BrushBuds: Toothbrushing Tracking Using Earphone IMUs

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Abstract

Inadequate toothbrushing habits are a leading cause of oral health problems such as tooth decay. Many individuals are uncertain if they are brushing effectively or over-focusing on specific areas. While high-end electric toothbrushes can address these concerns, manual toothbrushes remain widely used due to their simplicity and affordability. In this paper, we introduce BrushBuds, an earphone-based toothbrushing monitoring system aimed at tracking brushing areas, which leverages the ubiquitous presence of earphones to enhance manual toothbrushing. BrushBuds utilizes Inertial Measurement Units (IMUs) in earphones to detect subtle head movements incurred by toothbrushing. By capturing distinct motion patterns specific to brushing for each tooth region, BrushBuds can effectively track the toothbrushing process. Our evaluation demonstrates the feasibility of BrushBuds, showing an average accuracy of 84.3% in identifying six distinct tooth areas. By enhancing manual toothbrushing with IMU sensors in earphones, BrushBuds has the potential to significantly improve oral hygiene practices for a broad range of manual toothbrush users.

CCS Concepts

• **Human-centered computing** → *Ubiquitous and mobile computing design and evaluation methods.*

Keywords

Toothbrushing monitoring; IMUs; Earable devices

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1 Introduction

According to WHO statistics [26], over one-third of the world's population suffers from tooth decay, with the incidence rising notably in low- and middle-income countries. Toothbrushing is an effective method for preventing these conditions. Most dentists recommend people brushing all dental areas for a sufficient duration [1]. On the other hand, overbrushing for extended periods can result in tooth sensitivity and gum recession [1]. While some advanced smart electric toothbrushes offer features such as brushing timers and area detection, a significant portion of the global population continues to use manual toothbrushes. For example, more than 250 million Americans still use manual toothbrushes [31]. Consequently, improving oral hygiene practices for manual toothbrush users remains a critical issue.

Several methods have been explored to enhance manual toothbrushes with toothbrushing monitoring capabilities. Video-based systems [10] employ cameras positioned in front of the user's mouth to capture the overall brushing activity. However, they often encounter obstructions from the hands and mouth, limiting detection accuracy and raising privacy concerns. Audio-based methods utilize toothbrushing sound signals from a nearby smartphone [20] or external earpiece microphones [27] to monitor brushing. Yet, these techniques are susceptible to interference from ambient noise like running water or music [23]. IMUs-based solutions [5, 9, 19] integrate IMUs into manual toothbrushes or use them in wearable devices such as smartwatches to monitor brushing movements. Despite their effectiveness, they can be affected by irrelevant hand movements, limiting users' hand motions and brushing postures [12].

Earphones have gained widespread adoption in recent years. Equipped with sensors like microphones and IMUs, these devices have become integral to many users' daily lives and are highly prevalent. Their sensing capabilities have enabled numerous smart applications, such as health monitoring [22, 30] and enhanced communication [11]. IMUs in earphones, which are low-cost sensors commonly found in commercial earbuds, are promising for capturing head motions. The stable position of the human ear is unaffected by limb movements, allowing the IMU sensors in earphones to naturally capture head motions during toothbrushing. This sensing capabilities inspire us to explore the potential of earable IMUs to enhance manual toothbrushing.

In this paper, we introduce BrushBuds, an earable IMU-based system designed to enhance manual toothbrushing by integrating

Figure 1: BrushBuds uses earphone IMUs to capture subtle head motions for toothbrushing monitoring.

features typically available in high-end electric toothbrushes, *i.e.*, brushing area tracking. Specifically, we divide the mouth into six areas. Since brushing in different areas of the mouth results in distinct head movements and transitions, we extract relevant features from the IMU data and employ learning techniques to identify the corresponding brushing areas. As shown in Fig. 1, when users wear BrushBuds, it can monitor the toothbrushing process with manual toothbrushes.

Developing BrushBuds requires addressing the following challenges. First, because of the interference generated by the magnets of the speakers, very few of the earables in the market are equipped with a magnetometer [15]. Without the magnetic north as a reference, we could not rely on the existing calibration techniques to obtain the accurate head orientation with 6-degree of freedom (DoF) IMUs. Second, because of the slight rotation when the user wears the earbuds at different times, it will lead to random offset in IMU signals. This challenge requires a lot of user data to train a model that can be generalized to different wearing cases, which causes a huge data collection burden for users. Lastly, due to the similarity of head movements when brushing adjacent areas, there may be some ambiguity and occasional outliers in the detection results.

To overcome these challenges, we propose the following technical approaches. First, since the head motions caused by the toothbrushing occur and keep stable within the head's coordinate system, we convert the IMU readings from both earphones to a unified head coordinate system, allowing us to bypass the need for a magnetometer. To achieve this, we perform opportunistic calibration during the static period before toothbrushing by identifying the direction of gravity that aligns with the z-axis of the head coordinate system. However, people often lean slightly forward while brushing their teeth to prevent water from spilling, causing a small angle between gravity and the z-axis of the head coordinate system. To address this, we use data augmentation to randomly rotate the pitch of the head coordinate system by a small angle before opportunistic calibration. After these steps, we can mitigate the variations when the user places the earbuds on their head at different times. Furthermore, we utilize the temporal continuity of the toothbrushing process to refine the detection results, eliminating ambiguous predictions and occasional outliers. A comprehensive evaluation of BrushBuds shows the system's effectiveness in monitoring toothbrushing across six dental areas. To summarize, this paper makes the following contributions:

- To the best of our knowledge, BrushBuds is the first system to monitor toothbrushing using earable IMUs, enhancing manual toothbrushing by providing brushing area tracking, a feature typically found in high-end electric toothbrushes.
- To ensure robust toothbrushing monitoring, we developed a series of technical methods, including opportunistic coordinate calibration, data augmentation, and result refinement.
- We conducted a comprehensive evaluation of BrushBuds, which demonstrated an average detection accuracy of 84.3% for six regions. This system has the potential to significantly improve oral hygiene practices for many users of manual toothbrushes.

2 Related Work

2.1 Toothbruhsing Monitoring

Vision-based solutions utilize cameras to monitor brushing activities [12]. For example, Playful Toothbrush [10] utilized a webcam positioned in front of the user's mouth to track an LED-coded toothbrush extension, assisting users in learning proper brushing techniques. Akifusa et al. [4] integrated a miniature camera into the head of a UV-LED toothbrush to visually assess plaque removal effectiveness in electric toothbrushes. LiT [12] employs dual photosensors in commercial LED toothbrushes for monitoring brushing. Despite their capability to offer visual feedback, these systems can be obstructed by hands and the mouth. Besides, privacy concerns may arise due to the intrusive video recording.

Compared to vision-based approaches, audio-based methods have less privacy concerns. Korpela *et al.* [20] employed hidden Markov models (HMM) to recognize brushing regions using audio collected from nearby smartphones. Ouyang *et al.* [27] utilized two throat microphones and the external microphones of an earphone for toothbrushing monitoring. However, external microphones are easily disturbed by ambient noise [23]. EarSense [29] leverages in-ear audio to identify tooth activities, demonstrating the feasibility of toothbrushing monitoring, although it can only distinguish coarse-grained horizontal areas. ToothFairy [33] explores earphone-reversed signals and constructs an acoustic attenuation model to monitor toothbrushing. Despite achieving fine-grained recognition accuracy, it only performs on outer teeth regions with electric toothbrushes, limiting its applicability for manual ones.

IMUs can be mounted on the toothbrush handle to estimate brushing motions [9]. Li *et al.* [21] attached an IMU sensor and five pressure sensors to the brush handle to estimate brushing regions and forces using Random Forest models. However, integrating IMUs may require to modify the toothbrushes. Another approach is to use the IMU in a smartwatch worn on the user's wrist to monitor the toothbrushing process [5, 23]. Huang et al.[19] employed a Naive Bayes classifier to recognize brushing regions using IMU data from a wristwatch. Hygiea [23] utilizes wrist-worn IMUs to achieve fine-grained toothbrushing activity recognition with an LSTM model. Similarly, mORAL [6] and mTeeth [5] can detect oral health behaviors such as brushing and flossing passively using wrist-worn IMUs. While using wrist-IMUs does not require toothbrush modification, these systems constrain natural brushing posture because IMU data on the wrist is usually interfered with by hand motions. BrushBuds utilizes earable IMUs, which captures the inherent head motions

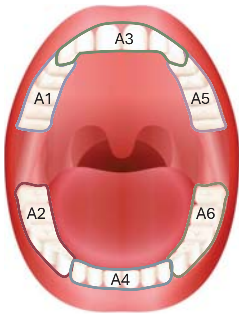

Figure 2: Oral anatomy.

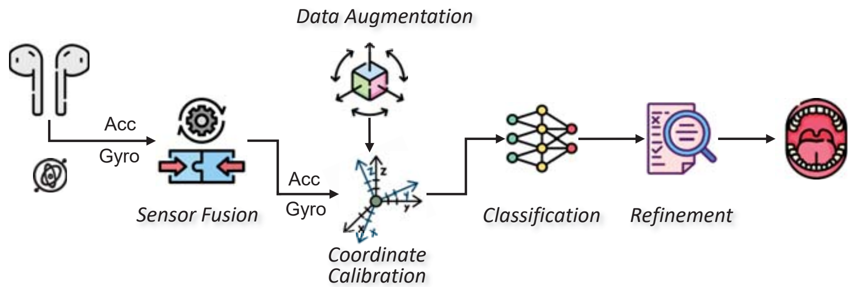

Figure 3: The system overview of BrushBuds.

caused by toothbrushing from a stable position on the human body. Additionally, BrushBuds has potential to complement and enhance wrist IMU approaches to achieve better tracking performance.

2.2 Earphone-based Applications

Earphones have become a significant sensing platform in recent years, facilitating a wide array of applications [13, 30]. OESense leverages the occlusion effect within the ear to identify human gestures and activities [24]. Additionally, researchers have explored the use of in-ear microphones to measure various physiological parameters, including respiratory function [22, 25], heart rate [8, 32], dietary habits [7], authentication [14, 16, 34], and lung function [35]. Furthermore, IMU sensors in earphones, which can capture subtle head motions, have also been employed in various applications, such as head motion tracking [15], step counting [28], speech enhancement [18], and augmented reality (VR) [36]. Building on these advancements, our work uses IMU sensors in earphones to track different areas of brushing to enhance manual toothbrushing.

3 BrushBuds Design

3.1 Objective

Failing to brush each area of the mouth thoroughly for enough duration can result in plaque buildup, leading to the risk of oral health problems such as cavities and gum bleeding. On the flip side, excessive brushing can lead to gum recession [1]. Dentists suggest brushing teeth twice daily for two minutes, ensuring even coverage of all areas [2]. As depicted in Fig. 2, current toothbrushing monitoring systems [5, 12, 19, 27] typically segment the mouth into six areas: left (A1, A2), middle (A3, A4), and right (A5, A6) for both the upper and lower jaws. The left and right sides each have three surfaces: inner, outer, and chewing surfaces, whereas the middle sections have two surfaces, resulting in a total of 16 surfaces. Most electric toothbrushes track brushing in four regions (left/right sides plus upper/lower jaws) or six regions. Only some high-end models, like the Oral-B iO10 (USD 550), can monitor all 16 surfaces. Our project aims to use IMU sensors in widely used headphones to enhance manual toothbrushing, providing effective six-area monitoring similar to most electric toothbrushes.

3.2 System Overview

Figure 3 shows the system overview of BrushBuds. The head movement caused by toothbrushing will be captured by the IMU sensors (*i.e.*3-axis accerlerometer and 3-axis gyroscope) of earphones and then forwarded to the sensor fusion module. The sensor fusion module (Sec. 3.3) is responsible for fusing accelerometer and gyroscope data, removing the sensory bias in the gyroscope readings. After that, the accelerometer and gyroscope data in the device coordinate are transformed to the head coordinate in the coordinate calibration module (Sec. 3.4). At the same time, the data augmentation module (Sec. 3.5) will randomly rotate the head coordinate to improve the data generalizibility. Following this, the 6-axis IMU data of both left and right earphones are concatenated and fed into the classification module (Sec. 3.6) to predict the brushing areas. Finally, the prediction results are fed into the refinement module (Sec. 3.7) to correct the occasional inaccurate output with temporal and spatial constraints.

3.3 Sensor Fusion

In this module, we first fuse accelerometer and gyroscope data to mitigate sensor bias and offset. This bias arises due to two factors. One is from manufacturing imperfections, temperature variations, and aging of the sensor; Another is that the gyroscope measures angular velocity, offering precise short-term measurements but suffering from cumulative drift over time. Consequently, this bias may be regarded as a fingerprint for different brushing areas, thereby leading to the overfitting problem for machine learning models. On the other hand, the accelerometer measures linear acceleration and is subject to less drift over time but is sensitive to external vibrations and transient forces. Therefore, we employ a Kalman filter [17] to compensate for the bias of the gyroscope with the stable reference of the accelerometer. Thus, we can fuse two sensors and mitigate the sensor offset.

3.4 Coordinate Calibration

There are slight device rotations when the user places the earphones on every time, leading to IMU coordinate inconsistency for both ears. To address this problem, ideally, we can utilize the IMU readings to estimate head orientation in a uniform earth coordinate as a feature to directly detect the different brushing areas. However, without the magnetic north as a reference, we can only estimate

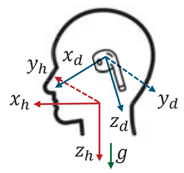

Figure 4: Coordinate calibration.

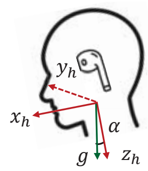

Figure 5: Pitch rotation augmentation.

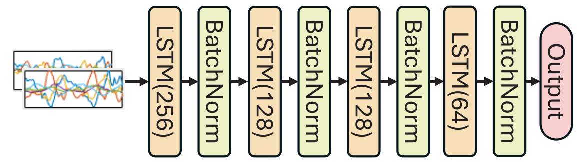

Figure 6: Model structure.

the relative head orientation, which suffers from yaw drift over time [3].

We have an observation that the toothbrushing motion actually is relative to the head instead of the global earth coordinate, so we propose an opportunistic calibration to transform the IMU data of both ears from the device coordinate to a unified head coordinate. Fig. 4 shows the coordinate definition of the head and the left ear IMU (the right ear is omitted but the calibration principle is the same). In the head coordinate system, the z-axis aligns with the direction of the neck, the x-axis points to the front of the user's head, and the y-axis points to the right. When the user wears the earphones, the z-axis of the head z_h is almost aligned with the gravity direction g. Thus, we can estimate the gravity direction in the device coordinate and rotate it accordingly to align the z-axis of the head. Specifically, we use the average acceleration in the static period of one second before the user starts brushing to estimate the gravity direction $\mathbf{g_d}$:

$$\mathbf{g_d} \approx \frac{1}{N}\sum_{i=1}^{N} \mathbf{a_i} \tag{1}$$

Where $\mathbf{a_i} = [x_i, y_i, z_i]$ is the ACC readings from three axes at time i in device coordinate. Therefore, we can calculate the rotation vector $\mathbf{u}$ and rotation angle θ between the gravity direction in the device coordinate $\mathbf{g_d}$ to the the gravity direction in the head coordinate $\mathbf{g_h} = [0, 0, 1]$:

$$\mathbf{u} = \frac{\mathbf{g_d} \times \mathbf{g_h}}{\|\mathbf{g_d} \times \mathbf{g_h}\|} \qquad \theta = arccos\frac{\mathbf{g_d} \cdot \mathbf{g_h}}{\|\mathbf{g_d}\|\|\mathbf{g_h}\|} \tag{2}$$

and then we can obtain the quaternion $\mathbf{q}$ as

$$\mathbf{q} = \left(\cos\left(\frac{\theta}{2}\right), u_x \sin\left(\frac{\theta}{2}\right), u_y \sin\left(\frac{\theta}{2}\right), u_z \sin\left(\frac{\theta}{2}\right)\right) \tag{3}$$

Thus, we can transform the IMU readings from the device coordinate to the head coordinate:

$$\mathbf{C_h} = \mathbf{q}\mathbf{C_d}\mathbf{q}^* \tag{4}$$

The same calibration method applies to the right ear. Then, we employ a bandpass filter on the transformed data with the cutoff frequencies of [2, 6]Hz to remove the low-frequency interference (*e.g.*, body motions) and the irrelevant high-frequency noise. Besides, this operation removes the bias effect of the gravity and unifis the data scale.

3.5 Data Augmentation

In the previous step, we assume the z-axis of the head z_h is almost aligned with the gravity direction g, which requires users to stand very straight. However, we observe that people often lean slightly forward while brushing their teeth to prevent water from spilling, which may lead to a small pitch offset α, as shown in Fig 5. To deal with this problem, we perform data augmentation by randomly rotating the gravity direction along the y-axis in the head coordinate. Specifically, we perform a random pitch rotation to the $\mathbf{g_h}$ in [0°, 30°] before coordinate calibration. We increase the dataset size by a factor of 30 through data augmentation.

3.6 Classification

After coordinate transformation, we segment the accelerometer and gyroscope data with a sliding window of 600 *ms*, stack the left and right channels, and feed them into a deep learning model. Concretely, we use four LSTM layers to capture the temporal relationship among the IMU data. Figure 6 shows the structure of the deep learning model. To prevent overfitting, each LSTM layer is followed by a batch normalization layer and a dropout layer with a dropout rate of 0.2. The output is a dense layer of size 6, using the softmax function. Considering the varied brushing habits of different users, the new user can contribute a small number of labeled data traces to fine-tune the model pretrained by the data of other users. Thus, BrushBuds can transfer the learned brushing monitoring knowledge to new users.

3.7 Refinement

After classification, the estimation results may exhibit sudden shifts and outliers due to inherent motion ambiguity and occasional prediction errors. Toothbrushing, however, is a process that is both temporally continuous, *i.e.*, the area being brushed should ideally show continuity over time. Therefore, we can apply continuity constraints over time to refine the model predictions. Specifically, we use a moving median filter with different window sizes (*i.e.*, 1, 3, and 5) iteratively to smooth the classification results across various time scales. This approach improves the overall coherence and accuracy of the toothbrushing tracking result.

4 Implementation and Evaluation

We developed a prototype earphone for our evaluation, as depicted in Fig. 7. A MPU6050 sensor was attached to a 3D-printed ear-mounted case, which was connected to a Raspberry Pi 4B to collect data at a sampling rate of 90 Hz. Figure 8 illustrates the experimental setup. We recruited 13 volunteers for our study, which was approved by our institution's Ethics Committee. Participants wore the earphone prototype and brushed their teeth once per day, over five different workdays. They followed a guide video instructing them on the brushing locations and durations, which provided our ground truth. Each brushing session lasted 2 minutes, consistent with ADA recommendations.

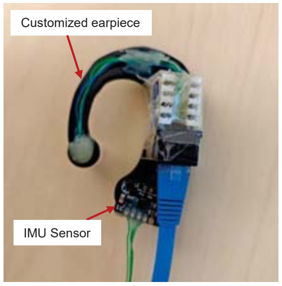

Figure 7: Hardware.

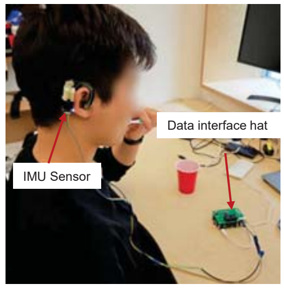

Figure 8: Experiment.

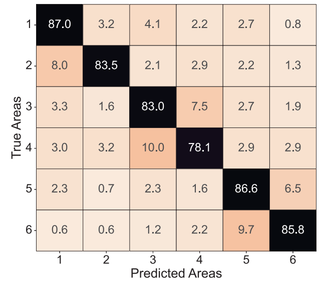

Figure 9: Cross-validation.

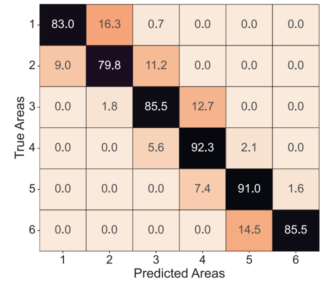

Figure 10: Cross-session

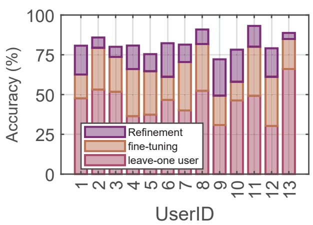

Figure 11: Impact of users.

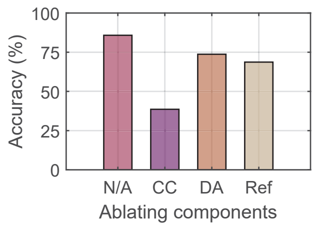

Figure 12: Ablation study.

4.1 Overall Performance

4.1.1 Cross-validation. Many electric toothbrushes on the market, such as the Oral-B iO Series 5, 6, 7, and 8, offer tracking capabilities limited to six regions of the mouth. Therefore, we first evaluated BrushBuds's tracking performance in these six areas. Figure 9 shows the confusion matrix from a 5-fold cross-validation for all data. The overall classification accuracy is 84.3%, indicating that BrushBuds can effectively detect six dental areas. An interesting observation is that the error rate is higher within areas on the same side of the mouth compared to areas on different sides. For instance, areas 5 and 6 tend to be misclassified since they are both on the right side. Similarly, areas 1 and 2, as well as areas 3 and 4, are often confused because they are on the same left and middle sides, respectively. This is due to the subtle difference in movements caused by similar head postures when brushing areas are on the same side.

4.1.2 Cross-session validation. Given that different brushing sessions may exhibit slight variations in habits, we conducted an experiment where the model was trained on data from two random sessions and tested on data from three different sessions. Figure 10 presents the confusion matrix for this cross-session validation, which achieved an overall accuracy of 85.9%, comparable to the cross-validation case. In this cross-session validation, where the testing data represent complete toothbrushing sessions, we employed refinement techniques to reduce ambiguity and enhance accuracy. Compared to Fig. 9, there was a notable reduction in ambiguity, particularly in non-adjacent areas. This highlights the effectiveness of refinement techniques in correcting occasional prediction errors and mitigating ambiguity issues.

4.2 Impact of Users

To evaluate system performance between different users, we conducted a leave-one-user-out analysis, where the model was trained on data from all but one user and tested on the data from the remaining users. As shown in Fig. 11, the average accuracies are only 45.3%. This result was expected, as brushing motions are closely tied to individual habits. Each user has unique brushing movements and habits, so testing the model on new users without prior data leads to significant bias.

To address this challenge, we propose a guided fine-tuning approach. When a new user first uses the system, they are guided through a video to brush all areas as one session, and then the data of this labeled session is used to perform fine-tuning. This allows the model, pre-trained on data from other users, to adapt to the new user. Specifically, we fine-tune the model using data from one session provided by the new user and then test the model on the user's data from four other sessions. We observed a significant improvement in accuracy, with performance increasing to 68.7%. This demonstrates the efficacy of the fine-tuning approach in enhancing the model's adaptability to different users. Furthermore, through refinement techniques, we further enhanced the model's predictions and improved its accuracy. As a result, the accuracy increased to 82.2%, highlighting the efficacy of refinement in reducing ambiguity and enhancing classification performance. For model adaptation, collecting a small amount of data is an acceptable trade-off in terms of user involvement. The performance can be further improved if users contribute more data (*e.g.*, two or more sessions). Another observation is that users 1, 6, and 10 show lower performance compared to others. This is because of their different brushing techniques across multiple attempts. For instance, on some days, they employed a Bass brushing method, while on other days, they used a modified Bass brushing technique (adding a vertical sweeping outward after brushing each tooth). This inconsistency in brushing motions across different sessions led to performance decrease.

4.3 Ablation Study

To assess the individual contributions of different components, we conducted an ablation study by replicating the cross-session experiment described in Sec. 4.1.2 while excluding various modules: coordinate calibration (CC), data augmentation (DA), and refinement (Ref). The system's performance without ablation (N/A) was 85.9%. Excluding coordinate calibration caused a significant performance drop to 38.6%, highlighting the impact of cross-session variations and the effectiveness of coordinate calibration in unifying the feature space. Omitting data augmentation reduced performance to

73.7%, demonstrating that data augmentation effectively captures the slight head lean before users begin brushing. Excluding refinement resulted in a performance decrease to 68.7%, underscoring the importance of refinement in mitigating ambiguity and effectively handling outliers.

5 Conclusion

We propose BrushBuds, a toothbrushing monitoring system that utilizes IMU sensors embedded in earbuds. This system enhances manual toothbrushing by providing users with brushing tracking information. By transforming and augmenting IMU data on both ears into a unified framework, BrushBuds captures brushing motion patterns and achieves an accuracy of 84.3% in tracking six tooth areas. BrushBuds empowers users of manual toothbrushes to enjoy the benefits typically associated with high-end smart toothbrushes using just a pair of earphones, which holds great promise for improving public dental health practices.

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