Predicting Oral Device Efficacy for Treatment of Obstructive Sleep Apnea Based on Snore Sound

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Abstract— **Obstructive sleep apnea (OSA) is an umbrella term describing a complex range of airway obstruction mechanisms. For a subset of these obstructions, oral devices (ODs) are an effective treatment. Predicting OD efficacy is challenging due to the difficulty in phenotyping OSA. This study investigates a novel deep learning approach that leverages the acoustic properties of snoring to predict OD efficacy. This can provide a non-invasive, accessible method for assessing OD suitability, potentially improving personalized treatment strategies for OSA patients.**

Clinical Relevance— **This readily available and non-invasive tool may guide OD treatment decisions in OSA with 0.80 sensitivity and 0.74 specificity.**

I. Introduction

Obstructive sleep apnea (OSA) is a prevalent chronic condition characterized by recurrent upper airway obstruction during sleep, leading to pauses in breathing (apnea) or significantly reduced airflow (hypopnea). OSA affects an estimated one billion people globally and is diagnosed based on the apnea-hypopnea index (AHI) – the average number of apneas and hypopneas per hour of sleep. One common treatment for OSA is the use of an oral device (OD). These devices, which can be custom-fitted by a dentist or self-fitted by the user, work by advancing the mandible (lower jaw) to keep the upper airway open. While studies suggest that 50–70% of OD users experience improvements in AHI, 30–50% see no improvement or even worsening.

Prediction of OD efficacy is crucial in guiding treatment choices for clinicians. While the site of airway obstruction and the broader OSA phenotype are key factors in OD effectiveness, drug-induced sleep endoscopy to determine location of airway obstruction is impractical, and phenotype identification is not well developed. Previous studies have shown that the acoustic characteristics of snoring can reflect the site of obstruction in the upper airway [1]. This study investigates a deep learning approach to directly predict the efficacy of ODs for managing OSA from snore sound.

II. Methods

Participants were 934 users (647 men and 287 women) of SoundSleep, an app that uses deep learning algorithms [2] to identify sleep-disordered breathing events from smartphone audio recordings, and thereby estimate the AHI. The following data were collected: self-reported OD usage, estimated AHI, and selected snores (20–25 snores per user per night). Of the users, 464 experienced a statistically significant reduction in AHI ($p < 0.05$) while using an OD, compared with 470 who did not. All users agreed to a privacy policy permitting the use of their anonymized data.

Snore samples collected without an OD were converted into 64-channel mel-spectrograms and used to train a convolutional neural network (CNN). The CNN predicted the normalized t-statistic (0–1) of a participant's AHI values with and without an OD. It consisted of three convolutional layers (16, 32, and 64 3x3 kernels, ReLU, batch normalization, 3x4 max-pooling, 50% dropout), a 512-unit dense layer (ReLU, batch normalization, 50% dropout), and a single-unit sigmoid output layer. Ten-fold cross-validation was used, and OD efficacy was predicted from the mean of the estimated t-statistics using a fold-optimized threshold.

III. Results

The system achieved a sensitivity and a specificity of 0.58 across all users. An analysis of individuals with severe OSA (AHI > 30 events/hour, 289 users, 216 men and 73 women) achieved a sensitivity of 0.60 and a specificity of 0.72. Given the varying number of nights of data collected per user (ranging from 2 to over 100), we investigated the impact of data availability. For the 134 subjects with at least 7 nights of data without an OD, the system's performance improved significantly, reaching a sensitivity of 0.80 and a specificity of 0.74. This finding suggests that a baseline of at least 7 nights of data is necessary to effectively predict OD efficacy, likely due to inherent inter-night variability. Lastly, examining individual fold performance revealed a wide range in sensitivity (0.45 to 0.88) and specificity (0.50 to 0.75). This variability, coupled with the large dataset size, suggests the presence of distinct subgroups within the data. Characterizing these subgroups may reveal additional phenotypic information.

IV. Discussion & Conclusion

Snore sound analysis offers a readily available and non-invasive tool for identifying OSA patients most likely to benefit from an OD without explicitly determining the site of obstruction. This may increase patient motivation to try or adhere to OD treatment if they know it is likely to be effective. It is also a tool to assist clinicians in selecting among treatment options. To further enhance prediction performance, future work will explore integrating demographic information (e.g., sex and body mass index), analysis of sleep-disordered breathing event timing (e.g., inter-snore intervals), and smartphone-derived anthropometric measurements (e.g., facial depth maps).

References

[1] Janott, C. et al., "Snoring Classified: The Munich-Passau Snore Sound Corpus" in *Computers in Biology and Medicine*, vol. 94, 2018.

[2] Romero, H. E. et al., "Acoustic Screening for Obstructive Sleep Apnea in Home Environments Based on Deep Neural Networks" in *IEEE Journal of Biomedical and Health Informatics*, vol. 26, n. 7, 2022.

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