine (SVM) gives the highest accuracy for all combinations of bandpass filter parameters.

Table 2 - The accuracy of the chewing detection system based on different bandpass filter values

Steepness	Fc1, Hz	Accuracy, %	Classifier
	0.5	97.2	Quadratic SVM
0.7	1.0	97.9	Quadratic SVM
	1.2	98.0	Quadratic SVM
	0.5	97.3	Quadratic SVM
0.75	1.0	98.1	Quadratic SVM
	1.2	97.9	Quadratic SVM
	0.5	97.1	Quadratic SVM
0.8	**1.0**	**98.5**	**Quadratic SVM**
	1.2	98.1	Quadratic SVM
	0.5	97.3	Quadratic SVM
0.85	**1.0**	**98.0**	**Quadratic SVM**
	1.2	98.1	Medium Gaussian SVM
	0.5	97.1	Quadratic SVM
0.9	1.0	98.0	Quadratic SVM
	1.2	98.2	Cubic SVM

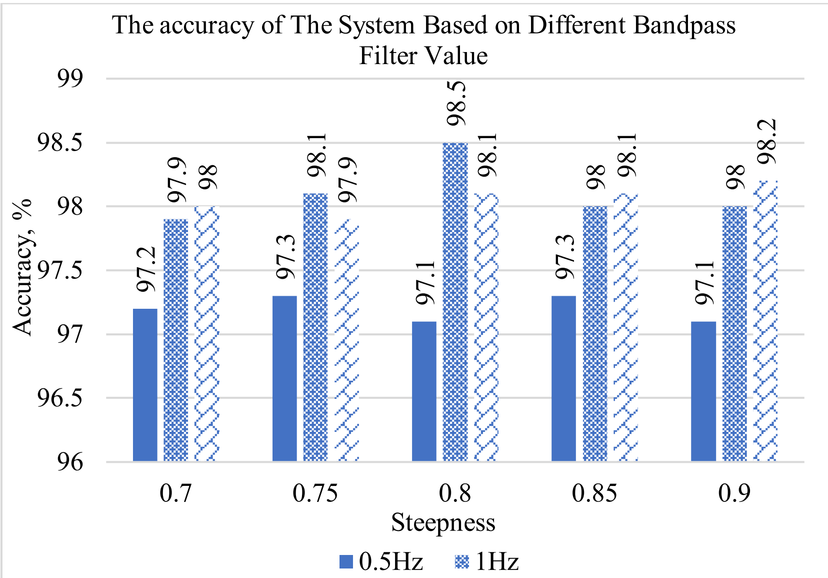


Fig. 7 - The accuracy of the chewing detection system based on different bandpass filter values

4.2 Feature Selection Based on Feature Domain

For this analysis, the features are group based on their feature domain, such as TD, FD, and TFD. t\The chewing detection system's accuracy is obtained based on the evaluated features domain group, either individually or combined. The analysis results are as in Table 3; then, the results are presented in a graph shown in Fig. 8. The system's accuracy based on the features domain group of TD, FD, and TFD is given by 95.8%, 85.8%, and 95.3%, respectively. While the combination of TD & FD, TD & TFD, and FD & TFD gives accuracy of 98%, 96.8% and 96.8%, respectively. Based on an individual group of a domain, TD gives the highest accuracy using fewer features. Overall, the combination of TF and FD gives the highest accuracy of 98% using 13 features; the accuracy is slightly reduced by 0.5% than the accuracy of using all 40 features. Eventhough this method could provide good accuracy; it identifies the specific features that contribute to the accuracy.

Table 3 - The accuracy of the chewing detection system based on different features domain

Features	No. of Features	Accuracy, %	Classifier
TD	10	95.8	Quadratic SVM
FD	3	85.8	Quadratic SVM
TFD	27	95.3	Ensembled Bagged Trees
TD & FD	13	**98.0**	Cubic SVM
TD & TFD	37	96.8	Ensembled Boosted Tree
FD & TFD	30	96.8	Quadratic SVM
All Features (TD,FD,TFD)	**40**	**98.5**	**Quadratic SVM**

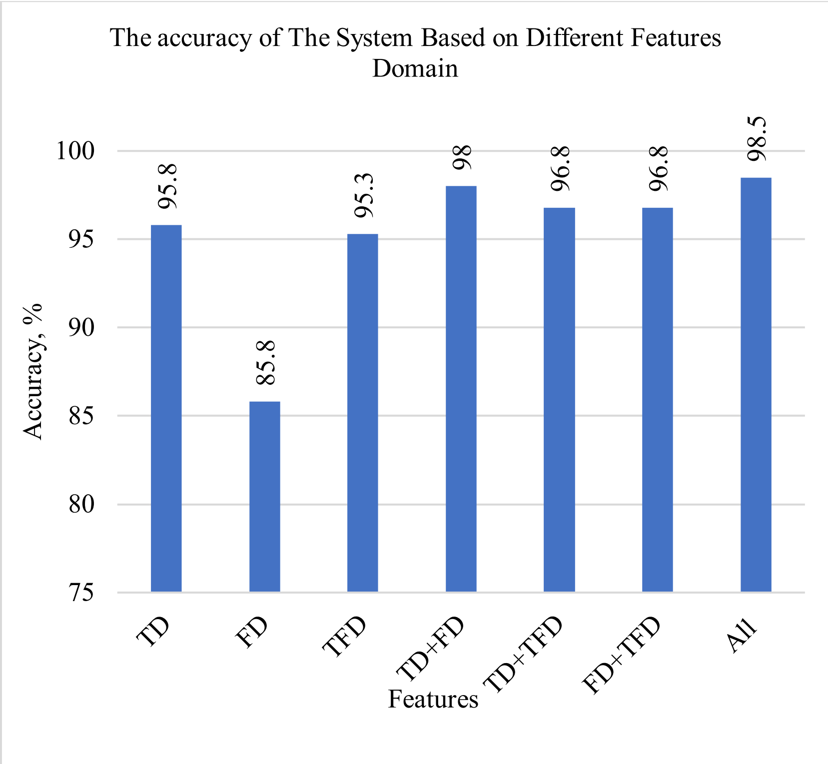


Fig. 8 - The accuracy of the chewing detection system based on different features domain

4.3 Feature Selection Based on Features Ranking (Importance)

This analysis identifies and selects the most valuable features that could provide a good accuracy by using fewer features. It works by ranking the features according to their importance, helping to reduce the number of evaluated features and eliminated redundant features. Three feature selection methods based on feature ranking are used for this analysis: minimum redundancy maximum relevance (MRMR) algorithm and diagnostic feature designer MATLAB application based on t-Test, and receiver operating characteristic curves (ROC). For a fair comparison, the same number of features of 10 and 20 for all three methods are evaluated for classification accuracy. The features number represented by 25% and 50% from the overall number of features. The accuracy for all methods is shown in Table 4, and the graphical representation of the results as in Fig. 9.

The accuracy of using 10 features is 98.2%, 85.8%, and 98% for MRMR, t-Test, and ROC, respectively. While the accuracy of using 20 features is 98.3%, 97.9%, and 98.3% for MRMR, t-Test, and ROC, respectively. As the features number increases from 10 to 20, the accuracy of using MRMR and ROC methods increases by 0.1% and 0.3%, respectively. The t-test shows a significant increase of 0.9%. Among all methods, MRMR gives the highest accuracy for both 10 and 20 features. However, increasing the feature number contribute to a slight increase of 0.1% for MRMR.

By observing the overall results, all accuracy in the results is contributed by the SVM classifier. Next, the selected features and their sequence is not the same for a different method. The accuracy of using all 40 features is given by

98.5%. Then by implementing the features selection method of MRMR, the feature could be reduced to 10 or 20 with a comparable accuracy of 98.2% and 98.3%. The accuracy slightly reduces by 0.3% and 0.2% if 10 and 20 features is selected using MRMR.

Table 4 - The accuracy of the chewing detection system based on different feature ranking methods

Features Selection	No. of Features	Features number in its sequence of importance										Accuracy, %	Classifier
mRmR	10	10	26	24	12	29	8	11	9	22	16	**98.2**	Quadratic SVM
	20	30	33	2	31	13	5	40	1	15	18	**98.3**	Quadratic SVM
t-Test	10	11	10	13	29	7	4	30	18	1	33	85.8	Quadratic SVM
	20	3	5	9	24	31	2	20	21	22	23	97.9	Quadratic SVM
ROC	10	10	11	6	7	13	4	18	16	17	15	98.0	Cubic & Quadratic SVM
	20	29	1	3	2	30	40	9	5	14	33	**98.3**	Cubic SVM

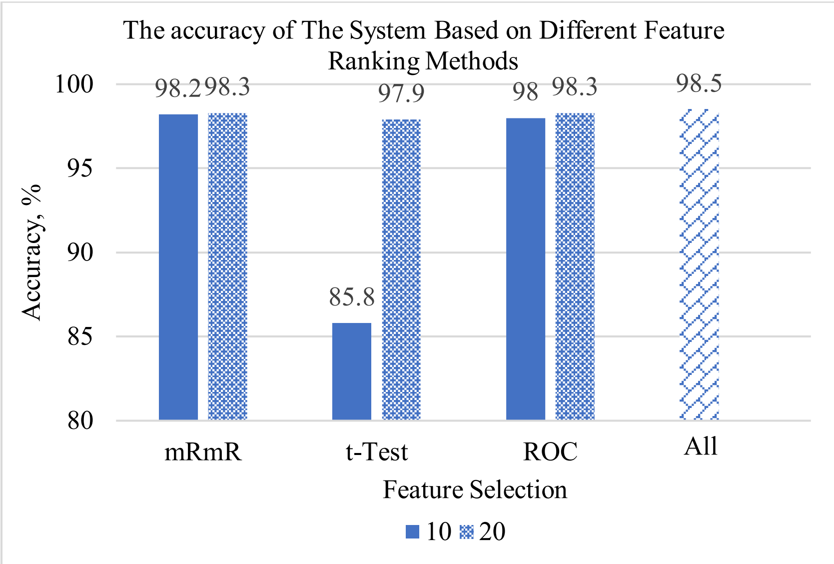


Fig. 9 - The accuracy of the chewing detection system based on different feature ranking methods

5. Conclusion

This work had presented the analysis of implementing the features selection method to the new approach of food intake detection based on chewing activity. As an extended paper, most of the data collection model, signal processing, cross-validation methods, classification method, validation method, and parameter set up is the same as the previous work, unless stated. The previous study has given an accuracy of 97.3% with Fc1 = 0.5Hz, Fc2 =5Hz, and steepness of 0.85. By varying the combination of bandpass filter values, using the Fc1 = 1Hz, Fc2 =5Hz, and steepness of 0.8, this paper had an accuracy of 98.5%.

This paper aims to analyze the effect of using the feature selection method in selecting fewer features and observed the effect on the system's accuracy. The feature selection method of the feature domain and feature ranking is considered. The accuracy of using all 40 features that are 98.5%, is used as the baseline. Feature domain methods select the features according to their domain type, of which the accuracy is obtained by either individual or combined. Individually the TD gives the highest accuracy of 95.8% (10 features), while the combination of TD and FD gives the highest accuracy of 98% (13 features). This method could provide a good result of 98% with a lesser feature (13 features). However, this is a trial-and-error method that might time consuming.

Additionally, it does not provide or identify which features more important than the others and does not eliminate the redundant features. The feature selection based on the features ranking of MRMR and the diagnostic features of the t-test and ROC is implemented. To be fair, the same feature numbers of 10 and 20 is selected. MRMR gives the highest accuracy of 98.2% and 98.3% for 10 and 20 features, respectively. It could observe that by adding another 10 features to MRMR, the accuracy only improved by 0.1%. Hence, it depends on the requirement of the system, which is more important, either the 0.1% accuracy or lower computational time by reducing the features to be evaluated.

In conclusion, a good combination of bandpass filter parameters does improve the chewing detection systems' accuracy, and the feature selection method helps reduce the feature number to be evaluated. Additionally, the feature selection method might require the user's decision to select more features to increase the accuracy by 0.1% or minimize the computational time by choosing fewer features. Most of the accuracy in this paper is based on the SVM classifier.

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References

[1] Bedri A, Haynes M, Kosaraju RP, Grover I, Prioleau T, Beh MY, Goel M, Starner T, Abowd G (2018). EarBit: Using Wearable Sensors to Detect Eating Episodes in Unconstrained Environments. In: Proc ACM Interact Mob Wearable Ubiquitous Technol. p 30

[2] Bedri A, Verlekar A, Thomaz E, Avva V, Starner T (2015). Detecting Mastication - A Wearable Approach. In: ICMI '15. pp 247–250

[3] Bi S, Wang T, Davenport E, Peterson R, Halter R, Sorber J, Kotz D (2017) Toward a Wearable Sensor for Eating Detection. In: Proceedings of the 2017 Workshop on Wearable Systems and Applications - WearSys '17. p 6

[4] Bi S, Wang T, Tobias N, Nordrum J, Wang S, Halvorsen G, Sen S, Peterson R, Odame K, Caine K, Halter R, Sorber J, Kotz D (2018) Auracle: Detecting Eating Episodes with an Ear-mounted Sensor. In: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies. p 27

[5] Chun KS, Bhattacharya S, Thomaz E (2018). Detecting Eating Episodes by Tracking Jawbone Movements with a Non-Contact Wearable Sensor. In: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies. p 21

[6] Chung J, Chung J, Oh W, Yoo Y, Lee WG, Bang H (2017). A glasses-type wearable device for monitoring the patterns of food intake and facial activity. Sci Rep 7:8. doi: 10.1038/srep41690

[7] Farooq M, Sazonov E (2016). A novel wearable device for food intake and physical activity recognition. Sensors (Switzerland) 16:13. doi: 10.3390/s16071067

[8] Farooq M, Sazonov E (2016). Automatic Measurement of Chew Count and Chewing Rate during Food Intake. Electronics 5:14. doi: 10.3390/electronics5040062

[9] Farooq M, Sazonov E (2017). Segmentation and Characterization of Chewing Bouts by Monitoring Temporalis Muscle Using Smart Glasses with Piezoelectric Sensor. IEEE J Biomed Heal Informatics 21:1495–1503. doi: 10.1109/JBHI.2016.2640142

[10] Farooq M, Sazonov E (2018). Accelerometer-Based Detection of Food Intake in Free-Living Individuals. IEEE Sens J 18:3752–3758. doi: 10.1109/JSEN.2018.2813996

[11] Fontana JM, Sazonov ES (2012). A robust classification scheme for detection of food intake through non-invasive monitoring of chewing. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS. pp 4891–4894

[12] Gao Y, Zhang N, Wang H, Ding X, Ye X, Chen G, Cao Y (2016). IHear Food: Eating Detection Using Commodity Bluetooth Headsets. In: Proceedings - 2016 IEEE 1st International Conference on Connected Health: Applications, Systems and Engineering Technologies, CHASE 2016. pp 163–172

[13] Hossain D, Imtiaz MH, Sazonov E (2020). Comparison of wearable sensors for estimation of chewing strength. IEEE Sens J 1748:9. doi: 10.1109/jsen.2020.2968009

[14] Lee K (2017). Food Intake Detection Using Ultrasonic Doppler Sonar. IEEE Sens J 17:6056–6068

[15] Liu J, Johns E, Atallah L, Pettitt C, Lo B, Frost G, Yang GZ (2012). An intelligent food-intake monitoring system using wearable sensors. In: Proceedings - BSN 2012: 9th International Workshop on Wearable and Implantable Body Sensor Networks. pp 154–160

[16] Nyamukuru MT, Odame KM (2020). Tiny Eats: Eating Detection on a Microcontroller. In: 2020 IEEE Second Workshop on Machine Learning on Edge in Sensor Systems (SenSys-ML). p 5

[17] Papapanagiotou V, Diou C, Zhou L, Van Den Boer J, Mars M, Delopoulos A (2016). A novel approach for chewing detection based on a wearable PPG sensor. In: Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS. pp 6485–6488

[18] Po JMC, Kieser JA, Gallo LM, Tésenyi AJ, Herbison P, Farella M (2011). Time-frequency analysis of chewing activity in the natural environment. J Dent Res 90:1206–1210. doi: 10.1177/0022034511416669

[19] Sazonov ES, Fontana JM (2012) A Sensor System for Automatic Detection of Food Intake Through Non-Invasive Monitoring of Chewing. IEEE Sens J 12:1340–1348

[20] Selamat NA, Ali SHM (2020). Automatic food intake monitoring based on chewing activity: A survey. IEEE Access 8:48846–48869. doi: 10.1109/ACCESS.2020.2978260

[21] Selamat NA, Md Ali SH (2021). A Novel Approach of Chewing Detection based on Temporalis Muscle Movement using Proximity Sensor for Diet Monitoring. In: 2020 IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES). pp 12–17

[22] Subhi MA, Ali SH, Mohammed MA (2019). Vision-Based Approaches for Automatic Food Recognition and

Dietary Assessment : A Survey. IEEE Access 7:35370–35381. doi: 10.1109/ACCESS.2019.2904519

[23] Taniguchi K, Chiaki H, Kurosawa M, Nishikawa A (2017) A novel earphone type sensor for measuring mealtime: Consideration of the method to distinguish between running and meals. Sensors (Switzerland) 17:14. doi: 10.3390/s17020252

[24] Wang S, Zhou G, Ma Y, Hu L, Chen Z, Chen Y, Zhao H, Jung W (2018). Eating detection and chews counting through sensing mastication muscle contraction. Smart Heal 9–10:179–191. doi: 10.1016/j.smhl.2018.07.004

[25] Zhang R, Amft O (2018) Monitoring Chewing and Eating in Free-Living Using Smart Eyeglasses. IEEE J Biomed Heal Informatics 22:23–32. doi: 10.1109/JBHI.2017.2698523

[26] Zhang R, Bernhart S, Amft O (2016). Diet eyeglasses: Recognising food chewing using EMG and smart eyeglasses. BSN 2016 - 13th Annu Body Sens Networks Conf 7–12. doi: 10.1109/BSN.2016.7516224

[27] Zhang S, Zhao Y, Nguyen DT, Xu R, Sen S, Hester J, Alshurafa N (2020). NeckSense: A Multi-Sensor Necklace for Detecting Eating Activities in Free-Living Conditions. In: Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies,. p 26