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Classification of Sleep Stages using Neural Networks

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Abstract. Sleep stages are considered important indicators for diagnosing neurological and psychiatric illnesses, so sleep disturbances have a major impact on a person's well-being. However, many sleep status analyzes are done visually by professionals in the field, which can be a slow task. For this reason, studies on sleep states automatically are of great importance in diagnosing neurological disorders quickly. In this article, an approach using the variance of the electroencephalogram (EEG) as an input to a multilayered neural network was used to classify sleep states. The EEGs were obtained from the Sleep-EDF Database Expanded database, obtained from two healthy patients, the first containing 7,950,100 records (22 total hours), and the second 8,490,100 (23 total hours), being extracted, filtered and subsequently classified automatically into five sleep states. A neural network used was fully connected with two intermediate layers and 12 neurons in each layer, with a learning rate of 0.01. The accuracy of the five-stage classification was 94.3%. These results showed that the proposed algorithm is favorable to obtain a classification of the stages with good precision in comparison to the other results found in the literature.

Keywords: Sleep; Neural networks; Electroencephalographs; Classification

1 Introduction

Sleep stages are important indicators in neurological and psychiatric diagnostics, therefore sleep disturbances have a major impact on a person's well-being. Several diseases can be assessed in the sleep stage, as well as insomnia, hypersomnia, parasomnias, sleep-related breathing, narcolepsy and cardiac rhythm disorders. Although many of these disorders are diagnosed clinically, other more sophisticated techniques can be considered [1] - [3].

The subjects' physiological signals are collected by polysomnography recordings during a full night's sleep. Polysomnography is a multivariate system that records signals such as electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG) and electromyogram (EMG) [4]. After collecting the signals, the annotations and classifications of the sleep stage are performed manually by the specialists. It's a tedious, labour intensive task. Therefore, several ways of designing automatic sleep classification were analyzed to understand how sleep goes through.

The criteria for classification of sleep stages is based on the guidelines proposed by the American Sleep Medicine (AASM) or those of Rechtschaffen and Kales (R&K). According to the R&K guidelines, a sleep stage can be classified as wake (W), four stages of non-rapid eye movement (NREM) (N1-N4) and rapid eye movement (REM). In addition, stages N3 and N4 can be analyzed by a single class as slow wave sleep (SWS), computing five stages, distinguished by frequencies and frequency patterns. Different individuals exhibit different behaviors during sleep [5]. For example, an adult has greater brain activity and a greater fluctuation between stages of sleep, which results in sleep being interrupted more easily, while an elderly person falls into sleep faster and more uniformly (low fluctuation between stages or brain activity). Therefore, people with different disorders will exhibit different behaviors, and the professional will be in charge of visualizing these differences.

EEG is one of the most common techniques for monitoring brain activity. Brain activity is recorded using electrodes placed on the scalp, which capture fluctuations in electrical tension. Each measurement is marked by it's moment during the EEG and it's frequency. Generally, neurology experts analyze readings visually, which is very time-consuming. EEG is not at all visually intuitive for human reading, making it difficult to separate patterns in them. To solve this problem, machine learning algorithms have been used for automatic detection of sleep stages and diagnosis of diseases. There is usually pre-processing for data extraction and artifact removal, followed by unattended data extraction. In this, the most important step is the extraction of significant data in the frequency domain. Pre-processing is commonly used to remove artifacts caused by muscle activity or the blink of an eye [5], [6]. Lately, a wide range of signal processing and machine learning has been adopted to classify sleep stages. Thus, some studies have already identified sleep stages fully automatically, for example, a Gaussian mixing model classifier was implemented using resources based on high order spectra (HOS) for two EEG data channels [7]. In addition, the SVM (Support Vector Machine) was used to classify the stages of sleep using a new database with wavelet filters located at a frequency of three bands [5]. In another study, a decision tree (TD) was used by a class machine for the automated recording of sleep stages [8]. Convolutional neural networks were also used to classify the sleep stage [9], [10]. However, there are still few studies using neural networks to classify sleep stages automatically. Therefore, this study presents a multilayer neural network for classification of sleep stages.

2 Methodology

2.1 Database

The proposed method consists of two phases, the characteristics extraction, and the sleep stages classification. The database used was the Sleep-EDF Database Expanded (available at: https://physionet.org/content/sleep-edfx/1.0.0/). The Sleep-EDF base contains recordings of electrode signals and hypnograms recorded from 197 patients at night, containing EEG, EOG, EMG and in some cases records of breathing and body temperature. The electrodes contained in the registers are: FPZ-CZ; PZ-OZ; Horizontal; Oro-Nasal; Submental chin; Rectal and Event Markers [11]. The database also provides records of sleep patterns (hypnograms), which are: W (awake), 1, 2, 3, 4, R (REM), M (movement), '?' (Not registered). For the purposes of this work, the M and '?' records were not considered. All of these records were collected manually by well-trained professionals, following the manual by Rechtschaffen and Kales (1968) [11]. The electrodes were recorded at 0.01 second intervals, in the case of FPZ-CZ, PZ-OZ, EOG, the rest of the electrodes were recorded at 1 second intervals. Table 1 shows how the data is organized. In this proposed work, two healthy patients were considered, the first containing 7,950,100 records (22 total hours), and the second 8,490,100 (23 total hours). Table 1 shows the organization of the electrode signals.

Table 1. Organization of electrode signals.

ElectrodeS	0.00s	0.01s
FPZ-CZ	146.39	951.52
PZ-OZ	37.41	34.36
HORIZONTAL EOG	255.75	4142.07
ORO-NASAL	103.5	NULL
SUBMENTAL COMPLAINT	57.9	NULL
RECTAL	93.32	NULL
EVENT MARKER	189.79	NULL

2.2 Character Extraction

In the data extraction phase, it was first necessary to map the signal records with the sleep patterns records, as they are on separate bases, so that we can say which sleep state the respective signals represented and, consequently, pass it for the neural network training process. As the number of instances of each patient exceeds, on average, the 7 million, the process of training and convergence of the neural network would require a very high computational power, and would require a long time to carry out its process, so it was necessary use a statistical measure that faithfully represents blocks of data so that it is possible to decrease the number of instances. The metric used was the variance (Equation 1):

$$\sigma^2 = \frac{\sum(x-u)^2}{n-1} \tag{1}$$

Where $\sigma^2$is the sample variance, x represent the value of the i^{th} element, u is the sample mean and n is the sample size. That represents the mean of the squares of the deviations of each value in relation to the average, that is, it provides a measurement of the dispersion of the data around the average. At work, the base was divided every 100 instances (every second), and after that, the variance of each block was calculated and stored in another base, with which the sleep record in those instances also came. As a result, the two databases had their instances reduced, to 79,501 and 84,490 records, respectively.

2.3 Proposed neural network architecture

For training and classification of the base to identify sleep states, a fully connected MLP neural network was used, with seven input neurons, two hidden layers with twelve neurons each, and an output layer with six neurons, each representing one different sleep state. Figure 1 presents the implemented network architecture. At first, the activation function chosen for the hidden layers was the Rectified Linear Unit (ReLU), as it has a very low computational cost, which leads to less training and convergence time. However, as the function is zero in all negative values, a neuron can "die" if it gets stuck in a negative value, and once it is negative, it is very unlikely to recover [5]. There are several variants of the ReLU function that counter this problem in the literature, the chosen one being the Linear Exponential Unit (ELU) [6], which instead of zeroing all negatives, places them very close to zero. In the data entry, there are seven neurons each representing a different electrode, and they will receive their generated signals. In the exit, there are six neurons that represent the six sleep states, W-1-2-3-4-R.

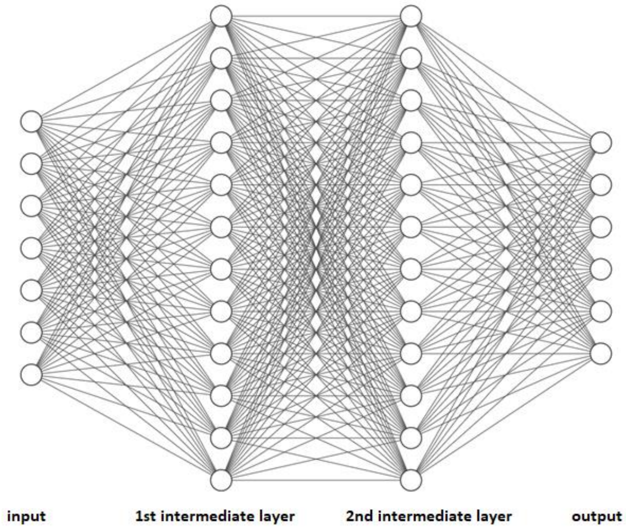

Figure 1. Representation of the proposed neural network diagram.

2.4 Training

A neural network was modeled and executed using a Python 3.7 language, in the Spyder integrated development environment. To assist in the modeling of the neural network, a Tensorflow Keras library was used. The recorded data from the electrodes makes the input of the network, while the records of the sleep states represent the output (which we want to classify). As the proposed application is a classification task, the custom function chosen was cross entropy, whereas the optimization technique applied was ADAM. The total number of information in the database is 164,398, which was divided into: 80% for training, 10% for validation and 10% for testing. As a criterion for stopping training, we used a threshold of 100 iterations in total.

3 Simulations and Results

The simulations were performed on a desktop with 8 GB of RAM, a 3.7 GHz Ryzen 3 3200g CPU and a 4 GB Radeon RX 570 GPU. The average time for the execution of 100 iterations was an average of 27.4 seconds. Figure 2 represents the evolution of accuracy, in the training and validation bases, in relation to the number of iterations.

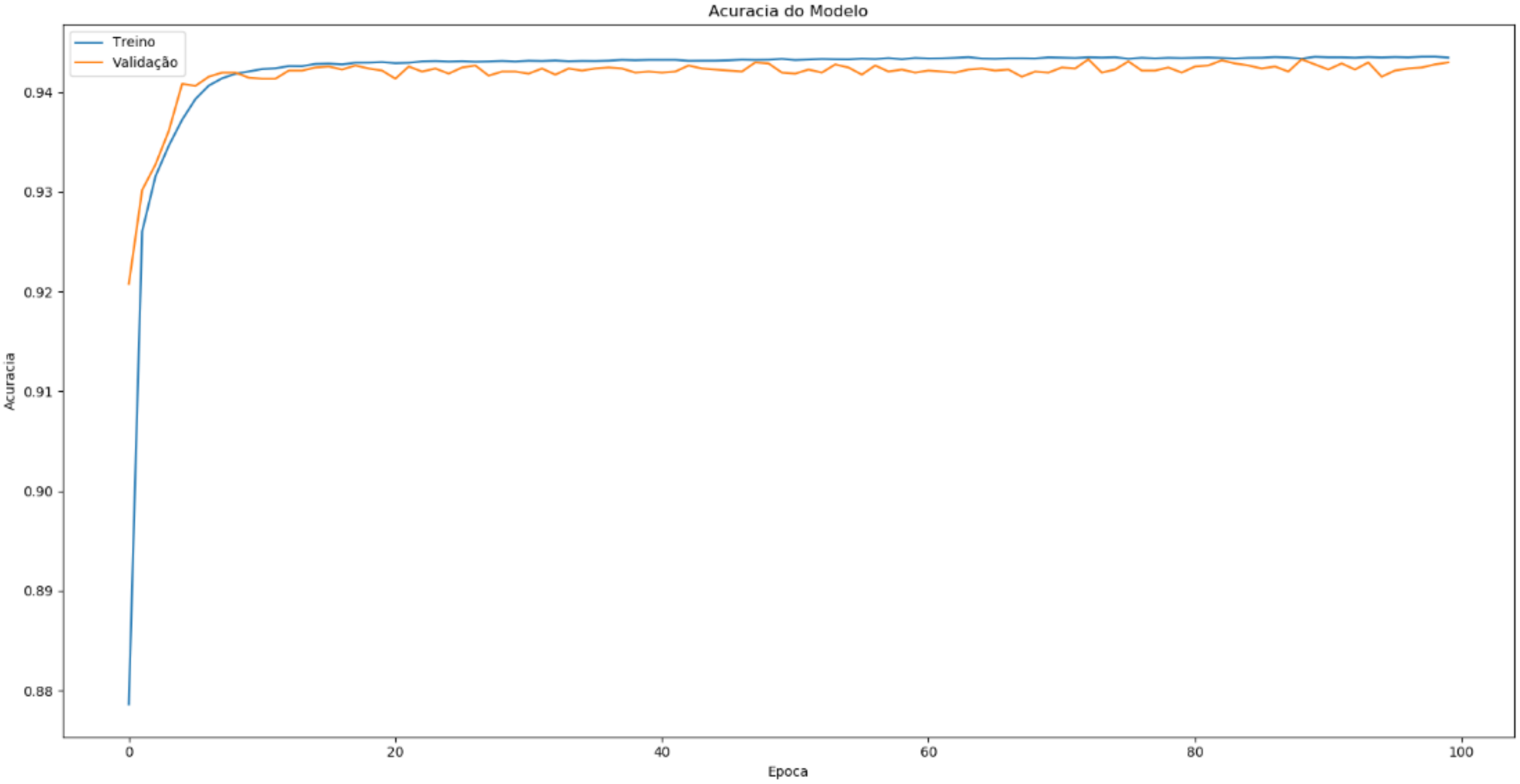

Figure 2. Accuracy of classification of sleep stages

As noted, the accuracy tends to increase as the seasons are being executed, showing that the neural network is managing to learn from the database to predict future states, reaching a value of 94.3% of general accuracy. However, it should also be noted that the model stagnates around the twentieth iteration. The cost function is minimized as the method passes through the seasons, reaching a value of 0.1412. The cost of the model follows the same pattern of accuracy, except that in its case, it stagnates close to the fiftieth season. To save computational resources, a stopping criterion was added: If the cost does not decrease for a defined number of iterations, the execution of the neural network is interrupted. To save computational resources, a stopping criterion was added: If the cost does not decrease for a defined number of iterations, the execution of the neural network is interrupted. With that, we managed to obtain a cost of 0.1448, very close to the previous one. A 10-fold cross-validation technique was used to show the accuracy of the model using different blocks from our training base, below the results graph.

Table 2. Results of cross-validation.

N° do Folds	*Accuracy*
1	0.9421
2	0.9421
3	0.9411
4	0.9433
5	0.9416
6	0.9421
7	0.9404
8	0.9404

9	0.9433
10	0.9415

Showing that the model performs well in several sets of the database. We will now use the model already trained to make predictions using the test set. Table 3 shows the accuracy for each sleep state. It is noticed that the state with the best classification was Wake (awake), this is due to the fact that it is the only one where the patient is not resting, which makes their patterns to be the most different among the database. The least correctly classified state was 1, an explanation would be because its patterns are very similar to those of state 2, making it difficult to differentiate one from the other.

It is observed that our results are in accordance with the literature, and in some stages, our accuracy was better. In some studies proposed using convolutional neural networks, there was an average accuracy of the proposed method was 92.2%. While the precision for stage W, stage N1, stage N2, stage N3 and stage REM was 90%, 86%, 93%, 97% and 90%, respectively. In addition, in another study, the model developed had the highest precision of 98.06%, 94.64%, 92.36%, 91.22% and 91.00% for the six classes of sleep (W-N1- N2-N3-N4-REM), respectively [1].

Table 3. Average accuracy for each state.

Estate	Accuracy
Wake	0.98
N1	0.89
N2	0.96
N3	0.95
N4	0.93
REM	0.91

4 Conclusions

Studies and records on sleep states are performed mainly to assist in the diagnosis of sleep-related illnesses. In this article, a method for the automatic classification of sleep states based on machine learning and measure of variance as feature extraction was proposed. In it we use signals registered in EEG's for training and testing the model. To reduce the number of instances we use the variance metric, in order to increase the speed of network convergence, reducing the computational cost. The results of the proposed method for the classification of 6 states (W-1-2-3-4-R) show an average accuracy of 94%. As a result of the excellent results shown, the method proved to be able to be used to help diagnose many sleep disorders.

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