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Deep Learning Method for Sleep Stages Classification by Time-Frequency Image

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Abstract
Classification of sleep stages is an important method in diagnosing sleep problems. This is done by experts, based on visual inspection of bio-signals such as EEG, EOGs, ECG, EMG, etc. The deep learning method is one of the newest and most important methods for analyzing, separating, and detecting images, which is becoming more and more widespread. In this paper, for the first time, the deep learning method is used to extract the EEG signal time frequency image to classify sleep stages. Here, from the one channel of EEG signal, the time frequency image of the signal is extracted and then feature extraction using the deep learning method is done. Finally, without changing the nature of the signal, the sleep steps are detected with acceptable accuracy. In this article, for the first time, time-frequency image (TFI) was provided from the one channel of the EEG signal. Then, using the AlexNet convolutional neural network by the Wigner-Ville distribution method (ANWVD), using Deeper layers contain higher-level features were extracted, and finally, using the SVM classifier, the sleep steps were classified with acceptable accuracy. The accuracy 97.6% and the time of calculations 0.36s have been reached.

Keywords: One Channel of EEG Signal, Sleep Stages, Classification, Deep Learning, Alex Net, Time Frequency Image.

1. INTRODUCTION

The standard method has been proposed by Rechtschaffen and Kales (R&K) for sleep recording. Sleep stages consist of six stages which namely are: Wake (W), Rapid Eye Movements (REM), Non-REM Stage 1 (S1),

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Non-REM stage 2 (S2), Non-REM stage 3 (S3) and Non-REM stage 4 (S4) [8]. The features extracted from biosignals are useful for the detection and classification of sleep stages. The power spectral features have been used for sleep stages classification from EEG signals [9]. The fast Fourier transform (FFT) features have been used for the classification of sleep stages [10]. The relative frequency bands' energy of EEG signals has been used for the NN classifier [11]. The time-frequency domain features have been used for the classification of sleep stages [12, 13]. The histograms of time-frequency image (TFI) have been used from EEG signals for automatic classification of sleep stages [7], [14]. Old classical methods and deep learning approaches have been proposed for processing and classifying the EEG signal [1]. Yet using a deep learning network model to classify sleep stages using TFI from a single-channel EEG signal has not been proposed. During signal processing of EEG, 3 steps are commonly taken, features extraction, features selection, and classification of classes [2]. Various feature extraction methods are employed by researchers, including linear and nonlinear methods, time and frequency domain methods and …, for feature extraction from EEG signal. [15, 16, 17]. The sleep stage classification is obtained using the time frequency features extracted from the EEG signal. [2]. Bajaj et al proposed a method which used time frequency images (TFIs) for EEG processing [7], [14]. This method classifies sleep stages using the SVM classifier and the features from TFIs. Deep learning is a successful method in image recognition, sound processing, and natural language processing [2]. Deep models have numerous applications in the biomedical area (biomedical signals (EEG, ECG, EMG, and EOG)) [18]. Deep learning methods were employed in the computer-based evaluations of ECG data [4, 18, and 19] and EEG signal processing for the detection of neurological disorders [20, 21, and 22]. Few studies in the deep learning models have used the sleep stage classification [1], [2]. Supratak et al. conducted a study on the deep learning method based on a convolutional neural network (CNN) for the sleep stages classification [23]. Tripathy and Acharya, classified sleep stages using a single-channel EEG signal with a deep neural network [24].

2. Alex Net Convolutional Neural Network (ANCNN) Method

The model is trained and tested on more than a million images and can classify images into 1000 classes [28] which has many applications in image analysis and classification that has acceptable accuracy [28]. Using the Layers property, this network comprises of 25 layers that 8 layers are with learnable weights: 5 convolutional layers, and 3 fully connected layers [28]. The Alex net network constructs a hierarchical representation of input images [28].

In this article, for the first time, the time-frequency image (TFI) was provided from the one channel of the EEG signal. Then, using Alex Net convolutional neural network (ANCNN together with Deeper layers contain higher-level extracted features, and finally, using the SVM classifier, the sleep steps were classified with acceptable accuracy.

3. MATERIAL AND METHODS

3.1. Dataset

This study uses the dataset available at physionet. The dataset is publicly available online at physionet adress [30]. The Sleep Heart Health Study (SHHS) is designed to investigate sleep stages. It consists of many channels of recordings from patients. EOG, EEG, EMG, ECG, nasal airflow (NAF), EEG were recorded. The standard European Data Format (EDF) was used.

These numerical values correspond to the sleep stage annotated by the expert according to the Rechtschaffen and Kales criteria. Table 1 presents the sleep stages and their labels.

3.2. Methods

In this study, for the first time, using the time-frequency image (TFI) of a single-channel EEG signal, the sleep steps are classified with high accuracy by deep learning method, learning and extracting deep features.

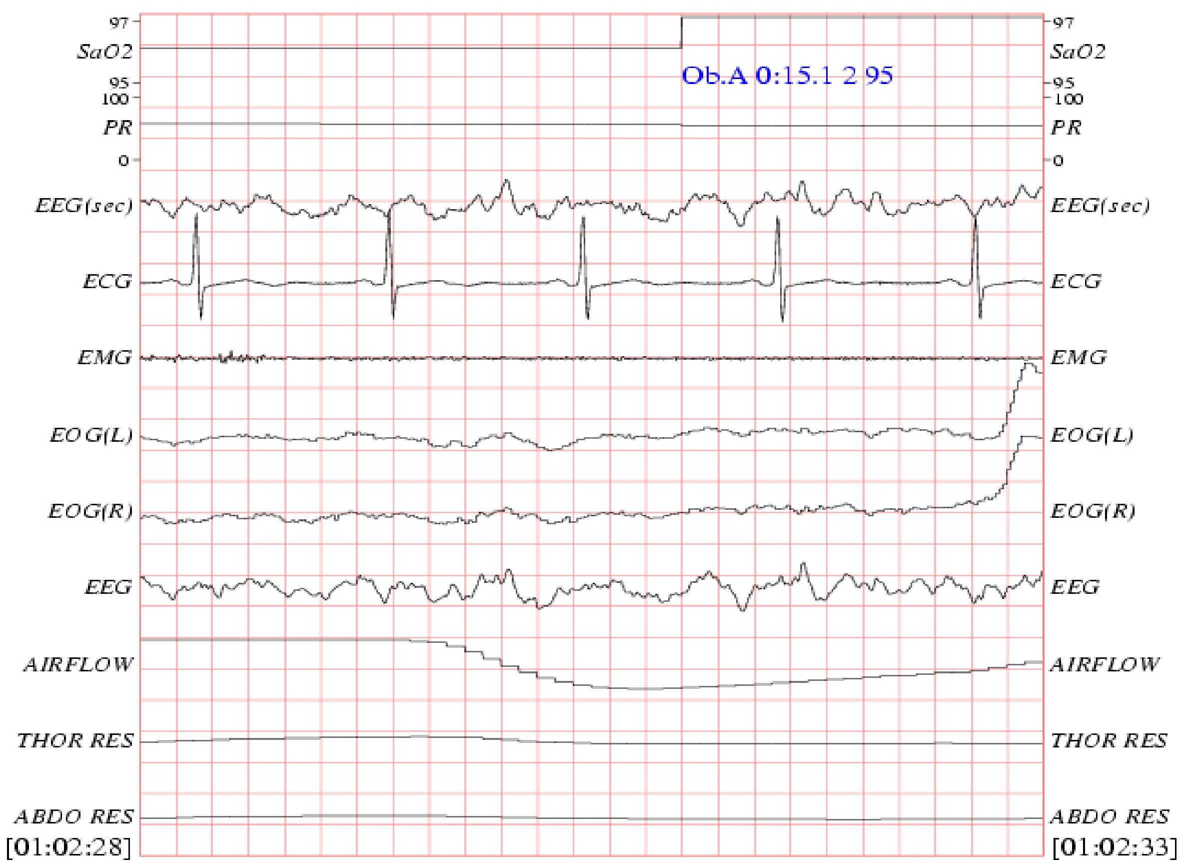

Fig.1. Image of all signals in the database [30].

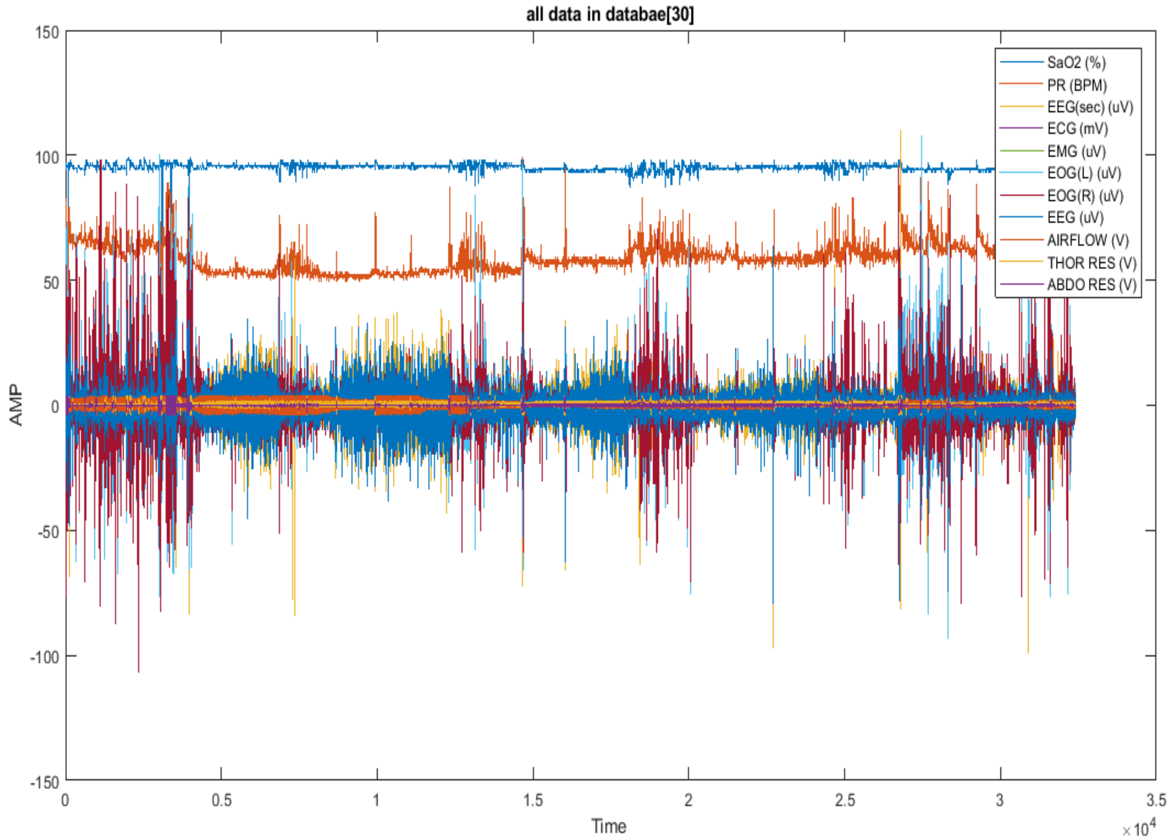

Fig. 2. All data in MATLAB software.

Table 1. ***The header of sleep stages in the database.***

Number sleep	**Sleep stage**
-1	Wake stage
0	REM stage
1	S1 stage
2	S2 Stage
3	S3 Stage
4	S4 Stage

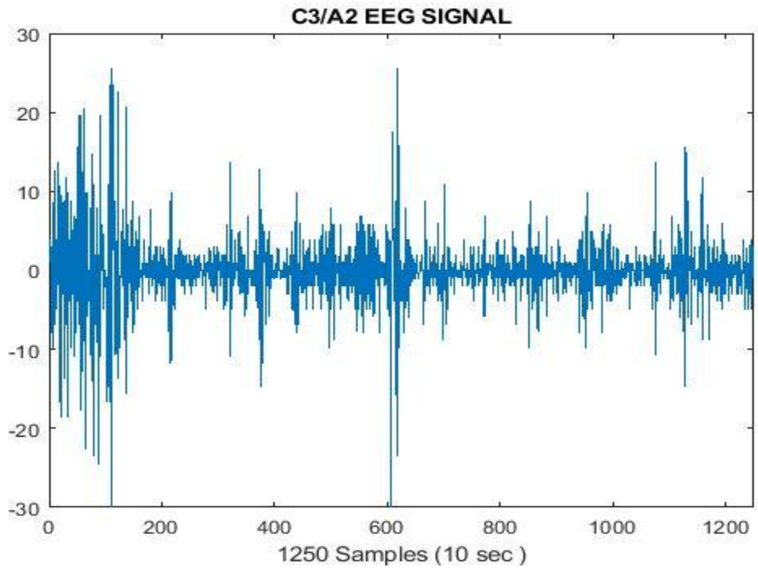

Fig. 3. EEG signal (10 sec).

In this research, a single channel C3 / A2 EEG signal with a sampling frequency of 125 has been used.

One of the tasks done in this project is to use a single signal channel to classify the stages of sleep. Figure 3 shows an example of an EEG signal.

3.3. Time-Frequency Image (TFI)

Then, according to the R&K standard, windowing was performed and from each window, a time-frequency image was extracted according to [7], [14].

To achieve the time-frequency image, the relationships in [29] have been used.

If this is true in the program, the spectrum sharpens the localization of spectral estimated by performing time and frequency reassignment. The reassign technique produces periodograms and spectrograms that are easier to read and interpret. . In this technique, each spectrum estimates the center of energy of its bin instead of the bin's geometric center. The technique provides an exact localization [29].

Figure 4 shows the Time-Frequency Image (TFI) from EEG data.

4. DEEP LEARNING AND FEATURES EXTRACTION

4.1. Alexnet Convolutional Neural Network (ANCNN) Method

The model is trained and tested on more than a million images and can classify images into 1000 classes [28] which has many applications in image analysis and classification that has acceptable accuracy [28]. Using the Layers property, this network comprises of 25 layers that 8 layers are with learnable weights: 5 convolutional layers, and 3 fully connected layers [28]. The alexnet network constructs a hierarchical representation of input images [28]. Deeper layers contain higher-level features, for construction using the lower-level features of earlier layers. To get the feature representations of the images, use activations on the fully connected layer 'fc7' [28]. In [1] ‘fc8’ by deep learning alexnet are used for feature extraction. In this study, two methods for feature extraction are used and the best result is expressed and selected.

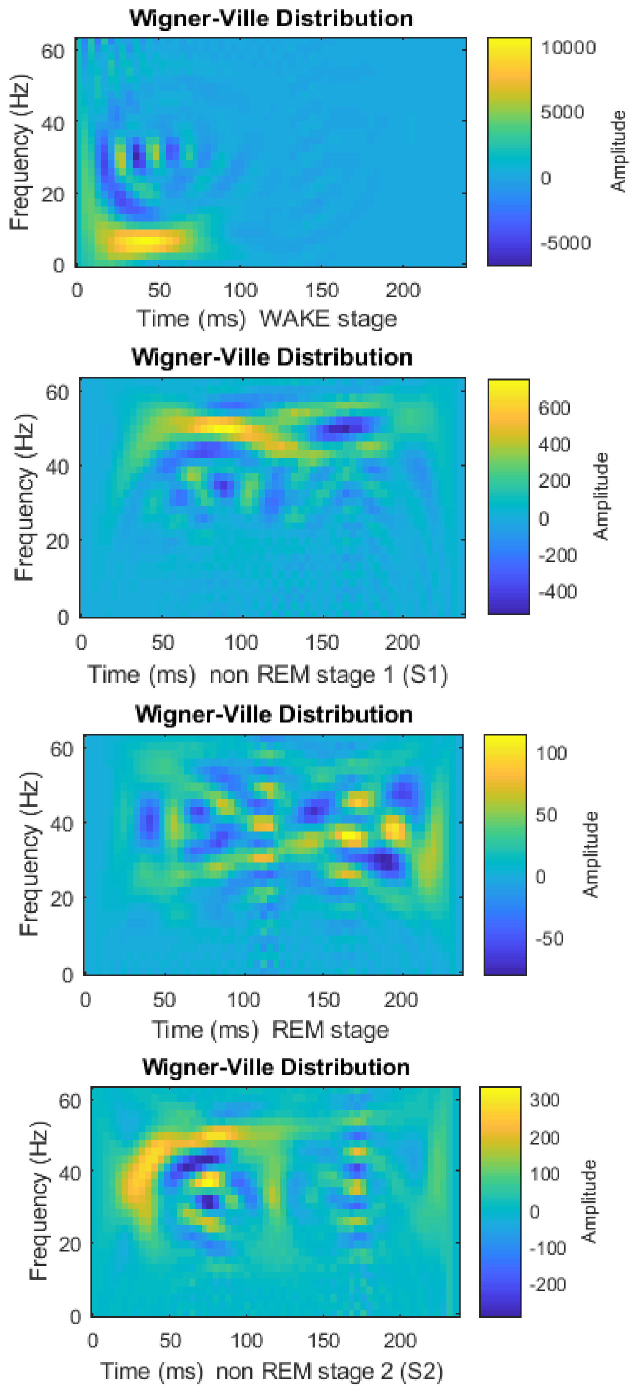

Fig.4. Time-Frequency Image (TFI) from EEG data.

Table 2. ***Properties of deep learning alexnet network.***

1	'data'	Image Input	227x227x3 images with 'zerocenter' normalization
2	'conv1'	Convolution	96 11x11x3 convolutions with stride[4 4]and padding[0 0]
3	'relu1'	ReLU	ReLU
4	'norm1'	Cross Channel Norm	cross channel normalization with 5 ch per element
5	'pool1'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0]
6	'conv2'	Convolution	256 5x5x48 convolutions with stride[1 1]and padding[2 2]
7	'relu2'	ReLU	ReLU
8	'norm2'	Cross Channel Norm	cross channel normalization with 5 ch per element
9	'pool2'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0]
10	'conv3'	Convolution	384 3x3x256convolutions with stride[1 1]and padding[1 1]
11	'relu3'	ReLU	ReLU
12	'conv4'	Convolution	384 3x3x192convolutions with stride[1 1]and padding[1 1]
13	'relu4'	ReLU	ReLU
14	'conv5'	Convolution	256 3x3x192convolutions with stride[1 1]and padding[1 1]
15	'relu5'	ReLU	ReLU
16	'pool5'	Max Pooling	3x3 max pooling with stride [2 2] and padding [0 0]
17	'fc6'	Fully Connected	4096 fully connected layer
18	'relu6'	ReLU	ReLU
19	'drop6'	Dropout	50% dropout
20	'fc7'	Fully Connected	4096 fully connected layer
21	'relu7'	ReLU	ReLU
22	'drop7'	Dropout	50% dropout
23	'fc8'	Fully Connected	1000 fully connected layer
24	'prob'	Softmax	Softmax
25	'output'	'output'	Class Output cross entropyex with 'tench' ,'goldfish', and …

According to Table 2, for a deep learning network, a 273 x 273 image is required, which has been converted to the desired size before processing and extracting the image feature. In this step, 4096 features were extracted from the deep layers of the signal, using the fc7 (ANCNN) method in [28] and

1000 features extracted using the ANCNN method in fc8 (softmax) [1].

4.2. Feature Selection

In this study, feature selection was performed using the neighborhood component analysis method (FSCNCA) presented in MATLAB [27]. Here, by classifying features into two modes, all features and characteristics are calculated with the threshold value.

4.3. Classification

In this research, after features extraction and selection, using 4 classifiers, sleep stages are separated and the results are expressed. Classifiers include CNN, Neural Network, SVM and LDA.

In this study, according to [3, 4, 5, 6, 7, 14, 25, and 26], etc. we used the SVM classifier.

Different kernels are used in each of these articles and because our proposed method is a new method, all three nonlinear kernels including Gaussian, RBF, and polynominal. Finally, the results are reported and the best result is expressed and selected.

5. RESULTS AND DISCUSSION

All steps in the study, shown in figure 5.

5.1. Data

In this study, the new PhysioNet website which is available at https://physionet.org is used**.** SHHS Polysomnography Database, includes C3/A2 and C4/A1 EEGs, sampled at 125 Hz. In this study, C3/A2 EEGs sampled at 125 Hz is used.

Figure 6 shows the EEG signal from 4 different sleep stages.

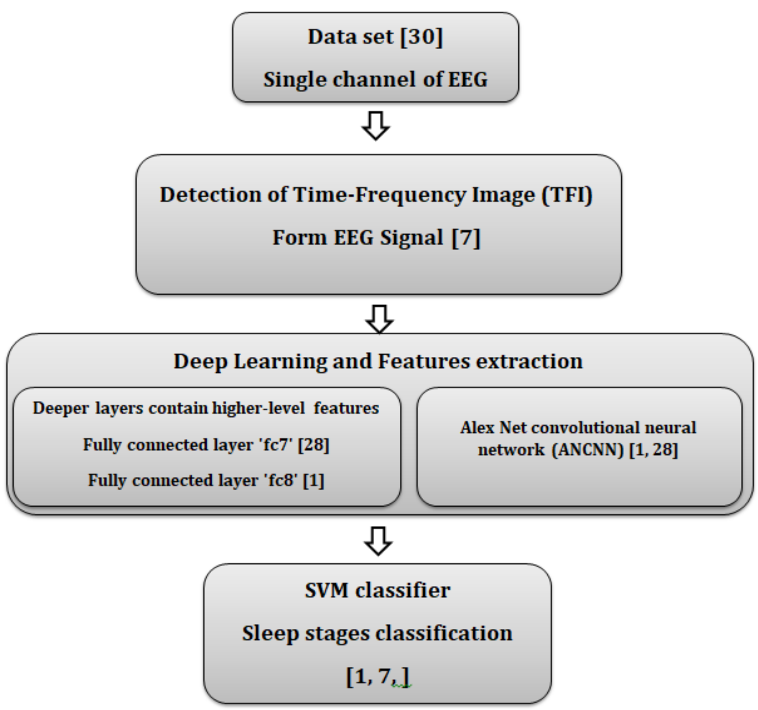

Fig. 5. All steps of sleep stages classification.

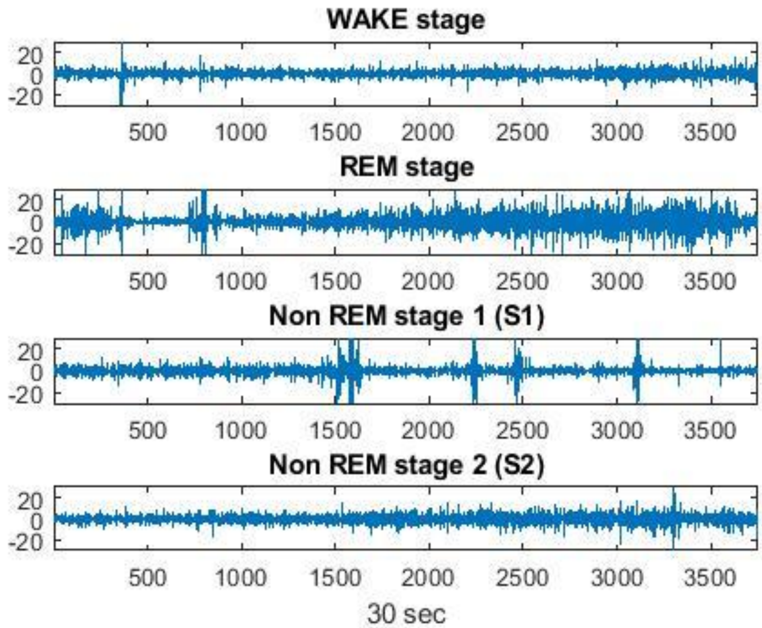

Fig. 6. sleep stages used/employed in the study.

A: WAKE stages B: REM stage C: Non REM stage 1 (S1) D: Non-REM stage 2 (S2)

Details of the classification steps are shown in Figure 7. which includes 120 steps.

5.2. Time-Frequency Image (TFI)

TFI obtains using the Smoothed Pseudo Wigner-Ville Distribution method in [7] and [29]. Here, to analyze the results, two methods Wigner-Ville distribution and smoothed pseudo-Wigner-Ville distribution have been investigated. [29]. The smoothed pseudo-WVD (SPWVD) based time-frequency representation has been selected from reference [7].

Figure 8 shows the two methods of obtaining TFI with the Wigner Ville method [1]. The first method is pseudo-smoothed and the second method is non-pseudo-smoothed.

5.3. Feature Extraction

Here, a deep learning method is used to extract features [28] and [1].In both methods, the ALEXNET network is used, with the difference that in [28] 4096 fully connected layer fc7 with 4096 features and in [1] 1000 fully connected layer fc8 (Softmax) with 1000 features are used. In this study, both methods have been used for better analysis.

5.4. Feature Selection

In this study, to get a better approach, two methods are used for classifying input data. First, all the features and in the next steps 10 of the total features are given to the classifier input.

During the 10 steps, in each step, features with a high-down impact factor are used.

For example, in the first step, Features that satisfy the condition of Formula 1 have been used.

Sif > 0.1 Max(ifa)$F_{if} > 0.1 \max(if_{all})$ (1)

Their F_{if} is Feature impact factor and if_{all} are Maximum impact factor of all features

In the second step, 0.2 impact factor and more, are shown in Figure 9.

In features selection step, 40 cases have been analyzed, that shown in Figure 7.

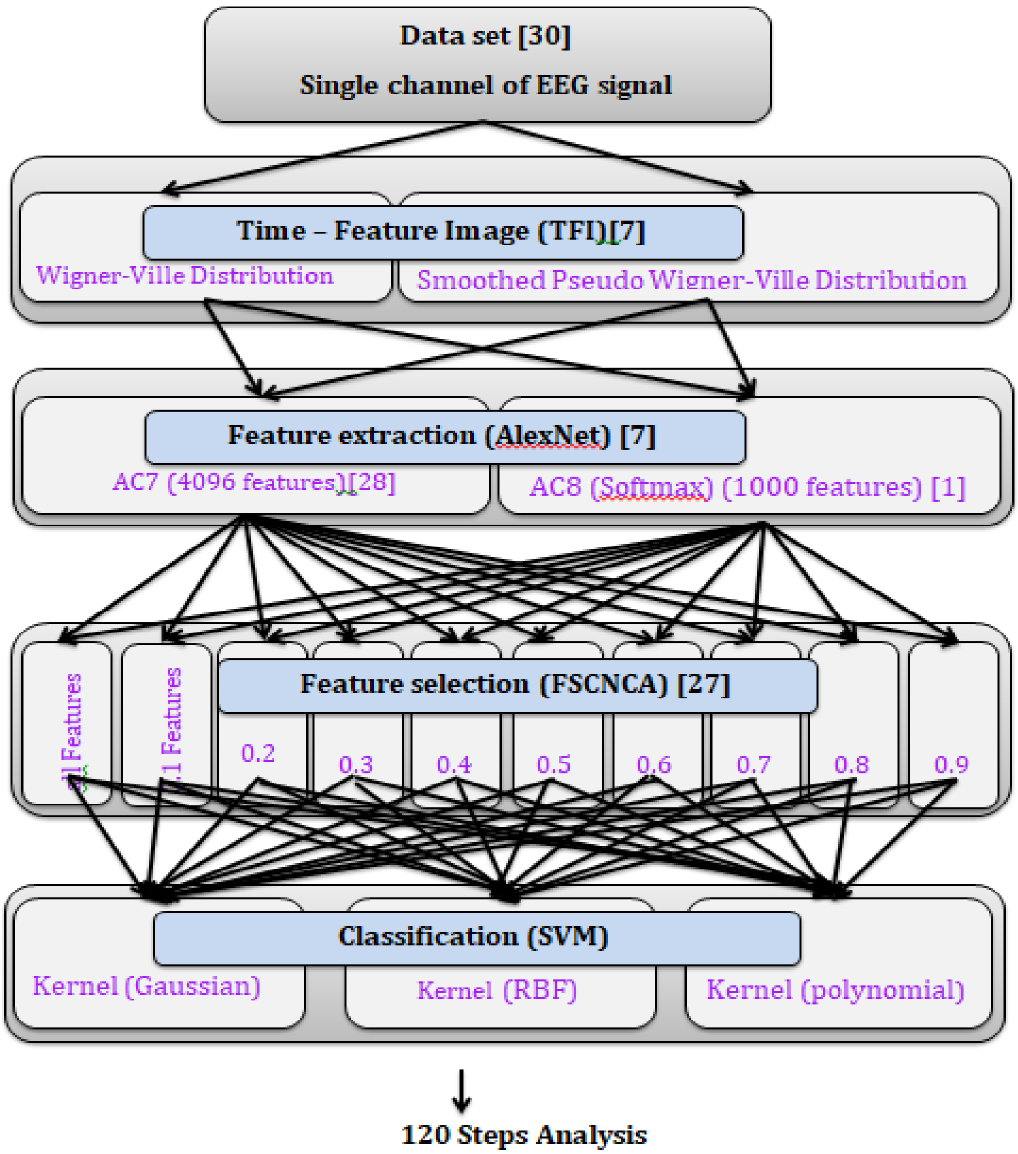

Fig. 7. 120 steps for classification.

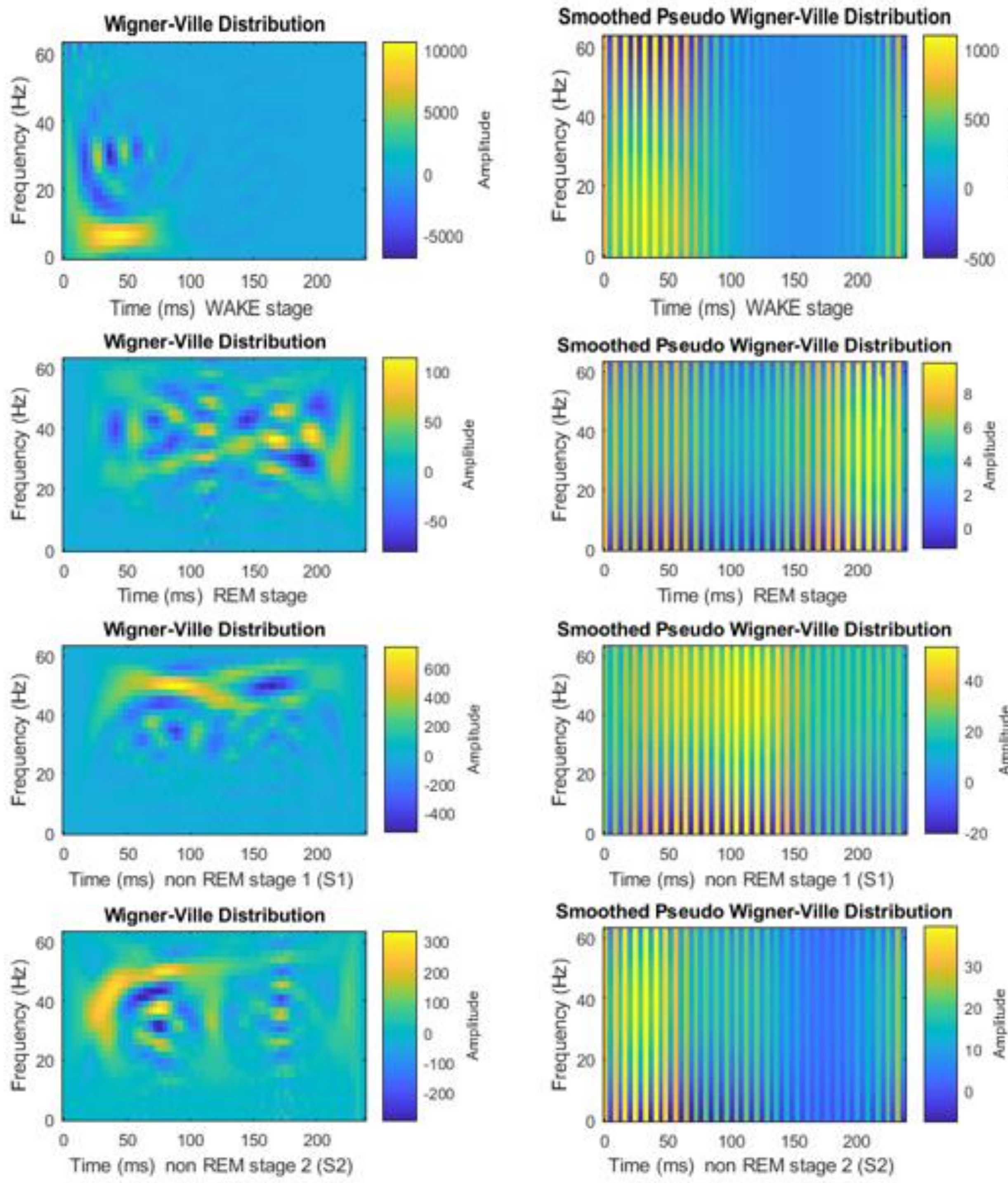

Fig. 8. two methods of obtaining TFI (a) sleep stages using Wigner-Ville Distribution and (b) sleep stages using Smoothed Pseudo Wigner-Ville Distribution.

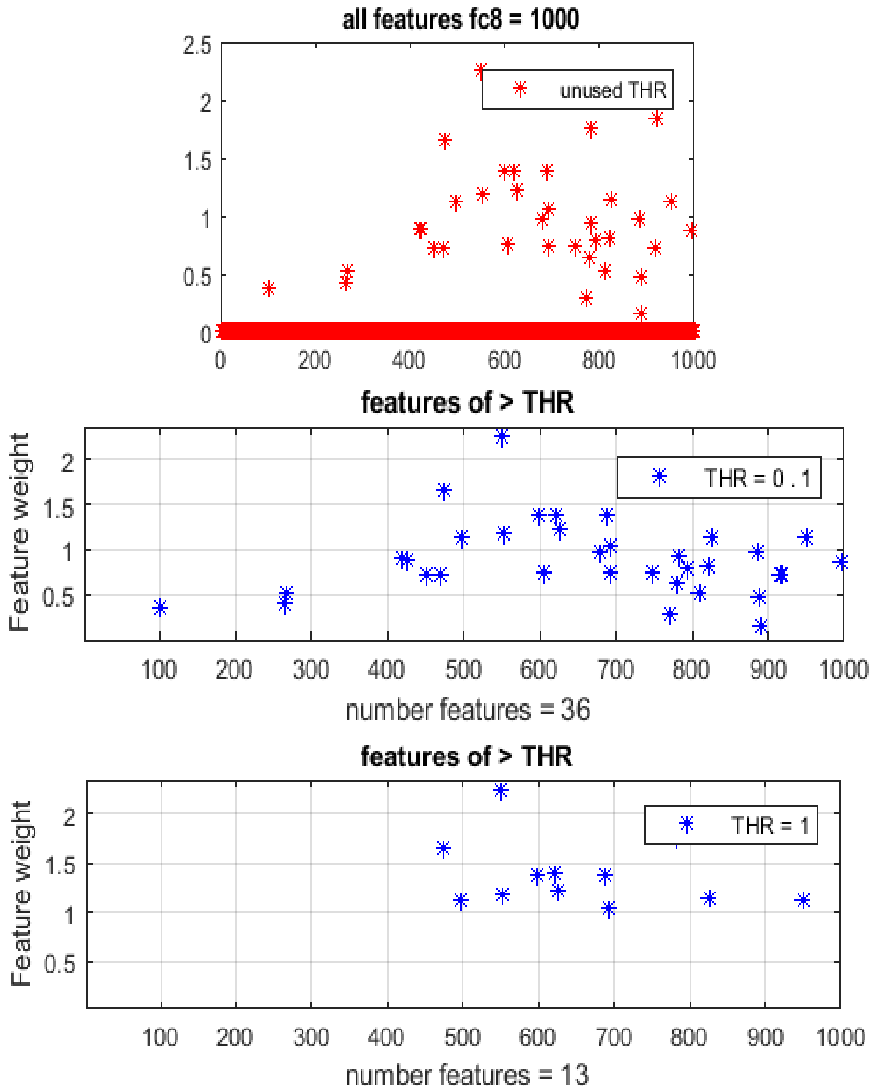

Fig. 9. Feature selection for classification input (a) All features (b) features selection > THR = 0.1 (c) features selection > THR = 1.

5.5. Classification

In this step, Due to the great attention paid to SVM, we have used this method. But because of the use of different kernels in valid rticles, we used all three kernels for analysis. The 3 kernels that have been used in valid article include Gaussian, RBF, and polynomial. We are using all kernels in this study. In the final step, 120 cases are analyzed. The time and accuracy results are presented in this section.

6. DISCUSSION

All processing steps have been done using HP laptop with the CORI7 processor and 4 GB RAM using MATLAB 2020a software.

The data has been received from the site with the validity and availability of the Physionet available at https://archive.physionet.org/physiobank/database/shhpsgb/

In this study, a new method is provided for the first time, to classify the sleep stages using the deep learning method, from the time-frequency image of the EEG signal. Most methods use EEG signal characteristics to classify sleep stages. In literature [7] features of Time-frequency image are established for sleep stages detection using the SVM classifier. We tried here, Inspired from literature[7], the time-frequency image of the signal is obtained .But with the difference that we analyzed two methods [WVD] and [SPWVD] to get the best method and report it. Then, in the feature extraction stage, unlike all deep learning methods used, which extract features from the EEG signal we use deeper features extracted from Time-frequency image, by fully connected ALEXNET without the handcraft method. And then to achieve real-time processing and fixed high accuracy we used feature selection method. To achieve this goal, due to the frequent use of many authoritative articles we use the SVM method for classification, unlike other methods. We used all the important kernels for classification, to choose the best method.

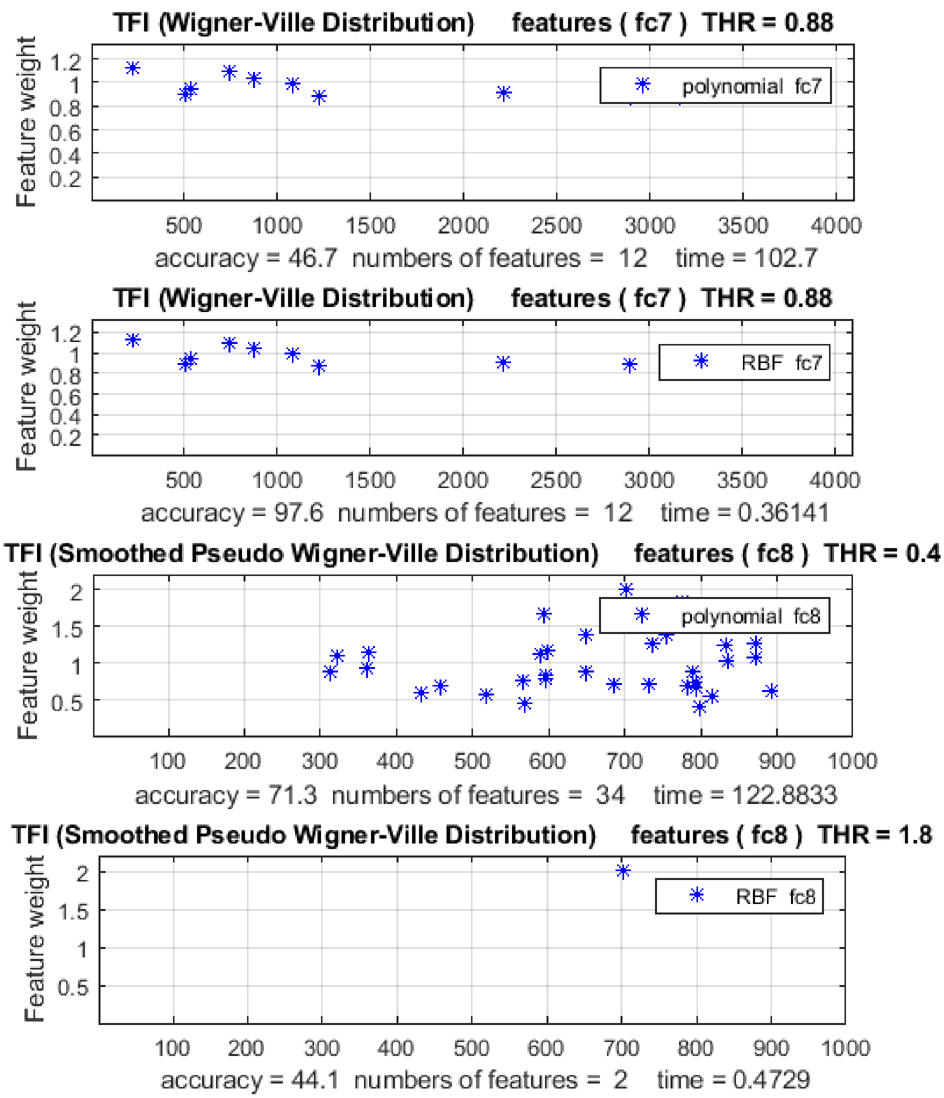

Fig.10. Examples of classification results.

Table 3. *Accuracy results of sleep stage classification using the SVM method.*

Kernel	Gaussian				RBF				polynomial			
TFI	SPWVD		WVD		SPWVD		WVD		SPWVD		WVD	
Network	FC7	FC8	FC7	FC8	FC7	FC8	FC7	FC8	FC7	FC8	FC7	FC8
All features	96.9	97.6	96.3	97.6	96.9	97.6	96.3	97.6	29.3	27.3	27.8	26.3
>THR =0.1	97.6	97.6	97.6	97.6	97.6	97.6	97.6	97.6	26.2	56.3	35.8	24.5
>THR =0.2	97.6	97.6	97.6	97.6	97.6	97.6	97.6	97.6	27.9	71.3	32.3	32.6
>THR =0.3	97.6	97.5	97.6	97.6	97.6	97.5	97.6	97.6	23.7	53.1	34.3	17.1
>THR =0.4	97.6	96.1	97.6	96.6	97.6	96.1	97.6	97.6	30.2	73	19.7	28.7
>THR =0.5	97.6	93.2	97.6	83.3	97.6	93.2	97.6	83.3	25.6	40.8	21.8	23.1
>THR =0.6	97.5	77.2	97.6	72.7	97.6	77.2	97.6	72.7	42.1	29	33.8	25.4
>THR =0.7	92.3	53.2	97.6	55.1	92.3	53.2	97.6	55.1	24.9	22.6	25	21.5
>THR =0.8	58.1	53.2	97.6	44.1	58.1	53.2	97.6	44.1	23.7	22.6	46.7	30.3
>THR =0.9	39	44.1	57.7	41.3	39	44.1	57.7	41.3	39	30.5	26.3	40.6
ranking	2	3	1	4	2	3	1	4	5	7	8	6

Table 4. ***Time results of sleep stage classification using the SVM method***

Kernel	Gaussian				RBF				polynomial			
TFI	SPWVD		WVD		SPWVD		WVD		SPWVD		WVD	
Network	FC7	FC8	FC7	FC8	FC7	FC8	FC7	FC8	FC7	FC8	FC7	FC8
All features	12.1	1.68	13.1	1.65	14.7	1.69	15.4	1.85	109.1	105.5	117.7	110.3
>THR =0.1	0.97	0.77	0.91	0.72	1.04	0.77	0.96	0.57	104.1	114.8	106.3	108.1
>THR =0.2	1.04	0.67	0.92	0.55	0.99	0.69	0.95	0.9 0	103.7	122.8	105.4	109.6
>THR =0.3	1.29	0.50	0.98	0.60	1.05	0.49	1.04	0.61	105.7	114.8	107.5	110.8
>THR =0.4	0.86	0.44	1.01	0.55	0.81	0.41	1.13	0.70	107.2	111.6	104.6	122.6
>THR =0.5	0.54	0.34	0.85	0.38	0.54	0.49	0.86	0.39	117.7	99.8	105.1	132.7
>THR =0.6	0.63	0.36	0.62	0.36	0.55	0.4 0	0.71	0.71	124.3	130.8	103.5	134.5
>THR =0.7	0.41	0.33	0.47	0.35	0.52	0.36	0.45	0.32	129.2	136.0	127.9	136.7
>THR =0.8	0.32	0.29	0.37	0.54	0.31	0.29	0.36	0.65	137.4	136.5	102.7	115.1
>THR =0.9	0.27	0.51	0.30	0.36	0.27	0.47	0.35	1.71	102.0	117.4	133.6	110.7
ranking	1	2	3	6	1	2	4	5	7	9	8	10

Figure 10 shows examples of frequency-time image extraction modes with WVD and SPWVD methods and convolution neural network architecture with fully connected FC and FC layers, as well as the feature selection threshold.

7. CONCLUSION

In this study, a new method introduced for the first time to classify the sleep stages using the deep learning method and a time-frequency image of the signal is provided. In the first step, the data was received the online Physionet site. Then, the time-frequency image of the single-channel EEG signal was obtained by two methods, SPWVD and WVD [7]. Figure 8 shows the time frequency image of the two methods. In the next step, from the obtained images, Deep Features are extracted by two methods, FC 7 and FC 8. Then, extracted features are analyzed for feature selection. And finally, according to the selected features, using the SVM classifier, sleep stages classify with different kernels. And the results of 120 different modes are presented and the best method is selected and reported. The results of the classifier accuracy are reported in Table 3 and the calculation time results in Table 4. As can be seen, the first Ranking of Accuracy, Belongs to the [TFI (WVD), ALEXNET (FC7), kernel (RBF)] method.

AlexNet convolutional neural network by the Wigner-Ville distribution method (ACNNWVD) is selected with an accuracy of 97.6% and a time of 0.36 sec.

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