ORIGINAL ARTICLE

Sleep Stages Classification Using Music Made from EEG by LSTM Networks

Hamidreza Jalali [1], Majid Pouladian [1*], Ali Motie Nasrabadi [2], Azin Movahed [3]

[1] Department of Biomedical Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

[2] Biomedical Engineering Department, Faculty of Engineering, Shahed University, Tehran, Iran

[3] Music Department, School of Performing Arts and Music, College of Fine Arts, University of Tehran, Tehran, Iran

*Corresponding Author: Majid Pouladian

Email: pouladianmajid6@gmail.com

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Abstract

Purpose: Automatic classification of sleep stages is one of the fundamental factors in diagnosing sleep disorders to prevent and treat various diseases, and it can significantly aid in saving specialists' time and energy. In this study, a new method for converting Electroencephalogram (EEG) signals to music for sleep stages classification is proposed.

Materials and Methods: A total of 15.233, 30-second data segments from the Sleep-EDF database were used as the statistical population for this evaluation. Initially, the performance of Long Short-Term Memory (LSTM) networks for music sequence generation is evaluated with the music database and the best structure is selected. Subsequently, single-channel EEG data are mapped to music pieces using the selected network. Seven features are extracted from the generated music sequences and applied to classification structures.

Results: The selected LSTM structure was able to identify musical sequences with an accuracy of 93.3% of the musical pieces. The overall classification accuracy for the five sleep stages according to the AASM standard is 85.3% for the Sleep-EDF database. Accuracy of classifying W, N1, N2, N3, and REM stages are 86.1%, 77.3%, 95.4%, 96.3%, and 71.4%, respectively. Another objective of this study is to present a novel single-channel EEG sonification method, achieving classification accuracy that is either higher than or comparable to contemporary methods.

Conclusion: The results of this study show that audio signal mapping with LSTM networks contains effective information for sleep stage classification, and the classification accuracy increased by 1% compared to the method of a similar study and by 3% compared to most studies.

Keywords: Single-Channel Electroencephalogram; Sleep Staging; Electroencephalogram Sonification; Long Short-Term Memory.

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1. Introduction

Sleep is a fundamental physiological process that plays a critical role in replenishing energy levels, regenerating biological cells, and enhancing memory function [1]. During sleep, the secretion of biological hormones by glands is pivotal to these restorative processes. However, the stressors of modern life have significantly impacted sleep quality, leading to various disorders. Despite its importance, sleep health often remains undervalued. A comprehensive analysis of sleep patterns and stages is crucial for preventing associated health issues and managing related disorders effectively.

Classifying sleep stages accurately is essential for identifying sleep-related disorders. Various studies have explored innovative methodologies for this purpose. For instance, some researchers emphasize signal mapping and feature extraction in alternative domains. In [2], signals are analyzed in the time-frequency domain to extract entropy features. Similarly, [3] demonstrates the application of Convolutional Neural Networks (CNNs) for feature extraction. In [4], the Fourier-Bessel decomposition method is employed to decompose time-series data into frequency bands, providing amplitude and frequency as time functions. Meanwhile, [5] highlights the use of frequency band filtering as a foundational step.

Another approach involves utilizing spatial covariance matrices. In [6], researchers classify sleep stages by analyzing covariance matrices in the tangent space of Riemannian manifolds. This study suggests a significant correlation between these matrices and multi-channel signal sleep stages. Additionally, [7] introduces three new localized bands combined with a wavelet filter bank. This study extracts log-energy, signal fractal dimension, and signal sample entropy features from three EEG levels, subsequently classifying them using a Support Vector Machine (SVM).

Adaptive Fourier analysis is explored in [8] to decompose non-stationary signals into Amplitude Modulation-Frequency Modulation (AM-FM) components. This technique enables the analysis of single and multi-channel signals across different states. Furthermore, [9] proposes quaternion-valued singular spectrum analysis and Ensemble Empirical Mode Decomposition (EEMD) as novel methods for sleep stage classification. Another innovative method introduced in [10] involves iterative filtering to break down RR time series into intrinsic mode functions. Dispersion entropy and variance features derived from these bands are used for classification. Lastly, [11] details the extraction of features such as standard deviation, sample entropy, and zero crossing rate from wavelet segments, along with residual mean value and median absolute deviation for sub-band classifications.

The essence of acknowledging and better understanding EEG signals is evident, and many researchers seek to assess them in other domains to better understand brain activities. The presentation of sound signals or converting EEG signals into sonification signals is one of the most significant issues in recent studies. Sonification can be used for disease detection or treatment [12-16]. For example, according to [17], congenital amusia is a lifelong impairment in music perception, often attributed to a fundamental deficiency in recognizing musical notes or frequency intervals. The role of tempo perception in music is explored in [18], where it is demonstrated that tempo significantly influences the alpha rhythm. Banerjee *et al.* [19] examine the impact of music on brain activity across alpha, theta, and gamma bands, revealing that listening to music enhances emotion-related processes. The influence of flash music on brain function is investigated in [20]. Furthermore, the effects of varying levels of music practice on cognitive processing and behavioral patterns are compared among non-musicians, amateur pianists, and professional pianists in [21].

Lu *et al.* [22] propose a method for generating music from time-series data derived from fMRI by modeling cortical neuronal activity and analyzing hemodynamic responses. A technique for converting encephalogram signals into music during sleep is presented in [23], using a coding model based on frequency features. This approach provides tools for creating music. To predict differences in flash music reconstruction, [24] uses EEG signals from the front and back of the head, showing significant frequency band variations across lobes. A review on improving sleep through music is conducted in [25], while [26] applies sleep signals to enhance the enjoyment of

subject-specific music. Moradi *et al.* [27] use a Recurrent Neural Network (RNN) to transform decomposed EEG frequency sub-bands into music.

In this study, a musical mapping of EEG signals is first created via LSTM models by musical rules. Then, by extracting features from the generated musical sequence, sleep stage classification is performed according to AASM [28] standards. A musical database has been created to train the deep LSTM networks.

2. Materials and Methods

This study presents a method to classify sleep stages. Initially, EEG sonification is performed using a new approach based on deep networks, transforming the EEG signal into a sequence of music. Different features are then extracted from the generated musical sequence and applied to the classification framework. The output of the classifier corresponds to one of the five sleep stages (N1, N2, N3, REM, W). The overall methodology is illustrated in Figure 1.

2.1. Databases

The process of creating a music database for training and testing classifiers is explained below, followed by a description of the EEG database utilized.

2.1.1. Music Database

The music database was created using an electric piano with precise tuning. The piano's sound was captured and transmitted through a software interface, recorded at a sampling rate of 44,000 Hz in a mono-channel format with 8-bit audio resolution. The compositions were designed based on the framework of tonal music and covered the 12 major scales, each containing seven consecutive notes played for 500 milliseconds. The process was structured as follows:

- Every possible sequence of the seven notes was generated, resulting in 5,040 unique audio pieces per scale.
- These sequences were played across three octaves—220 Hz, 440 Hz, and 880 Hz—all centered around the note "A" (La).
- This approach produced a total of 181,440 audio pieces, representing all combinations of seven notes in the 12 major scales across the three octaves. Each piece had a duration of 3.5 seconds.
- Each music scale class was assigned a unique identifier, and the sequence of notes in each composition was documented for reference.

Table 1 reports details about the majority scale labels and their note sequences.

2.1.2. The Sleep-EDF Database

We have used EEG signals from the Sleep-EDF database [29] to validate our proposed method. In addition, stages 3 and 4 have been merged into one N3 step, according to the AASM standard. The details of the database are tabulated in Table 2.

2.2. Preprocessing Step

2.2.1. Music Signal

To ensure accurate classification, the length of each music piece is standardized to 3.5 seconds. Due to hardware limitations, the duration of each note is set to 500 milliseconds. To remove resonances from other octaves, unnecessary frequencies are removed using a 10^{th}-order band-pass Butterworth filter with cutoff frequencies corresponding to each musical octave on each musical piece.

2.2.2. EEG Signal

A 10th-order Butterworth filter is applied to the EEG within the meaningful frequency range (e.g., 0.5



Figure 1. Schematic representation of the proposed workflow

Table 1. Description Majority scales labels & notes sequence of each

				Grade 1 Note			Grade 2 Note	Grade 3 Note
Major Scale-Note Sequence	**C**	**D**	**E**	**F**	**G**	**A**	**B**	**C**
Labels	1	3	5	6	8	10	11	1
Major Scale-Note Sequence	**G**	**A**	**Si**	**C**	**D**	**E**	**# F**	**G**
Labels	2	10	12	1	3	5	7	8
Major Scale-Note Sequence	**D**	**E**	**# F**	**G**	**A**	**B**	**# C**	**D**
Labels	3	5	7	8	10	12	2	3
Major Scale-Note Sequence	**A**	**B**	**# C**	**D**	**E**	**# F**	**# G**	**A**
Labels	4	12	2	3	5	8	9	10
Major Scale-Note Sequence	**E**	**# F**	**# G**	**A**	**B**	**# C**	**# D**	**E**
Labels	5	8	9	10	12	2	4	5
Major Scale-Note Sequence	**B**	**# C**	**# D**	**E**	**# F**	**# G**	**# A**	**B**
Labels	6	2	4	5	8	9	11	12
Major Scale-Note Sequence	**F**	**G**	**A**	**b B**	**C**	**D**	**E**	**F**
Labels	7	8	10	11	1	3	5	6
Major Scale-Note Sequence	**b B**	**C**	**D**	**b E**	**F**	**G**	**A**	**b B**
Labels	8	1	3	4	6	8	10	11
Major Scale-Note Sequence	**b E**	**F**	**G**	**b A**	**b B**	**C**	**D**	**b E**
Labels	9	6	8	9	11	1	3	4
Major Scale-Note Sequence	**b A**	**b B**	**C**	**b D**	**b E**	**F**	**G**	**b A**
Labels	10	11	1	2	4	6	8	9
Major Scale-Note Sequence	**b D**	**b E**	**F**	**b G**	**b A**	**b B**	**C**	**b D**
Labels	11	4	6	7	9	11	1	2
Major Scale-Note Sequence	**b G**	**b A**	**b B**	**b C**	**b D**	**b E**	**F**	**b G**
Labels	12	9	11	12	2	4	6	7

Table 2. Details of EEG Sleep-EDF database used

Sleep-EDF database					
Stages	W	N1	N2	N3	REM
Number of epochs	8055	604	3621	1344	1609

to 45 Hz for healthy individuals and similarly for pathological recordings).

2.3. Mapping EEG to Music

This section describes a novel technique to map EEG signals to music and evaluates its usefulness in sleep stages classifying. To extract the sequence of music, each EEG signal is first divided into 3.5-second segments, and the dominant frequencies for each segment are extracted based on 500-millisecond time windows. In the next step, the ratio of dominant frequencies in each window to the previous window is calculated, forming a 7-bit sequence of frequency ratios. This sequence is fed into an LSTM structure, which outputs a 7-bit sequence representing musical note changes. The LSTM structure is trained using a custom-built music database.

2.3.1. Extracting Time-Frequency Sequences

Frequency variations in music, such as changes in treble, bass, or the distance between two notes, determine the pitch and sequence of notes. The instantaneous frequency of a nonstationary signal is a time-dependent parameter that characterizes the signal's average frequency content at each moment. The instfreq function estimates this frequency as the first conditional spectral moment of the signal's time-frequency distribution. This function is simulated in the MATLAB environment and, specifically, performs the following steps [30]:

- Calculates the spectrogram power spectrum $P(t,f)$ of the input signal using the pspectrum function, interpreting it as the time-frequency distribution.
- Derives the instantaneous frequency from the resulting time-frequency representation, as specified in Equation 1.

$$f_{inst}(t) = \frac{\int_0^\infty fP(t,f)\,df}{\int_0^\infty P(t,f)\,df} \quad (1)$$

The following steps outline the process:

1. **Extract Instantaneous Frequencies**: Retrieve the sequence of instantaneous frequencies from the music signal.
2. **Determine Frequency Timing**: Record the occurrence time of each frequency.
3. **Calculate Frequency Ratios**: Create a sequence of ratios between consecutive instantaneous frequencies.
4. **Numerical Note Differences**: Quantify the difference between consecutive notes. For example, if the first note is **Re** (3), the second note **Fa** (6), and the third note **Mi** (5), the sequence would be: 3, -1. If no frequency change occurs, the entry is 0.
5. **Classifier Input and Output Formation**: The input consists of sequences of frequency ratios extracted via **Instfreq**, while the output contains sequences of consecutive note changes as classifier labels.

Note: After training the classifiers on music sequences, momentary frequency ratios from EEG signals are used to determine the sequence of changes or note numbers at the output.

2.3.2. Note Sequence Determination

LSTM, a variant of RNN, is designed to learn long-term dependencies. It employs gates to regulate information flow and utilizes a cell state to preserve long-term memory.

Forget Gate (f_t): Decides which information to forget from the cell state according to Equation 2.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \quad (2)$$

Input Gate (i_t) and Candidate Memory ($\tilde{C}_t$): Decides which information to add to the cell state according to Equation 3 and Equation 4, respectively.

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (3)$$

$$\tilde{C}_t = \tanh(W_C.[h_{t-1}, x_t] + b_C) \quad (4)$$

Update Cell State (C_t): Updates the cell state with the forget and input gates according to Equation 5.

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (5)$$

Output Gate (o_t) and Hidden State (h_t): Decides the output of the LSTM according to Equation 6 and Equation 7, respectively.

$$o_t = W_o.[h_{t-1}, x_t] + b_o \quad (6)$$

$$h_t = o_t \odot \tanh(C_t) \quad (7)$$

x_t is the input at time t, h_{t-1} is the previous hidden state, C_t is the cell state at time t, W_f, W_i, W_c, W_o are the weight matrices, b_i, b_f, b_C, b_o are the bias terms. σ, *tanh* and $\odot$ stand for the sigmoid activation function, the hyperbolic tangent activation function, and element-wise multiplication, respectively.

Considering the short- and long-term dependencies of the note sequence in a piece of music, applying an LSTM structure is highly effective for classification [31, 32]. The input of this classifier is a 7-bit sequence, where each bit represents the ratio of the instantaneous frequency extracted from the music signal to its previous instantaneous frequency during training, and a similar 7-bit sequence is extracted from the EEG signal during testing. The output of this classifier is a 7-bit sequence, where each bit represents the pitch difference between the current note and the previous note. This sequence indicates the pitch difference between the current note (or piano key) and the previous note.

The LSTM network is a type of RNN [33, 34] with the main components, a sequence input layer and a short-term long-term memory layer able to learn short or long-term dependencies among successive data time steps. The input layer enters the sequence of time series data into the network and the LSTM layer learns the dependencies between the time steps of the successive data.

Figure 2 illustrates the architecture of an LSTM model designed for music classification and generation, with an input sequence layer size of 7 and a fully connected layer configured with 7 units.

The control parameters of the LSTM layer count, the neuron count, and the forgetting parameter are considered and reported after being assessed.

2.3.3. Creating a Music Repertoire

To create the musical repertoire, the primary scale and key are determined based on the first LSTM output label. Then, the seven output labels, representing 3.5 seconds of EEG variations, are combined to identify the corresponding note numbers on a standard piano keyboard. In the final step, consecutive identical notes are merged, resulting in notes with varying durations. The final musical sequence includes the frequency of the desired musical notes and the timing of each event. Figure 3 illustrates the process of repertoire creation.

2.4. Features Extraction from the Music of the Brain

Based on the musical mapping of the EEG signal, various features related to voice and speech were analyzed. Among these, four features were selected: absolute jitter, proportional jitter, absolute shimmer, and proportional shimmer [35]. These features are computed using Equation 8–Equation 11.

$$shimmer = \frac{1}{N-1}\sum_{i=1}^{N-1}|A_i - A_{i+1}| \tag{8}$$

$$\text{shim} = \frac{\frac{1}{N-1}\sum_{i=1}^{N-1}|A_i - A_{i+1}|}{\frac{1}{N}\sum_{i=1}^{N} A_i} \tag{9}$$

where, A is the signal amplitude.

$$\text{Jitter} = \frac{1}{N-1}\sum_{i=1}^{N-1}|T_i - T_{i+1}| \tag{10}$$

$$\text{jitt} = \frac{\frac{1}{N-1}\sum_{i=1}^{N-1}|T_i - T_{i+1}|}{\frac{1}{N}\sum_{i=1}^{N} T_i} \tag{11}$$

where, T stands for a duration of periods (second).

Also, variance, kurtosis, and skewness are extracted from signals, finally, we have 7 features.

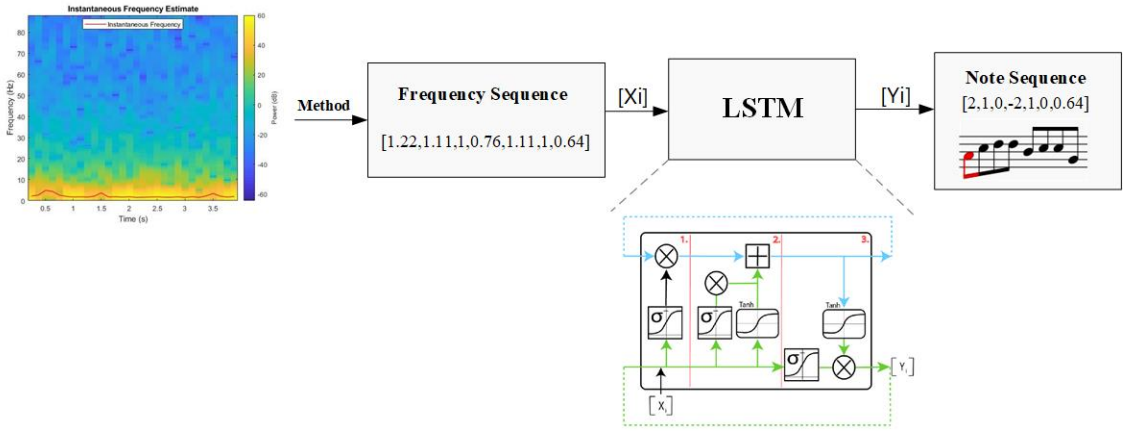


Figure 2. Represents the production of note sequence with the LSTM model

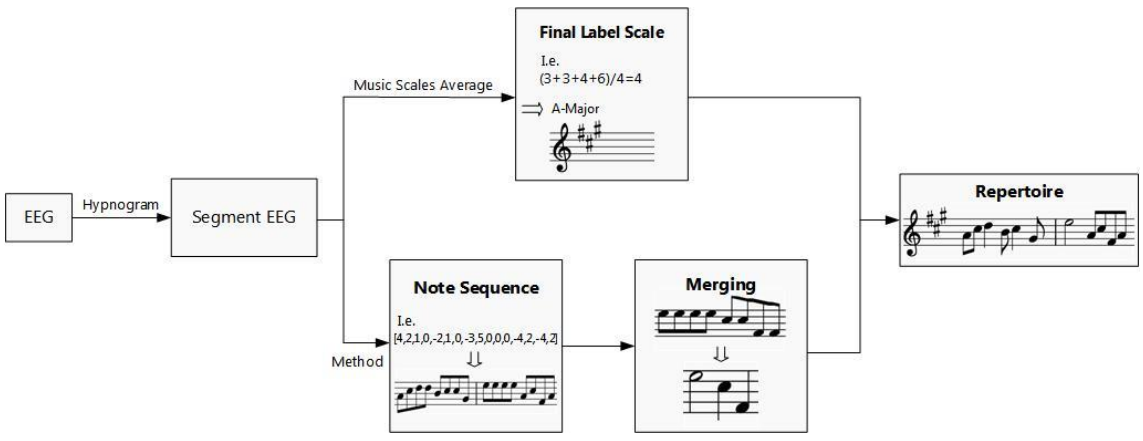


Figure 3. Process of repertoire creation

2.5. Sleep Stages Classification

To classify sleep stages, seven features extracted from the music generated from EEG signals are applied as inputs to the classification frameworks. The output of these classifiers corresponds to one of the five sleep stage labels. In this study, two standard classifiers of -SVM and KNN-with different structures are employed for classification [36], and the results of each are presented and analyzed.

3. Results

As explained in Section 2.3.2, an LSTM network is used to generate a music sequence from EEG signals. The input to this network is a 7-bit sequence representing the dominant frequency ratio between two consecutive windows, and the output is a 7-bit sequence where each bit indicates the pitch change of a note at each moment. To train this network, the music database described in Section 2.1 is utilized.

To select the optimal parameters for this network, several different structures were developed, and their test results on the music database are presented in Table 3. In this study, the network structure that achieved the best results on the generated music database is employed for EEG sonification. According to the results, an LSTM structure with three layers and 32 hidden units was chosen for mapping the brain signals (Figure 4).

After selecting the LSTM network and extracting the notes, the musical repertoire is generated according to the rules outlined in Section 2.3.3. Figure 5 illustrates the conversion of EEG signals from two sleep stages into music.

Table 3. Accuracy percentages for different LSTM models to determine note sequence in the music database

	Number of Hidden Units		
Number of Block	16	32	64
LSTM(2)	79.4	83.8	81.4
LSTM(3)	88.4	**91.3**	89.4
LSTM(4)	84.7	88.3	86.1

After extracting the seven features described in Section 2.4 from the note sequences generated from EEG signals, two structures were designed and tested for sleep stage classification. Models were implemented in the MATLAB environment and using Neural Network Toolbox, version 2018b.

SVM and KNN classifiers, based on various configurations and theories, were applied, and their parameters were examined to identify the optimal configurations, which are reported. The input for each classifier consists of the seven features extracted from the musical pieces generated from EEG signals, and the output is one of the five sleep stage labels (N1, N2, N3, W, REM). The classifiers' performance was investigated by computing accuracy (Acc), sensitivity (Se), and specificity (Sp).

The highest results for the SVM structure were achieved using a cubic kernel, while the best results for the KNN structure were obtained using three

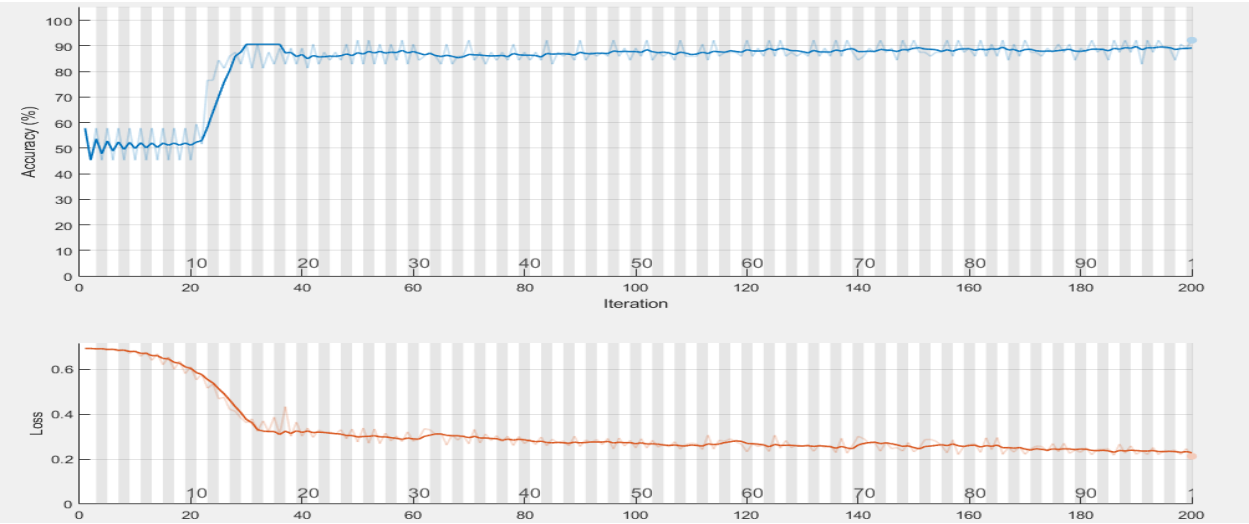


Figure 4. Training accuracy and validation over iterations for selected LSTM structures on music databases



Figure 5. An example of instantaneous frequency for various sleep stages (N3, W) and corresponding notes

Tables 4. Confusion matrix for sleep stage classification of Sleep-EDF database with SVM classifier

	Predicted					**Pre-class [%]**		
True	W	REM	N1	N2	N3	Se	Sp	Ac
W	6898	624	443	68	28	85.6±2.1	87.7±2.3	86.1±2.1
REM	126	1160	248	56	19	72.1±3.2	69.9±3.4	71.4±3.2
N1	63	112	403	19	7	66.7±2.9	98.6±1.1	77.3±3.6
N2	12	44	156	3321	88	91.7±2.3	97.5±1.7	95.4±2.1
N3	6	12	19	168	1139	84.7±2.1	98.6±0.9	96.3±1.9
Average Accuracy(%)								85.3±2.1

Table 5. Confusion matrix for sleep stage classification of Sleep-EDF database with KNN classifier

	Predicted					**Pre-class [%]**		
True	W	REM	N1	N2	N3	Se	Sp	Pr
W	6795	664	482	78	36	84.3±3.8	87.1±3.1	85.2±2.8
REM	156	1094	274	63	22	68.1±4.6	96.4±1.9	71.2±3.4
N1	67	126	386	20	5	63.9±4.3	98.6±0.9	73.8±3.1
N2	15	53	223	3194	136	88.2±2.9	96.6±1.4	88.9±2.6
N3	25	46	94	264	915	68.1±2.6	97.1±1.1	87.4±2.4
Average Accuracy(%)								81.3±3.8

neighbors with Euclidean distance measurement. The outcomes are reported in Tables 4 and 5.

The dataset is partitioned into training (80%), validation (10%), and testing (10%) subsets. To ensure robust evaluation, a 10-fold cross-validation technique is applied during classification. Class distribution is maintained consistently across all stages, with results averaged over 10 tests. Furthermore, the validation data are utilized to monitor training and implement early stopping to prevent overfitting.

As shown in Tables 4 and 5, the superior performance belongs to the SVM structure, which achieves 85.3% accuracy (Acc) in classifying the five sleep stages. In Table 4, for the selected 5-class classification structure, some segments of stage W are misclassified as N1 and REM stages. Similarly, some segments of N1 are misclassified as REM stages, and vice versa. Additionally, some segments of N2 are misclassified as N3. Other misclassification values for the 5-class classification are negligible. The overall performance for each sleep stage classified by the selected SVM structure is as follows:

86.1%, 77.3%, 95.4%, 96.3% and 71.4% for stages W, N1, N2, N3, and REM, respectively.

4. Discussion

Classifying and scoring sleep stages is a complex and labor-intensive process that was traditionally performed manually by specialists. This study introduces an innovative approach for the automatic classification of sleep stages and presents a groundbreaking auditory mapping of EEG signals. The results of this study are compared with previous studies in Table 6. All studies used the same database and signal type but used different sleep standards.

Researchers in [37] generated visually interpretable images through multilevel feature extraction, which were analyzed using CNNs, yielding an accuracy of 85.1%. Meanwhile, a study [38] employed a two-stage cascaded classifier, extracting 55 features from raw data and applying them to a two-layer LSTM network. A method was proposed by [39] in which the EEG signal is decomposed using the ensemble empirical mode decomposition (EEMD) and various statistical moment-based features are extracted. Then a new random boost technique (RUSBoost) is used to classify sleep stages and the overall accuracy for 5 classes (according to AASM) is calculated to be 83.4%. The researchers in [40] proposed a method for sleep stage classification using the sonification of EEG signals. In their study, the musical scale parameter was extracted using CNN, and a database of musical pieces with a scale label for each piece was created to train the deep structures, and the tempo parameter was obtained through a multi-stage algorithm. The obtained parameters were used to generate a musical sequence and 19 features were extracted from it. In the last stage, the extracted features were applied to a hierarchical classification structure. In our study, the LSTM structure was used to generate musical sequences. 7 features were extracted from the musical sequence and applied to simple classifier structures. Due to the removal of complex musical parameters that can be detected by deep neural structures, the reduction in the number of features, and the single-stage classification, the running time was reduced from 273 minutes to 191 minutes, and the overall sleep stage classification accuracy for the Sleep-EDF database improved by 1%. Among the limitations of our study is the need for a database of musical sequences with the labels of the notes used in the piece to train the LSTM structure.

An analysis of these studies shows that, despite employing advanced techniques, such as deep networks and diverse feature extraction methods, the improvements in accuracy remained marginal. This highlights the critical need to explore alternative signal mappings and feature extraction strategies to advance classification performance.

In the current study, a novel framework for sleep stage classification from EEG signals is introduced. The EEG signals are first transformed into a music sequence, from which features are extracted for classification. Another objective of this study is to present an auditory mapping of EEG signals based on deep networks, which demonstrates reliable performance in sleep stage classification. The sonification method proposed in this paper is a mapping based on instantaneous frequency changes, which is performed by converting EEG signal waves (such as delta, theta, alpha, and beta in different sleep stages) into musical sequences in different octaves. By increasing the scale of frequency intervals, the understanding of the time-frequency patterns of sleep stages becomes better and subtle changes become visible. Also, due to the rhythmic nature of music, sleep rhythms such as sleep spindles and K-complexes can be identified more clearly. Extracting the audio

Table 6. Comparison of recent studies of the same database

Ref.	Scoring rule	Method	Classifier	Accuracy	Evaluation method
[37]	AASM	Interpretable images	CNN	85.1%	10-fold Cross-validation
[38]	AASM	Extract features for each epoch	LSTM	86.7%	10-fold Cross-validation
[39]	AASM	EEMD > statistical moment features	RUSBoost	83.4%	10-fold Cross-validation
[40]	R&K	Sonification method with musical rules	SVM+RNN-SVM	84.3%	10-fold Cross-validation
Proposed method	AASM	EEG sonification with LSTM> E.F	SVM	85.3%	10-fold Cross-validation

and speech domain features of music performed well in recognizing minor patterns and discovering the frequency characteristics of each sleep stage, improving the accuracy of sleep stage classification with a smaller number of features.

To address challenges associated with multichannel recordings, this study employs single-channel EEG signals, simplifying the process while maintaining classification accuracy.

The use of multi-channel EEG signals can pose limitations to the proposed mapping, and to overcome this, methods for generating harmonic music should be explored. Additionally, creating a database for training network structures that incorporate complex musical parameters such as rhythm, genre, and timbre is highly challenging and may adversely affect the proposed audio mapping and sleep stage classification.

5. Conclusion

A novel technique for sleep stage discrimination based on EEG sonification is proposed. For the classification process, raw EEG data are first preprocessed and converted into a music sequence using an LSTM network. A dedicated music database was created for training the network. In the next step, features are extracted from the musical pieces generated from EEG signals and applied to classification models.

Future research could adopt a harmonic or quartet-based approach by utilizing multiple EEG channels. Moreover, incorporating additional musical parameters such as tempo, scale, and rhythm could further enhance the quality of the auditory mapping.

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