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Published in:
44th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC): Proceedings

Document Version:
Peer reviewed version

Queen's University Belfast - Research Portal:
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Download date:14. Sep. 2023
A Wearable-based Preventive Model To Promote Oral Health Through Personalized Notification

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Abstract—Wearable technology has great potential to develop human-centric healthcare applications. It reshapes our lifestyle by providing information related to physical activities, sleep monitoring, or heartbeat rhythms. In this paper, we present an innovative model for oral healthcare, which is prevention-focused to notify individuals about cleaning teeth activity. It is based on a wrist-worn accelerometer device and has two components—first, a computationally lightweight feature extractor—secondly, a robust feed-forward neural network to recognize the cleaning teeth activity. The model performance is measured using standard performance metric $F_1$-score (i.e., 98%), which shows the applicability in a real-life scenario. The trained model can reside inside the smartwatch as a wrist-worn wearable. It would generate personalized notifications if s/he skipped the toothbrush activity. Furthermore, it notifies the users to change the toothbrush after three months, reducing the cognitive burden.

Clinical Relevance—This work help the individuals to maintain their oral health using smartwatches as a wearable device.

I. INTRODUCTION

Oral health is essential for personal well-being, which consists of cleaning teeth and gums daily. It helps prevent the accumulation of tartar and bacterial plaque, which might lead to gum disease and tooth decay. According to American Dental Association (ADA), dentists generally recommend brushing teeth activity twice a day for two minutes [1]. However, many people do not fully practice this recommendation or skip the tooth cleaning before bed. According to a report from an adult dental health survey in the United Kingdom (UK), 25% of adults cleaned their teeth less than twice a day [2]. The low frequency of tooth brushing increases oral health problems in older adults. Poor oral health may cause respiratory diseases, cardiovascular diseases, endocarditis, pregnancy, and birth complications [3]. There is a need to develop technology-based effective methods to modify the health risk behaviours in daily routines. To maintain optimal oral health, a preventive model through a personalized notification can provide a sustainable solution and assist individuals in engaging with their oral hygiene. Consequently, it will reduce the dentistry problems financial burden and shift the control from healthcare providers to the individuals.

The wearable technology provides unique opportunities and successfully reshapes personal well-being and healthcare. Several embedded sensors in wearables ranging from the accelerometer, gyroscope, skin conductance, Bluetooth thermometer, and photoplethysmography (PPG) sensors are supporting continuous health monitoring [4]. These wearable sensors are ubiquitous and exist in fitness bracelets, smartphones, smartwatches, jewellery, garments, shoes, etc. An accelerometer sensor is particularly common and used for physical health to recognize daily activities like step counter, walking, jogging, running, etc. There is limited technology to assess the daily routines of teeth cleaning at home. A few technologies exist which are based on accelerometer and gyroscope sensors in a smart electric toothbrush. It helps to provide detailed information about brushing regions, angels, timers or different cleaning modes, etc. It is not a cost-effective solution because the toothbrush needs to be changed frequently [5]. However, the major focus of the developed models is to support toothbrush activity properly.

In contrast, our objective is to assist the individual in fully practising dentists’ general recommendation (i.e., teeth cleaning twice a day) with personalized notification. The motivation behind such research is to provide a simple, robust, and cost-effective solution as a preventive model for oral health. Our proposed preventive model is based on an embedded accelerometer sensor of a wearable (i.e., one of the primary sensors in smartwatch) to detect the teeth cleaning activity. The proposed model is based on a machine learning approach feed-forward neural network to recognize the motion behaviour of the hand. It is an intelligent model to generate the notification in case an individual skips the toothbrush activity. Thus, it promotes self-care, which can help individuals maintain costly and invasive dental treatment in the future and improve the quality of life. Furthermore, it can be easily integrated with the existing healthcare platform, which includes monitoring personal biomarkers such as heart monitoring, body temperature, physical activities, and sleeping patterns in a single platform.

The rest of the paper is organized as follows. Section II describes the related work and background. Section III describes the proposed model with technical details and challenges. The obtained results of the model and discussion details are provided in Section IV. Finally, conclusions are drawn in Section V with possible future extensions.

II. RELATED WORK

The research community has been significantly focused on technology-based solutions for oral healthcare in recent years. The models are developed for teeth cleaning activity over the different sensor modalities, including audio signals, video frames, and wearable sensors. In the early days, Korpela et al. [6] used a smartphone audio signal to recognize
the toothbrush activity. Their method is based on 12-order
Mel-Frequency Cepstral Coefficients (MFCC) features, and
the classification model is based on a statistical technique
Hidden Markov Model (HMM), to recognize the teeth cleaning
activity. Such a solution requires the smartphone in
the vicinity of the washbasin to recognize the teeth brush
activity. Similarly, Marcon et al. [7] developed a model to
analyze the toothbrush motion from a tablet camera and help
children to learn proper tooth brushing. They attached
a simple 3D coloured object at the end of the toothbrush,
and the colour scheme helped to detect different angles
of the toothbrush. For adults, Liang et al. [8] developed
OralCam that enables self-examination and awareness of oral
health using a smartphone camera. They developed a deep
Convolutional Neural Network (CNN) to process the images
for classification and localization of the issues present in the
teeth images.

Akther et al. [3] proposed mTeeth based on a wrist-
worn accelerometer sensor in a free-living environment.
The objective is to ensure that the brush covers all the
teeth surfaces during the teeth cleaning activity adequately.
Their approach is based on the probabilistic graphical model
Hierarchical Bayesian Network (HBN) to train the model.
They also provide the collected dataset with precise labels of
brushing surface timings as well as moments of transition.
Hussain et al. [5] also emphasized the importance of oral
health. Their approach is based on an inertial measurement
unit attached to the handle of the brush and easily detached
or attached with a brush. The objective of the study was
to capture the brush motion behaviour and identify the sub-
activities, and the model was based on the machine learning
technique random forest.

Luo et al. [9] developed a model called Hygiea, which
can monitor tooth brushing activity via a wrist-worn gesture
sensor. Their technique is also based on a deep learning
sequence model, Long-Short Term Memory (LSTM), with
an attention mechanism to detect toothbrush activity. Fur-
thermore, they emphasize the importance and potential of
common wrist-worn devices for a wide range of healthcare
applications. Recently, Mekruksavanich et al. [10] use a
smartwatch sensor for human activity recognition which also
includes the toothbrush activity. The proposed system is
based on a hybrid deep learning model, including LSTM
and CNN.

The developed models support the toothbrush activity
analysis or recognition rather than notifying the individuals
in case of skipping activity. Thus, our developed model
is preventive-focused, and it is based on a multi-layer
perceptron as a feed-forward neural network. It supports
personalized notification to encourage individuals to take
care of their oral health.

III. MODEL AND MATERIALS

The proposed model is presented in Fig. 1. It consists of
an accelerometer sensor of the wearable device on the wrist.
The tri-axial accelerometer signal is pre-processed in
the form of the segment, and computationally lightweight
features are extracted. It becomes the input to our feed-
forward multi-layer perceptron network to recognize the
teeth cleaning activity. The output of the model is used to
generate personalized notifications. The details are provided
as follows.

A. DATASET AND PRE-PROCESSING

We used a public dataset of wrist-worn tri-axial accelerom-
eter signals for human motion primitives’ detection from UCI
Irvine machine learning repository [11] and details can be
found in [12]. The available dataset is sampled over 32Hz
and annotated. It can be used for the creation and validation
of acceleration-based models. We consider the brush teeth
motion primitive from the personal hygiene class to train
our model. A sample acceleration of toothbrush activity is
presented in the following Fig. 2.

The tri-axial accelerometer signal along x, y, and z-axis

In Fig. 2, the vertical axis represents the acceleration, and
the horizontal axis represents the time.

B. FEATURE EXTRACTION

The lightweight features are extracted from the accelerom-
eter signal over a fixed segment of three seconds with a no-
overlapping window. The extracted features are mean (\(\mu\)),
standard deviation (\(\delta\)), median \(\text{Med}\) interquartile (\(IQR\)),
and correlation (\(r(a_i, a_j)\)). The features are extracted using
the following expressions and presented as a feature vector
as shown in Fig. 3.

\[
\mu = \frac{1}{n} \sum_{i=1}^{n} a_i^2
\]

(1)

\[
\delta = \frac{1}{n} \sum_{i=1}^{n} a_i - \bar{a}
\]

(2)

\[
\text{Med} = \frac{\left(\frac{n}{2}\right)^{th} \text{Observation} + \left(\frac{n}{2} + 1\right)^{th} \text{Observation}}{2}
\]

(3)

\[
IQR = Q_3 - Q_1
\]

(4)

\[
r(a_i, a_j) = \frac{\text{Cov}(a_i, a_j)}{\delta_i \delta_j}
\]

(5)
Fig. 3. The feature vector is computed over the accelerometer signal along x, y, and z-axis. In Fig. 3, it presents the feature vector along x, y and z-axis of accelerometer signal. In literature, complex features are extracted from accelerometer signals to classify accelerometer-based motion activities [13]. In the case of teeth brush activity, the above features are sufficient to provide meaningful information to the neural network.

C. NEURAL NETWORK

The designed network is based on a feed-forward multi-layer perceptron to classify the cleaning teeth activity. The architecture of the network is defined as follows:

In Fig. 4, the model consists of three hidden layers with 128, 64, and 32 units, respectively. We used the binary cross-entropy to calculate the loss function and Adam [14] optimizer to converge the network.

In Eq. 6, c represents the two classes either teeth brush activity or not. The model learning rate was set by experiment (i.e., 0.001) and its effect is presented in Fig. 5 (i.e., Result and Discussion Section).

D. PERSONALIZE NOTIFICATION

The user attention is valuable, and notification should be delivered without negative effects. One of the possible ways to generate the notifications is only when needed, which may have a positive effect on the user. To support personalized notification, our model generates the notification only in case the user skips the toothbrush activity. For instance, the user can set the time before going to bed, and the model will send a notification if cleaning teeth activity is missing. The whole model algorithm is presented in the following Algorithm 1.

IV. RESULTS AND DISCUSSION

The experiments are performed on a MacBook Pro machine with a 2.8 GHz Intel Core i7 processor and 16 GB RAM. The model is trained in a Python programming environment using PyTorch library [15]. The wrist-based wearable smartwatch interfaces are developed in Android studio Arctic Fox for Wear OS. The model training and validation are presented in Fig. 5.

The dataset is split into training and test set with 70% and 30%. Furthermore, we also divide the training set into train and validate set with 70%, 30% split. The trained model performance is measured using the four standard metrics, such as accuracy (A), precision (P), recall (R), and F1-score over the test set. The metrics are computed by Eq. 7, 8, 9, and 10.

Where TP, TN, FP, FN is true positives, true negative, false positives, and false negatives. These are calculated using the values of the confusion matrix as presented in Table I.

Algorithm 1 The algorithm for personalized notification.

Input: Accelerometer sensor data (ax, ay, az)
Output: Personalized notification
1: Segment ax, ay, az (3Sec)
2: Feature vector(fv) ← [μ, σ, Med, IQR and r]
3: M = TrainNeuralNetwork (fv, label)
4: run M inside smartwatch
5: Cleaning Teeth (Δmax ← time)
6: if (time > Δmax) then
7: User notification
8: end if
9: days ← Toothbrush purchase date
10: if (days > 90) then
11: User notification
12: end if
TABLE I

THE CONFUSION MATRIX OF CLEANING TEETH ACTIVITY

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted 0</th>
<th>Predicted 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>92</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>124</td>
<td>0</td>
</tr>
</tbody>
</table>

Table I presents our model confusion matrix with actual and predictive values. It correctly predicts the cleaning teeth activity instances and is confused only once. Similarly, negative instances are predicted negative, and only two instances are confused with cleaning teeth activity. The results of performance metrics are reported in Table II.

TABLE II

THE PERFORMANCE METRICS ACCURACY (A), PRECISION (P), RECALL (R), AND F1-SCORE.

<table>
<thead>
<tr>
<th>Cleaning Teeth</th>
<th>A</th>
<th>P</th>
<th>R</th>
<th>F1-score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.99</td>
<td>0.98</td>
<td>0.99</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Table II shows that model achieved a $F_1$-score of 0.98, which makes our model confident to recognize the cleaning teeth activity. The personalized notification is designed and developed in wearable operating system for smartwatches. Fig. 6 presents the setup interfaces for the user to personalize the notification for morning and evening. In case the cleaning teeth activity is missed, it generates an alert to the user as shown in Fig. 7. Furthermore, it also presents an interface to send a notification to change the toothbrush.

**V. CONCLUSION**

Wearable technology has become ubiquitous in our daily life, which provides a sensor platform to numerous health care applications ranging from walking to hearth monitoring. This paper utilizes the existing wrist-worn wearable technology and assists individuals to focus on oral health. The developed model is based on an embedded tri-axial accelerometer sensor of a wearable device. It can generate a personalized notification for the users by asking the time to remind the toothbrush activity in case s/he forget to perform it. Consequently, it helps to maintain personal oral hygiene on a daily basis. In future work, we have a plan to measure the duration of the toothbrush activity and the adoption of such technology for active participants to promote oral health.

**REFERENCES**


