DeepSleep: A Ballistocardiographic-based Deep Learning Approach for Classifying Sleep Stages

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ABSTRACT

Purpose: According to a 2009 study by the Center for Disease Control and Prevention [4] in the USA, 35.3% of 74,751 people reported having less than 7 hours of sleep, 48% reported having snoring-related issues, 37.9% reported unintentionally falling asleep during the day and 4.7% reported nodding off while driving. Sleep-related disorders such as sleep deprivation [3] and sleep apnea [8] can be studied and diagnosed at sleep clinics. Sleep clinics typically use Polysomnography (PSG), a test conducted to study sleep and to diagnose different forms of sleep disorders [1]. To date, PSG is considered as the most accurate method for diagnosing sleep-related problems and considered the gold standard in clinical sleep medicine. However, it suffers from the fact that it is expensive, complex, time-consuming, and uncomfortable for the users [2]. In this early work, we aim to model a sleep classification system using an unobtrusive Ballistocardiographic (BCG)-based heart sensor signal collected from *Dozee*[1], a commercially available non-contact, unobtrusive pressure-sensitive sensor sheet. Here, we ask: *How can a sleep classification system be modelled using BCG sensor data, in order to achieve a performance comparable with PSG?.*

Methods: In this work, we aim to classify four sleep stages [10]: (1) Wake state (2) Rapid Eye Movement (REM) (3) Light sleep, and (4) Deep sleep. This study is based on four datasets: *Dozee*'s *BCG* dataset[2], *Dozee*'s *ECG* data, the *MIT-BIH Polysomnographic* dataset [5, 6] and the *PPG*-based Fitbit data [9] provided by *Fitabase*[3]. In this work, the model is trained using the *Dozee*'s BCG dataset while the *Dozee ECG*, *MIT-BIH PSG* data and the *Fitbit*'s PPG data are used for transfer learning. To study the effect of sleep on our cardiac rhythm, a specific set of features called the *Heart-rate Variability* (HRV) features need to be extracted [10]. Our approach is to extract such features automatically using deep neural network architectures. Here, we present *DeepSleep*, a hybrid deep neural network model that can automatically extract heart-related features and learn the time-dependent nature of the sleep patterns for classification. We show how pre-training and subsequently fine-tuning the model can

[1]https://www.dozee.io
[2]Dozee: https://www.dozee.io
[3]Fitabase: https://www.fitabase.com/research-library/

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help tackle the limited amount of labelled sensor data, and allows us to contribute a pre-trained model. This training strategy enables us to test the pre-trained model's classification ability on ECG and PPG sensor data. A combination of stacks of 1-dimensional convolutional networks (1D-CNNs) and Bidirectional Long-Short Term Memory (bi-LSTM) [7] layers are incorporated in the model design to enable unsupervised feature learning and sequential learning, respectively. Lastly, we test how well the sleep quality scores calculated by our DeepSleep model correlate with the perceived quality score as reported by users.

Results: We present early results from our *DeepSleep* model, a hybrid deep neural network architecture comprising of CNN and LSTM layers, which is able to classify sleep stages with a mean F1-score of 74% using the BCG signal. We further employed a 2-phase training strategy to build a pre-trained model and to tackle the limited dataset size. With a classification accuracy of 82%, 77% and 63% using MIT-BIH's ECG, Dozee's ECG and Fitbit's PPG datasets, respectively, we contribute a pre-trained model that can be used in a transfer learning setting as well. Furthermore, with a correlation coefficient of $r = 0.43$, our model shows a positive correlation with the SATED questionnaire perceived sleep quality scores, by contrast to a coefficient of $r = 0.48$ with PSG, and $r = 0.54$ between SATED and PSG. Although our current proposed model's performance is not yet comparable to PSG, we show that heart rate signals alone are an effective means for long-term sleep monitoring, but currently not suitable for medical diagnostic purposes. Our next steps is to validate our approach using leave-one-subject out cross-validation, and to test our model against non-Artificial Neural Network approaches.

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