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ADVANTAGES OF FEATURE SELECTION IN IDENTIFYING AND DIFFERENTIATING SLEEP APNEA BASED ON A SINGLE-CHANNEL EEG SIGNAL

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Abstract

Sleep apnea is a sleep disorder that can have serious health consequences. Its detection and differentiation between the types obstructive (OSA), central (CSA), and mixed (MSA) is crucial for selecting appropriate therapy. The aim of this study was to compare three feature selection methods: Particle Swarm Optimization (PSO), Neighbourhood Components Analysis (NCA), and Principal Component Analysis (PCA) in the context of detecting sleep apnea and its types using single-channel EEG signals. In the study, the EEG signals were pre-processed, divided into 30-second segments, and analyzed using a two-stage feature extraction approach. Feature selection methods (PSO, NCA, and PCA) were then applied to reduce data dimensionality and identify the most informative parameters. Parameter optimization was also conducted for each method. Classification was performed using the k-NN algorithm. The results showed that the PSO method achieved the highest average classification accuracy of 98.03%, reducing the number of features from 379 to 134, while NCA achieved an accuracy of 97.96%, reducing the number of features from 424 to 127. Although PCA was effective in dimensionality reduction, it achieved a lower accuracy of 85.56%. The applied methods enabled clear differentiation between normal breathing and sleep apnea episodes, with classification errors occurring only in distinguishing between apnea types.

Keywords: single-channel EEG, sleep apnea detection, feature selection method, optimization of signal processing, medical decision support.

1. Introduction

Sleep is essential for the regeneration of the body, allowing rest and restoring the balance necessary for healthy functioning. One of the most common respiratory disorders occurring during sleep is sleep apnea, characterized by periodic and cyclical breathing disturbances, which may manifest as a reduction in amplitude (hypoventilation) or complete cessation of breathing (apnea). This leads to sleep fragmentation and a decrease in sleep quality, negatively impacting health. The three main types of sleep apnea are: *obstructive sleep apnea* (OSA), *central sleep apnea* (CSA), and *mixed sleep apnea* (MSA). OSA is caused by physical blockage of the upper airway despite continued respiratory muscle activity. In the case of CSA, the problem lies in the lack of a signal from the brain's respiratory center, resulting in a temporary pause in breathing. MSA combines features of both types and may present a more complex clinical course [1, 12].

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The most commonly performed examination to assess sleep quality and diagnose sleep disorders is *polysomnography* (PSG). This method involves the simultaneous recording of multiple biomedical signals during sleep, which is why the examination is carried out in a specially adapted laboratory. The signals recorded most frequently during PSG include the *electrocardiogram* (ECG), *electromyogram* (EMG), *electroencephalogram* (EEG), and *electrooculogram* (EOG). Analysis of these data enables the assessment of sleep quality and the calculation of indices such as the *apnea index* (AI) and the *apnea-hypopnea index* (AHI) [1–3].

Research on sleep and respiratory disorders requires not only monitoring biological processes but also advanced data analysis and modelling, which facilitates a better understanding of their mechanisms. The use of modelling and simulation methods based on metrology principles enables a detailed analysis of EEG signals. By applying direct and inverse analysis methods, it is possible to gain a deeper insight into distributed processes and EEG signal characteristics, facilitating their interpretation in the context of apnea diagnosis [4–6].

Electroencephalography is a method of recording the brain's bioelectrical activity using electrodes placed on the scalp. This examination allows for the evaluation of central nervous system functions by observing changes in the activity of specific brain waves. Typically, 19 to 21 electrodes are used, arranged according to the 10-20 system [2]. In healthy adults, EEG signals enable the differentiation of *delta*, *theta*, *alpha*, *beta*, and *gamma* rhythms, which correspond to different functional states of the brain.

Recording EEG signals during sleep is of significant diagnostic importance due to the possibility of respiratory disorders intensifying during sleep. At night, the EEG signal shows an increase in delta and theta waves, as well as the appearance of sleep spindles and *K-complexes*. Sleep consists of two main phases: *non-rapid eye movement sleep* (NREM) and *rapid eye movement sleep* (REM). Normal undisturbed sleep includes cyclical transitions between the NREM and REM phases, with 4-5 cycles lasting approximately 90 minutes each. Each cycle is followed by a phase of awakening and sleep lightening, during which brief awakenings may occur [1,2]. In individuals suffering from sleep apnea, EEG signals often reveal so-called arousals, characterized by short-term changes in signal frequency lasting from 3 to 15 seconds, usually occurring after episodes of apnea. Another method of detecting respiratory disorders is the spectral power density analysis of EEG signals before, during and after apnea episodes. Automated diagnostics using portable EEG recorders can therefore improve the detection efficiency of apnea episodes, even in home settings [7].

In recent years, numerous studies have examined various preprocessing, decomposition, feature selection, and classification methods for signals recorded during PSG to detect sleep apnea. However, only a small portion of these studies have focused on single-channel EEG analysis [8]. Most of the research has focused on distinguishing between normal breathing and apnea without differentiating apnea types [8,9]. When the types of apneas were differentiated, the focus was often on obstructive apnea [8,10]. A single-channel EEG system simplifies measurement setup, increases patient comfort, and enables use in mobile, home-based diagnostic devices. Despite its limited spatial resolution, the applied signal processing and feature selection methods allow for effective detection and differentiation of sleep apnea types. Some studies have also utilized two symmetrical EEG channels to detect apnea types [10]. Differentiating apnea types (OSA, CSA, MSA) using single-channel EEG has been achieved in only a few studies [10]. In these, the highest binary classification accuracy using *support vector machines* (SVM) for single-channel EEG was 99.98% [11], and the lowest was 69.9% [12]. For the classification of the three apnea types, the average accuracy ranged from 82.3% [11] to 88.9% [9].

The most common feature extraction methods for detecting sleep apnea and other neurological disorders included *band-pass filtering* (BPF) [8, 9, 13], *discrete wavelet transform* (DWT) [8, 9, 13], *empirical mode decomposition* (EMD) [10, 14, 15], and *variational mode*

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decomposition (VMD) [13]. Among two-stage methods, the *Hilbert-Huang transform* (HHT) was frequently used [10, 13]. Common feature selection methods included *minimum redundancy, maximum relevance* (MRMR) [16], *linear regression* [10], *analysis of variance* (ANOVA) [10], *Neighbourhood Components Analysis* (NCA) [9, 14], *Principal Component Analysis* (PCA) [16] and the *Particle Swarm Optimization algorithm* (PSO) [14, 17].

The best average classification accuracy achieved using NCA with *convolutional neural networks* (CNN) was 93.8% [14], while PCA combined with *Random Forest* yielded 95.42% [18]. The PSO algorithm, optimized for *multi-layer perceptron neural networks* (MLPNN), achieved 97.66% [19]. Common classification methods included both traditional algorithms and deep learning approaches. Among traditional methods, *support vector machines* (SVM) [16], *Random Forest* [18], *Decision Trees*, and *Bagged Trees* [16] were widely used, along with *k-nearest neighbors* (k-NN) [16]. In deep learning, *convolutional neural networks* (CNN) [14] and *artificial neural networks* (ANN) [16] were dominant.

The aim of this study was to compare three feature selection methods (PSO, NCA, and PCA) applied to features extracted from EEG signals to detect sleep apnea and its types. The study demonstrates that applying these selection methods facilitates optimal parameter tuning and achieves maximum classification accuracy using the k-NN model to detect EEG epochs associated with normal breathing and sleep apnea episodes, including the differentiation of apnea types.

2. Materials and methods

2.1. EEG data from the St. Vincent University Sleep Apnea Database

The study utilized the *University College Dublin Sleep Apnea Database*, available on the *PhysioNet* platform, which contains polysomnographic recordings (EMG, EEG, ECG, EOG, blood oxygen saturation, and chest movements) from 25 patients aged 38–68 (4 women and 21 men) [20]. The recorded signals were originally sampled at a frequency of 128 Hz and originated from two electrode locations, C3-A2 and C4-A1. For further analysis, a single-channel EEG signal from the C3-A2 location was selected [13]. Sleep phase annotations and information on the onset and duration of respiratory events, including obstructive, central, and mixed apnea, as well as hypopnea, were provided by specialists with precision of one-second.

2.2. Approach and Methods

The developed methodology focuses on comparing three feature selection methods using a dataset obtained after feature extraction from EEG signals. In the initial stage, techniques reported in the literature with high classification accuracy for EEG signal analysis in sleep studies were identified. Three feature selection methods were chosen for comparison: *Particle Swarm Optimization* (PSO), *Principal Component Analysis* (PCA), and *Neighbourhood Components Analysis* (NCA). The input parameters for the PSO algorithm were optimized through sensitivity analysis to achieve the best fit. For PCA, the criterion of explaining more than 90% of the data variance was applied, as recommended in the literature. In the case of NCA, the optimal parameter values *were determined by minimizing the loss* function while testing various proportions of training and testing data, with a constant proportion of validation data [9]. The classification process was carried out using the *k-nearest neighbors* (k-NN) algorithm with *32-fold cross-validation* [10]. The effectiveness of the feature selection methods was evaluated using *Student's t-tests* for *independent samples at a signi*ficance level of $\alpha = 0.05$, allowing for the determination of whether the differences between the methods were statistically significant.

All analysis stages were performed in the MATLAB (R2023b) environment (*The MathWorks, USA*). The process included feature selection, classifier parameter optimization, and performance evaluation using cross-validation and statistical tests (Fig. 1). This approach enabled a comparison of the effectiveness of the three feature selection methods (PSO, NCA, PCA) in the context of detecting sleep apnea based on EEG signals.

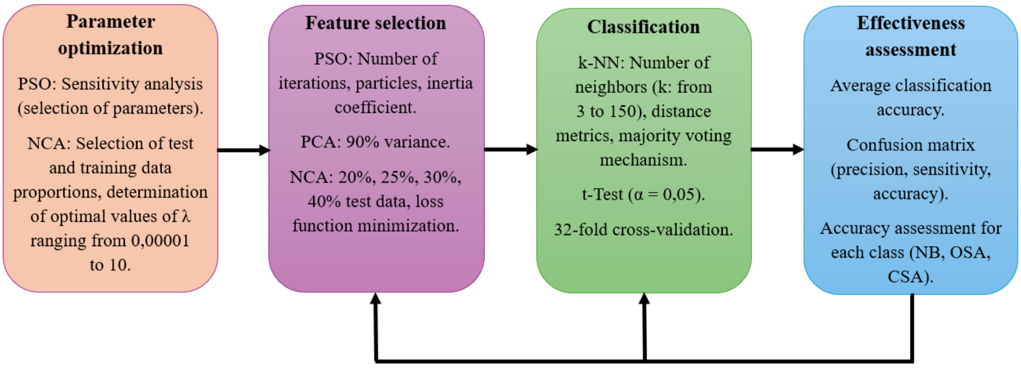

Fig. 1. Adopted method for processing a single-channel EEG signal (explanations of abbreviations can be found in the text).

2.3. Preprocessing

To reduce noise in the EEG signal, low-pass filtering was applied using a second-order Chebyshev type II filter with a cutoff frequency of 45 Hz, along with notch filtering at 50 Hz and 60 Hz (second-order filter) to eliminate power line interference. Signal segments with amplitudes exceeding threshold values, defined as outliers based on z-score statistics, were removed together with saturation artefacts. The data were then standardized and detrended to normalize their energy characteristics and minimize the influence of external noise sources [21].

The signals were divided into 30-second segments, taking into account respiratory events lasting more than 10 seconds. In the case of shorter segments, missing data were supplemented with normal breathing signal, while longer segments were trimmed to 30 seconds to maintain a uniform epoch length. Finally, data were classified into three groups: normal breathing (NB), obstructive apnea/hypopnea (OSA), and central apnea/hypopnea (CSA). To ensure balance between the classes, the number of epochs was equalized based on the smallest available group. Each class (NB, OSA, CSA) contained 1373 epochs, resulting in a total of 4119 epochs used for further analysis [10].

2.4. Feature extraction

Feature extraction from EEG signals was performed in two steps. First, single- and two-stage decomposition methods were applied, followed by the calculation of 12 scalar features describing the obtained components.

In single-stage decomposition: *band-pass filtering* (BPF) [8, 9, 13], *discrete wavelet transform* (DWT) [8, 9, 13], *empirical mode decomposition* (EMD) [10, 14, 21], and *variational mode decomposition* (VMD) [13] were used. Two-stage methods included the *Hilbert-Huang transform* (HHT) and the combination of DWT and VMD with the Hilbert transform (DWT+HT, VMD+HT) [10, 13].

BPF adjusted the signal to frequency bands corresponding to brainwaves (gamma, beta, alpha, theta, and delta). DWT enabled decomposition into five sub-signals using the *Daubechies 3* wavelet, while VMD and EMD extracted intrinsic *mode functions* (IMFs) representing EEG oscillations.

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To simplify the analysis, a maximum of 13 IMFs was considered. The Hilbert transform allowed for the determination of *instantaneous frequency* (IF), *instantaneous amplitude* (IA), and *weighted frequency* (WIF) [10, 13].

In the second stage of analysis, 12 scalar features were extracted, including statistical parameters (skewness, kurtosis, median) [9, 10, 14], energy-related features (energy, mean power), Hjorth parameters (activity, mobility, complexity) [9, 10], Shannon entropy [10, 13], and maximum amplitude [10, 13].

2.5. Feature selection

Based on a literature review, three feature selection methods: *Particle Swarm Optimization* (PSO) [14, 17], *Neighbourhood Components Analysis (NCA)* [9, 14], and *Principal Component Analysis* (PCA) [16, 18] were chosen as commonly used and effective in EEG signal analysis, particularly for sleep apnea detection. These methods represent three different approaches to dimensionality reduction: PSO as an optimization algorithm, NCA as a supervised classification-based method, and PCA as a classical unsupervised technique based on variance analysis.

Particle Swarm Optimization (PSO) is a metaheuristic optimization method inspired by the collective behavior of animal swarms, such as birds or insects. The primary goal of PSO is to identify the optimal feature vector by iteratively adjusting the weights or positions of particles within the search space. The particle parameters are updated based on their velocity and the best local and global positions achieved so far, until a specified number of iterations is completed. The literature suggests the following optimal input parameter values: 100 iterations, the number of particles equal to the number of features before selection, an inertia coefficient of 0.4, and learning coefficients of 2 [22]. To verify the efficiency of these settings, a sensitivity analysis was conducted, testing four parameter sets that varied in the number of particles, the inertia coefficient, and the iteration count.

Neighbourhood Components Analysis (NCA) optimizes input data by selecting the most informative features for the classification process. This algorithm minimizes the distances between points belonging to the same class while maximizing the distances between points from different classes. It iteratively adjusts the feature weights using training and validation data. To achieve optimal classification conditions, different proportions of test and training data were analyzed, maintaining a fixed proportion of validation data at 10%. The test data proportions were set at 20%, 25%, 30%, and 40%, while training data proportions were 80%, 75%, 70%, and 60%. Additionally, the regularization parameter λ was tuned within the range of 0.00001 to 10 [9].

Principal Component Analysis (PCA) is a dimensionality reduction technique that transforms a large set of features into a smaller set of uncorrelated variables, referred to as principal components. According to the literature, the threshold for explained variance was set at 90% [23]. The PCA algorithm transforms the original variables by finding eigenvectors of the covariance matrix, identifying directions of maximum data variance [24].

To evaluate the effectiveness of each method, the k-NN *algorithm* was used, with the number of neighbors and the distance metric optimally tuned for each method: $k = 30$ for PSO, $k = 121$ for NCA, and $k = 17$ for PCA, using the *Manhattan distance metric* [9]. The number of neighbors was determined based on the best results obtained for the feature set extracted using the HHT method without prior feature selection. After the initial selection of features for each extraction method, subsets of features with the highest average classification accuracy were combined, and a second round of feature selection was performed on the entire dataset using the corresponding selection method.

2.6. Classification and assessment of efficiency

Classification using a trained model is crucial for automating decision-making processes, particularly in medical diagnostics. To identify EEG signal segments corresponding to normal breathing and apnea episodes (OSA and CSA), the *k-nearest neighbors* (k-NN) algorithm was applied [9, 10, 13, 16]. This nonparametric classifier assigns data to classes based on their similarity to examples in the training set.

The k-NN algorithm involves calculating the distances between new data points and elements of the training set, followed by selecting the k nearest neighbors. Classification is performed using a majority voting mechanism. To optimize the classifier's parameters, the classification accuracy was compared for different values of k (ranging from 3 to 150) and eight distance metrics: Chebyshev, Minkowski, Euclidean, correlation, cosine, city-block, standardized Euclidean, and Jaccard [25].

The model evaluation was conducted using 32-fold cross-validation to ensure reliable results through statistical averaging. In each iteration, a confusion matrix was generated, and classification performance metrics such as accuracy, precision, and sensitivity were calculated for both individual classes and the overall model [14].

3. Results

After the initial preprocessing of overnight EEG recordings (7–8 hours), the signals were divided into 30-second epochs. Most of the epochs corresponded to normal breathing (NB), while those associated with respiratory disturbances were classified as apnea episodes (complete cessation of airflow) or hypopnea episodes (partial reduction in airflow). A total of 586 apnea epochs were identified (288 CSA, 170 OSA, 128 mixed), along with 2541 hypopnea epochs (1401 OSA, 1038 CSA, 102 mixed). Due to the lower number of CSA epochs, class balancing was performed by randomly selecting 1373 epochs from the OSA and NB classes. As a result, a total of 4119 epochs were obtained for further analysis.

During the feature extraction stage, both single-stage (BPF, DWT, VMD, EMD) and two-stage (DWT + HT, VMD + HT, HHT) decomposition methods were applied. The signal was decomposed into 5 components (BPF, DWT, VMD), 13 intrinsic mode functions (EMD), and 15-39 components for the two-stage methods. For each component, 12 scalar features were computed, resulting in feature sets of varying sizes: 60 (BPF, DWT, VMD), 156 (EMD), 180 (DWT + HT, VMD + HT), and 468 (HHT). In total, 1164 features were obtained per EEG epoch (Table 1), allowing detailed signal representation and serving as the foundation for subsequent feature selection and classification.

To obtain an optimal feature set for classifying three EEG signal classes (normal breathing, obstructive apnea, and central apnea), feature selection was performed using three methods: PSO, NCA, and PCA. For each feature extraction method, a sensitivity analysis of initial parameters was conducted to determine their optimal values.

The PSO algorithm was tested with various parameter combinations, including the *number of swarm particles* (55, 132, 180, 255, 468, 500, 550), the *number of iterations* (100, 325, 550, 775, 1000, 1625), and the *inertia coefficient* (0.4; 0.525). Each parameter set was evaluated using the k-NN *algorithm* with $k = 30$ neighbors, the *Manhattan distance* metric, and 32-fold cross-validation. Table 2 presents the number of features obtained after selection for various feature extraction methods, along with the optimal input parameter values and the best average classification accuracy among the tested cases.

Based on the results presented in Table 2, it can be observed that the highest values of average classification accuracy were achieved with the following set of parameters: 100 iterations, an inertia coefficient of 0.4, and the number of particles corresponding to the number of features in

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Table 1. Number of features remaining after selection for each extraction method following the applied techniques.

Extraction Method	Number of Components after Decomposition		Number of Features			
	Stage 1	Stage 2	Before Selection	PSO	NCA	PCA
				After Selection		
One-step Methods						
BPF	5	Lack	60	12	22	39
EMD	13	Lack	156	50	58	105
VMD	5	Lack	60	11	22	40
DWT	5	Lack	60	13	22	44
Two-step Methods						
HHT	13	3	468	178	168	396
DWT + HT	5	3	180	57	66	158
VMD + HT	5	3	180	58	66	155

Table 2. Optimal input parameters for feature selection, as well as average classification accuracy after feature selection using three methods: PSO, NCA, and PCA.

Extraction Method	PSO					NCA					PCA	
	Classification Accuracy [%]	Number of Features	Particle Swarm Algorithm Parameters			Classification Accuracy [%]	Number of Features	NCA Algorithm Parameters			Classification Accuracy [%]	Number of Features
			Number of Particles	Number of Iterations	Weight Coefficient			λ	*Mean Loss* (MSE)	Test set Proportion [%]		
DWT	96.1 ± 1.8	13	60	100	0.4	88.8 ± 1.7	22	0.5456	0.4570	20	86.9 ± 2.4	44
VMD	94.5 ± 1.5	11	60	100	0.4	93.1 ± 1.5	22	0.007	0.4474	25	95.8 ± 4.1	40
EMD	89.1 ± 1.3	50	418	10	0.4	88.7 ± 1.7	58	0.0016	0.5752	20	89.8 ± 2.1	105
BPF	84.7 ± 1.2	12	60	100	0.4	91.7 ± 1.4	22	0.0144	0.4511	25	85.6 ± 4.2	39
HHT	81.9 ± 0.9	178	468	100	0.4	80.8 ± 1.4	168	0.007	0.5117	30	87.9 ± 2.7	155
DWT+HT	93.8 ± 1.4	57	180	100	0.4	91.1 ± 1.4	66	0.0034	0.3902	25	84.8 ± 2.3	158
VMD+HT	91.8 ± 1.7	58	180	100	0.4	91.2 ± 1.5	66	0.007	0.404	25	69.9 ± 3.2	396

the vector before selection. The lowest average classification accuracies after feature selection were recorded for the BPF method (55.1% ±1.6%) and HHT (81.9% ± 0.9%), while the best results were obtained for signal decomposition using DWT (62.5% ± 1.8%) and VMD (94.5% ± 1.5%). These findings clearly indicate that feature selection contributed to an improvement in average classification accuracy in every case.

After combining the initially selected feature subsets from each extraction method, a consolidated vector of 379 features was created and subsequently subjected to final selection. The sensitivity analysis for this vector identified the optimal parameters as 379 particles, 200 iterations, and an inertia coefficient of 0.4. In this configuration, the application of PSO increased the average classification accuracy to 97.9% ± 1.2% and reduced the number of features to 134.

In Neighbourhood Components Analysis (NCA), various proportions of training and testing data were evaluated, with the validation data proportion fixed at 10%. The regularization parameter λ was optimized within the range of 0.00001 to 10 by minimizing the loss function. Evaluation using the k-NN algorithm (k = 121) showed the best results for 20% test data (DWT and EMD), 25% test data (VMD, BPF, DWT+HT, VMD+HT), and 30% test data for HHT (Table 2).

After merging the feature subsets, a comprehensive vector containing 424 features was created. Feature selection using the NCA method reduced the number of features to 127, while simultaneously increasing the average classification accuracy to 96.8% ± 1.4%.

The application of *Principal Component Analysis* (PCA) with a 90% explained variance threshold reduced the number of features in the full vector from 937 to 798. However, performance evaluation using the k-NN *algorithm* (k *=17*) showed a lower average classification accuracy of 88.5% ± 1.5%, suggesting that PCA is less effective compared to PSO and NCA methods.

Table 3 presents the best average classification accuracy results for each feature selection method (PSO, NCA, and PCA) for the full vector, as well as the number of features obtained after additional selection. The results indicate that PSO was the most effective method, achieving the highest classification accuracy with a significant reduction in the number of features.

Table 3. Summary of average classification accuracy and final number of selected features for each tested algorithm, applied to the combined feature vector obtained after initial selection (P – average classification accuracy, SD – standard deviation).

Feature Selection Method	P ± SD [%]	Number of Features
PSO	97.9 ± 1.2	134
NCA	96.8 ± 1.4	127
PCA	85.5 ± 1.5	798

The optimization of the *k-nearest neighbors* (k-NN) classifier parameters was carried out by determining the best distance metric and the optimal number of neighbors using a majority voting system. The best results were achieved with the *Euclidean metric* and k = 7. Further analysis was conducted using these parameters, generating confusion matrices and calculating accuracy, precision, and sensitivity for each class, as well as average values for the entire dataset after applying different feature selection methods (Table 4).

The classification accuracy, assessed through 32-fold cross-validation, was 98.1% ± 1.8% for PSO, 97.9% ± 1.6% for NCA, and 85.6% ± 1.5% for PCA. Statistical tests showed a significant difference between PSO and PCA (p = 0.023), while no significant differences were observed between NCA and PSO (p = 0.25) or NCA and PCA (p = 0.056) at the 0.05 significance level.

The classification results for the three feature selection methods (Table 4) show that both NCA and PSO allowed the k-NN classifier to achieve 100% accuracy in distinguishing normal breathing from sleep apnea, regardless of the apnea type. The PSO method achieved the highest effectiveness, with an average accuracy of 98.03%, precision of 98.05%, and sensitivity of 98.07%. The classifier optimized using NCA also performed highly effectively, with average values of 97.96% (accuracy), 96.94% (precision), and 97.11% (sensitivity). In contrast, the PCA method yielded lower results, with an average accuracy of 85.56%, precision of 85.58%, and sensitivity of 85.86%. These results indicate that PSO is the most effective feature selection method for the k-NN classifier in the analyzed application.

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Table 4. Confusion matrix for the tested feature selection methods, including classification accuracy, sensitivity, and precision calculated for each class, along with the averaged values of these parameters (A_i – accuracy, P_i – precision, R_i – recall, A_c – overall accuracy, P_μ – average precision, and R_μ – average recall).

	Confusion Matrix				Classifier Performance [%]					
					In Classes			Averaged		
PSO		**NB**	**OSA**	**CSA**	**A_i**	**P_i**	**R_i**	**A_c**	**P_μ**	**R_μ**
	NB	1373	24	29	100	100	96.28	98.03	98.05	98.07
	OSA	0	1331	10	98.73	96.94	99.25			
	CSA	0	18	1334	98.61	97.16	98.67			
NCA		NB	OSA	CSA	A_i	P_i	R_i	A_c	P_μ	R_μ
	NB	1373	42	63	100	100	92.9	97.96	96.94	97.11
	OSA	0	1311	0	98.47	95.42	100			
	CSA	0	21	1310	97.96	95.41	98.42			
PCA		NB	OSA	CSA	A_i	P_i	R_i	A_c	P_μ	R_μ
	NB	1369	68	205	93.28	99.71	83.31	85.56	85.58	85.86
	OSA	3	1169	181	90.59	85.18	86.39			
	CSA	1	136	987	87.33	71.85	87.87			

4. Discussion

The objective of this study was to develop a processing procedure for single-channel EEG signals to maximize the accuracy of automated sleep apnea detection and accurately differentiate between its types. This procedure was based on a classical approach, including preprocessing, feature extraction and selection, and then classification using the *k-nearest neighbors* (k-NN) algorithm. The key aspect of the study was to compare three feature selection methods: *Particle Swarm Optimization* (PSO), Neighbourhood Component Analysis (NCA), and Principal Component Analysis (PCA) to identify the most effective techniques for optimal feature selection and maximizing classification accuracy.

In the preprocessing stage, excessive amplitudes were eliminated, and low-pass and notch filtering were applied to remove power line noise, forming the basis for subsequent feature extraction and selection. Feature extraction was conducted in two steps, with single- and two-stage signal decomposition methods applied in the first stage, followed by calculation of 12 scalar features for each obtained component in the second stage. Methods such as BPF, DWT, EMD, VMD, and combinations of HHT, DWT+HT, and VMD+HT enabled the extraction of statistical, energetic, and dynamic features, which were then compiled into matrices for feature selection [13].

In the literature, few studies focused on feature selection for detection of sleep apnea using EEG signals. For example, studies [8, 11] used various feature selection techniques, such as the minimum redundancy maximum relevance (MRMR) algorithm [11], Fisher's method [8], analysis of variance (ANOVA) with MRA [8], and calculation of t-test p-values [13]. In other studies, the feature vectors were not reduced, and the number of features was small. In contrast, this study compared three advanced feature selection methods (PSO, NCA, PCA), allowing a more comprehensive assessment of their effectiveness. In studies with and without feature selection, high classification accuracy was achieved for detection of sleep apnea, ranging from 89.01% to 99% without feature selection [7, 12] and from 89.9% to 99.53% with feature selection [8, 11].

A comparative analysis of these methods showed that PSO and NCA were more effective than the traditional PCA. The PSO method achieved the highest average classification accuracy of 97.9%, reducing the number of features from 379 to 134. NCA achieved a very similar accuracy of 96.8%, with an even greater reduction in features (down to 127). PCA, despite its popularity in dimensionality reduction, demonstrated significantly lower effectiveness, with an accuracy of 85.5%.

The k-NN algorithm was optimized by selecting the most suitable distance metric and the number of neighbors, with the best performance achieved using the Euclidean distance and $k = 7$. For the classifier based on the NCA method, the average accuracy reached 97.96%, with a precision of 96.94% and a sensitivity of 97.11%. The PSO method yielded even better results, with an accuracy of 98.03%, precision of 98.05%, and sensitivity of 98.07%, indicating its higher effectiveness compared to PCA. The confusion matrix analysis (Table 4) showed that both PSO and NCA enabled perfect distinction between normal breathing and apnea episodes. PSO proved particularly effective in distinguishing between apnea types (OSA and CSA), confirming its ability to identify the most informative features. Statistical tests revealed a significant difference between the results of PSO and PCA ($p = 0.023$), highlighting PSO's advantage over the traditional approach. However, no significant differences were found between NCA and PSO ($p = 0.25$) or between NCA and PCA ($p = 0.056$), suggesting that both PSO and NCA are comparably effective and suitable for classifying sleep apnea episodes.

In the context of other studies on sleep apnea detection, many use either single- or dual-channel EEG, especially when distinguishing the types of apneas. Studies using two symmetric EEG channels [10] achieved a high binary classification accuracy, ranging from 94.33% to 99.68%. For apnea type differentiation, only a few studies [9, 11] focused on three-class classification (NB, OSA, and CSA), achieving average accuracy between 82.3% and 88.9%. This single-channel EEG-focused study achieved an average classification accuracy of 96.8% for NCA and 97.9% for PSO, representing a significant improvement compared to most previous studies, especially in distinguishing apnea types. These results confirm that advanced feature selection methods can compensate for the limitations of using a single EEG channel, offering high classification accuracy while simplifying the diagnostic system.

Similar results are observed in other studies, where optimization-based methods (PSO) and neighbourhood components analysis (NCA) outperform traditional dimensionality reduction methods. For example, Chen [22] applied PSO in the context of OSA diagnosis, achieving high classification accuracy. Additionally, Shahnaz and Minhaz [26] used a genetic algorithm (GA) for feature selection, achieving improved classification accuracy, which is consistent with our findings on PSO.

Among other classification methods, such as support vector machines (SVM) [16, 21], Random Forest [18], and the k-nearest neighbors (k-NN) algorithm [16], the study by Alimardani and de Moor is noteworthy, achieving a binary classification accuracy of 99.98% using the SVM method [11]. This result is slightly higher than the results in this study; however, their study focused primarily on binary classification and feature selection methods specific to their approach. In our study, by selecting the most relevant features, we were able to improve classification accuracy and reduce computational complexity, which is especially important for applications in portable devices and home care systems.

Although the study yielded very promising results, several limitations should be noted. First, the data were obtained from a single public database, which limits the generalizability of the results. Second, the number of epochs corresponding to central apnea was relatively small, which may have affected the quality of the classification for this class. Third, the analysis focused on epochs in which apnea was centered within the segment a condition that may not always reflect real clinical scenarios. Future research should involve larger and more diverse datasets, analysis of multi-channel EEG recordings, and integration of feature selection methods with deep learning techniques, such as convolutional neural networks (CNN). This would allow for the development of even more accurate and adaptive diagnostic systems capable of real-time operation and suitable for practical, real-world use.

5. Conclusions

The approach presented in this study, based on single-channel EEG analysis and feature selection using three methods (*PSO*, *NCA*, and *PCA*), confirmed the feasibility of an effective and accurate classification of sleep apnea episodes. The results demonstrate that even with a limited amount of input data, it is possible to achieve very high classification performance through appropriately selected signal processing and dimensionality reduction techniques.

The use of the PSO algorithm enabled the highest average classification accuracy (98.03%) while significantly reducing the number of features. NCA achieved a remarkably similar performance (97.96%). PCA, although widely used, proved less effective in this context. The k-NN algorithm, optimized with suitable parameters ($k = 7$, Euclidean distance), classified the data with high sensitivity and precision. This study shows that single-channel EEG analysis can provide a reliable foundation for developing simple, low-cost, and effective devices for sleep apnea diagnosis. Such solutions can be especially useful in ambulatory or home settings. The high accuracy achieved in three-class classification represents a significant advancement over previous studies and paves the way for further development of EEG-based systems enhanced by advanced feature selection methods and artificial intelligence.

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