ORIGINAL ARTICLE

AS3-SAE: Automatic Sleep Stages Scoring Using Stacked Autoencoders

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Abstract

Purpose: Sleep is a subconscious state, and the brain is active during it. Automatic classification of sleep stages can help identify various diseases. In recent years, automatic sleep monitoring using deep learning networks has attracted the attention of researchers.

Materials and Methods: In this paper, a deep learning type neural network called Stacked Autoencoders (SAEs) is used for automatically classifying sleep stages. SAEs are a kind of neural network with encoder and decoder blocks. The function of these networks is similar to the human brain and is capable of automatically processing signals; also SAEs are robust to noise. To prove the efficiency of this network, in addition to examining the effect of various biological signals such as Electrocardiogram (ECG) and Electroencephalogram (EEG) on the performance of sleep stage classification, Sleep Heart Health Study (SHHS) and ISRUC standard databases have been used, which include night recordings of 30 and 10 healthy humans, respectively.

Results: The accuracy of classifying 2 to 6 classes by SHHS database are 0.995, 0.983, 0.9780, 0.9688, 0.961, and on ISRUC database accuracies are 0.996, 0.994, 0.9511, and 0.9431. Moreover, the proposed network can classify wake, deep sleep, and light sleep using the ECG signal (acc = 0.75, kappa = 0.69).

Conclusion: In the review of the results, it is concluded that sleep stages classification based on EEG signal has better results, still acquisition of ECG signal and its acceptable results can be a good alternative to use. In addition to its high ability of the proposed method to detect sleep stages, this network is robust to noise, which is very necessary and important for the clinical processing of sleep signals.

Keywords: Sleep Stages; Stacked Autoencoder; Single Channel Electroencephalogram; Deep Learning; Electrocardiogram.

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1. Introduction

Sleep is a natural state in the humans and all creatures in which the brain can be stimulated and respond to internal stimuli. Because of this, sleep status is one of the most important pieces of evidence for the diagnosis of mental illness [1]. An abnormal state at the frequency of each stage of sleep represents a particular condition. For this reason, recognizing the stages of sleep, abundant therapeutic and research uses such as examining types of sleep disorders [2], diagnosis of various diseases such as epilepsy [3], depression [4], sleep apnea [5-9], and sleep scoring [10-12]. In recent years, considering the high cost of using a human expert in the study of high-volume sleep signals and their error in sleep investigation, many studies have recently used Deep Learning (DL) based methods, including autoencoders for sleep scoring [4, 10-16]. Sleep is already a known process, in which the human brain is active during sleep time [13].

In a healthy human brain, several psychological states and different frequencies occur during sleep, which are referred to as sleep stages. These stages can be classified according to two global standards, named Rechtschaffen and Kale (R&K) [14], and the American Academy of Sleep Medicine (AASM) [15]. According to the R&K scoring standard, a sleep cycle involves six stages. These stages include wake, first sleep stage (S1), second sleep stage (S2), third sleep stage (S3), fourth sleep stage (S4), and Rapid Eye Movement (REM) [16]. The AASM manual for scoring the sleep presented in 2007 and it is a newer standard than R&K. According to the AASM sleep scoring manual, a whole night sleep includes five stages, which are wake, S1, S2, SWS (S3 + S4), and REM. In all clinical applications, it is not necessary to identify all six or five stages of sleep, but depending on the type of application, it may be essential to locate fewer stages of sleep, so there are five different categories to classify the stages of sleep, which are: 2-classes, 3-classes, 4-classes, 5-classes, and 6-classes. Table 1 shows the various classification methods for different stages of sleep. In all medical applications, it is not necessary to distinguish 6 classes of sleep, and sometimes, depending on the need, it may be required to classify them into fewer stages of sleep and more quickly. But most previous research has only analyzed the results of 6 or 5 classes of sleep [17, 18].

In this study, we classified all sleep classes for Electroencephalogram (EEG) and Electrocardiogram (ECG) signals that are examined separately to be suitable

Table 1. Various classification methods of different stages of sleep by EEG signal

Number of class	Stages
6 class (R&K)	Wake, REM, S1, S2, S3, S4
5 class (AASM)	Wake, REM, S1, S2, SWS (S3+ S4)
4 class	Wake, REM, (S1+ S2), (S3+ S4)
3 class	Wake, REM (deep sleep), NREM (S1-S4) (light sleep)
2 class	Wake, sleep (REM-NREM)

for all medical uses. The best type of signal recording for sleep monitoring is Polysomnography (PSG) recording [19]. PSG type of sleep study is a multi-parameter study of sleep that is a procedure that utilizes EEG, Electro-oculogram (EOG), Electromyogram (EMG), ECG, and pulse oximetry. In fact, PSG recording has been considered by researchers because it is comprehensive and completes all the bio signals during sleep, so that all sleep-related databases are polysomnographic recordings [4-7, 20], which include EEG, EOG, and EMG recordings. PSG is a non-invasive bio-signal captures during whole night sleep. This recording is usually done in sleep clinics or hospitals. Before going to record the signal, the person should refrain from consuming chocolate, coffee, or caffeine and go to the clinic with appropriate clothing and equipment that makes sleep easier. The technician will be with the patient during the night. In addition to the signals mentioned, in PSG recording, vital parameters such as blood oxygen, body temperature, respiration rate, and heart rate are recorded. PSG usually has a large amount of information because it involves about 6-8 hours of sleep a night [21]. Figure 1 shows PSG signals record leads.

Some previous research has used a combination of all PSG signals [22]. But the patient cannot use PSG effectively at home because of a large number of leads and problems with recording simultaneous signals.

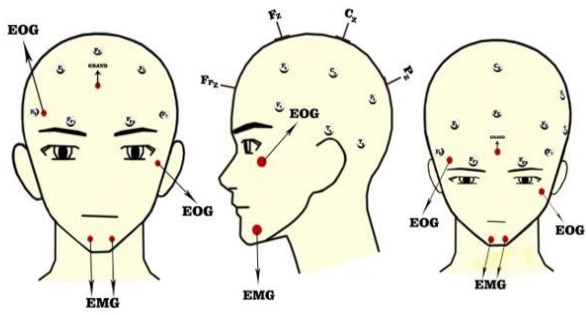

Figure 1. PSG signals record leads [1]

This is why recent sleep research has led to the introduction of intelligent algorithms for signals other than PSG [23-25]. Among the recorded PSG signals, the single-channel EEG signal is the best signal, which has useful information and can meet the needs of sleep monitoring alone. In addition to the EEG signal [10, 26], the ECG signal is another valuable signal for sleep monitoring that has attracted the attention of sleep researchers in recent years [27-30]. The ECG signal is recorded bipolar during sleep and can provide the information needed to monitor sleep. The ECG and EEG signals are very efficient and useful for sleep monitoring. However, there is no comparison and comprehensive research on the effects of these signals in sleep stages classification simultaneously in the literature.

Observing the EEG and ECG signals manually to study the sleep process may not be the right option due to human errors and high costs. Moreover, we need an automated and robust noise network to monitor sleep, given the high volume of data and the possibility of noise contamination. Research on the automatic classification of sleep stages based on the type of used features can be divided into three categories. Applying statistics and wavelet transform features [17, 31], using chaotic and entropy-based features [16, 19], and automatic feature selection by deep learning neural networks [32, 33].

Statistical and frequency features such as mean, variance, and wavelets are the most common features used in classic signal processing methods. Hassan *et al*. [34] used the statistical and wavelet transform features and used different classifiers and bagged them to classify five sleep stages with 93.6% accuracy. Saifpour *et al*. [35], by presenting an algorithm based on the local statistical features of the EEG signal, were able to classify five stages of sleep with 91.8% accuracy. In our previous study [1], we were able to classify 2-6 classes of sleep by single-channel EEG using statistical, frequency, and entropy features and the Laplacian feature selector. Despite the applicability of the method using EEG signals, it could not work with ECG signals, while the goal is to use algorithms that are efficient and useful for all biological signals. Sheykhivand *et al*. [18] used statistical features and composition of the genetic algorithm and neural networks to select the best features and use the single-layer perceptron network to the classification of sleep stages. Dursun *et al*. [17], used correlation and wavelet transform algorithms to remove the EOG from sleep EEG. In this category, considering the use of statistical and frequency features alone, we will not have acceptable accuracy. Use of statistical and frequency features is very sensitive to noise, even if they are reasonably accurate in classifying sleep stages. Besides, using statistical features, even if metaheuristic feature selectors are used to perform classification operations using the best features [36], still do not provide acceptable accuracy.

Using chaotic features such as fractal, Poincare, and entropy is an excellent option to process the EEG signal due to its chaotic behavior. Pejman Memar *et al*. [19] used chaotic features and a random forest classifier for the sleep study, and they were able to classify five stages of sleep. Shivani *et al.* [37] classify sleep stages by using Wigner–Ville Transform and entropy features. Rajeev Sharma *et al*. [16], to study the sleep stages, designed an iterative filter to decompose the EEG into the essential component. Afterward, using domain measurements and calculating instantaneous frequency functions, draw the Poincare plot, and the result of the Poincare plot is considered a feature for the different classifiers to classify different sleep stages. The use of chaotic features in the processing of the signal in a classical way, despite the high accuracy in the classification of the sleep stages, is very complicated, and due to the high volume of sleep data, the computational speed is deficient. It is also very sensitive to noise, as the first category method. In addition, in manual signal processing, which includes feature extraction and feature selection, part of the signal information may be lost due to human error in selecting these operators.

The third category of research is deep learning-based. Deep learning neural networks, including Convolutional Neural Networks (CNN), Long Short Time Memory (LSTM), and Stacked Auto Encoders (SAEs) promote perceptron networks with a high number of hidden layers. CNN networks can provide a classified output using a kind of filter on input data and a much more regular network than perceptron [38]. SAEs networks provide classified results using a more straightforward method than CNN by input encoding and decoding. Michielli *et al.* [39] classified five sleep stages by using a Cascaded LSTM network. Akara Supratak *et al*. [32] designed a CNN which consists of 12 sub-layers for automatic classification of sleep stages. Zhang *et al*. [40] proposed a rapid recognition Convolution Neural Network with integral value to extract the features and classification of sleep stages. Wei *et al*. use ECG signals and autoencoders to classify three sleep stages [41]. Sors *et al*. [42] design a deep convolution neural network with 14 hidden layers to classify five stages of sleep. Yuan *et al.* [43] introduced a Variable-Wise weighted Stacked Autoencoder network (VW-SAE) which is very useful for practical processing applications in sensors. Also, Yuan *et al*. [44], in another study, presented a more advanced model than VW-SAE. Its name is Layer-Wise Data Augmentation SAE (LWDA-SAE) which has less learning error than other deep learning methods and can therefore converge at a higher processing speed. The automatic classification of sleep stages requires computational speed and high accuracy. CNN, due to their complexity, have deficient computational speed and cannot be suitable for clinical use. Given the high volume of sleep data, the sleep survey requires an algorithm that gives us the best possible result in the shortest possible time. Moreover, due to the long recording time of sleep signals, the signal is much more likely to be contaminated with noise. Given this, for the sleep study, we need robust networks that are not noise sensitive. Deep learning networks are not noise-sensitive and can accurately classify even noisy signals, but contrary to both anti-noise capabilities and fully automatic signal processing, not much research has been done on these networks regarding sleep.

SAEs are a kind of artificial neural network with two block encoders and decoders and several sub-layers per block. These networks also pre-train a hidden layer at a time, making network learning more accurate [45]. SAEs automatically perform all operations related to sleep signal processing and the accuracy and computational speed of sleep data upgrade with SAEs. The advantage of these networks over other deep learning networks is that in addition to high accuracy, they have a relatively low computational complexity, and therefore the computational time of these networks. Computation time includes two parts: training and testing. Training time in SAEs for five classes of sleep is about 90 minutes, and test time is about 2 minutes (computer CPU Intel core i7 (7700HQ) 280GHz and 16.0 GB). In clinical applications, the network is trained once, and then only new data is tested with the network, so this network can be beneficial. In clinical applications, the network is trained once and then only new data is tested with the network, so this network can be very useful. Because the purpose of this type of simulation research is to be used for clinical purposes, and in our applied applications, we do not encounter a large number of patients per day or week to check their sleep with high speed and accuracy can make them superior to CNN.

SAEs networks consist of two parts of an encoder and an automatic decoder, which will process the input information in two steps. In the first step, the original complex and high-dimensional data are encoded nonlinearly on a space with lower dimensions, and in the second step, after processing and extracting the hidden features, the signal is reconstructed [46]. This ability of the network leads to the identification of the true pattern of the signal and provides the possibility of automatic noise removal. Such nonlinear dimensionality reduction is not possible in classical machine learning methods [47].

In this paper, a new method for sleep stages scoring is proposed based on Stacked Autoencoders networks called AS3-SAE. AS3-SAE method includes ten hidden layers in each encoder and decoder block. Due to the high volume of sleep information, we need high-speed and high-accuracy networks that have resolved this problem by SAEs. SAEs networks have been used to classify sleep stages into different classes (2-6 classes of sleep) so that the results are suitable for all processing and clinical use. Also, for the investigation of various biological signals in sleep studies, two EEG and ECG signals have been used separately on one deep learning network so that the results of the classification of sleep stages by these two essential signals can be easily compared and analyzed. Furthermore, Sleep Heart Health Study (SHHS) and ISRUC standard database have to prove the capabilities of the proposed method.

The structure of the remainder of the paper is as follows. First, we will examine the deep learning network and required databases in section 2. Afterward, in Section 3, the results of the simulation and evaluation criteria with noisy and preprocess signals are mentioned. Finally, in the fourth part, we will examine the conclusions obtained from the simulation of the paper.

2. Materials and Methods

2.1. Database

In this section, the databases used for the automatic classification of sleep stages in the proposed method are reviewed.

2.1.1. SHHS Database

The SHHS includes recording vital signals from 6,441 men and women aged 40 years and older during sleep that can perform various sleep research on this database

[48]. The recording of this database lasted from 1995 to 2003, and it was presented in two SHHS1 and SHHS2 groups. Initially, SHHS1 was introduced, which records the vital signals from 3,146 people, and then SHHS2 was introduced, which includes sleep recording signals from 3,295 people. The sleep signals provided in this database are: C3/A2 and C4/A1 EEGs, sampled at 125 Hz, right and left EOG has been sampled at 50 Hz, EMG sampled at 125 Hz, airflow, ECG from a bipolar lead, sampled at 125 Hz for most SHHS-1 studies and 250 Hz for SHHS-2 studies, heart rate, and body position. Every 30 seconds of this signal is considered a window, and it was labeled by skilled technicians [49]. In the proposed method, we have used EEG (channel C3-A2) and ECG for 30 people from the SHHS-1 group, and the number of epochs related to each stage for these 30 people has been shown in Table 2. Sleep database labels are known as hypnograms. Figure 2 shows the hypnogram of the first person in the SHHS database.

Table 2. The number of epochs associated with each step in the SHHS1 database (30 people)

Stage	Wake	REM	S1	S2	S3	S4
Epoch	11399	3445	932	10666	3986	370

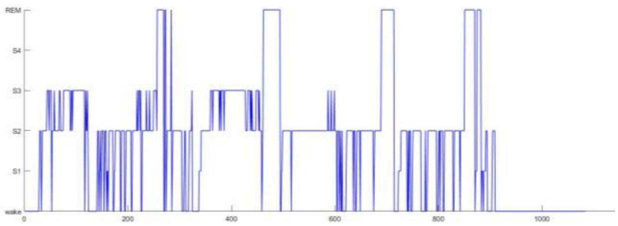

Figure 2. Hypnogram of the first person in the SHHS database

2.1.2. ISRUC Sleep Database

This database has been presented in 2016 for various sleep research [50]. The people in the database are healthy adults and several people who took sleeping pills. The ISRUC database is labeled according to the AASM standard for five sleep classes. Every 30 seconds of this signal was labeled as an epoch, and the last 30 available labels are invalid from the available vector label. This dataset includes PSG records from 3 subcategories [50]:

- Sleep information was recorded from 100 healthy human beings; one signal was recorded from each person.
- Recorded PSG from 8 healthy people, 2 of which were recorded each time, and is useful for monitoring PSG signal changes over time.
- PSG recording of 10 healthy people to check the sleep of healthy people and people who have insomnia.

The recording of each PSG has been reviewed and tagged by two skilled technicians with a sampling frequency of 200 Hz. The proposed method uses the EEG subgroup 3 of this database, including the PSG recordings of 10 healthy humans. Table 3 shows the number of epochs associated with each step in the ISRUC database. Figure 3 shows the hypnogram of the first person in the ISRUC database.

Table 3. The number of epochs associated with each step in the ISRUC database

Stage	Wake	REM	S1	S2	S3
Epoch	1674	1066	1217	2616	2016

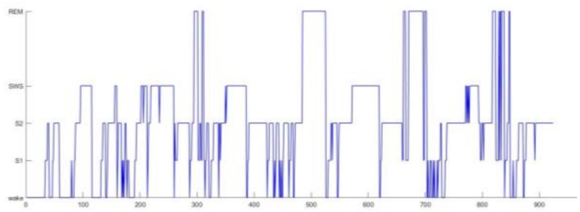

Figure 3. hypnogram of the first person in the ISRUC database

2.2. Autoencoders Deep Learning Network

Autoencoders (AEs) are a kind of advanced artificial neural network with deep learning training that in the first layer of this network, data is automatically converted to a code [51] and introduced by Pascal Vincent *et al.* [52]. AEs are used for unlabeled data, and they have unsupervised training [53]. In AEs, it operates on the signal in one layer and prepares the output as the next layer input [45]. These networks use useful data features and prioritize various aspects of data after data entry. Initially, AE networks are used to reduce the dimensions of the feature and data classification and included three layers: encoder, hidden layers, and decoder. Figure 4 shows the structure of AEs networks [53]. At present, improved AEs networks can perform all signal processing operations by recognizing the pattern from the input data [51].

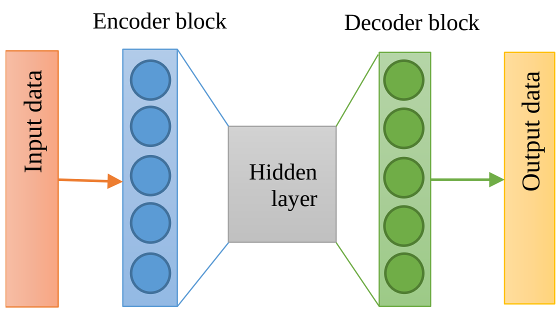

Figure 4. Structure of AEs networks

2.3. Stacked Autoencoder Deep Learning Network

Stacked Autoencoders (SAEs) are a kind of improved AEs containing several hidden layers in each block encoder and decoder [53], unlike AEs that have no hidden layer in the encoder and decoder blocks. SAEs are a deep neural network with semi-supervised learning and introduction for the first time by Bengio [54]. SAEs are able to learn complicated and non-linear patterns [45]. The production of the decoder block is entered into the Softmax layer for the final classification and the final output is obtained from the Softmax layer. Figure 5 shows the structure of SAEs.

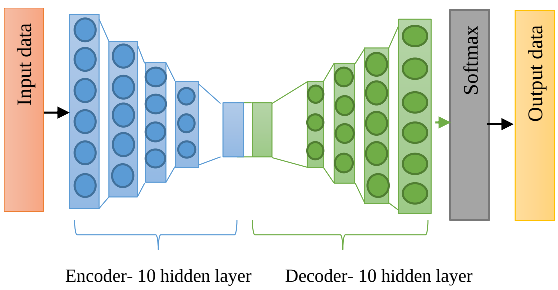

Figure 5. Structure of SAEs networks

If the SAEs network has one encoder layer and one decode layer, inputs and outputs are calculated according to Equations 1 and 2. Equation 1 calculated the activation of neurons [55].

$$h(x) = tanh(W_1 x + b_1) \tag{1}$$

h(x) refers to a vector of neuron activation function, W_1 refers to the weight matrix, and b_1 is a bias vector. Equation 2 calculated the output of the SAEs.

$$\hat{x} = tanh(W_2 h(x) + b_2) \tag{2}$$

x is the output value, W_2 refers to the weight matrix, and b_2 is a bias vector. W_1 and W_2 are calculated according to Equation 3 (backpropagation) [56, 57]. Backpropagation acts on the gradient descent and is used to train neural networks [51].

$$W = \sum_{i=1}^{p} \left\| x^{(i)} - \hat{x}^{(i)} \right\|^2 \tag{3}$$

$x^{(i)}$ refers to input patterns.

The network used in this paper is SAEs with ten hidden layers in the decode and encode blocks. In SAEs networks, at first, it is necessary to set a threshold for each hidden unit and the neuron response to the threshold is specified. In neurons, electrical stimulation can activate the cell when it reaches the threshold, as in artificial neural network nodes. Equation 4 shows a state in that neuron reacts to the input and the threshold. Otherwise, it will be zero [55].

$$f_i(x) = 1\{s_i h_i(x) \geq t_i\} \tag{4}$$

t_i is a unit threshold, h is the activation measure and s refers to the unit sign function.

In a nerve cell, electrical stimulation by an axon to the cell membrane causes the valves to open, and the cell's potential to change. In neural networks, we are justified by the large number of artificial cells on which all normal nerve cell operations must be performed. In artificial neural networks, the transfer function plays the role of electrical stimulation of the cell. In each hidden layer, procedures such as transfer function, computation of superior input features, etc., were performed. In the first step, we need a transfer function that prepares the output of the hidden layer to enter the next layer. According to the latest research on SAEs networks, the best transfer functions for this network encoder are Logsig and Satlin and the best transfer functions that yield the highest network efficiency are Logsig, Satlin and Purelin functions [58]. We select Satlin transfer function for encoder block [58, 59] and purelin function as the decoder activation function by reviewing recent research and trial and error, and it has obtained favorable results in many recent types of research [60-62].

The L2 coefficient is created to control the learning of the network (avoid overfitting) and maintain the generalization of the network [63]. The training rate of the network depends on the correct selection of this parameter. The best value for L2 weight optimization is between 0-0.1. The value of the L2 weight regulator is also different according to the application of the network and the selection of this value is determined according to recent research and the type of network efficiency. For example, Luo *et al.* [63] have chosen 0.014 for the L2 weight regulator. Omer *et al.* [64] chose 0.001 for L2 weight. And in the same way, in other researches, different values have been chosen according to the type of network [65-67]. For the automatic classification of sleep stages, in this method, we chose the value of 0.01 for the L2 weight adjuster, which brought the most efficiency of the network.

2.3.1. Softmax Layer

After passing the raw data through different SAEs, the final data is entered into the Softmax layer to be assigned a weight for each value and optimally classified. The Softmax layer is used to estimate classes and train the SAEs with standard backpropagation [68]. Cross entropy is based on hypothesis Kullback–Leibler divergence [69]. Cross entropy for discrete-time series between p and q time series are calculated according to Equation 5.

$$H(p,q) = -\sum_{x \in X} p(x)\, log\, q\,(x) \tag{5}$$

$p(x)$ and $q(x)$are time series.

2.4. Proposed AS3-SAE Method in Sleep Stages Scoring

In this paper, we use SAEs with ten hidden layers in the encoder block and ten hidden layers in the decoder block and each hidden layer has many neurons instead of features of data. In the proposed method, using the above relations, a network of SAEs is designed that can perform sleep signal processing operations well. In the proposed method, L2 weight regulator with a coefficient of 0.01 has been used to update the weights and also Satlin transfer function is used for the encoder part and Purelin transfer function is used for the decoder. Satlin and Purelin transfer functions are calculated according to Equations 6, 7.

$$f(z) = \begin{cases} 0, if\,(z \le 0) \\ z, if\,(0 < z < 1) \\ 1, if\,(z \ge 1) \end{cases} \tag{6}$$

$$f(z) = z \tag{7}$$

Z activated *h(x)* and it arrives as an input.

In the proposed method, the AS3-SAEs use cross-entropy as a Softmax function. Regarding the full description of the proposed method, it can be said that, at first, EEG or ECG signal is acquired from the person during sleep. Received data enters the SAEs network for processing. In this network, as mentioned, all operations related to signal processing are performed thoroughly and automatically. After completing the necessary operations on the data by the network, the output is received, which includes the classification of different sleep stages. It is necessary to emphasize that once the EEG signal enters the network and we record the output, the ECG signal is entered separately and the results are received, the effects of these signals are investigated independently. Figure 6 shows different steps of signal processing using the proposed SA3-SAE algorithm.

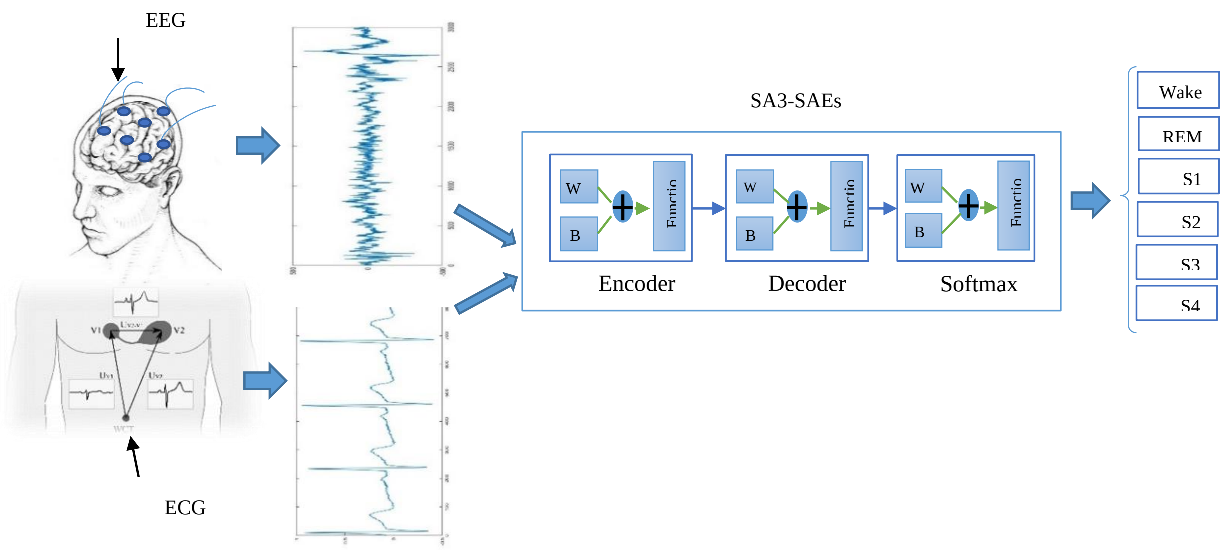

Figure 6. Different steps of signal processing using the proposed algorithm

3. Results

Simulation of the proposed SA3-SAE method has been performed using MATLAB R2018b. The evaluation criteria of a proposed algorithm contain accuracy, sensitivity, and specificity calculated according to Equations 8-10.

$$Sensitivity = \frac{T_{pos}}{T_{pos} + F_{neg}} \tag{8}$$

$$Specificity = \frac{T_{neg}}{T_{neg} + F_{pos}} \tag{9}$$

$$Accuracy = \frac{T_{pos} + T_{neg}}{T_{neg} + F_{neg} + T_{pos} + F_{pos}} \tag{10}$$

In these equations, T_{POS} is correctly identified target class and F_{POS} is incorrectly identified target class. Also T_{neg} refers to the correctly identified non-target class and F_{neg} refers to the incorrectly identified non-target class. The accuracy, sensitivity, and specificity for five sleep stages classification using SA3-SAEs with a single-EEG signal are shown in Table 4. The best value for all these criteria is one and the closeness to one is the desirability of the result. As it can be seen, the proposed algorithm in both databases has detected the waking stage with the highest accuracy. However, since the identification of S1 is very complicated due to its high similarity with wake, it can be seen that the proposed algorithm has done this step well in both databases.

For a better comparison, Figure 7 shows the accuracy, specificity, and sensitivity results for five sleep classes by single-channel EEG and two different databases.

Table 5 shows the sensitivity, specificity, and accuracy values of six sleep classes using the EEG signal by the

Table 4. Results of sensitivity, specificity, and accuracy for five sleep stages by EEG signal

	SHHS Database			ISRUC Database		
Stages	**Sensitivity**	**Specificity**	**Accuracy**	**Sensitivity**	**Specificity**	**Accuracy**
Wake	0.9236	**0.9481**	0.9967	0.7968	0.9848	**0.9968**
REM	**0.9542**	0.9470	0.8110	0.6902	0.9847	0.9206
S1	0.4583	0.9478	0.9217	0.7195	0.9812	0.9947
S2	0.9174	0.9475	0.9949	**0.8569**	**0.9959**	0.9966
SWS	0.821	0.9300	**0.9969**	0.8472	0.9776	0.8509

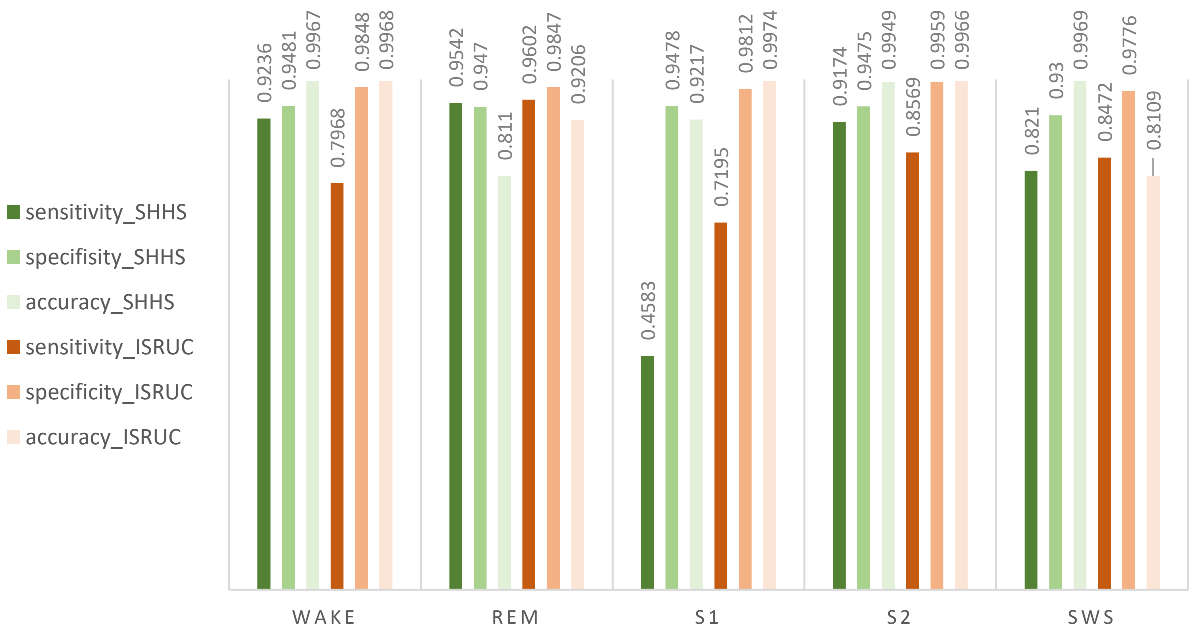

Figure 7. Accuracy, specificity, and sensitivity results for 5 sleep classes by two different databases and EEG signal.

proposed algorithm. Table 5 shows the values of the SHHS database for classifying six sleep classes, because the ISRUC database is labeled for a maximum of five sleep classes. As shown in Table 6, the proposed algorithm is very capable of identifying stage 3 sleep. It also shows the highest sensitivity to determine the wake stage.

Table 5. Sensitivity, specificity, and accuracy values of the 6-classes of sleep using EEG signal

SHHS Database			
Stages	**Sensitivity**	**Specificity**	**Accuracy**
Wake	0.9087	0.9961	**0.9938**
REM	0.8456	0.9762	0.8160
S1	0.3808	**0.9997**	0.9217
S2	**0.9314**	0.9772	0.9810
S3	0.7693	0.9993	0.9658
S4	0.2274	0.9908	0.9629

Table 6 shows the accuracy of classifying the different stages of sleep by the EEG signal from the SHHS database. In 3-class result, stage 1 is instead of NREM (3-class means wake, REM, and NREM).

Immediately after falling asleep, the person enters stage 1 and the diagnosis of stage 1 due to the similarity to waking is always one of the challenges of classifying sleep stages, as can be seen in all sleep classes, the proposed method uses the EEG signal to recognizes stage 1 well.

Table 7 shows the classification values of each sleep step separately for 2-5 sleep classes using the ISRUC database and single-channel EEG. As can be seen in Table 7, the 2 and 3 classes of sleep are correctly identified using the ISRUC database. However, in sleep studies using EEG signals, the classification of 5 sleep stages according to the AASM standard is useful. The proposed algorithm classifies five stages of sleep with high accuracy, which can be suitable for clinical use.

Table 6. Accuracy of classifying the different sleep stages by the EEG signal from the SHHS database

Class	Stages
2 class	NREM/ REM 1.00/ 1.00
3 class	Wake/ REM/ NREM 0.999/ 0.989 / 0.999
4 class	Wake/ REM / light sleep/ deep sleep 0.9960/ 0.8641/ 0.9622/ 0.9987
5 class	Wake/ REM/ S1/ S2/ SWS 0.9967/ 0.8110/ 0.9217/ 0.9949/ 0.9969
6 class	Wake/ REM/ S1/ S2/ S3/ S4 0.994/ 0.825/ 0.987/ 0.958/ 0.996/ 0.983

Table 7. Classification accuracy of each sleep steps separately for 2-5 sleep classes using the ISRUC database by EEG

Class	Stages
2 class	NREM/ REM 1.00/ 1.00
3 class	Wake/ REM/ NREM 1.00/ 1.00 / 1.00
4 class	Wake/ REM / light sleep/ deep sleep 0.9871/ 0.9960/ 0.9978/ 0.9981
5 class	Wake/ REM/ S1/ S2/ SWS 0.996/ 0.920/ 0.994/ 0.996/ 0.850

Table 8 shows the results of accuracy, sensitivity, and specificity for classifying different stages of sleep by

Table 8. Results of accuracy, sensitivity, and specificity for classifying different sleep stages by ECG signal on SHHS database

Signal	Evaluated criteria	2 class	3 class	4 class	5 class	6 class
SHHS1 (EEG)	Sensitivity	1.00	0.9990	0.8601	0.8149	0.8456
	Specificity	1.00	0.9835	0.9824	0.9440	0.9896
	Accuracy	0.995	0.983	0.9780	0.9688	0.961
SHHS1 (ECG)	Sensitivity	0.8901	0.6942	0.5285	0.4501	-
	Specificity	0.9837	0.7429	0.6695	0.5116	-
	Accuracy	0.9400	0.7513	0.6070	0.601	-

EEG and ECG signal on the SHHS database (sensitivity and specificity values are expressed as averages). As mentioned, the classification of different sleep stages by the ECG signal is usually done up to 4 levels of sleep because this type of classification is due to the limited information obtained from the ECG signal. In addition, it can be seen that the classification accuracy using EEG offers higher accuracy than the ECG signal. As you can see in Table 8, the ECG signal, due to its elementary recording number, and its ability to use in any situation, cannot classify 5 or 6 classes of sleep well. Of course, in most clinical needs, by identifying 3 or 4 classes of sleep, they can also diagnose sleep disorders and do not examine a person's sleep. So, it can be seen that the EEG signal has a higher ability to classify the 5th and 6th classes of sleep, but this signal is more difficult to record than the ECG signal. So, in cases where it is necessary to identify a smaller number of steps, an ECG can be used, which has a much easier recording.

Table 9 shows the classification accuracy of different sleep stages in various classes using the ECG signal.

Table 9. Classification accuracy of each sleep steps separately for 2-4 sleep classes using ECG

Class	Stages
2 class	NREM/ REM 0.931/ 0.716
3 class	Wake/ REM/ NREM 0.826/ 0.6604 / 0.801
4 class	Wake/ REM / light sleep/ deep sleep 0.788/ 0.4806/ 0.628/ 0.5806

One of the most essential criteria for agreement between two or more cases is Cohen's kappa coefficient [70, 71]. The Kappa coefficient is calculated according to Equation 11.

$$k = 1 - \frac{1 - p_o}{1 - p_e} \qquad (11)$$

In Equation 11, $p_o$is a relative observed agreement among raters and $p_e$is a hypothetical probability of chance agreement. The ideal case for the kappa coefficient is 1. Table 10 shows the Cohen's kappa of the proposed method with two databases for 2-6 sleep classes by EEG signal compared to the recent study on sleep by EEG. As can be seen in Table 10, the kappa coefficient obtained for the classification of 2-6 classes of sleep in the proposed method is higher than other methods, which can be a reason for the superiority of the network over other proposed methods.

As mentioned, in recent years, a lot of research has been done on the classification of sleep stages using deep learning networks based on EEG signals. Table 11 shows the results of some of these studies and the classification results of the proposed SA3-SAE method. As can be seen, the results of the proposed method have increased the accuracy of classification compared to previous research. Previous research has often used CNN networks to classify sleep phases, but these networks have computational complexity and do not provide acceptable accuracy.

Little research has been done on the use of deep learning networks to classify different sleep stages using ECG signals. Table 12 compares the kappa results and the accuracy of previous research and the proposed method

Table 10. Cohen's kappa of the proposed method with two databases for 2-6 sleep classes by EEG

Method	Network	Database	2 class	3 class	4 class	5 class	6 class
Supratak [32]	CNN	SHHS	-	-	-	0.72	-
Sors [42]	CNN	SHHS	-	-	-	0.81	-
Chui [72]	CNN	ISRUC	-	-	-	0.922	
Al-Hussaini [73]	SLEEPER	ISRUC	-	-	-	0.839	-
Diego [74]	CNN	SHHS	-	-	-	0.650	-
Liu [75]	XGBoost	SHHS	-	-	0.811	0.795	-
Blanco [76]	DS-CNN	SHHS	-	-	-	-	0.80
AS3-SAE	SAEs	SHHS	0.972	0.966	0.9199	0.9210	0.8913
AS3-SAE	SAEs	ISRUC	0.980	0.9726	0.9214	0.931	-

Table 11. Accuracy of 2-6 sleep stages classification of recent studies and proposed method by EEG

Method	network	database	signal	2 class	3 class	4 class	5 class	6 class
Sors [42]	CNN	SHHS	EEG	-	-	-	0.87	-
Supratak [32]	CNN	SHHS	EEG	-	-	-	0.820	-
Zhou [77]	CNN	SHHS	EEG	-	-	0.849	-	-
Liu [75]	XGBoost	SHHS	EEG	-	-	0.875	0.858	-
Blanco [76]	DS-CNN	SHHS	EEG	-	-	-	-	0.8606
AS3-SAE	SAEs	SHHS	EEG	0.995	0.983	0.9780	0.9688	0.961
AS3-SAE	SAEs	ISRUC	EEG	0.996	0.994	0.9511	0.9431	-

Table 12. Comparison of the kappa results and the accuracy of previous research and the proposed method using ECG signals

Method	Database	Network		2 class	3 class	4 class	5 class
Li [24]	SHHS	CNN	**Accuracy**	-	-	0.65	-
			kappa			0.47	
Miriam [78]	SHHS	CNN	**Accuracy**	-	-	-	0.769
			Kappa				0.58
Li [79]	SHHS	CNN	**Accuracy**	0.8149	-	0.68	-
			Kappa	0.58		0.44	
Proposed method	SHHS	SAEs	**Accuracy**	0.9400	0.7513	0.6070	0.601
			kappa	0.8824	0.6915	0.532	0.553

using ECG signals. As shown in Table 12, the proposed method has classified two classes of sleep among ECG signal sleep studies with the highest accuracy and kappa. But it cannot classify more classes of sleep using the ECG signal. So, it is better to use the proposed network with EEG signals, because by using EEG, it has a higher capability compared to other networks that have been provided so far.

In this method, a SA3-SAEs network with 10 hidden layers in two encoder and decoder blocks is used. The number of hidden layers has been selected for this network with trial and error. Table 13 shows the results of accuracy of AS3-SAEs network with 8 and 12 hidden layers for five-stage sleep classification on SHHS database. According to Table 13, accuracy of automatic classification of sleep stages with SAEs with 12 hidden layers on single channel EEG is 81.9% and accuracy of automatic classification of sleep stages with SAEs with 8 hidden layers on single channel EEG is 70.6%. As can be seen in this table, the number of hidden layers less or greater than 10 does not produce the desired results. Also, the number of layers less or more than 10 cannot detect REM stage. REM stage is very similar to Wake and the network's ability to recognize this stage from single channel EEG.

Tables 13. Results of the accuracy of AS3-SAEs network with different hidden layers for five-stage sleep classification on SHHS database

Layers Stages	8 layer	10 layer	12 layer
Wake	0.98	0.9967	0.56
REM	0.40	0.8110	1.00
S1	0.18	0.9217	0.53
S2	0.98	0.9949	1.00
SWS	0.99	0.9969	1.00

3.1. Investigation of Robustness Capability of SAEs

SAEs networks consist of two parts of an encoder and an automatic decoder, which will process the input information in two stages. Due to the special structure of the network, which includes two separate blocks, and signal processing operations are performed separately in each block, noisy data will be quickly identified and removed by the network itself. To verify the robustness of the network against noise and its behavior in the presence of a noisy EEG signal, we manually contaminate the signal with the noise, and the result has been checked. SHHS database signals are available without any noise. To do this, the following steps are performed to make this signal noisy. Initially, the original signal is normalized. Signal normalization for *x(n)* time series is calculated according to Equation 12.

$$x\_norm = \frac{x(n) - min(x(n))}{max(x(n)) - min(x(n))} \tag{12}$$

According to recent research on sleep stages, sleep signals are mostly contaminated with Gaussian noise, and Gaussian noise is used to investigate the effect of noise on network performance [80, 81]. After normalizing the signal, a Gaussian noise [82] with zero mean and variance of 0.1, 0.05, and 0.01 is added to the primary signal of the SHHS and ISRUC database. In this way, we have noisy and unprocessed signals which we can reclassify the stages of sleep with them and see if the proposed network can perform well with noisy signals or not. Considering the nightly recording of sleep signals and the long recording time, the probability of signal contamination by noise is very high, and it is necessary to design networks that are resistant to noise. For this reason, in this section, we classify the stages of sleep with the proposed network using noisy signals to see the capabilities of the network in this regard. To test the resistance of the networks to noise, five stages of sleep are classified with a noisy signal from these databases with a single-channel EEG. Table 14 shows the accuracy of each stage in the automatic classification of the five stages of sleep by a noisy EEG signal with different variances by SA3-SAEs. As can be seen in Table 14, in the classification of 5 stages of sleep, all the stages are recognized well when the pre-processed signal is used (with a maximum difference of 3%), and the network proves its ability in different noise levels. For a better comparison, Figure 8 shows the accuracy of classifying five classes of sleep, using the noisy signal and the processed signal (on ISRUC and SHHS database), by the SA3_SAEs network. As can be seen in Figure 8, the proposed network recognizes the stages of wake, S2, and SWS well in noisy and non-noise modes.

4. Conclusion and Future Works

In this paper, a new deep learning network called AS3-SAEs has been proposed to classify sleep stages by single-channel EEG and ECG. AS3-SAEs are a Stacked Autoencoder with 10 hidden layers and perform all operations related to processing all signals with high accuracy and speed. The EEG and ECG signals were each processed separately by the proposed network, and the different stages of sleep were classified by these two signals according to international standards. Among recent research that have used EEG signal and deep learning networks to identify sleep stages, our proposed network has been able to increase the stage classification accuracy by 4-5% on average, and due to the high accuracy of this network it can be suitable for clinical use. In addition, a proposed method for examining 2-6 classes has been presented, while in recent research, only one or two classes of sleep have been investigated. The

Table 14. The accuracy of each stage on automatic classification of the five stages of sleep by a noisy EEG signal by different variances by SA3-SAEs

Stages	**SHHS Database**			**ISRUC Database**		
	Variance					
	0.01	**0.05**	**0.1**	**0.01**	**0.05**	**0.1**
Wake	0.990	0.993	0.971	0.933	0.871	0.864
REM	0.895	0.838	0.772	0.926	0.944	0.920
S1	0.886	0.8443	0.711	0.973	0.985	0.917
S2	0.963	0.977	0.948	0.995	0.994	0.995
SWS	0.997	0.994	0.985	0.917	0.953	0.928
Total ACC	0.9630	0.960	0.932	0.960	0.955	0.930

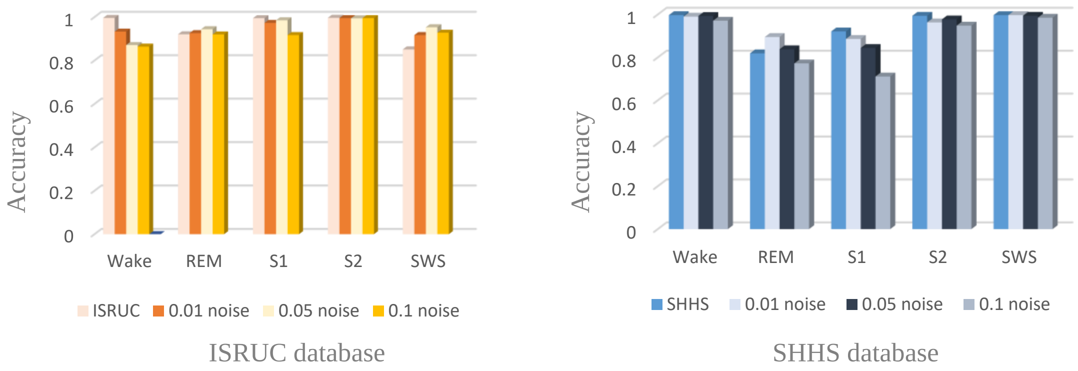

Figure 8. Accuracy of classifying five classes of sleep, using the noisy signal and the processed signal (on ISRUC and SHHS database), by the SA3_SAEs network

comprehensiveness of this network can make it easy for everyone to compare and use this network because, in different clinical uses, it is necessary for a network to show its ability to examine all stages of sleep. Compared to other research conducted in the field of sleep using ECG signals, the proposed network has increased classification accuracy in identifying two and three classes of sleep compared to other methods, which indicates the high ability of the network to detect the awakening stage and deep sleep using ECG signals. Also, considering that for the first time in this paper EEG and ECG results are presented simultaneously for classifying sleep stages. According to the results, it can be seen that the signal EEG is very accurate in classifying sleep stages, still ECG signal can replace the EEG in the future due to the ease of recording. In future research, powerful algorithms can be used to increase the accuracy of sleep stage classification using ECG signal, which at the same time has the advantages of easy signal recording and high accuracy in identifying sleep stages.

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