Visual Analytics for the Analysis of Sleep Quality

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Keywords: Sleep Analysis, Visual Analytics, Spindle Detection, Healthcare, Sleep Stage Classification, Interactive Visualization, Sleep Monitoring.

Abstract: Monitoring the quality of sleep in patients of sleep disorders is often a time-consuming process, where the clinician manually navigates through large volumes of recorded polysomnography data in an effort to visually detect sleep patterns, such as sleep spindles, sleep stages and hints of disorders. We propose an application that provides healthcare professionals with advanced tools for sleep analysis and spindle detection through visual analytics for pattern detection, AI-based sleep scoring, and an interactive user interface. The system processes multiple physiological signals and provides both raw data visualization, advanced feature analysis capabilities, and a two-dimensional embedding of sleep intervals. By combining signal processing, spindle detection, sleep stage identification and interactive visualization tools, this work helps researchers to efficiently identify, validate, and analyze sleep and spindle characteristics with higher precision than traditional methods.

1 INTRODUCTION

Millions of people around the world battle sleep disorders that significantly impact public health and quality of life. Healthcare professionals analyze these disorders through polysomnography (PSG) studies, which generate extensive physiological data. While automated systems exist, there remains a need for tools that combine automatic analysis with interactive visualization to support clinical decision-making.

This paper presents a sleep analysis application featuring an interactive interface, visual analytics, and AI-driven capabilities for sleep classification and spindle detection. Our approach enhances conventional methods by combining automated detection with interactive exploration tools.

2 RELATED WORK

Sleep monitoring is essential for improving health and well-being, as well as for diagnosing and treating sleep disorders. Visual analytics (VA) tools have been developed to support the interpretation of sleep data. Advancements in sensor technology and computing methods has brought access to a large amount of sleep data. This section reviews existing work on sleep monitoring methods, visual analytics applications, and their integration with machine learning.

2.1 Visual Analytics for Sleep Monitoring

Sleep monitoring is traditionally based on polysomnography (PSG), which involves recording physiological signals such as electroencephalogram (EEG), electrooculogram (EOG), and electromyogram (EMG). Although effective, PSG is resource intensive and often limited to clinical studies. In addition, the recordings are conduced typically to specialized sleep labs, which may not accurately represent a patient's usual sleep patterns (Markun and Sampat, 2023). Despite being resource-intensive, PSG data remain helpful in sleep monitoring and analyzing sleep disorders. The following systems greatly improve sleep data analysis.

Sleep (Combrisson et al.,) is a Python-based application offering GPU-accelerated visualization of sleep data, automatic feature detection, and manual scoring capabilities. While it provides valuable basic analysis tools, our application extends these functionalities to address clinical needs through advanced vi-

Tsiobra, M., Nikolis, G., Diamantakis, C., Salanitro, M., Kalamaras, I., Lwlis, V., Penzel, T., Votis, K. and Tzovaras, D.
Visual Analytics for the Analysis of Sleep Quality.
DOI: 10.5220/0013376500003912
Paper published under CC license (CC BY-NC-ND 4.0)
In *Proceedings of the 20th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2025) - Volume 1: GRAPP, HUCAPP and IVAPP*, pages 983-991
ISBN: 978-989-758-728-3; ISSN: 2184-4321
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sual analytics, including interactive 2D visualizations for sleep pattern analysis.

V-Awake (Caballero et al., 2019) is a visual analytics system for exploring and correcting deep learning-based sleep stage predictions when ground truth data is unavailable. While it primarily focuses on model validation through interactive views of predictions and patterns, our system extends beyond this to provide comprehensive clinical analysis tools. In addition to signal visualization, our application incorporates spindle detection, feature extraction, and temporal pattern analysis capabilities specifically designed to support sleep disorder diagnosis.

SleepExplorer (Liang et al., 2016) analyzes relationships between commercial sleep tracker data and lifestyle factors affecting sleep quality. While it focuses on personal sleep patterns, our system extends beyond this by integrating advanced analytics and visualization tools specifically designed for clinical sleep disorder diagnosis and research. Through enhanced precision and interactivity, we transform sleep data into meaningful clinical insights.

2.2 Automated Algorithms for Sleep Monitoring

In this section, related work in the field of automated identification of sleep spindles and sleep stages is briefly presented.

2.2.1 Spindle Detection

Sleep spindles are EEG events characterizing the N2 sleep stage. They may be an indicator of intellectual ability, memory consolidation, as well as quality of sleep (Fogel and Smith, 2011). They are frequency related events and usually consist of short bursts in the range of 11 - 16 Hz that last 0.5 to 2.5 seconds. Studies suggest that they may be associated with neurodegenerative diseases, like Alzheimer (Weng et al., 2020). Consequently, this electroencephalography activity can be very significant for the diagnosis and treatment of many disorders, even beyond sleep. Sleep technicians usually notice these events by visually examining raw data, which can take a lot of time and could be counterproductive in long sleep recordings. Thus, an automated mechanism for the detection of such events could be very useful for them.

Researchers have applied many techniques to detect spindles, from algorithmic approaches to Deep Learning. The 'A7 Algorithm' (Lacourse et al., 2019) attempts to mimic the way sleep experts detect spindles, by analyzing physical properties like frequencies and amplitudes. A popular deep neural network approach has achieved impressive performance (You et al., 2021), while the hybrid CNN-LSTM architecture (Tapia and Estévez, 2020) has also been successfully applied.

2.2.2 Sleep Stage Classification

Automatic classification of sleep stages has aroused a lot of interest (Loh et al., 2020) from the scientific community, since manual sleep scoring requires a substantial amount of time, as well as a lot of expertise. Sleep stages are classified into three categories: Wake, Non Rapid Eye Movement (NREM) and Rapid Eye Movement (REM). The NREM category can be further split into three subcategories (N1, N2, N3). Each stage is characterized by specific activity in the brain and the body, which can be captured with polysomnography. PSG recordings are synchronized and split into segments of 30 seconds, which are called 'epochs'.

The most common modeling approach is the implementation of a Convolutional Neural Network (CNN) with a single EEG channel (Wei et al., 2017). Another effective approach is the Long Short Term Memory (Hochreiter and Schmidhuber, 1997) model which can achieve impressive results (Morokuma et al., 2023). In general, significant progress has been made in this research field and an application that presents the results of such techniques in a user-friendly way could be of paramount importance.

3 PROPOSED METHOD

In this section, we present the proposed methodology for the development of the application. It includes data processing, feature extraction, automated sleep scoring, spindle detection and visualization.

3.1 Overall Architecture

The purpose of this application is to assist healthcare professionals in analysing sleep data in a more efficient way. Thus, the design process involved consultation and feedback from sleep clinicians from the Charité Universitätsmedizin Berlin (CUB). Expert consultation led to the collection of functional and non-functional requirements, including:

- temporal navigation of raw signals alongside overall statistics.
- detection of sleep spindles.

- extraction of specialized features (e.g. frequency bands) that are relevant for sleep quality assessment.
- 2D projection of the extracted features to provide research insights into sleep stage grouping and clinical scoring patterns.
- improved user experience by filtering the visualization output based on patients' age, gender, sleep stage, etc.
- a dynamic timelapse, on the 2D visualization space, of the recording of patients during their sleep.

The design of the system has been made to accommodate for the above requirements. The proposed sleep analysis application implements an architecture (Figure 1) that integrates raw polysomnography data processing with AI analysis and visualization capabilities.

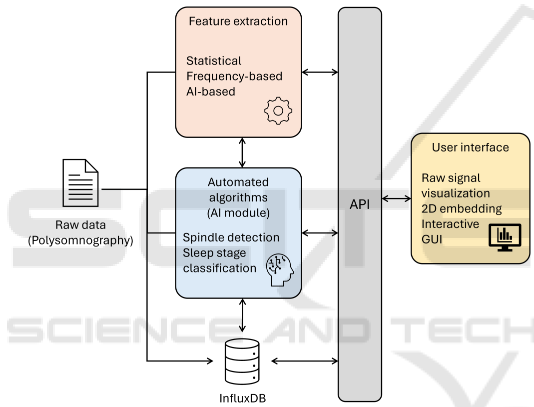

Figure 1: Application architecture diagram.

The core process focuses on two main components: a feature extraction module and a specialized AI analysis component. By employing statistical methods, frequency-based techniques, and AI-driven approaches, the feature extraction process uncovers patterns within the sleep data. The AI module utilizes deep learning architectures to classify sleep stages and detect sleep spindles.

The system offers a user-friendly visualization and interaction layer within an interactive graphical user interface. The visualization framework provides options for raw signal visualization as well as 2D representations. The interactive GUI integrates all analysis outputs and provides intuitive access to sleep analysis results.

The data used in this study consists of polysomnography (PSG) recordings from the CUB sleep laboratory database, stored in European Data Format (EDF). The dataset includes recordings from patients diagnosed with sleep apnea syndrome according to AASM criteria, comprising EEG and EOG signals (256 Hz), respiratory (128 Hz), and SpO2 (1 Hz). The recordings include standardized annotations marking clinical events such as respiratory events, sleep stages, arousals, and movement artifacts, manually scored by sleep technicians.

For data management, we utilized InfluxDB[1] to store and manage the extracted physiological signals. Its timestamp-based storage aligns naturally with PSG recordings, while supporting concurrent signal storage, flexible retention policies, and built-in functions for downsampling and aggregation. This design enhances computational efficiency and enables effective management of high-frequency PSG data.

3.2 Feature Extraction

Feature extraction transforms raw physiological signals into measurable characteristics, highlighting key aspects for analysis by reducing data dimensionality while preserving essential information. In the presented visual analytics system, three sets of features were extracted from the raw signal, one capturing statistical information, another encoding frequency-domain characteristics and and a third consisting probabilities features extracted from a sleep stage classification model.

3.2.1 Statistical Feature Extraction

Temporal statistical features were extracted from each signal segment to capture time-domain characteristics. For a given signal segment $x[n]$ of length N, the following statistical measures were computed, offering complementary information to the spectral analysis:

- The mean (μ) indicates baseline shifts in the EEG signal, which can be relevant for identifying sustained changes in brain state.
- The standard deviation (σ) quantifies the signal's variability, often correlating with overall neural activity levels.
- The maximum and minimum values ($x_{\max}, x_{\min}$) capture extreme excursions in the signal, which can be indicative of specific neural events or artifacts.

3.2.2 Frequency Domain Feature Extraction

The frequency-domain features are particularly significant for sleep stage analysis, as different sleep

[1]https://www.influxdata.com/products/influxdb/

states enclose distinct behaviors in the brain. These brain patterns serve as fundamental markers for sleep stage classification.

Signal Preprocessing: Prior to spectral analysis, the EEG signals are preprocessed through resampling to a uniform sampling frequency of 100 Hz. The continuous signals are then segmented into 30-second epochs, aligning with the standard duration used in sleep staging.

Power Spectral Analysis: For each epoch, the power spectral density (PSD) is estimated using a Fourier Transform (FT) of the EEG signal:

$$PSD(\omega) = \frac{|F(\omega)|^2}{N}$$

Where $F(\omega)$ represents the Fourier Transform of the EEG signal and N is the length of the discretized sample.

Frequency Band Analysis: Following the power spectral computation, features based on five frequency bands were extracted, commonly used in neuroscience, Table 1:

Table 1: Description of EEG Frequency Bands.

Frequency Band	Description
Delta (0-4 Hz)	Dominant in deep sleep (Stage III/IV)
Theta (4-7 Hz)	Prominent during drowsiness and light sleep
Alpha (7-12 Hz)	Associated with relaxed wakefulness
Beta (12-30 Hz)	Characteristic of active wakefulness
Gamma (30-50 Hz)	Linked to complex cognitive processing

Multi-Channel Analysis: The spectral analysis is performed on three EEG channels (F4, O2, and C4), enabling the capture of spatial variations in brain activity. For each channel and each 30-second epoch, the bandpower features are extracted independently, resulting in a set of frequency-domain features that characterize different regions of the brain during sleep. The bandpower for a frequency band is computed by numerical integration of the power spectral density function over the frequency band of interest:

$$bp(x, f_{\text{lower}}, f_{\text{upper}}) = \int_{f_{\text{lower}}}^{f_{\text{upper}}} PSD(\omega)\, d\omega$$

The relative bandpower is calculated as:

$$bp_{\text{relative}}(x, f_{\text{lower}}, f_{\text{upper}}) = \frac{bp(x, f_{\text{lower}}, f_{\text{upper}})}{bp(x, 0, \infty)}$$

3.2.3 CNN Feature Extraction

Long multivariate time series can be difficult to interpret. In addition, the decision making process of AI applications is not always clear. For this purpose, this application will use an AI model, which is described in a following section (3.3.2), for the visualization of the computed probabilities (CNN features) of each class in order to make the system more transparent, apart from the visualization of the predicted sleep stages.

The complete feature vector for each window consists of five relative bandpowers ($\delta, \theta, \alpha, \beta, \gamma$), four statistical measures ($\mu, \sigma, x_{\max}, x_{\min}$) and five probabilities, one of each class.

3.3 Automated Methods for Sleep Monitoring

In this section, the development of an automated sleep scoring and a spindle detection mechanism are presented. At first, the design process of their architecture is described and afterwards, the input data as well as its preprocessing are explained. Both of them are meant to be used as additional functionalities of the application to showcase the kind of capabilities that can be included.

3.3.1 Spindle Detection

Architecture: Due to the lack of labels of this specific dataset, the spindle detection is based on the Python implementation (Kaulen et al., 2022) of the 'A7 Algorithm' (Lacourse et al., 2019). This approach attempts to automate the way human experts detect spindles. Sleep technicians may visually notice a small frequency burst in a part of a signal that could indicate a spindle. Four parameters that can capture information about these events are calculated and compared to some thresholds that decide whether a spindle is detected or not. Since the equipment that was used for the recording of these signals can impact their overall shape, in terms of amplitude or noise, these thresholds were adjusted in order to fit the signals that are used in this application, compared to the ones described in the original implementation. The algorithm detects spindles in length ranging from 0.3 to 2.5 seconds. Finally, we consider events in the frequency range of 12-14 Hz as spindles, in order to decrease the false positive detections.

Data Preprocessing: The sleep spindles are mostly apparent on the central EEG channels. Thus, the C4

EEG signal was used as an input for the above algorithm. The signal is passed through a band-pass filter of 0.3 - 30 Hz and is sampled at 100 Hz. Apart from the filtering done in the scope of the A7 implementation, no further preprocessing has been done. The results and their evaluation are described in section 4.1.

3.3.2 Sleep Stage Classification

Architecture: The main purpose of this implementation was to isolate certain layers in order to extract features from raw data. Several well known implementations were tested. The selected model is inspired by the architecture of DeepSleepNet (Supratak et al., 2017). Since the application focuses on feature extraction and visualization, only the CNN part of the model was used. The architecture consists of two main branches with a series of layers. This technique is capable of capturing information from the input effectively, since the sizes of the filters vary. Overall, each branch consists of four convolutional layers with some pooling and dropout layers between them. Finally, the two branches are merged together and a softmax layer is added for classification. The functional API of tensorflow was used, in order to add the option to easily isolate layers for further examination of the feature extraction mechanism.

Data Preprocessing: Since the goal was to extract features, many combinations of signals were tested. However, the addition of multiple channels did not seem to improve the overall performance of the model in terms of complexity and accuracy and thus, the two central EEG channels were selected (C4, F4). The data were split into 30-second-epochs at 100 Hz and passed through a band-pass filter of 0.3-100 Hz. The annotations were synchronized and measures were taken to verify that no gaps or NAN values existed. The severe class imbalance was dealt with the use of the Synthetic Minority Oversampling Technique (SMOTE) (Chawla et al., 2002) by the imbalanced-learn package (Lemaître et al., 2017). After applying it and verifying that no leakage of information occurred to the test or the validation set, the dataset was ready for the training process. The results and their evaluation are described in section 4.2.

3.4 Interactive Visual Analytics Interface

The visualization of sleep data plays a crucial role in understanding patterns and relationships within polysomnography datasets. In this section, the two most important panels of the application are presented, regarding the visualization of raw signals as well as of temporal segments as points in a two-dimensional space.

3.4.1 Signal Visualization and Analysis

The raw signal visualization panel (Figure 2) presents multi-channel physiological data through synchronized time-series plots. The interface supports the display of specifically selected channels (EEG, ECG, respiratory signals) with individual y-axis scaling optimized for each signal type. At the top of the screen, users can select records as well as adjust viewing preferences. Specifically, they can select a 30-second or 1-minute view of raw data, while navigation controls allow precise temporal exploration with 5-second and 30-second steps. In the middle of the panel, the predicted sleep stages graph provides the ability to view the raw data of each time window by clicking on it. At the bottom of the screen, some overall statistics provide a quick overview of the recording. Lastly, the detected spindles are highlighted in red in both the C4 EEG signal as well as on the sleep stages graph.

3.4.2 Dimensionality Reduction and Visualization

To enable the identification of similar patterns that could indicate different sleep stages, anomalies, or disorders, temporal segments (30-second windows) of PSG signals are visualized as points in a two-dimensional space. This visualization is generated by initially extracting features from each segment and applying t-Distributed Stochastic Neighbor Embedding (t-SNE) (van der Maaten and Hinton, 2008), which has been previously used on sleep scoring models (Guo et al., 2024). This method was selected because it manages to create effective 2D visualizations of data that lie in highly non-linear manifolds in the high-dimensional space (including statistical, frequency-domain, and CNN features), revealing complex relationships and patterns such as clusters and outliers. The results of this visualization are described in section 4.3

The t-SNE visualization page (Figure 3) displays the two-dimensional embedding of the sleep intervals in an interactive manner. The vertical menu on the left offers multiple filtering options that are important for sleep analysis, such as gender, age group and sleep stage. At the top of the panel, users can select the patients that they want to review on the 2D map. Moreover, they have the option to select the way that the data points are colored, either by patient or by sleep stages. In addition, both manual sleep stage coloring

Figure 2: Signal visualization panel.

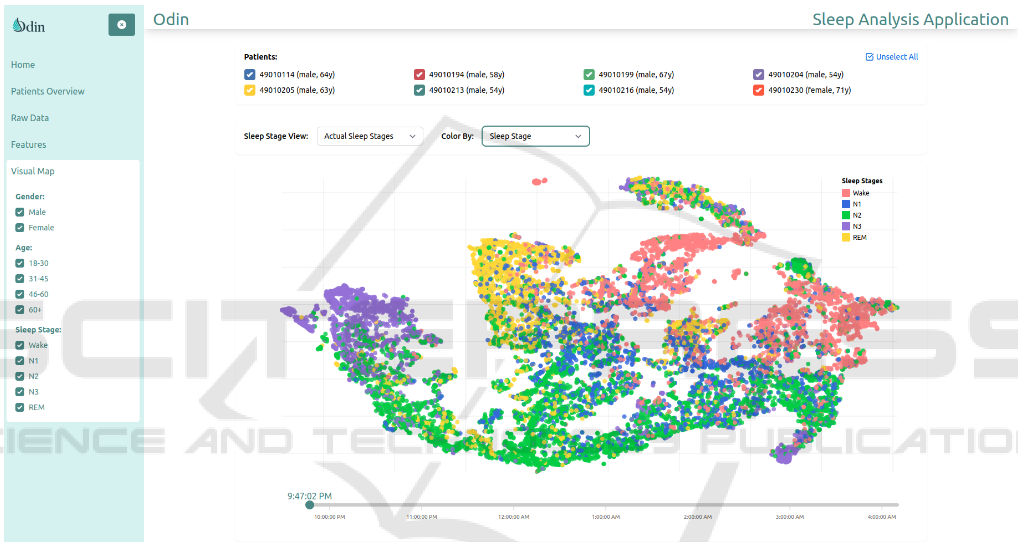

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Figure 3: Interactive t-SNE visualization interface showing the two-dimensional embedding of sleep intervals.

and AI predicted sleep stage coloring are supported. At the bottom of the screen, there is a timelapse functionality for animating sleep progression in time with a rolling bar, which allows clinicians to see how these dots and their corresponding sleep stages are created throughout the recording.

During daily practice, a clinician would use the signal visualization panel to examine the stored polysomnography recordings, and would use the outputs of the spindle detection and sleep detection methods to quickly identify areas of interest in the raw data, without having to manually examine the whole signal, which is a tedious process. Furthermore, the clinical researcher would examine the 2D visualization in order to collectively view information from several patients, to have a comprehensive overview of the sleep patterns appearing in the complete dataset and distinguish segments of recordings that divert from the usual pattern.

4 EVALUATION RESULTS

This section presents evaluation results for the spindle detection, the automated sleep stage identification, and the two-dimensional visualization. Regular qualitative assessments and feedback from CUB clinicians guided system development and fine-tuning.

4.1 Spindle Detection

Figure 4 shows the detected spindles and their duration. Since there is not a ground truth set for this dataset it is difficult to properly evaluate the performance in an objective way. By visually inspecting the results thoroughly and receiving feedback from experts, the spindle detection seems adequate to be used as a recommendation feature in the application, which could assist sleep technicians in recognizing these events in a much more quick and efficient way. The detection of spindles is a very important additional functionality and despite the lack of labels, it is included in our implementation to showcase the value that it can offer.

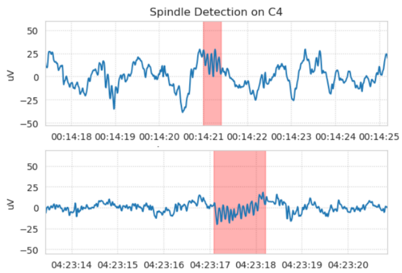

Figure 4: Spindle detection by the A7 Algorithm.

4.2 Sleep Stage Classification

The final results (Table 2) show that the model has mediocre performance compared to state-of-the-art publicly available implementations. Specifically, taking a closer look into the confusion matrix (Figure 5), the misclassification of 'N1' and 'N2' observations seem to cause the drop in performance. The overall model structure and consistency of labels have probably played a significant role in its performance, as many attempts to improve it were not successful. Despite its mediocre performance, the feature extraction mechanism can provide useful information to the sleep technician, even if a misclassification occurs.

Table 2: Scores of sleep stage classification model on the test set.

	precision	recall	f1-score	support
W	0.95	0.81	0.88	393
N1	0.49	0.24	0.32	288
N2	0.63	0.51	0.56	860
N3	0.47	0.98	0.63	421
REM	0.70	0.56	0.63	442

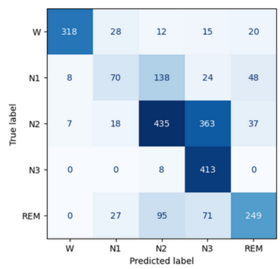

Figure 5: Confusion matrix of sleep scoring model.

4.3 Visualization Evaluation

The two-dimensional representation is presented in Figure 6. Each dot represents an index of the feature vector that derives from a 30 second window of raw data. It should be noted that the two axes do not have a specific meaning in this case. However, the way these points are grouped together provides significant insight into how sleep stages and disorders are formed among patients in a direct way. Figure 6a presents the points from three patients, as an example. At a glance, it is clear that data seem to group at specific areas for each patient.

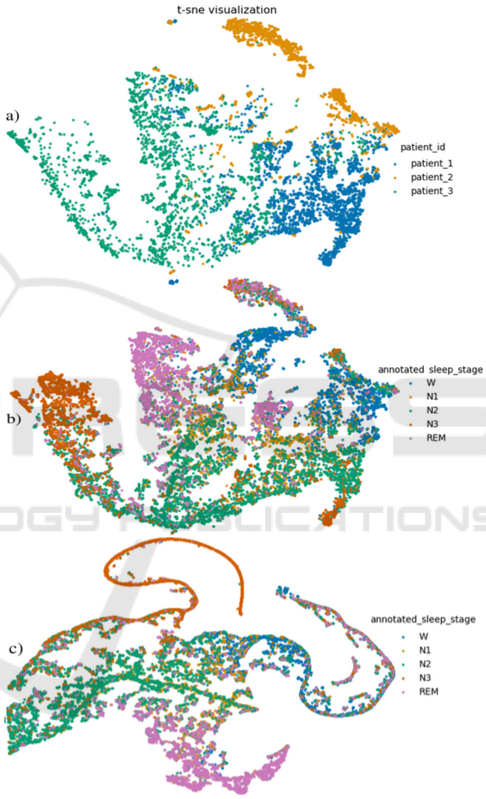

Figure 6: Two-dimensional representation of: (a) all features of three patients colored by patient, (b) all features of all patients colored by sleep stage, (c) cnn features colored by sleep stage.

A representation of all the patients is shown in Figure 6b, where each dot is colored based on the annotated sleep stage. It can be observed that sleep stages cluster in specific areas of the plot, which could provide very valuable information to sleep technicians about quality of sleep. It is also very interesting that 'N1' seems to be the sleep stage in the center of the plot, which could indicate that it is the most difficult to distinguish among the others, while 'N3' seems to be the most easily distinguished one.

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The same procedure is shown in Figure 6c with only the CNN features. A similar behavior is present, as sleep stages seem to group in certain areas with some overlappings. Judging by the coloring of the manually annotated sleep stages, the CNN features can group the sleep stages in a relatively accurate way. Finally, Figure 6c enhances the explainability of the model, since it shows which classes are most frequently misclassified and in which areas.

5 CONCLUSIONS

We introduce an advanced sleep monitoring system which combines AI-based analysis and interactive visualization tools. Three key components—a spindle detection method, a sleep stage identification model and a two-dimensional embedding of sleep intervals—combined with raw signal visualization in an interactive dashboard, enable the system to implement a multi-view approach. The detection of spindles on raw EEG data is a powerful tool that can enhance the capabilities of sleep analysis. The stage classification model demonstrated varying performance across sleep stages which reflects the inherent complexity of sleep classification. Moreover, t-SNE visualization with large datasets can place limitations due to its high computational cost. Future work includes the installation of the system at the CUB premises, and a thorough assessment of its usefulness and usability with standardized questionnaires (e.g. SUS scale) after a pilot usage. In addition, we will focus on quantitative evaluation of spindle detection using expert ground truth and extending the 2D visualization framework for apnea analysis.

ACKNOWLEDGMENT

This work has been supported by the EU H2020 project ODIN (H2020-DT-ICT-12-2020, grant agreement no. 101017331).

REFERENCES

Caballero, H., Westenberg, M., Gebre, B., and Wijk, J. (2019). V-awake: A visual analytics approach for correcting sleep predictions from deep learning models. *Computer Graphics Forum*, 38:1–12.

Chawla, N. V., Bowyer, K. W., Hall, L. O., and Kegelmeyer, W. P. (2002). Smote: Synthetic minority oversampling technique. *Journal of Artificial Intelligence Research*, 16:321–357.

Combrisson, E., Vallat, R., Eichenlaub, J.-B., O'Reilly, C., Lajnef, T., Guillot, A., Ruby, P. M., and Jerbi, K. Sleep: An open-source python software for visualization, analysis, and staging of sleep data.

Fogel, S. M. and Smith, C. T. (2011). The function of the sleep spindle: A physiological index of intelligence and a mechanism for sleep-dependent memory consolidation. *Neuroscience & Biobehavioral Reviews*, 35(5):1154–1165.

Guo, Y., Nowakowski, M., and Dai, W. (2024). Flexsleep-transformer: a transformer-based sleep staging model with flexible input channel configurations. *Scientific Reports*, 14.

Hochreiter, S. and Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, 9:1735–80.

Kaulen, L., Schwabedal, J. T. C., Schneider, J., Ritter, P., and Bialonski, S. (2022). Advanced sleep spindle identification with neural networks. *Scientific Reports*, 12(1).

Lacourse, K., Delfrate, J., Beaudry, J., Peppard, P., and Warby, S. C. (2019). A sleep spindle detection algorithm that emulates human expert spindle scoring. *Journal of Neuroscience Methods*, 316:3–11. Methods and models in sleep research: A Tribute to Vincenzo Crunelli.

Lemaître, G., Nogueira, F., and Aridas, C. K. (2017). Imbalanced-learn: A python toolbox to tackle the curse of imbalanced datasets in machine learning. *Journal of Machine Learning Research*, 18(17):1–5.

Liang, Z., Ploderer, B., Liu, W., Nagata, Y., Bailey, J., Kulik, L., and Li, Y. (2016). Sleepexplorer: A visualization tool to make sense of correlations between personal sleep data and contextual factors. *Personal and Ubiquitous Computing*, 20:985–1000.

Loh, H. W., Ooi, C. P., Vicnesh, J., Oh, S. L., Faust, O., Gertych, A., and Acharya, U. R. (2020). Automated detection of sleep stages using deep learning techniques: A systematic review of the last decade (2010–2020). *Applied Sciences*.

Markun, L. C. and Sampat, A. (2023). Clinician-focused overview and developments in polysomnography. *Journal of Clinical Sleep Medicine*.

Morokuma, S., Hayashi, T., Kanegae, M., Mizukami, Y., Asano, S., Kimura, I., Tateizumi, Y., Ueno, H., Ikeda, S., and Niizeki, K. (2023). Deep learning-based sleep stage classification with cardiorespiratory and body movement activities in individuals with suspected sleep disorders. *Scientific Reports*, 13.

Supratak, A., Dong, H., Wu, C., and Guo, Y. (2017). Deepsleepnet: A model for automatic sleep stage scoring based on raw single-channel eeg. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 25(11):1998–2008.

Tapia, N. I. and Estévez, P. A. (2020). Red: Deep recurrent neural networks for sleep eeg event detection. In *2020 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8.

van der Maaten, L. and Hinton, G. (2008). Visualizing data using t-sne. *Journal of Machine Learning Research*, 9(86):2579–2605.

Wei, L., Lin, Y., Wang, J., and Ma, Y. (2017). Time-frequency convolutional neural network for automatic sleep stage classification based on single-channel EEG. pages 88–95.

Weng, Y.-Y., Lei, X., and Yu, J. (2020). Sleep spindle abnormalities related to alzheimer's disease: a systematic mini-review. *Sleep Medicine*, 75:37–44.

You, J., Jiang, D., Ma, Y., and Wang, Y. (2021). Spindleu-net: An adaptive u-net framework for sleep spindle detection in single-channel eeg. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, PP:1–1.

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