Have Your Cake and Log it Too: A Pilot Study Leveraging IMU Sensors for Real-time Food Journaling Notifications

Arpita Kappattanavar[a,*], Marten Kremser[b,*] and Bert Arnrich[c]
Digital Health - Connected Healthcare, Hasso-Plattner-Institut, University of Potsdam, Germany

Keywords: Eating Activity, Classification, Notification, Real-time.

Abstract: To monitor diet, nutritionists employ food journaling approaches, which rely on the subject's memory. Accordingly, a real-time reminder during eating can help subjects adhere to a journaling routine more strictly. Although previous works used sensors to detect eating activities, no study accounted for the time impact of delivering notifications. Our study presents an approach to notify subjects for food journaling within three to six minutes from eating. We achieved this by collecting wrist motion data using an inertial measurement unit. Twenty-two features were extracted from the collected data. Those were used as input to a random forest model to classify an eating activity. To train and test the model, we collected data from four subjects in a semi-controlled environment and daily life. The f1-score for testing data was between 0.74 to 0.78 for four subjects, but they still received notifications for all meals. Additionally, we tested this approach with data collected for one and a half days from a new subject. We observed notifications for four out of five meals. The robust detection criterion reduced the false notifications. Our pilot study results suggest that considering the delivery time of notification can lead to better food journaling

1 INTRODUCTION

According to the World Health Organization fact sheet, the number of people with diabetes rose from 108 million in 1980 to 422 million in 2014 (WHO, 2021). The prevalence of diabetes has increased rapidly in low and middle-income countries and is a significant cause of amputation of lower limbs, blindness, heart attack, and kidney failure. The majority of people have Type 2 diabetes, which can be prevented, or its onset delayed, by maintaining normal body weight with healthy diet and physical activity (WHO, 2021). A healthy diet requires monitoring food intake frequency, the quantity, and what is eaten (Bedri et al., 2017). To monitor diet, nutritionists employed self-reporting tools and food diaries, which answer these questions by relying on subjects' memory. In the study conduct by Helander, E., et al., only 2.58% out of 189,770 users who downloaded 'The Eatery' application were active in food journaling (Helander et al., 2014). These methods of food journaling are prone to errors, as people tend to forget the food consumed on stressful days (Shim et al., 2014; Thompson et al., 2010). Some studies do offline eating activity classification using different sensors, but they do not send reminders in real-time for food journaling (Bedri et al., 2017; Biallas et al., 2015; Dong et al., 2009; Dong et al., 2013; Amft et al., 2005). Hence, we do this study to develop a mechanism to remind people to adhere to food journaling by sending real-time notifications to the smartphones of the subject within 3-6 minutes of the start of their food consumption.

We accomplish our aim of notification by first collecting wrist motion tracking Inertial Measurement Unit (IMU) data, extracting 22 best features from the collected data, and using these features as input to Random Forest (RF) model for classifying eating activity to other activities. Finally, to reduce false-positive and false-negative notifications, a detection criterion (a threshold which is applied to the output of the RF model to identify two consecutive peaks to send notifications) is applied to send correct reminders to the subject for food journaling.

The organization of this paper is as follows: in Section II, we present the state of the art and its limitations. Section III introduces the data collection protocol, preprocessing and feature engineering techniques, classification models, and real-time im-

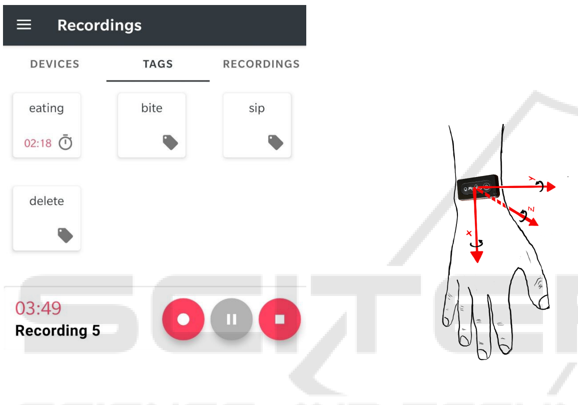
[a] https://orcid.org/0000-0002-7322-0704
[b] https://orcid.org/0000-0002-6907-3158
[c] https://orcid.org/0000-0001-8380-7667
*These authors contributed equally

Kappattanavar, A., Kremser, M. and Arnrich, B.
Have Your Cake and Log it Too: A Pilot Study Leveraging IMU Sensors for Real-time Food Journaling Notifications.
DOI: 10.5220/0010845500003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 5: HEALTHINF*, pages 532-541
ISBN: 978-989-758-552-4; ISSN: 2184-4305

plementation of eating activity detection. In section IV, we present the results of preprocessing, feature engineering techniques, and model performance. In Section V, we discuss the results and methods applied. Finally, in Section VI, we conclude and provide an outlook on our future work.

2 RELATED WORK

The early works on eating activity classification included offline intake gestures in the lab and daily life. The data in these works were collected using sensors placed on the neck, ears, upper and lower arms (Bedri et al., 2017; Biallas et al., 2015; Dong et al., 2009; Dong et al., 2013; Amft et al., 2005).



(a) (b)

Figure 1: Sensor Setup used for data collection. (a) SensorHub application for tagging and (b) GaitUp tri-axis IMU sensors placement on the wrist.

There are very few studies that have worked on the real-time classification of eating activity in the daily life. Sougata Sen et al. worked on Annapurna, which is an automated eating journal that detects eating activity gestures on a smartwatch using the inbuilt accelerometer and gyroscope sensor data and triggers the smartwatch to take images of the food (Sen et al., 2018). This work extracted more than 30 features from the raw data for every 500 msec, and the authors have not mentioned the details. They then trained the model on a decision tree, RF and support vector machine, which had a false positive of 6.5% and a false negative of 3.3%. Nevertheless, capturing images could be a privacy concern in monitoring eating activity.

Simon Stankoski et al. also carried out real-time eating activity detection using a tri-axis accelerometer, and gyroscope in their work (Stankoski et al., 2020). They collected data from 10 subjects in real life. They used three stages to provide the results. In the first two stages, they trained the machine learning algorithm (RF), which had many false positives. In the third stage, they used the hidden markov model to smoothen the prediction. They achieved a precision of 0.7 and a recall of 0.83 by using 60 features. Training three models on the smartphone increases the complexity of the algorithm. Moreover, they do not report the time taken by the algorithm to detect the eating activity.

In our study, we do real-time eating activity detection classification using a single RF classifier with 22 features. We also send real-time notifications to the subject within 3-6 minutes of eating start for food journaling. The correct notification is sent by applying detection criteria to the output of the classifier.

3 METHODS

This Section provides the information on the sensor setup used to collect the data, the data collection protocol, and the steps followed in preprocessing. We further explain the different approaches to extract and select features, the eating activity classifier, and finally introduce the real-time implementation.

3.1 Sensor Setup

To collect the data and provide real-time notifications to the subjects, we used the sensorHub an internally developed application. This application facilitates the collection of data from different sensors on one application. It has a backend server and dashboard to store and retrieve collected data. The application also has a tag functionality to label events. We utilized this application to collect GaitUp IMU sensors tri-axis accelerometer and gyroscope data at a sampling rate of 64 Hz. Figure 1 presents the sensorhub application along with the location of IMU placement on the wrist. We used GaitUp sensors as it has sufficient battery life, Bluetooth functionality to transfer collected data to the sensorHub application, and the data quality has been verified in previous studies (Zhou et al., 2020). Nonetheless, smartwatches will be considered in the future studies as they have integrated IMU sensors and also allows onboard data collection and processing.

We further extended this application within the scope of this paper to perform real-time notification by introducing machine learning for eating activity classification. We also retrieved the data collected from the sensors and machine learning output on the backend server.

3.2 Study Protocol

To test and train RF model, we collected data in the controlled environment to detect food intake gestures and in the semi-controlled environment to collect daily life data. Finally, a third experiment was performed to evaluate the accuracy of the device to detect eating activities, the details of which are in Section 3.6

3.2.1 Food Intake Gesture Data

This data was collected while the subjects had a meal to detect food intake gestures. Food intake gesture (Bite) involves the movement of the dominant hand from plate to mouth and back and is as presented in Figure 2 (Dong et al., 2009). Seven subjects participated in this study. One of the experimenters stayed with the subjects during these meals and recorded each gesture manually using the sensorHub application's tag functionality. Tag functionality is presented in Figure 1 a. We recorded the data for 13 meals. The subjects in these recordings used a spoon, fork, or knife to eat 11 meals. They ate two other meals using chopsticks and hands. The mean time for eating the meal by the seven subjects was 9.8 minutes. The mean number of food intake gestures during the recording was 38.5.

3.2.2 Semi-controlled Environment Data

The data was collected using the sensors mentioned in the Sensor Setup in a semi-controlled environment by four subjects (two male and two female). The subjects used sensorHub application to collect the data and tag the label while eating meals in their personal spaces. All subjects wore the sensor on their dominant hand. We asked the subjects participating in the experiment to collect data that included 45 minutes of different activities (home office, cleaning the house, resting, shopping, walking, and chatting (either seated or standing)) before and after the meal, along with the mealtime in their private spaces. The collected data set contained 52 hours of data, which included 4 hours of eating. We used this data for training, testing, and tuning hyperparameters of the RF model and for training the real-time RF model on the smartphone for notifications.

3.3 Preprocessing

3.3.1 Filtering

Filtering of the IMU data was performed to reduce the noise caused due to high-frequency signals and dynamic body movements. Butterworth and Gaussian filters were applied.

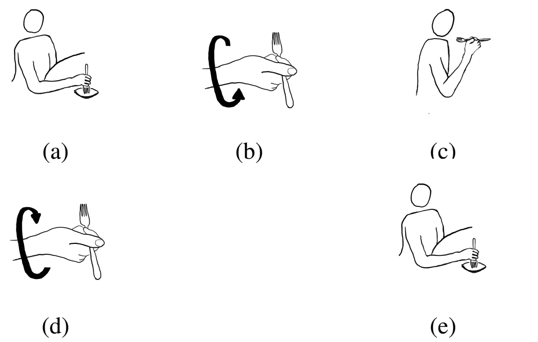


Figure 2: The wrist roll pattern for food intake. (a) Pick the food, (b) Movement from plate to mouth, (c) Food placed in the mouth, (d) Movement back to plate, (e) Hand at rest.

Butterworth Filtering: The accelerometer data was filtered using Butterworth low pass filter at a cutoff frequency of 1Hz and filter order of 5 to get the orientation data (Stankoski et al., 2021). Parallelly, the same data was band pass filtered between 2 and 8 Hz to get dynamic movements performed by the hand. The gyroscope data was only low pass filtered below 2Hz, to remove high-frequency noise (Gallego et al., 2010). The filtered tri-axis accelerometer and gyroscope signal magnitudes were also calculated (Kappattanavar et al., 2020).
Gaussian Filtering: To smoothen the x-axis gyroscope signal, a Gaussian filter with a window size of 128 and a standard deviation of 20 was used (Dong et al., 2009; Dong et al., 2013).

3.3.2 Intake Gesture Algorithm

The Gaussian filtered gyroscope data is the input to this algorithm. We modified the original (Dong et al., 2009; Dong et al., 2013) bite detection algorithm using the x-axis gyroscope data and a different threshold to detect the intake gesture. The food intake gesture is presented in Algorithm 1.

In Algorithm 1, Vt measured angular velocity of gyroscope x-axis data at time t, $T1$ is the threshold in deg/s which detects roll motion while moving the hand from plate to the mouth, $T2$ is the threshold in deg/s which detects the roll motion when moving the hand from the mouth back to the plate, $T3$ is the threshold in seconds to detect the wrist motion while putting food into the mouth, and $T4$ is the threshold in seconds to detect hand resting before the start of the next intake gesture.

The algorithm detects an intake gesture from a negative gyroscope x peak (T1), by a short break of putting food into the mouth (T2), a positive gyroscope x peak (T3), followed by a long break of resting the

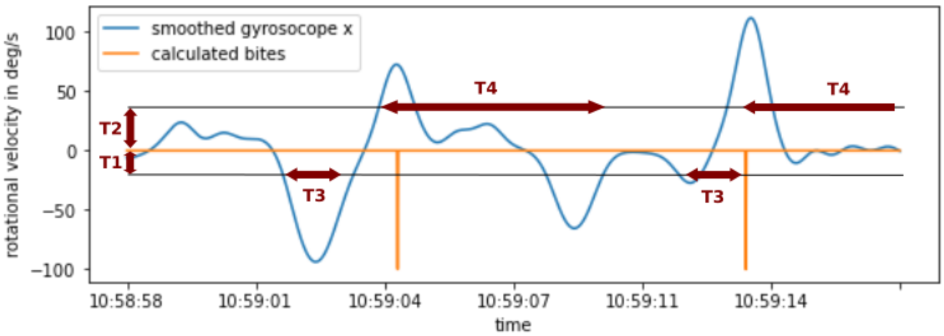


Figure 3: Gaussian filtered gyroscope-x signal with threshold for intake gesture (bite).

Algorithm 1: Intake Gesture Algorithm.

Result: Intake gesture detected
Input: Smoothened gyroscope-X ($GyrX$);
for i *in* $GyrX$ **do**
  Vt= $GyrX[i]$
  if $Vt < -T1$ *and* $EVENT = 0$ **then**
    $EVENT = 1$
    Let s = t
  if $Vt > T2$ *and* $t - s > T3$ *and* $EVENT = 1$ **then**
    Intake gesture detected
    Let s = t
    $EVENT = 2$
  if $EVENT = 2$ *and* $t - s > T4$ **then**
    $EVENT = 0$

hand near the plate (T4), which we have presented in the Figure 3. We ran the algorithm for T1 = 15, T2 = 35, T3 = 1.5, T4 = 5 using trial and error method.

3.3.3 Segmentation

We windowed the Butterworth filtered signals and the magnitude calculated signal into 20 seconds segments to extract features. These windows were overlapped at 80% (Sen et al., 2018; Stankoski et al., 2020). The output of the intake gesture algorithm is windowed at 20 seconds with 80% overlap, plus 20 seconds of data were added both at the beginning and in the end, resulting in a window size of 60 seconds for each of the intake gesture detected data. This was carried out as the larger window provided us additional information about the periodicity and density of food intake gestures (Sen et al., 2018).

3.4 Feature Engineering

In this Section, we introduce the feature extraction performed using libraries and from the intake gesture algorithm. We further explain two methods utilized for feature selection.

3.4.1 Feature Extraction

Library Extracted Features: We extracted features from the 20 seconds window in the time domain, frequency domain, and statistical domain using the python library TimeSeriesFeatureExtractionLibrary (TSFEL) (Barandas et al., 2020).
Intake Gesture Features: From the output of the intake gesture algorithm, we extracted features for 60 seconds window. The features extracted were the number of intake gestures, mean, and variances in the distance between the gestures.

3.4.2 Feature Selection

Many input features result in considerable computational inefficiency for the training of machine learning models (Guyon and Elisseeff, 2003; Stankoski et al., 2020). Therefore, we used the following methods to reduce the number of features:
Correlation Technique: We calculated the correlation between all the features. We selected the signal pairs which correlated greater than 0.8. For each of the signals in the pair, we calculated the Mutual Information (MI) in regard to the label. We discard one of the signals from the pair which had lower MI with the label (Stankoski et al., 2021).
Recursive Feature Selection Method: A set of well-performing features was constructed by recursively selecting the best feature added to the set (Guyon and Elisseeff, 2003). The process starts with no features selected and trains and evaluates the RF model for all single features. First, a single feature that allowed the model to perform best was selected as the first feature of the final set. Further, we trained the model for all the remaining features in combination with the best feature added in the previous step. The iteration of adding new best features continued until no further addition of a single feature increased model performance. We used the f1-score to evaluate the model performance.

3.5 Random Forest Classifier

Feature selection was performed using the RF model, as this model has performed better in the previous studies (Thomaz et al., 2015). The classification was done by both balanced and unbalanced RF using the Scikit-learn library (Pedregosa et al., 2011).

3.5.1 Validation and Evaluation

The Leave-One-Subject-Out (LOSO) cross-validation is performed on the data set for classification. In this, one test set consists of all data collected by one participant, while the train set consists of the data of all other participants (Stankoski et al., 2020). The Evaluation of the data is done with the confusion matrix using the Scikit-learn library (Buitinck et al., 2013). Here only the f1 score, precision, and recall are used for evaluation.

3.5.2 Detection Criterion

Ten output samples of the classification were windowed with a sliding window of one sample. The window having positive predictions for eight output samples for the eating class is considered as a peak. When a peak is detected, the next peak's search window will start again between 15 output samples (i.e., 60 sec after the detection of the peak) till the 75th output sample (i.e., before 300 sec) from the detected peak sample. The subject gets the notification of the eating activity only when the second peak is detected.

3.6 Real-time Implementation of Eating Activity Detection

SensorHub is an internally developed data collection android application. We extended this application for eating activity detection by introducing real-time machine learning and notification functionality. We present the overview in Figure 4. We used Kotlin programming language with Java libraries for extending the application.

3.6.1 Preprocessing

We used the Java library (Porr, 2021) to implement the filter mentioned in the 3.3.1 Section. We did not have access to all the data during real-time notification. Hence, we used 40 seconds of data to filter. Out of the 40 seconds of filtered data, we used the middle 20 seconds for extracting features. In the Section 5, we have mentioned the reasons for taking the middle 20 seconds of data.

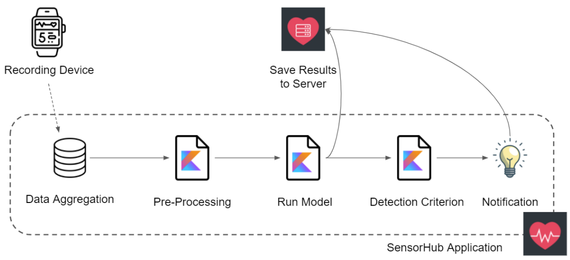


Figure 4: Overview of the real-time classification Sensor Setup.

3.6.2 Feature Extraction

We implemented the shortlisted features from the 3.4.2 Section on the smartphone. Some of these features we implemented using the java library JDSP (Paul, 2020). While few other features we implemented manually based on their implementations in the TSFEL python library, and six features were not at all implemented, the details of which are mentioned in the Section 5.

3.6.3 Model Transfer

We implemented the RF with the best hyperparameter found during the feature selection in 3.4 Section on the android smartphone. We did the implementation using Java, Predictive Model Markup Language (JPMML), and applying JPMML-SkLearn (Ruusmann, 2016), JPMML-Evaluator (Ruusmann, 2014), and JPMML-Android (Ruusmann, 2017) libraries. We trained the model from the data set collected in a semi-controlled environment, and we tested its performance with the data collected in real-time.

3.6.4 Detection Criterion

We follow the same detection criterion procedure followed in 3.5.2 Section to send the notification, but wrote the pipeline in Kotlin and Java programming language. Based on detection criterion, the smartphone sends a notification whenever the eating activity is detected.

3.6.5 Evaluation

In real-time testing, the four subjects who collected data in Section 3.2.2 again collected data in daily life for one recording, each collected for about three hours of data. They also labeled each of their beginning and end of eating using the tag functionality in the application. The subjects also received notifications for food journaling. We used this data only for testing.

The data of the fifth subject was not included in training but used for testing. We collected the data from this subject for one and a half days. The subject was a female with a dominant right hand.

Table 1: Comparison of weight balanced and unbalanced random forest model. Abbreviations: P = Precision, R = Recall, f1 = f1-score, RF = Random Forest, NB = Not Balanced, B = Balanced.

Classifier	P	R	f1
RF (NB)	82.3%	**59.5%**	0.673
RF (B)	**85.4%**	58.2%	**0.678**

4 RESULTS

This section analyses and explores the results of our real-time food journaling notification in intermediate steps. First, we present the filtered output of the intake gesture. Secondly, we present the matrix used to select the model, the hyperparameter tuning results, and give an account of the features selected. Further, we present the evaluation results of the real-time notification.

4.1 Feature Extraction and Model Selection

We present in Figure 3 the Gaussian filtered gyroscope x data and the thresholds applied for intake gesture. We extracted the number of peaks (intake gesture), mean, and variance of the distance between the peaks as the features from the output of the intake gesture algorithm. From the 11 signals which were Butterworth filtered, we extracted 1969 features using TSFEL library.

We implemented the feature selection methods offline to know the best features and extract only these for training and testing in real-time. Initially, we obtained 617 features out of 1969 after the application of the correlation technique to reduce features. We further applied the recursive feature selection method with the balanced and unbalanced weights for the RF model using default parameters present in Scikit-learn libraries. Table 1 presents the f1-score, recall, precision, and the number of features selected for 20 seconds window for the balanced and unbalanced RF model. In Table 1, we observe that the balanced RF model had a higher precision of 85.4% and f1-score of 0.678 when compared to the unbalanced RF model, which had a precision of 82.3% and f1-score of 0.673.

Since the balanced RF had higher precision and f1-score, we further tuned the depths of the tree, and the results are as presented in Table 2. In Table 2 we can observe that the model's performance for the training set increases with an increase in the depth of the tree. We observe a maximum precision value of 87.0% at a depth of 45. The highest recall, 86%, is found at a depth of 5, and the highest f1-score of 0.711 is at a depth of 20. We also notice a trade-off between the depth, the number of features, f1-score, precision, and recall in the test data set. We decided to choose the depth of the model based on the f1-score to train and test. Hence, we chose the model with a maximum depth of 20.

Table 3 presents the 28 best features for the model with a maximum depth of 20. Most of the features derived were either low pass or band pass Butterworth filtered signals from IMU. We also derived one feature from the Gaussian filtered gyroscope-x signal, which was the output of the intake gesture algorithm.

4.2 Model Performance

In the real-time implementation of notification of eating, we implemented only 22 out of the 28 features. F1 score calculated offline after LOSO reduced marginally from 0.711 to 0.696 even after taking out 6 features that were related to Linear prediction cepstral coefficients, Mel frequency cepstral coefficients, and wavelet entropy of the signal. Moreover, in the real-time eating activity notification on the same four subjects, the f1-score was above 0.74, and we present the evaluation results in Table 4. Furthermore, all four received at the right time notification for eating activity (i.e., within 3-6 minutes of the start of the eating activity in real-time) due to the application of detection criteria.

We performed real-time notification testing on the fifth subject for 1.5 days, whose data was used only for testing. We can observe three recordings for the fifth subject in the Figure 5. Recording 0 was the data collection on the first day. Recording 1 and 2 were on the second day. The recordings in the second day were disrupted for a few hours due to the Bluetooth packet loss. The Figures 5 a., c., and e. represent the eating activity classification output (predictions are smoothened only for the graph). Figures 5 b., d., and f. represent the time notifications were sent to the subject after applying the detection criterion (i.e., within 3-6 minutes).

5 DISCUSSION

This section discusses our interpretations and explains the implications of our findings regarding data

Table 2: Results of feature selection method for different maximum depth for random forest using balanced weights.

Maximum depth	Features	Performance on train data			Performance on test data		
		Precision	Recall	f1-score	Precision	Recall	f1-score
5	14	47.5%	91.2%	0.624	47.9%	**86.0%**	0.590
10	25	70.7%	98.8%	0.824	62.7%	79.8%	0.686
15	19	80.4%	99.8%	0.891	70.4%	73.8%	0.706
20	28	88.7%	100%	0.940	78.0%	67.6%	**0.711**
25	25	90.4%	99.9%	0.949	79.0%	65.7%	0.704
30	20	94.9%	99.8%	0.972	82.6%	61.5%	0.687
35	29	98.9%	99.3%	0.993	86.7%	59.8%	0.695
40	27	99.7%	99.8%	0.997	86.1%	58.9%	0.686
45	25	100%	99.9%	0.999	**87.0%**	57.7%	0.680
50	19	100%	99.9%	0.999	85.5%	58.1%	0.678

Table 3: Twenty-eight features selected for training and testing random forest model offline. Abbreviation: LPF = Low Pass Filter, HPF = High Pass Filter, GF = Gaussian Filter, Acc = Accelerometer, Gyr = Gyroscope, Mag = Magnitude.

Filter	Signal	Feature
LPF	Acc X	3rd histogram bucket
		10th histogram bucket
		Peak to peak distance
	Acc Y	3rd histogram bucket
		Median difference
	Acc Z	Maximum
		Spectral roll-on
	Acc Mag	Slope
		Positive turning points
	Gyr X	2nd histogram bucket
		Skewness
		Spectral decrease
		2nd FFT mean coefficient
		5th MFCC coefficient*
	Gyr Y	Area under the curve
		Slope
		8th FFT mean coefficient
	Gyr Z	Spectral positive turning points
		Maximum
		1st FFT mean coefficient
	Gyr Mag	0th LPCC coefficient*
		Spectral decrease
BPF	Acc X	5th MFCC coefficient *
	Acc Y	5th MFCC coefficient*
		5th histogram bucket
	Acc Z	0th MFCC coefficient*
	Acc Mag	wavelet entropy*
GF	Gyr X	Time variance of detected gestures

Note: * Features not included in real-time eating activity classification.

segmentation, feature engineering, model selection, and model evaluation for real-time food journaling.

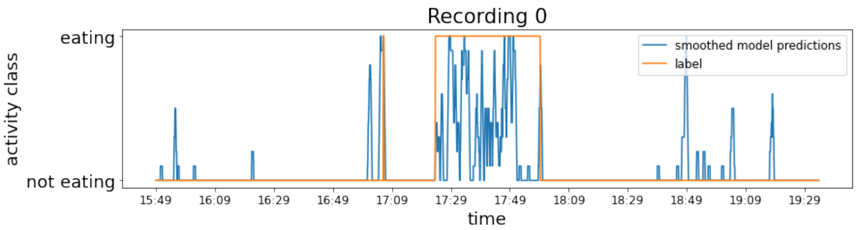
Table 4: Performance of real-time classification during validation recordings.

Recording	Precision	Recall	f1-score
1	62.4%	91.5%	0.742
2	72.7%	80.0%	0.761
3	95.8%	63.0%	0.760
4	72.5%	85.7%	0.785

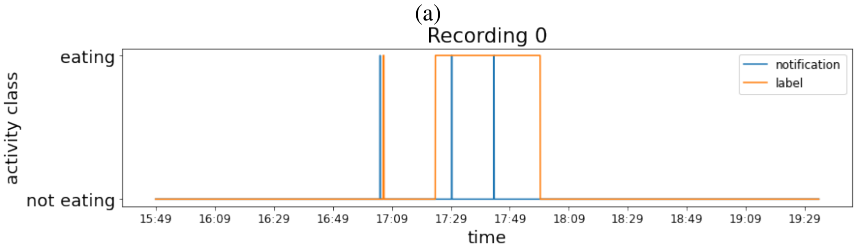
5.1 Preprocessing

All the signals obtained are windowed for different window sizes, including 15 seconds windows, as mentioned in the previous studies (Stankoski et al., 2020). However, the window size of 20 seconds with 80% overlap leads to better identification when compared to the 15 seconds window. We, therefore, used 20 seconds window segments to extract features using the TSFEL library. We filtered 40 seconds of the IMU sensor data in the real-time implementation, as it would take us longer to get more data. However, we used only the center 20 seconds of data to extract features, as filtering signal using the Java library led to distortion in the beginning and end of the signal.

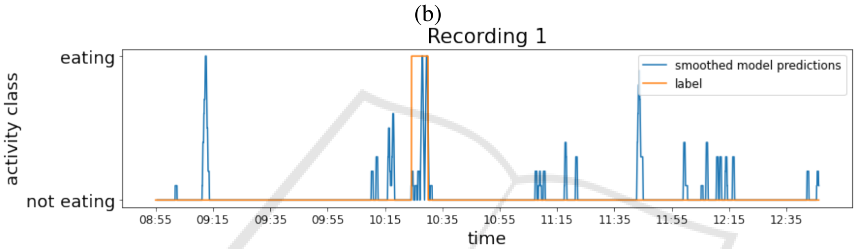
We segmented the output data of the intake gesture algorithm similar to the other signals mentioned above. Additionally, we added 20 seconds of data before and after the selected 20-seconds segment to make 60 seconds window. We did this in contrast to the 20 seconds window, as choosing a larger window for feature extraction can gather additional information about the periodicity and density of bites (Sen et al., 2018). Thus, the time variance between detected gestures extracted in the 60 seconds window is an important feature that was selected in all the models presented in Table 2.



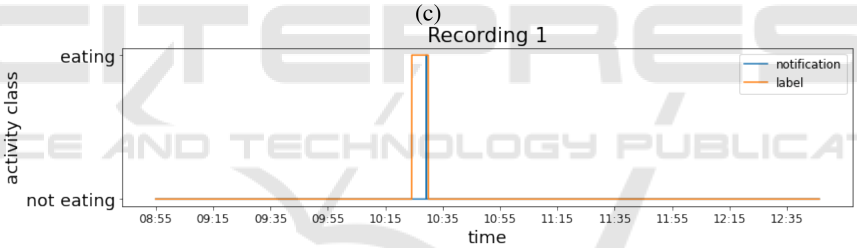
(a)



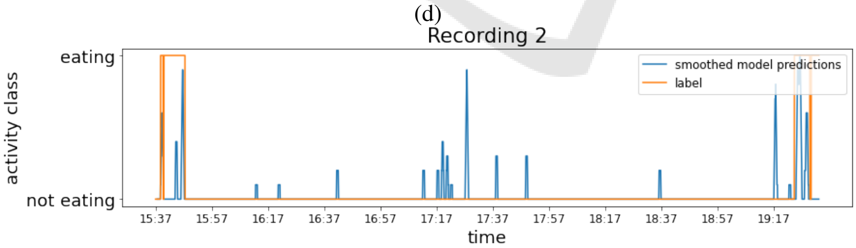
(b)



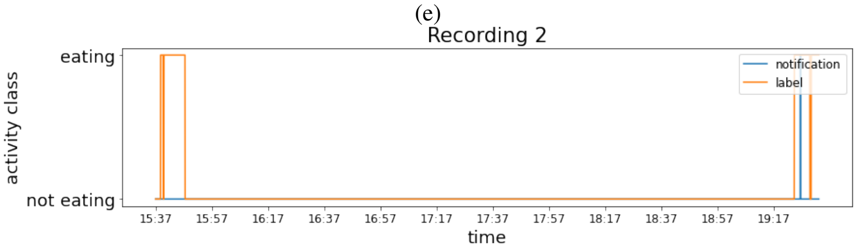
(c)



(d)



(e)



(f)

Figure 5: Outputs of the random forest and the notifications sent for the labels. Figure (a), (c), and (e) are smoothed prediction outputs. Figure (b), (d), and (f) are the notification outputs.

5.2 Feature Engineering

To decrease the computational complexity and improve the performance of the classification algorithm, we performed feature selection using two stages. In the first stage, we used the correlation technique to remove redundant features conveying the same information, which was also used in previous studies (Stankoski et al., 2020). This did not reduce too many features. Therefore, we extended the work to the second stage of feature selection. The feature selection technique required a computational time of 45 hours. This reduced time was achieved by using the correlation technique prior to feature selection.

5.3 Model Selection

Although we trained our data on different models (Quadratic Discriminant Analysis, Ada Boost, K-Nearest Neighbour and Support Vector Machine), we found that the evaluation time and F1 score did not match 3-6 minutes and .71, respectively with that of the RF model. Since our goal was to do real-time notification, we trained on RF as it was also used in the previous literature (Sen et al., 2018; Stankoski et al., 2020).

We train the RF model with and without weight balancing. We understand from the previous studies that when there is an unbalanced data set, balancing could improve the classification performance (Stankoski et al., 2021). Our study has an unbalanced eating activity data set (i.e., 4 hours of eating and 48 hours of non-eating activities). In a direct comparison of Table 4, the weight-balanced model performed better than the unbalanced one. Hence, we considered the weight-balanced model for further parameter tuning.

During the model selection, we chose the model with a maximum f1-score of 0.711 and a depth of 20. We chose a higher f1-score than the models with higher precision and recall, as f1-score is interpreted as a weighted average of precision and recall (Stankoski et al., 2021).

5.4 Real-time Implementation

The RF model with a depth of 20 was used to train the real-time classification and notification algorithm on the smartphone. We trained the model with only 22 features out of 28 best features. Implementing the six features without libraries was complex. Moreover, by not including the six features related to Mel-frequency cepstral coefficients, Linear prediction cepstral coefficients, and wavelet entropy, the f1-score decreased from 0.711 to 0.696. The decrease of 0.015 in the f1-score was not a very significant decrease for the test data.

Figure 5 presents many false positive predictions for the data collected continuously for one and half days. The detection criterion proved successful in transforming the continuous predictions of the RF into a single notification to subjects during their meals. Hence, in the Figure 5 we observe that the labels are longer and the notifications are sent only for few seconds after eating commences. In Figure 5 b. the label is present after notification. Here, the subject had forgotten to label the food. Therefore, she was reminded to label the same after receiving the notification. One of the eating activities, in Figure 5 f., was not recognized, as the subject ate with a spoon and did not have much of the roll motion in hand, while for the rest of the eating periods, she used a fork or hand. Here, we can conclude that people eat differently with different cutlery. Although the system recognized 4 meals out of 5, it still needs more model training due to variations in eating gestures for different food types.

6 CONCLUSION

We present a pilot study to send real-time notifications for food journaling. We accomplish the aim of sending real-time notifications using sensorHub application, which collects the data from the wrist-worn IMU sensor and performs preprocessing of the data on the smartphone. We further extract the 22 best features from the preprocessed data and use it as an input to a RF model for classifying the eating activity. Finally, a detection criterion is applied to reduce false notifications and notify the subjects for food journaling within 3-6 minutes of eating. Therefore, the method is unobtrusive and could be applied in everyday life to track meals and provide treatment reminders to people with diabetes, hypertension, and dementia.

In different cultures, people eat the same food differently by using different utensils or in hand. We can eat wraps/rolls in hand without roll motion or eat with a knife and fork. In this study, we classified the eating activities which involved roll motions. However, in the future, we will incorporate eating activities that do not include wrist-roll movement (wraps/rolls and snacks eaten in hand) to avoid false-negative notifications. Hence, we would consider these cultural aspects of eating and train the model, which includes different hand motions involved in eating. Furthermore, another arena to be considered along with eating activity classification is the classification of drinking habits, such as beverages and alcohol intake.

We can avoid the Bluetooth connection issues between IMU and smartphone by implementing the RF model on the smartwatch. Finally, a further test of the pipeline on more subjects would be required for validating these results.

ACKNOWLEDGEMENTS

We thank all our subjects who gave data for this study. We are grateful to the Federal Ministry of Economic Affairs and Energy for generously funding this project with funding number ZF4776601HB9. We also extend our gratitude to Dr.-Ing.Harry Freitas da Cruz and Pascal Hecker for proofreading the paper.

REFERENCES

Amft, O., Junker, H., and Troster, G. (2005). Detection of eating and drinking arm gestures using inertial body-worn sensors. In *Ninth IEEE international symposium on wearable computers (ISWC'05)*, pages 160–163. IEEE.

Barandas, M., Folgado, D., Fernandes, L., Santos, S., Abreu, M., Bota, P., Liu, H., Schultz, T., and Gamboa, H. (2020). Tsfel: Time series feature extraction library. *SoftwareX*, 11:100456.

Bedri, A., Li, R., Haynes, M., Kosaraju, R. P., Grover, I., Prioleau, T., Beh, M. Y., Goel, M., Starner, T., and Abowd, G. (2017). Earbit: using wearable sensors to detect eating episodes in unconstrained environments. *Proceedings of the ACM on interactive, mobile, wearable and ubiquitous technologies*, 1(3):1–20.

Biallas, M., Andrushevich, A., Kistler, R., Klapproth, A., Czuszynski, K., and Bujnowski, A. (2015). Feasibility study for food intake tasks recognition based on smart glasses. *Journal of Medical Imaging and Health Informatics*, 5(8):1688–1694.

Buitinck, L., Louppe, G., Blondel, M., Pedregosa, F., Mueller, A., Grisel, O., Niculae, V., Prettenhofer, P., Gramfort, A., Grobler, J., et al. (2013). Api design for machine learning software: experiences from the scikit-learn project. *arXiv preprint arXiv:1309.0238*.

Dong, Y., Hoover, A., and Muth, E. (2009). A device for detecting and counting bites of food taken by a person during eating. In *2009 IEEE International Conference on Bioinformatics and Biomedicine*, pages 265–268. IEEE.

Dong, Y., Scisco, J., Wilson, M., Muth, E., and Hoover, A. (2013). Detecting periods of eating during free-living by tracking wrist motion. *IEEE journal of biomedical and health informatics*, 18(4):1253–1260.

Gallego, J. A., Rocon, E., Roa, J. O., Moreno, J. C., and Pons, J. L. (2010). Real-time estimation of pathological tremor parameters from gyroscope data. *Sensors*, 10(3):2129–2149.

Guyon, I. and Elisseeff, A. (2003). An introduction to variable and feature selection. *Journal of machine learning research*, 3(Mar):1157–1182.

Helander, E., Kaipainen, K., Korhonen, I., and Wansink, B. (2014). Factors related to sustained use of a free mobile app for dietary self-monitoring with photography and peer feedback: retrospective cohort study. *Journal of medical Internet research*, 16(4):e109.

Kappattanavar, A. M., Da Cruz, H. F., Arnrich, B., and Böttinger, E. (2020). Position matters: Sensor placement for sitting posture classification. In *2020 IEEE International Conference on Healthcare Informatics (ICHI)*, pages 1–6. IEEE.

Paul, S. (2020). psambit9791/jdsp. https://doi.org/10.5281/zenodo.5137347. Accessed :2021-09-14.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al. (2011). Scikit-learn: Machine learning in python. *the Journal of machine Learning research*, 12:2825–2830.

Porr, B. (2021). An efficient iir filter library written in java. https://github.com/berndporr/iirj. Accessed :2021-09-14.

Ruusmann, V. (2014). Jpmml-evaluator. https://github.com/jpmml/jpmml-evaluator. Accessed :2021-09-14.

Ruusmann, V. (2016). Jpmml-sklearn. https://github.com/jpmml/jpmml-sklearn. Accessed :2021-09-14.

Ruusmann, V. (2017). Jpmml-android. https://github.com/jpmml/jpmml-android. Accessed :2021-09-14.

Sen, S., Subbaraju, V., Misra, A., Balan, R., and Lee, Y. (2018). Annapurna: building a real-world smartwatch-based automated food journal. In *2018 IEEE 19th International Symposium on" A World of Wireless, Mobile and Multimedia Networks"(WoWMoM)*, pages 1–6. IEEE.

Shim, J.-S., Oh, K., and Kim, H. C. (2014). Dietary assessment methods in epidemiologic studies. *Epidemiology and health*, 36.

Stankoski, S., Jordan, M., Gjoreski, H., and Luštrek, M. (2021). Smartwatch-based eating detection: Data selection for machine learning from imbalanced data with imperfect labels. *Sensors*, 21(5):1902.

Stankoski, S., Resçiç, N., Mezic, G., and Lustrek, M. (2020). Real-time eating detection using a smartwatch. In *EWSN*, pages 247–252.

Thomaz, E., Essa, I., and Abowd, G. D. (2015). A practical approach for recognizing eating moments with wrist-mounted inertial sensing. In *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*, pages 1029–1040.

Thompson, F. E., Subar, A. F., Loria, C. M., Reedy, J. L., and Baranowski, T. (2010). Need for technological innovation in dietary assessment. *Journal of the American Dietetic Association*, 110(1):48–51.

WHO (2021). Diabetes. https://www.who.int/news-room/fact-sheets/detail/diabetes. Accessed: 2021-09-06.

Zhou, L., Tunca, C., Fischer, E., Brahms, C. M., Ersoy, C., Granacher, U., and Arnrich, B. (2020). Validation of an imu gait analysis algorithm for gait monitoring in daily life situations. In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*, pages 4229–4232. IEEE.