DSxHealth application

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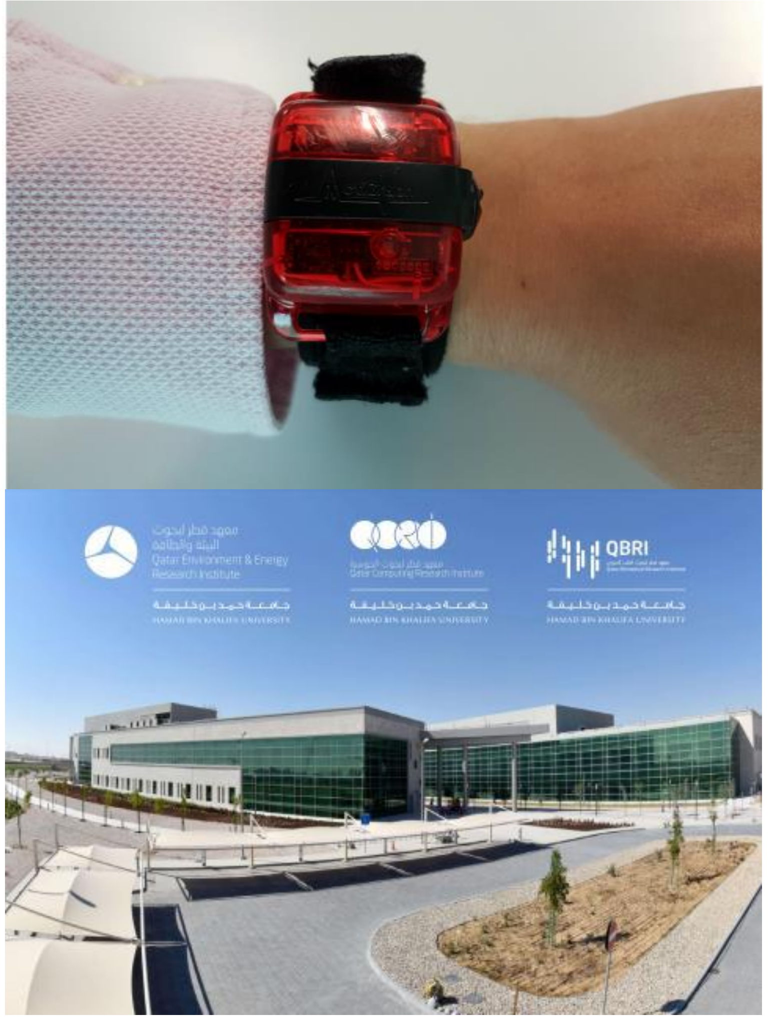
Topic: Wearable Devices for Prevention



JMIR MHEALTH AND UHEALTH

Original Paper

Sleep Quality Prediction From Wearable Data Using Deep Learning

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Related Article:
This is a corrected version. See correction statement in: http://mhealth.jmir.org/2016/4/e130/

Content

Importance of the Sleep and connection to Physical activity

- **Insufficient sleep can reduce** physical, emotional, and mental **well-being** and can lead to a multitude of health complications
- Physical **activity and sleep** are highly **interrelated** health behaviors.
- Our **physical activity** during the day (ie, awake time) **influences** our quality of sleep, and vice versa

- The current popularity of **wearables for tracking** physical activity and sleep, including actigraphy devices**, can foster** the development of new advanced data analytics.
- This can help to **develop new** electronic health (eHealth) **applications** and provide **more insights** into sleep science.

Role of Wearables in Sleep Health and eHealth

- Sleep researchers in the early 1990s developed a **technique** called **actigraphy** to study sleep interactions using wearable devices.
- There are hundreds of consumer-grade **physical activity and sleep tracking devices** (e.g. Fitbit) collecting motion
- There are successful examples of the **integration of physical activity wearable data into eHealth** tailored **applications** (e.g. Smart Watch)
- Sensors **monitor** and **observe** a patient overnight and can be **used for diagnosing** different sleep disorders

Objectives of the study

- To test the feasibility of **predicting poor or good sleep efficiency based on physical activity** data from the awake periods from a wearable device (i.e. actigraphy)

Two-fold importance of the research	
First, since our approach can be **used** in cases **where sleep sensor data is not available**, our models can be used in the early detection of potential low sleep efficiency.	**Second**, our study was **focused** on **advanced deep learning** methods while traditional prediction models are based on e.g. logistic regression

Methods of the Study

1. The collection of wearable data (sleep patterns & physical activities)
2. Data processing and representation
3. Data modelling
4. Performance evaluation

Methods of the Study

The collection of wearable data (sleep patterns & physical activities)

The dataset used contained complete actigraphy data from a subset of 92 adolescents over 1 week.

There were 322 total sleep instances:

- 102 from boys and
- 220 from girls.

Figure 1. ActiGraph Gt3X+.

Methods of the Study

Data processing and representation

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Figure 2. Sleep efficiency equation as defined by sleep specialists.

$$Sleep\ Efficiency = \frac{TotalSleepTime}{TotalMinutesinBed}$$

Figure 3. The adapted wake after sleep onset calculation.

$$WASO = \sum_{\substack{Sleep\\Onset\\Time}}^{\substack{Sleep\\Awakening\\Time}} \begin{cases} \|WakefulPeriod\|, & \|WakefulPeriod\| > 5 \\ 0, & \text{otherwise} \end{cases}$$

WASO is the sum of all moments of wakefulness lasting longer than 5 minutes

- Those achieving a sleep efficiency score of ≥85% are thought to be **good-quality** sleepers,
- and those with a score of <85% are thought to have **poor-quality** sleep

Methods of the Study

Data processing and representation

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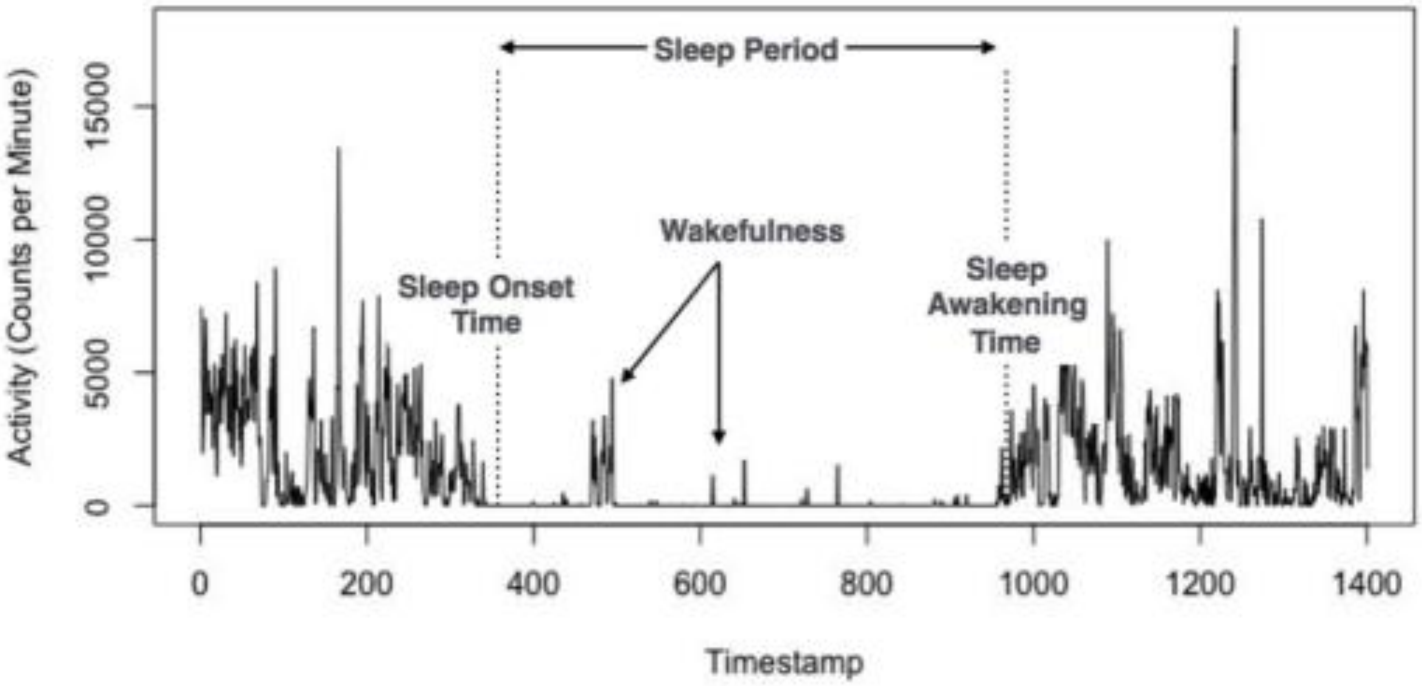
Figure 4. Example of sleep definitions on accelerometer data of an actigraphy device.



Methods of the Study

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Data modelling

The **input** of the models is time series vectors, X=(x1 , · · · , xT),

The **output** of the model was a binary classification decision between good and poor sleep quality based on sleep efficiency (%)

- **Logistic regression**, a non-deep learning model
- Multi-layer perceptron's (**MLPs**), a deep learning model
- Convolutional neural network (**CNN**), a deep learning model
- Recurrent neural networks (**RNN**), a deep learning model
- Long short-term memory (**LSTM**) RNN, a deep learning model
- Time-batched long short-term memory (**TB-LSTM**) RNN, a deep learning model

The data were split with a

- 70% training
- 15% testing
- 15% validation

Methods of the Study

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Performance evaluation

Accuracy
It is computed as the **proportion of correct predictions**, both positive and negative

Precision
It is the fraction of the number of **true positive predictions** to the number of **all positive** predictions

Specificity
It is the fraction of the number of **true negative predictions** to the actual number of **negative instances** in the dataset

Recall or Sensitivity
It is the fraction of the number of **true positive predictions** to the actual number of **positive instances** in the dataset

F1-Score
An **inverse** relationship between **precision and recall** (harmonic mean of precision and recall)

Area Under the ROC Curve
It represents the probability that a classifier will rank a randomly chosen positive instance higher than a randomly chosen negative instance

Results of the study

Model	AUC	F 1-Score
TB-LSTM	0.97	0.85
CNN	0.95	0.94
MLP	0.94	0.91
TB-LSTM	0.85	0.92
RNN	0.71	0.77
LR	0.64	9.81

Results of the study

Model	Sensitivity	Specificity
TB-LSTM	1	0.71
LR	0.97	0.33
CNN	0.97	0.85
LTSM	0.97	0.47
RNN	0.91	0.23
MLP	0.88	0.9

Conclusions of the study

- We can predict sleep quality using only physical activity
- Deep learning overperforms classical methods

Discussion & Limitations

- Models can be re-used using wearable's data
- What about the age?
- Binary simplification
- Deep learning models understanding
- Data cleaning

Data Science for Health