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AUTOMATIC DETECTION OF SLEEP SPINDLES BY NEURAL NETWORKS ALGORITHMS

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Abstract.

Sleep constitutes an essential aspect of human existence, with the average individual dedicating approximately one-third of their life to this physiological activity. Consequently, comprehending and accurately analyzing sleep patterns is of paramount importance. This research aims to introduce, formulate, execute, and assess diverse machine/deep learning methodologies tailored for the processing of EEG signals geared explicitly towards identifying sleep spindles. The learning algorithms underwent training using meticulously annotated data from the Montreal Archive of Sleep Studies (MASS) data center. The convolutional neural network emerged as the most effective classification model, achieving an accuracy surpassing 67 %.

Keywords: Deep learning, EEG data standards, EEG workflows, EEG pipelines, electroencephalography, event-related potentials, human brain, machine learning.

1. Introduction

Sleep, comprising approximately one-third of human life, is crucial for bodily rejuvenation and mental relaxation. However, the prevalence of sleeping disorders in modern society underscores the significance of research in this domain to enhance sleep quality.

The brain's activity undergoes distinct changes during sleep, categorized into REM and non-REM phases; a specific phenomenon within the non-REM phase is known as a sleep spindle. Sleep spindles are brief bursts of neural oscillatory activity during non-REM sleep and play a crucial role in memory consolidation. These spindle events are essential indicators of sleep quality and cognitive functions.

Electroencephalography (EEG), the fundamental method and technique for measuring and collecting electrical activity of the human brain, is also used in sleep data collection; their abundance and complexity necessitate further computer processing. This mitigates human error and promotes more efficient and accurate data analysis.

Machine and deep learning, particularly neural networks such as Convolutional Neural Networks (CNN), Long Short-Term Memory Networks (LSTM), and Dense Networks, offer a promising approach to EEG signal and sleep data processing.

This paper focuses on identifying sleep spindles. This is accomplished by designing, implementing, and assessing deep learning methods (neural networks). The general aim is to improve understanding and interpretation of EEG data, contribute to advancements in automated sleep analysis, and enhance our knowledge of sleep-related phenomena.

The paper is organized in the following way. The state-of-the-art section provides insight into EEG and sleep stages classification, sleep spindle characteristics, and sleep data platforms and archives. It is followed by the sections describing the dataset and neural network architectures used. Then, the dataset processing is presented, and the results are provided. The outcomes and future perspectives are summarized in the conclusion section.

2. State of the art

The typical use case in EEG signal classification is to compare methods for categorizing preictal, postictal, and interictal classes when epileptic seizures are detected. The model proposed in [1] integrated a two-layer LSTM and a four-layer enhanced neural network (NN) deep learning architecture using improved one-dimensional gradient descent activation functions. The study used the pre-processed Bonn University database; statistical features were extracted. Conventional methods used for the classification included Support Vector machines (SVM) with different kernels, logistic regression, and NNs. The results showed that the improved NN algorithm achieved the highest accuracy (nearly 79 %), surpassing LSTM (71 %), NN neural network (61 %), and SVM (70 %), while logistic regression had the lowest accuracy (about 53 %) [1].

In collaboration with the Department of Medical Engineering and Technomathematics in Germany, Aachen University of Applied Sciences used a machine learning approach [2] to score pre-REM sleep stages in mice automatically. Using a dataset of polysomnographic recordings from 18 mice over 52 days, the study investigated the impact of dietary variation on sleep. The mice, chronically implanted with EEG and EMG electrodes, underwent data pre-processing, including low-pass filtering and synthetic data augmentation for a balanced training set. The neural network architecture, consisting of eight convolutional layers and a classifier with two fully connected layers, demonstrated high accuracy in classifying Wake, REM, and NREM segments, achieving over 98 %, more than 94 %, and close to 92 % accuracy, respectively. The pre-REM stage was correctly classified in 58 % of the segments. The classifier showed robust performance, correctly predicting human-expert assigned stages for segments predicted to be Wake, REM, and NREM, demonstrating the effectiveness of the network in the automated classification of sleep stages in mice [2].

A 1D CNN-LSTM algorithm for automatic sleep staging (Wake, REM, Non-REM) on the Sleep-EDF dataset, achieving 93.47 % accuracy with the Fpz-Cz EEG channel, is described in [3]. The dataset comprises 197 PolySomnoGraphic sleep recordings with manually scored hypnograms. With seven layers (four 1D CNN and three LSTM layers), the algorithm exhibited robust performance across various physiological signals. Evaluations on single-channel EEG and EOG classifications, using five test sets for each group, confirmed the model's reliability. Achieving 94.15 % accuracy when incorporating Fpz-Cz EEG and EOG signals, the algorithm demonstrates promise for automated sleep staging in future sleep-related research. It offers an efficient alternative to manual expert inspection in large-scale Polysomnography (PSG) signal analysis, showcasing the effectiveness of deep learning in discerning similar sleep periods [3].

Figure 1 displays a characteristic sleep spindle evident in the EEG waveform during non-rapid eye movement (non-REM) sleep. This spindle, observed in frontal and central brain regions, manifests as a brief burst of rhythmic oscillations lasting 0.5 to 2 seconds, with frequencies ranging from 11 to 16 Hz. The figure provides a visual representation of the spatial and temporal dynamics of the sleep spindle, contributing to the understanding of its electrographic features. Recognized for its role in memory consolidation, the accurate identification and analysis of sleep spindles, as illustrated in Figure 1, are crucial for investigating sleep disorders and neurological conditions, enhancing comprehension of neural activities during sleep. Due to its characteristic properties, it is suitable for testing processing techniques like machine learning and neural networks further to refine the detection and interpretation of sleep spindles.

The Massive online data annotation (MODA) platform is pivotal in generating standardized datasets for training and validating automated detectors of biological signals, including EEG [5]. A Canadian study using MODA compared the results of expert, researcher, and non-expert scorers with seven spindle detection algorithms, revealing that only two algorithms performed comparably to human experts, showcasing MODA's significance in benchmarking automated sleep analysis methods.

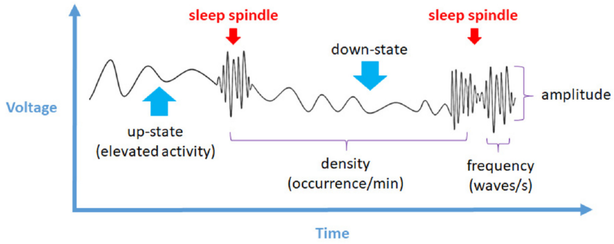

FIGURE 1. Example of EEG sleep spindles; adopted from [4].

The Montreal Archive of Sleep Studies (MASS) also serves as an open-access repository, providing PSG data for benchmarking automated sleep analysis systems [6]. Established as part of the MODA project [5], MASS is a comprehensive and openly accessible repository of PSG recordings with annotated EEG signals, supporting large-scale collaborations in sleep studies [6]. The MAAS database is structured into cohorts, with subsets categorizing recordings based on specific characteristics [6].

3. Sleep Spindles Dataset

This study used EEG data from the MASS archive's stage SS2 (described in Table 1). The data preparation of EEG recordings involves addressing challenges such as the unique occurrence of sleep spindles in specific sleep segments, constituting about two percent of the overall recording. Given this imbalance, set balancing is crucial for effective neural network training. The measured voltage values in the EEG signal range from 10^{-4} to 10^{-6} Volts, necessitating normalization. The EEG records from only the Pz-CLE channel were further processed, as this channel provides optimal visibility for sleep spindles. The EEG records were subdivided into smaller segments for neural network processing; each segment was further divided into sets using annotations. The dataset's imbalance, where segments without spindles make up about ninety-eight percent of the dataset, is reduced using a Python random number generator for unbiased set balancing, avoiding pattern-based distortions during training.

4. Neural network architectures

This section briefly overviews the methods (neural network architectures) employed for the automated detection of sleep spindles in the dataset described above. Furthermore, these architectures were complemented by their combinations, with the anticipation of preserving the advantages and properties inherent in each architecture.

4.1. Dense Neural Network

The Dense Neural Network (DNN) depicted in Figure 2, also known as a fully connected neural network, exhibits a structure where each node in one layer connects to every node in the next. This dense connectivity allows comprehensive EEG signal processing

Stage 2 (SS2)	
Memory size	7.26 GB
Total number of measurements	19
Total number of spindles	11204
Average number of spindles in a measurement	217
Time length	151 h
Maximum number of spindles in a measurement	569
Minimum number of spindles in a measurement	86
Maximum duration of spindle	2.218605 s
Minimum duration of spindle	0.335915 s
Average length of an EEG measurement	7 h 59 min

TABLE 1. Characteristics of stage SS2.

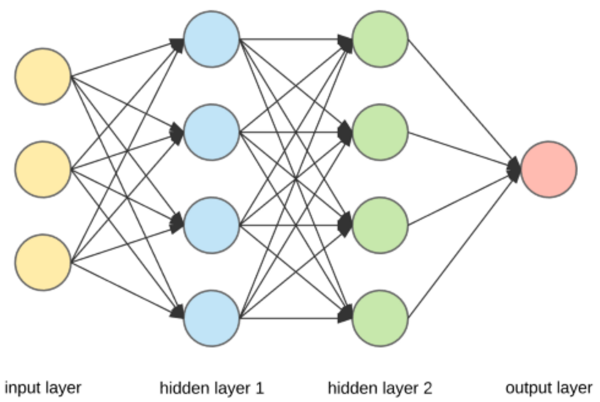

FIGURE 2. An example of a standard dense neural network. The network has one input, two hidden, and one output layer, adopted from [7].

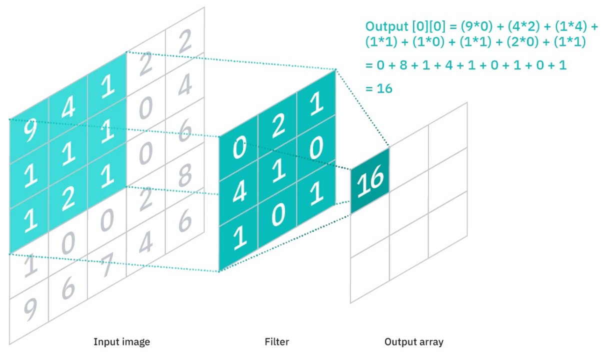

FIGURE 3. An example of an application of filter on an image inside a CNN network, adopted from [8].

and feature extraction, enabling the network to capture intricate data relationships. DNNs are widely applied in domains such as image recognition, natural language processing, and signal processing due to their ability to learn complex patterns from extensive datasets.

4.2. CNN

The Convolutional Neural Network (CNN) illustrated in Figure 3 is a specialized class of artificial neural networks designed for processing structured grid data, particularly effective for tasks involving image analysis and recognition. With distinctive architectural elements, including convolutional layers, pooling layers, and fully connected layers, CNNs excel at capturing hierarchical features and spatial hierarchies in input data. Convolutional layers use filters to convolve across input data, extracting local features and patterns. Pooling layers reduce spatial dimensions, preserving crucial information while minimizing computational complexity. Fully connected layers enable high-level abstraction and decision-making. CNNs demonstrate notable efficacy in applications like image classification, object detection, and facial recognition, underscoring their significance in computer vision and pattern recognition research.

4.3. LSTM

The Long Short-Term Memory (LSTM) neural network, a specialized recurrent neural network (RNN) architecture, addresses the challenge of capturing long-range dependencies in sequential data by incorporating memory cells with input, forget, and output gates, making these networks particularly suitable for tasks involving memory and temporal patterns. The gates selectively control information flow, allowing the network to retain relevant context over extended sequences and mitigating the vanishing gradient problem. LSTMs excel in natural language processing, speech recognition, and time series analysis, effectively capturing temporal dependencies. Their role in mitigating the vanishing gradient problem has positioned LSTMs as a cornerstone in developing advanced deep-learning models for sequential data processing, contributing to diverse areas of artificial intelligence research. The network architecture is depicted in Figure 4, showcasing its capability to detect specific EEG signals.

5. DATASET PROCESSING

The current research incorporates three prominent neural network architectures discussed above: DNN, LSTM, and CNN. The strategic use of these architectures underscores a sophisticated approach to ad-

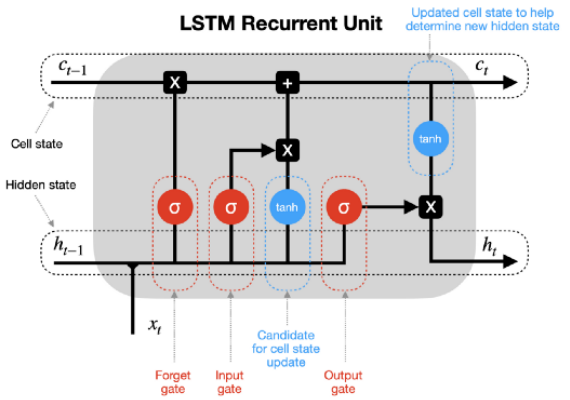

Figure 4. LSTM neural network scheme, adopted from [9].

dressing the complexities associated with sleep spindle detection in research studies.

The DNN architecture was the primary choice for sleep spindle dataset processing; it provides a basic model for initial exploration and understanding of the dataset. The LSTM architecture has been incorporated to process the data further. The inclusion of LSTMs is motivated by their ability to detect subtle signals that precede the occurrence of sleep spindles.

To enhance the data processing capabilities, the CNN was introduced into the architecture. In the context of sleep spindle detection, treating EEG data as an image allows CNNs to capture hierarchical features and spatial hierarchies efficiently. The convolutional layers in CNNs facilitate extracting local features and patterns, contributing to a comprehensive understanding of the dataset.

Various combinations of DNN, LSTM, and CNN architectures provide a diverse and comprehensive approach to the data processing to improve sleep spindle detection algorithms; we chose the following simple architectures: LSTM, Dense, CNN and CNN and their combinations of architecture: CNN-LSTM implemented in Keras python package and CNN-LSTM implemented in Torch python package.

The proposed CNN-LSTM implemented in Keras package architecture is shown in Figure 5. It consists of seven layers, with the initial four layers characterized by convolutional structures, each having 32 neurons. Following the non-convolutional layer is a linear layer with 384 neurons, introducing a deeper level of abstraction. Subsequently, the penultimate layer is also linear, incorporating 64 neurons. Ultimately, the final layer consists of two neurons.

5.1. Validation dataset

The validation dataset encompasses nearly 200,000 instances, with 51.2 % attributed to non-sleep spindles, and the remaining instances dedicated to sleep spindles. This meticulously constructed dataset is a subset derived from the extensive data repository provided by the Montreal Archive of Sleep Studies (MASS) center. The deliberate balance between the two classes ensures a representative and unbiased sample for thorough evaluation, fostering the reliability and generalizability of the neural network's performance assessment.

The training and testing of the neural network architectures has been performed on a normalized data set. The parameters for the neural networks, such as the size of the input layer and the number of epochs, were determined using genetic algorithms. The number of epochs varies for each architecture.

The last method used to process the sleep spindle dataset, the value-based method, is a simple analytic method. Its principle is that it sums the measured values on a specific interval and compares the resulting values with each other. For this method, it is crucial to set the border correctly.

At the outset of the algorithm, the border was initialized to zero. Subsequently, the EEG signal underwent segmentation, with each segment consistently comprising 64 measured values. The absolute sum of all values within the segment was computed and compared against the border. If the computed value exceeded the border threshold, the segment was annotated as a sleep spindle. The algorithm then tallied the number of correctly and incorrectly classified segments, following which the border was incrementally adjusted by a small increment. The optimal threshold value for classification was determined as the one yielding the highest number of correctly identified spindles.

6. Results

Table 2 summarizes the results obtained from testing various classifiers and their combinations. Also the Figure 6 shows peak accuracies achieved by the used classifiers.

Network architecture	**Accuracy**
Dense	64.63 %
LSTM	52.81 %
CNN	60.87 %
CNN-LSTM in Keras	52.81 %
CNN-LSTM in Torch	67.15 %
Value-based method	64.12 %

Table 2. Best results provided by the used classifiers.

Figures 7 and 8 present the accuracy and loss function values corresponding to the optimal neural network configuration evaluated on the validation dataset. Both figures are structured with the number of the validation set epochs delineated on the x-axis, visually representing the network's performance metrics across multiple epochs.

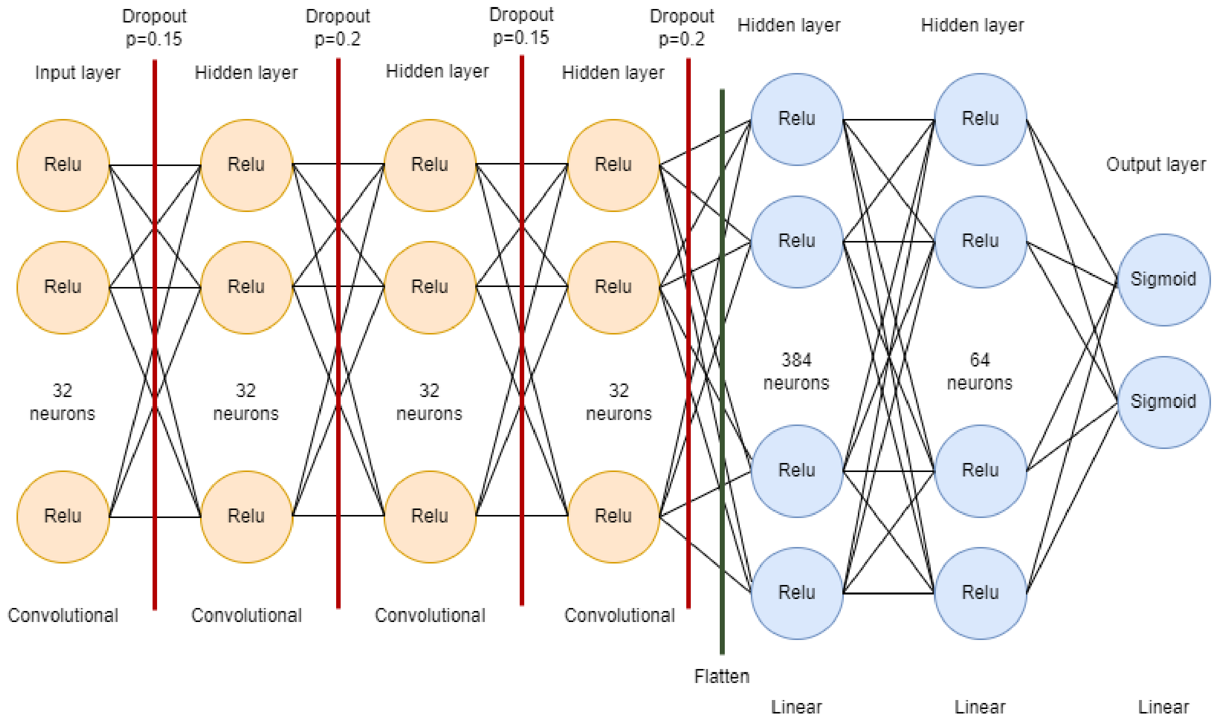

FIGURE 5. The CNN-LSTM architecture implemented in Torch package. The dropout layer prevents getting stuck in the local minimum; Flatten links CNN and the Linear layer.

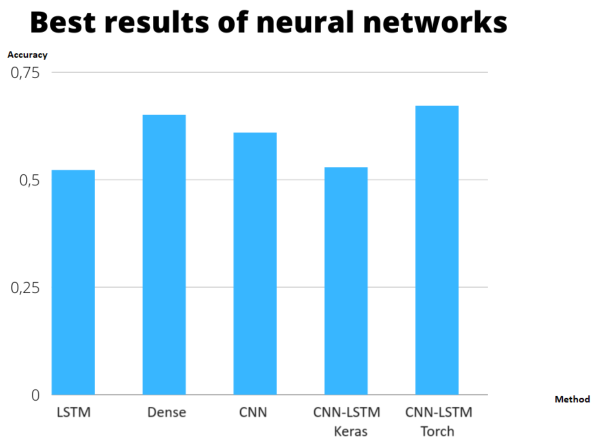

FIGURE 6. The best classification results (peak accuracies) achieved by the used classifiers.

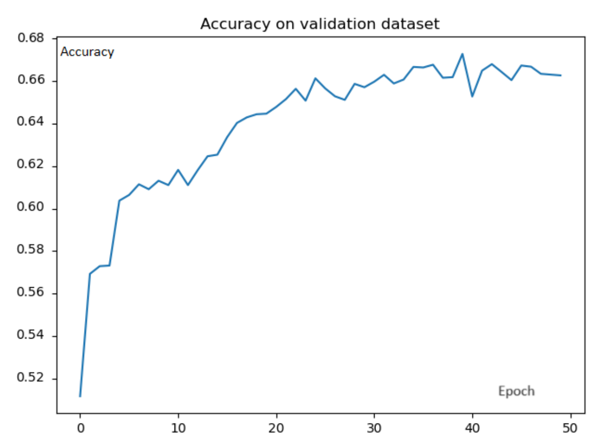

FIGURE 7. The accuracy on the validation dataset; X-axis = number of epochs over the validation dataset; Y-axis = the accuracy value.

7. Conclusion

The paper examines the processing of EEG signals during sleep to identify sleep spindles using mostly various simple and hybrid neural network architectures. The study used data from the recognized MASS archive. The used dataset was balanced, divided into training and testing sets, and used to train neural networks. The classification accuracy of LSTM and LSTM-CNN networks was the lowest at 52.81 %. Keras' Dense and CNN networks showed slightly better results with an accuracy of 60–65 %. The most successful network was the CNN network implemented in the Torch package, achieving accuracy exceeding 67 %.

The achieved classification results are consistent with those reported in the literature, where the best results for EEG sleeep artifact classification reached 70–75 %. The value-based method achieved an accuracy of 64.12 %, slightly below the state-of-the-art.

It may be worth refining the neural network parameters by extending the state area of input parameters to improve performance. Also, the potential benefits of the next alternative hybrid deep learning architectures in identifying sleep spindles can be considered.

Acknowledgements

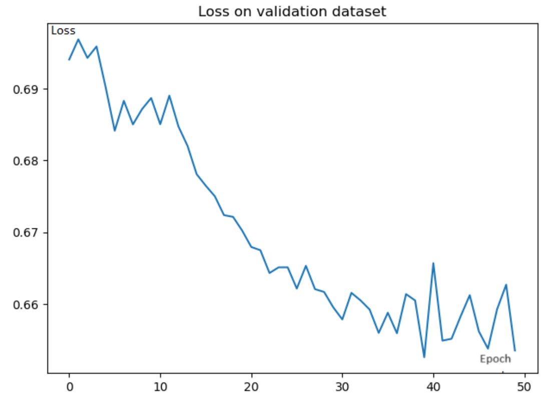

Figure 8. The loss function on the validation dataset; X-axis = number of epochs over the validation dataset; Y-axis = the loss value.

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