ASIS: A Smart Alarm Clock Based on Deep Learning for the Safety of Night Workers

Daniele Lozzi[a], Alessandro Di Matteo[a], Enrico Mattei[a]
Alessia Cipriani[a,b], Pasquale Caianiello[a],
Filippo Mignosi[a], Giuseppe Placidi[a]

[a]A2VI-Lab University of L'Aquila, [b]Università Cattolica del Sacro Cuore

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Sleep

Sleep is a fundamental physiological process that follows a 24-hour cycle and is influenced by external factors.

- 1968: Rechtschaffen and Kales (RK) [1] classified sleep into five stages (4 NREM, 1 REM, AWAKE) based on EEG, EMG, EOG;
- The AASM [2] merged stages 3 and 4 of the RK classification into a single stage N3 [3].

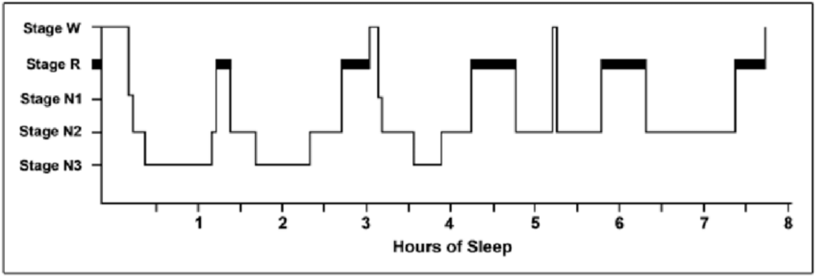


Figure: Example of an hypnogram [4]

AASM	% of the sleep AASM	RK	% of the sleep RK	Characteristics	Characteristics AASM
N1	2 - 5%	Stage 1	2 - 5%	closed eyes, alpha rhythm	-
N2	45 - 55%	Stage 2	45 - 55%	spindles, k-complex	-
N3	7.5 - 15.5%	Stage 3	3 - 8%	20% slow wave activity, high voltage	low-wave sleep (SWS), high amplitude, low frequency
		Stage 4	10 - 15%	50% slow wave activity, high voltage	
REM	25%	REM	25%	desynchronization, low voltage	-
Awake	0%	Awake	0%	desynchronization, low voltage	-

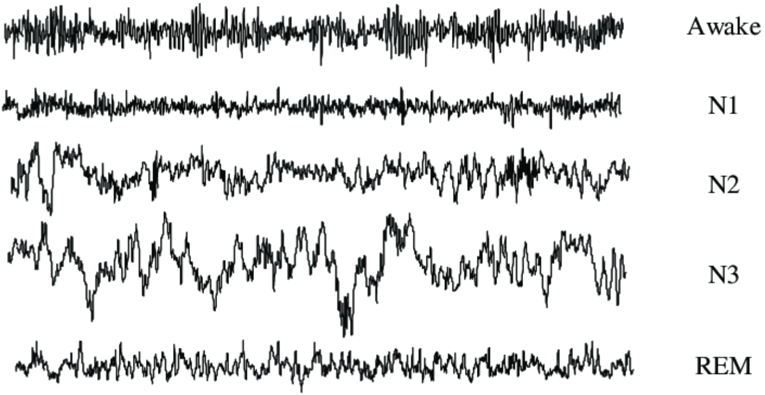


Figure: Different sleep pattern on EEG signal [5]

Sleep Inertia

Sleep inertia, a post-wake phenomenon, is characterized by drowsiness and cognitive deficits.

- Its duration varies based on chronotypes.
- Awakening during slow-wave sleep (SWS) leads to high sleep inertia [6].
- Awakening during lighter stages (N1, N2, REM) results in less.
- Identifying optimal wake-up times (N1, N2, REM) can mitigate sleep inertia. This could potentially reduce accidents at work by improving physical and cognitive performance.

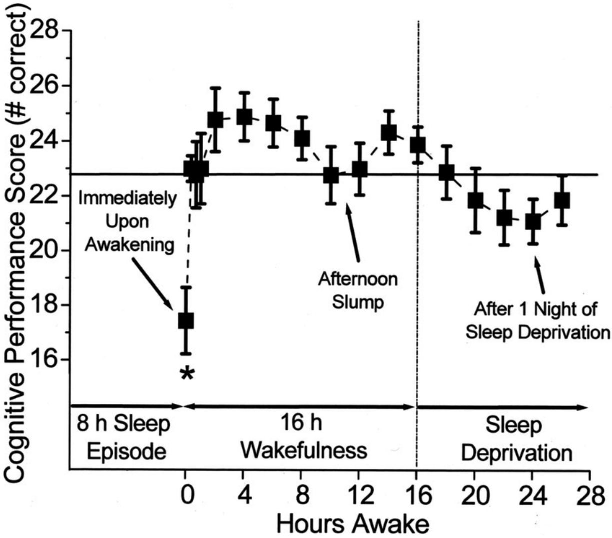


Figure: Impact of sleep inertia [7]

The aim

The aim is to find a model able to wake people up at the optimal time using EEG signals using only two EEG signals to predict the best time to wake up the person to minimize sleep inertia condition, maximize the sleep period, and optimize performance at the wake-up moment.

In this work, we conceptualize the **ASIS** - Anti Sleep Inertia System, to identify the best moment to wake someone up, predicting the sleep stage N1, N2, REM, Awake and avoiding N3.

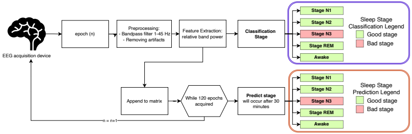


Figure: The system.

Related Works

Traditional methods rely on manual inspection of EEG data, which is time-consuming and subjective. Recent studies have explored automatic classification using deep learning models, achieving high accuracy [8], but not sleep prediction.

- Choi and Sung [9] aimed to improve current sleep stage classification by predicting the next stage,
- Slyusarenko et al [10] used actigraph data to predict the best wake-up time.

Architecture

This is done using a system composed of two machine learning models, (1) a *classifier* and (2) *predictor*.

1. The classifier categorize all segment of EEG in real-time
2. The predictor (LSTM) forecast the next 30 minutes of sleep stages, searching the best moments to wake up within a prefixed time-range

- The classifier checks the correctness of the prediction when the expected time is reached
- The alarm clock sounds at the first predicted good epoch verified by the classifier or at the upper limit of the time range if no good epoch is predicted or verified.

The reason to use two models instead of one is that the classifier in general has higher level of accuracy, precision, and recall with respect to the prediction based on past data.

EEG Data and Feature Extraction

Dataset: Sleep-EDF Expanded

- 74 subjects, 148 nights, EEG sampled at 100 Hz.
- Sleep stages classified using AASM criteria (N1, N2, N3, REM).

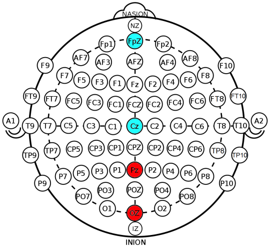
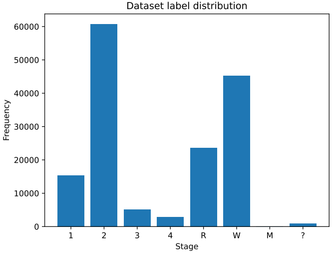


Figure: 10-20 system electrodes position. With the same color the two pairs of channels used in this dataset in bipolar reference mode are depicted.

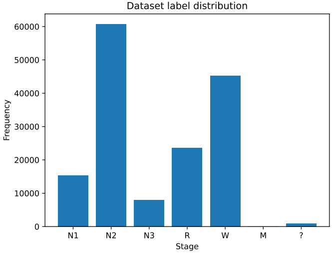
Feature Extraction

- Relative Band Power **(RBP)** from EEG signals in five frequency bands (delta, theta, alpha, beta, gamma) for both channels: 12 features.
- Each segment analyzed over 30-second intervals, based on the label provided by authors.

Frequency Band	**Label**
1 - 4 Hz	Delta
4 - 8 Hz	Theta
8 - 12 Hz	Alfa
12 - 30 Hz	Beta
30 - 45 Hz	Gamma



((a)) RK classification



((b)) AASM classification.

Figure: Differences in the dataset after the conversion of sleep stages from RK to AASM.

RK to AASM

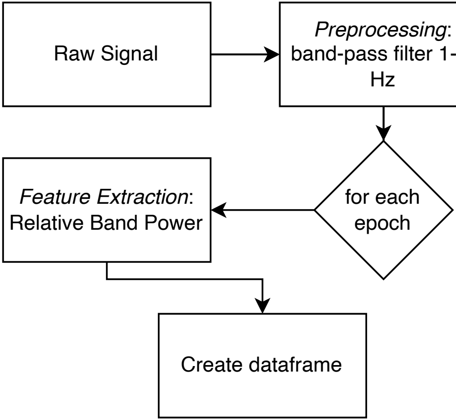


Figure: Feature extraction flow-chart used in this work.

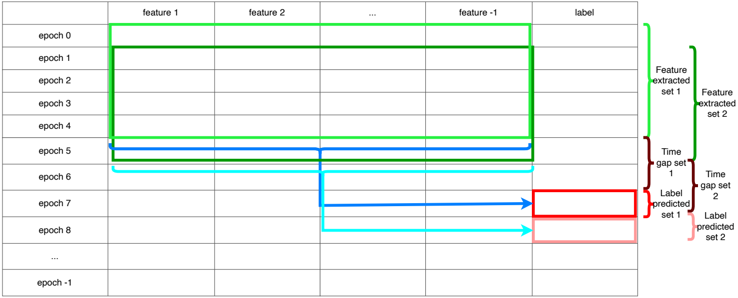


Figure: LSTM dataset generator. A matrix of data are extracted, and the label associated with data are misaligned with the input data. The label of each input matrx data (i.e. the sample), correspond to the label of the 181^{th} row of the dataframe, starting from the 0^{th} of each input matrix data.

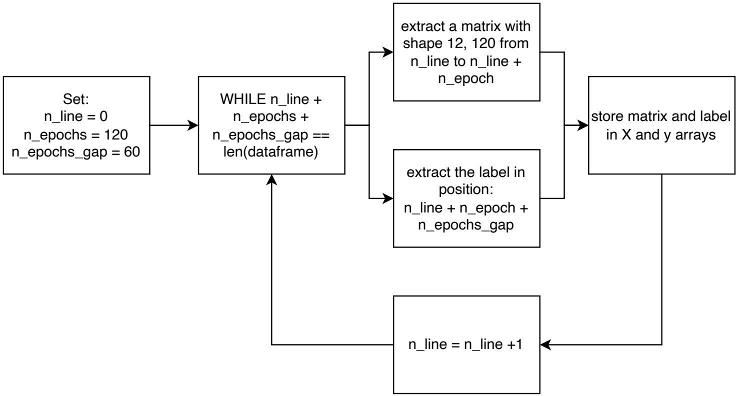


Figure: LSTM flowchart dataset generator.

LSTM

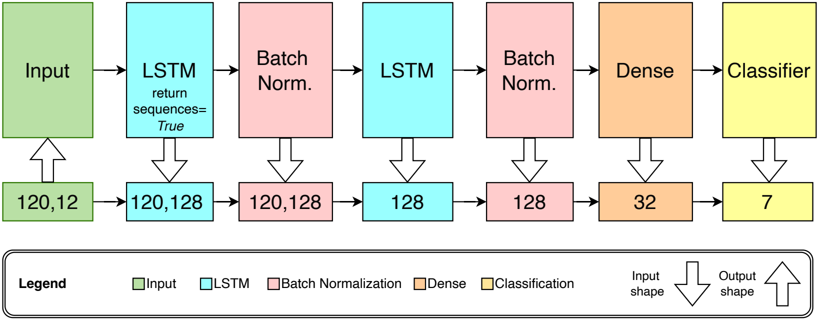
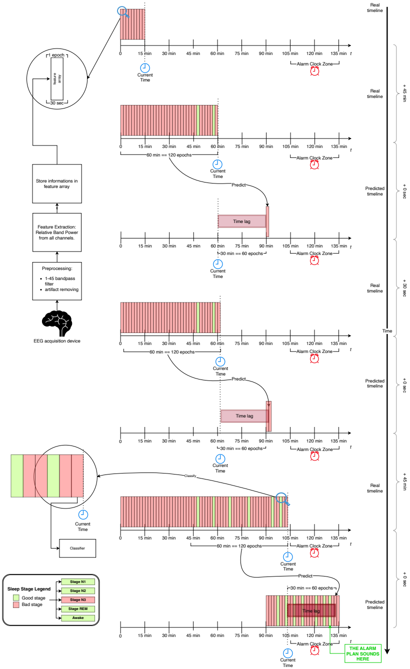
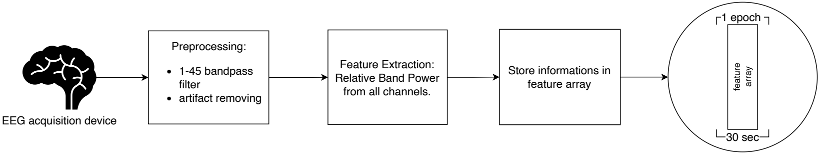


Figure: LSTM network architecture

The System


1 epoch
feature array
30 sec
Store informations in feature array
Feature Extraction: Relative Band Power from all channels.
Preprocessing:
1-45 bandpass filter
artifact removing
EEG acquisition device
Real timeline
Predicted timeline
Time
0
15 min
30 min
45 min
60 min
75 min
90 min
105 min
120 min
135 min
t
Current Time
Alarm Clock Zone
60 min == 120 epochs
Predict
Time lag
30 min == 60 epochs
+ 45 min
+ 0 sec
+ 30 sec
Classify
Classifier
Sleep Stage Legend
Good stage
Bad stage
Stage N1
Stage N2
Stage N3
Stage REM
Awake
THE ALARM PLAN SOUNDS HERE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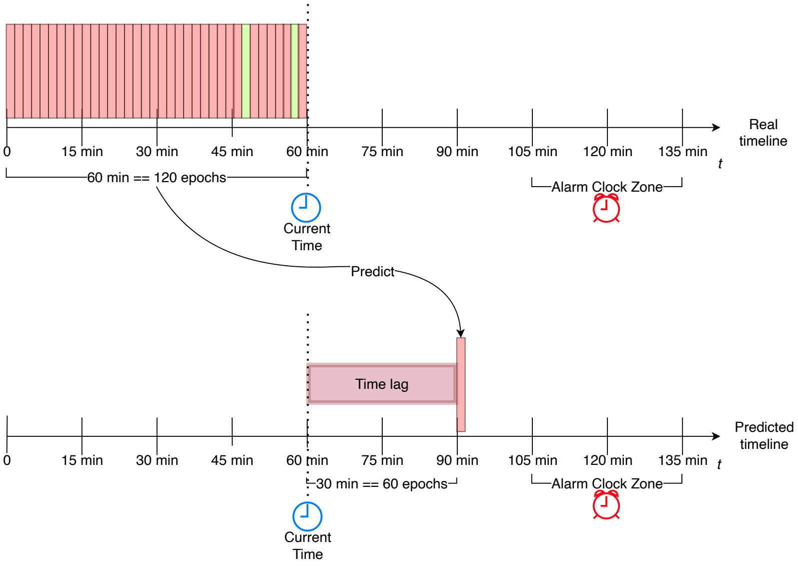
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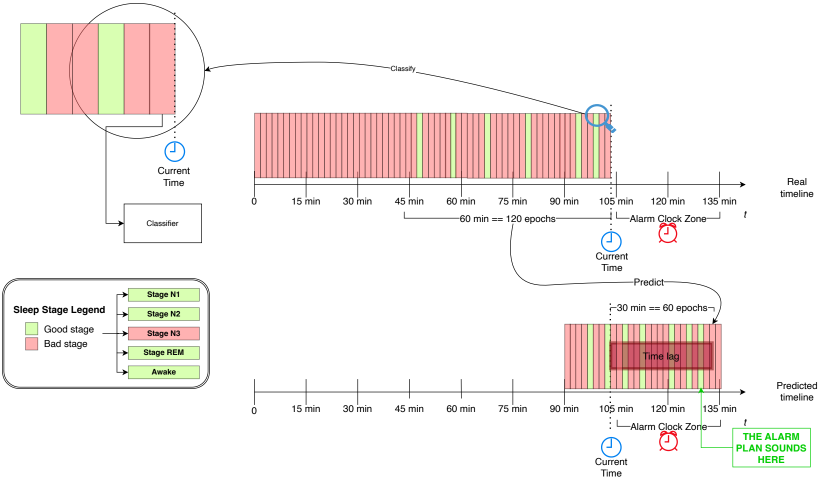
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THE ALARM
PLAN SOUNDS
HERE

Confusion matrix

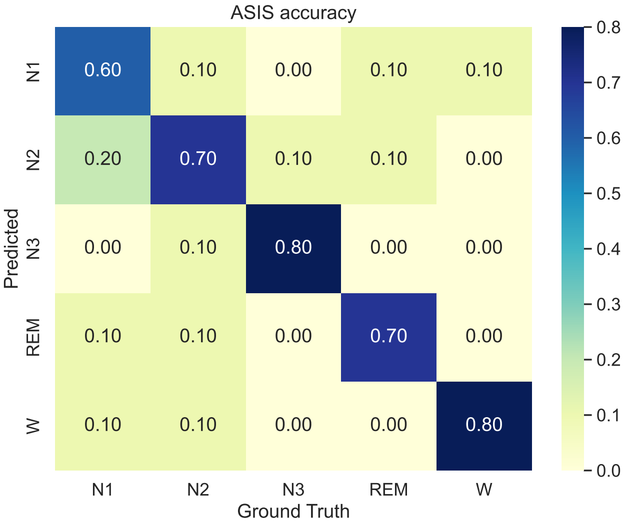

Figure: Confusion matrix for prediction stage.

Metrics

Model	Total sample set	After Sleep stage ? exclusion	Balanced	Training	Test	Validation
LSTM	127313	126352	26490	17748	8742	10% of training

Table: Sample number of the training set for LSTM.

Performance on prediction with LSTM on AASM labels

	Precision	**Recall**	**F1-score**	**Support**
Sleep stage N1	0.60	0.70	0.65	1733
Sleep stage N2	0.65	0.53	0.58	1805
Sleep stage N3	0.84	0.91	0.87	1682
Sleep stage R	0.74	0.76	0.75	1758
Sleep stage W	0.84	0.79	0.81	1764
Accuracy			0.74	8742
Macro avg	0.74	0.74	0.73	8742
Weighted avg	0.74	0.74	0.73	8742

Table: Performance on Prediction with LSTM on AASM labels

Metrics for prediction using LSTM

Metrics	**Value**
Accuracy	0.7353
Balanced Accuracy	0.7378
F1 Score	0.7331
Recall Score	0.7353

Table: Metrics for Prediction with LSTM

Machine Learning Models

Classifier Model:

- Trained to classify sleep stages based on EEG data.
- High accuracy achieved using 120 epochs (1 hour of data).

Predictor Model:

- LSTM (Long Short-Term Memory) model predicts sleep stages 30 minutes into the future.
- Overall accuracy: 0.73

Results

- **Overall performance:** Achieved a prediction accuracy of 73%.
- **Key metric:** F1-score for different sleep stages showed high reliability.
- **Practical application:** Minimizes sleep inertia by predicting optimal wake-up stages.

Impact:

- Reduces workplace accidents and improves alertness for night workers.

Conclusion and Future Work

Conclusion:

- ASIS effectively predicts optimal wake-up times based on EEG data.
- Can significantly reduce sleep inertia, enhancing worker safety and performance.

Future Work:

- Explore additional features for improved prediction.
- Implement artifact rejection systems to enhance signal quality [11].

Question time

Thanks for listening!

Questions?

A^2VI-lab

A^2VI-Lab Group: Prof. Giuseppe Placidi, Dott. Matteo Polsinelli (*Univ. Salerno*), Prof. Filippo Mignosi, Alessandro Di Matteo, Enrico Mattei, Daniele Lozzi, Lorenzo Nazzicone, Alessia Cipriani, Flavio D'Amato, Alessio Erasmo, Alessandro Pio, Stefano Rosini.

DISIM
Dipartimento di Ingegneria e Scienze dell'Informazione e Matematica

UNIVERSITÀ DEGLI STUDI DELL'AQUILA

MESVA
Dipartimento di Medicina Clinica, Sanità Pubblica, Scienze della Vita e dell'Ambiente

A^2VI Lab

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References IV

[11] Giuseppe Placidi, Luigi Cinque, and Matteo Polsinelli. "A fast and scalable framework for automated artifact recognition from EEG signals represented in scalp topographies of independent components". In: *Computers in Biology and Medicine* 132 (2021), p. 104347.