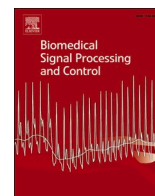




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An automated snoring sound classification method based on local dual octal pattern and iterative hybrid feature selector

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ABSTRACT

In this research, a novel snoring sound classification (SSC) method is presented by proposing a new feature generation function to yield a high classification rate. The proposed feature extractor is named as Local Dual Octal Pattern (LDOP). A novel LDOP based SSC method is presented to solve the low success rate problems for Munich-Passau Snore Sound Corpus (MPSSC) dataset. Multilevel discrete wavelet transform (DWT) decomposition and the LDOP based feature generation, informative features selection with Relieff and iterative neighborhood component analysis (RFINCA), and classification using k nearest neighbors (kNN) are fundamental phases of the proposed SSC method. Seven leveled DWT transform, and LDOP are used together to generate low, medium, and high levels features. This feature generation network extracts 4096 features in total. RFINCA selects 95 the most discriminative and informative ones of these 4096 features. In the classification phase, kNN with leave one out cross-validation (LOOCV) is used. 95.53% classification accuracy and 94.65% unweighted average recall (UAR) have been achieved using this method. The proposed LDOP based SSC method reaches 22% better result than the best of the other state-of-the-art machine learning and deep learning-based methods. These results clearly denote the success of the proposed SSC method.

1. Introduction

Snoring is one of the common sleep problems for humans. It negatively affects the sleep partner and sleep quality of the person [1–3]. If snoring is not treated, health risks such as insomnia, psychological problems, heart conditions, and sleep apnea can occur [4]. People snore unconsciously during sleep, and snoring is caused by some problems in the respiratory system [5,6]. It is formed by the vibration of the tissues between the palate and the small tongue while breathing. Snoring is not a disease alone [4].

However, it negatively affects the quality of life of the person. Low sleep quality causes poor performance during the day. During sleep, there is a decrease in the amount of oxygen in the blood from snoring. This may reveal the risks of various health problems [7,8]. It can be the underlying cause of health problems such as heart conditions, hypertension, stroke, diabetes. It can also cause deterioration of family relationships. Snoring is a treatable problem [9–11]. Treatment of this problem is possible with therapies and surgical interventions. The application of the treatment depends on the correct determination of the source of the snoring problem. Therefore, Drug-Induced Sleep

Endoscopy (DISE) is applied for diagnosis before treatment. The long-term video recordings have been examined to diagnose snore type [12]. This technique has a high time cost and not comfortable for the person since the drug is used. When the diagnosis is unsuccessful, this process is repeated. Detecting snoring problems with automatic classifiers using sound signals is a much faster and more comfortable method [13,14]. Computer-aided automatic detection systems increase the success of accurate diagnosis and treatment. Snoring sound signals can be analyzed to diagnose the sleep diseases of the person. Snoring sounds are irregular, and frequency bands differ from person to person. It is difficult to distinguish breath sounds [15]. Therefore, it is necessary to recommend a general snore sound classification method [16]. There are many studies about snore sound classification in the literature, and some of them are listed in Table 1.

The used abbreviations in Table 1 are given as follows. SVM: support vector machine [28], HOG: histogram of oriented gradients [29], GRU: gated recurrent unit [30], MFCC: Mel-frequency cepstrum coefficients [31], CNN: convolutional neural networks [32], LBP: local binary pattern [33], RNN: recursive neural network [34], GMM: Gaussian mixture model [35], DNN: deep neural network [36], SCAT: deep

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Table 1
Literature Review about snore sound classification.

Studies	Year	Method	Dataset	Criteria and result
[17]	2017	MFCC, ELM, SVM	MPSSC [14]	Unweighted Average Recall (UAR) 49.38%
[18]	2017	CNN and Alexnet, VGG19	MPSSC [14]	UAR 67.0%
[19]	2018	LBP and HOG	MPSSC [14]	UAR 66.5%
[20]	2017	Deep CNN	MPSSC [14]	UAR 72.6%
[14]	2018	SVM, MFCC	MPSSC [14]	UAR 55.8%
[21]	2019	RNN	Their Dataset	Accuracy, Sensitivity, F1 Score 99.2%
[22]	2017	SVM	MPSSC [14]	UAR 49.58%
[23]	2017	GMM, SCAT and DNN	MPSSC [14]	UAR 69.71%
[24]	2020	CRNN	A3-Snore dataset [24]	Average Precision 94.92%
[25]	2018	CNN- Dual Conv. GRU	MPSSC [14]	UAR 63.8%
[26]	2019	Conditional Generative Adversarial Networks	MPSSC [14]	UAR 67.4%
[27]	2019	Wavelet Features	MPSSC [14]	UAR 69.4%
[12]	2020	SVM	Their Dataset	Recognition Rate 91.14%

scattering spectrum [37], CRNN: convolutional recurrent neural networks [38].

Our presented feature extraction function is named Local Dual Octal Pattern (LDOP). A multileveled feature generation network is presented using LDOP and multileveled discrete wavelet transform (DWT) [39,40] with sym8 filter. ReliefF [41,42] and iterative neighborhood component analysis [43] (RFINCA) method selects the most informative and discriminative features. kNN [44,45] classifier is used in the classification phase, and the testing-validation strategy is selected to leave one out cross-validation (LOOCV) [46].

Our main motivation is to solve the classification problem of the snore types on the MPSSC dataset. As can be seen from Table 1, previously presented automatic snoring sound classification (SSC) methods did not achieve high success rates on MPSSC. Therefore, we presented this LDOP and RFINCA based SSC method. The contributions of our SSC method are given below.

- SSC is one of the difficult problems for machine learning methods. A novel feature extractor (LDOP) is presented to solve this problem using this model.
- The optimal number of features selection problems is solved using the RFINCA feature selector.
- A high accurate SSC method is presented using the proposed LDOP and RFINCA together. General results are also presented using the LOOCV validation and testing strategy. The proposed LDOP based SSC method achieves approximately 22% higher classification rates to the best of others.

2. The used snore sound dataset

The MPSSC dataset was presented at the INTERSPEECH 2017 Computational Paralinguistic Challenge. Dataset was collected from patients who used DISE. Snoring sounds were collected by *three* different medical centers. These sounds were labeled in four classes. These four classes are named as VOTE [14]. V, O, T, and E represent vibration levels of Velum, oropharyngeal area, tongue, and epiglottis, respectively [47]. The collected sound signals were preprocessed to 16 bit with 16 kHz

frequency [14]. There are 828 sounds in this dataset with three main folders (train, development, test). The attributes of the used dataset are given in Table 2.

3. Local dual octal pattern

The proposed LDOP is utilized as the primary feature generation function of this model. The main objective of the LDOP is to generate discriminative features from a sound signal. It is a one-dimensional feature generation function. It uses *two* octal blocks and one center value. Therefore, 17 sized overlapping blocks are utilized for feature generation. The used overlapping block is shown in Fig. 1. To better express this method, steps are given below.

Step 1: Divide sound signal into 17 sized overlapping windows.

$$window^t = sound(i : i + 16), t = \{1, 2, \dots, L - 16\}, i = \{1, 2, \dots, L\} \quad (1)$$

where $window^t$ represents t th overlapping window with a size of 17, i , and t are index values.

Step 2: Assign center value and contamination area of it.

Step 3: Generate the left and right bits using the signum function.

$$bit^{left}(i) = sig(window(9), window(i)), i = \{1, 2, \dots, 8\} \quad (2)$$

$$bit^{right}(i) = sig(window(9), window(9 + i)) \quad (3)$$

$$sig(s, d) = \begin{cases} 0, & s - d < 0 \\ 1, & s - d \geq 0 \end{cases} \quad (4)$$

where $sig(\cdot, \cdot)$, s and d define the signum function, the first input, and the second input of the signum function. The values are utilized as the immune power of these elements. If the immune power of the center value bigger than other values, it can infect them. Therefore, the signum function is selected to generate binary features.

Step 4: Calculate decimal left and right values.

$$left(t) = \sum_{i=1}^8 bit^{left}(i) * 2^{8-i} \quad (5)$$

$$right(t) = \sum_{i=1}^8 bit^{right}(i) * 2^{8-i} \quad (6)$$

Step 5: Extract histograms of the left and right signals. These signals are coded with 8-bits. Therefore, the length of their histograms is calculated as $2^8 = 256$. Therefore, two arrays are defined as left, and right histograms and initial values of them are assigned as zero. Histograms calculation phase is described in Eqs. 7–8 mathematically.

$$hist^{left}(left(t)) = hist^{left}(left(t)) + 1 \quad (7)$$

$$hist^{right}(right(t)) = hist^{right}(right(t)) + 1 \quad (8)$$

where $hist^{left}$ and $hist^{right}$ represent left and right histograms.

Step 6: Concatenate the extracted left and right histograms to obtain a feature vector with a size of 512.

$$featvec(j) = hist^{left}(j), j = \{1, 2, \dots, 256\} \quad (9)$$

Table 2

The properties of the used MPSSC dataset [47]. The MPSSC has three folds, and these are train, development, and test. There are four classes, and these classes are named V, O, T, and E.

Class Name	Train	Development	Test	Total
V (Velum)	168	161	155	484
O (Oropharyngeal)	76	75	65	216
T (Tongue)	8	15	16	39
E (Epiglottis)	30	32	27	89
Total	282	283	263	828



Fig. 1. The used 17 sized windows. The 9th value of this window assigned as center value and contamination area of it is shown. The contamination area is categorized into two groups, and these groups are called left and right.

$$featvec(j + 256) = hist^{right}(j) \quad (10)$$

where *featvec* defines feature vector.

As it can be seen in these five steps, the proposed LDOP generates 512 features. In the proposed SSC method, the LDOP is utilized as a fundamental feature generation function. The procedure of the proposed LDOP is also shown in Fig. 2 to implement this method easily.

Feature generation is processed using the defined LDOP procedure.

4. Proposed snore sound classification method

A new SSC method is presented in this paper. The primary components of this SSC method are the multilevel feature generation, feature selection using RFINCA, and classification with LOOCV. To present a multilevel feature generation network uses the proposed LDOP feature generator as a primary feature extraction function and DWT [48]. Here, DWT is utilized as a decomposition/level creation method. To generate features, LDOP is applied to each level. ReliefF and NCA are weight-based feature selectors. RFINCA is presented to use effectiveness both of them and select the optimal features automatically (without using trial and error method). In the classification phase, a conventional/shallow classifier (kNN [44,45]) is used. The LOOCV is used to obtain general results.

Graphical illustration of the proposed LDOP and RFINCA based SSC method is shown in Fig. 3.

This method uses a multileveled feature extraction network. LDOP is utilized as a feature extraction function, and 7-leveled one dimensional DWT with Symlet 8 filter is used as a decomposition method. This network has *eight* levels (we used raw snoring sound and *seven* low pass filters of it), and LDOP extracts 512 features from each level. Therefore, 4096 features are generated using the proposed LDOP and DWT based feature generation network. Two feature selectors are used in the feature selection phase. These are ReliefF [41,42] and NCA [49,50]. Both of them have weight calculation capability using a distance-based fitness function. Therefore, each feature is normalized to use these feature selectors effectively. While NCA generates positive weights, ReliefF can generate both positive and negative weights. The generated negative

weighted features with ReliefF can be assigned as superfluous features. Therefore, ReliefF is applied to extracted and normalized 4096 features. Superfluous features are eliminated using generated weights with ReliefF. One of the fundamental problem of the NCA is to not select optimum number of features automatically. To solve this problem, an iterative method is used and kNN is utilized as loss value calculator in this phase. In this work, ReliefF selected 2553 of these 4096 features and iterative NCA select 95 of the selected 2553 features. These selected 95 features are utilized as input of the kNN classifier. LOOCV is selected for training and testing. Steps of the proposed LDOP and RFINCA based SSC method are given in below.

Step 0: Load snoring sound (SS).

Step 1: Apply 7 leveled DWT to SS applying symlet 8 filter.

$$[L^1, H^1] = DWT(SS, sym8) \quad (11)$$

$$[L^G, H^G] = DWT(L^{G-1}, sym8), G = \{2, 3, \dots, 7\} \quad (12)$$

where L^G and H^G are Gth leveled low pass filter and high pass filter sub-bands, respectively. $DWT(.,.)$ defines DWT function, and *sym8* is symlet 8 filter.

Step 2: Generate features using LDOP. Details of the LDOP are explained in Section 3, and the pseudo-code of this procedure is shown in Fig. 3.

$$f_t^1 = LDOP(SS) \quad (13)$$

$$f_t^T = LDOP(L^{T-1}), T = \{2, 3, \dots, 8\} \quad (14)$$

where f_t^T is feature vector of the Tth level.

Step 3: Concatenate the generated features and obtain a 4096 sized feature vector (f_v).

$$f_v((j-1)*512+i) = f_t^j(i), j = \{1, 2, \dots, 8\} \quad (15)$$

The steps 1–3 defines LDOP and DWT based feature generation networks.

Step 4: Apply min-max normalization to f_v .

Procedure: <i>LHDP(SS)</i>
Input: Sound signal (SS) with size of M.
Output: Feature vector (<i>featvec</i>) with size of 512.
00: Load SS
01: for i=1 to M-16 do
02: <i>window</i> = SS(i:i + 16); // Divide SS into 17 sized overlapping blocks.
03: <i>left</i> (i) = 0; <i>right</i> (i) = 0; // Assign initial values as 0.
04: for j=1 to 8 do
05: <i>right</i> (i) = <i>right</i> (i) + (<i>window</i> (9) – <i>window</i> (j)) * 2 ^{j-1} ;
06: <i>left</i> (i) = <i>left</i> (i) + (<i>window</i> (9) – <i>window</i> (9 + j)) * 2 ^{j-1} ;
07: end for j
08: end for i
09: Extract histograms of the <i>right</i> and <i>left</i> signals.
10: Concatenate these signals and obtain feature vector with size of 512.

Fig. 2. LDOP feature generation procedure.

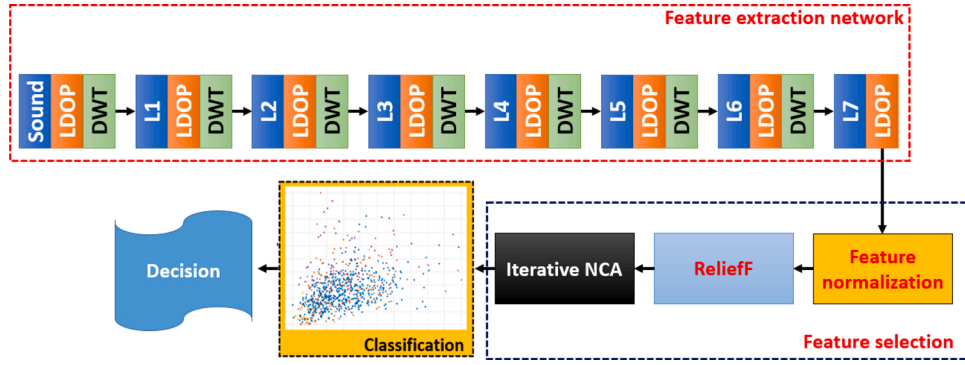


Fig. 3. Graphical summarization of the proposed LDOP and RFINCA based method.

$$X = \frac{fv - \min(fv)}{\max(fv) - \min(fv)} \quad (16)$$

where X denotes normalized features.

Step 5: Calculate weights of the ReliefF using ReliefF function, X and target (actual classes). Using these weights, choose positive weighted features.

$$w^r = \text{ReliefF}(X, \text{target}, 10) \quad (17)$$

$$\text{counter} = 1 \quad (18)$$

$$X^p(\text{counter}) = X(i) \text{ and } \text{counter} = \text{counter} + 1, \text{ if } w^r(i) > 0, i = \{1, 2, \dots, 4096\} \quad (19)$$

where w^r is weights of the ReliefF, X^p defines positive weighted features.

Step 6: Apply NCA to X^p and calculate the sorted index of the features.

$$\text{index} = \text{NCA}(X^p, \text{target}, \text{sgd}) \quad (20)$$

where sgd is stochastic gradient descend optimization function. In the NCA, initial weights are assigned randomly. Then, these weights are updated using a Manhattan distance based fitness function and an optimization method.

Step 7: Use the iterative feature selection procedure and calculate the loss value of each selected feature. In this step, a range of the number of features is determined to decrease computational cost. Our range is from 40 to 540. Optimal features are selected using minimum loss valued features. Eqs. 21–24 defines Step 7 mathematically.

$$\text{feat}^k(i) = X^p(\text{index}(i)), K = \{1, 2, \dots, 501\}, i = \{1, 2, \dots, K + 39\} \quad (21)$$

$$\text{loss}(K) = \text{kNN}(\text{feat}^k, \text{target}, 1, \text{Manhattan}) \quad (22)$$

$$[\text{mini}, \text{ind}] = \min(\text{loss}) \quad (23)$$

$$\text{feature}(i) = X^p(i), i = \{1, 2, \dots, \text{ind} + 39\} \quad (24)$$

where feat^k is Kth selected features by NCA, $\text{kNN}(\dots)$ represents kNN classifier, and parameters of it are used features, target, k value, and distance metric, respectively. mini and ind define minimum loss value and index of the minimum value.

Step 8: Classify final selected features (feature) using kNN classifier. k value, distance metric, and testing and training strategy of this classifier are 1, Manhattan distance, and LOOCV, respectively. The results are calculated using this classifier.

5. Results

In this work, we used a publicly and freely published snore sounds dataset, and it is called as MPSSC. This dataset contains 828 snore

sounds with 4 (classes of the MPSSC are V, O, T, E) classes. These sounds are divided into three categories, and these categories are named as training, testing, and development. In the previously presented methods which used the MPSSC dataset, two of these three categories were used for training, and one of them was used to tests. In this work, a novel training and testing strategy is used. We used all of the sound signals, and testing and training were processed using LOOCV. Here, all of the sounds have been used (testing, training, and validation). Using LOOCV, a general result of the model was achieved. For example, Janot et al. [14] presented six results ($P\left(\frac{3}{2}\right) = 6$). Using 6 results, evaluation of the used machine learning model on this dataset is difficult. Because, 6 different success rates are calculated for a dataset. Therefore, LOOCV was used to obtain a general result for these three categories. MATLAB2019b programming environment was used on a desktop computer to implement our proposed SSC method. This desktop computer has Windows 10.1 operating system, i7 7th generation 3.2 GHz microprocessor, and 16 GB main memory. The proposed LDOP and DWT based feature generation network. RFINCA feature selector were coded using MATLAB m files. In the classification phase, we used MATLAB Classification Learner (MCL) toolbox. In the MCL toolbox, there are only hold out validation and k-fold cross-validation testing and training options. Therefore, we selected a k-fold cross validation option, and k was set as 10. Fine kNN classifier was selected, and the distance metric of it chosen as the city block (Manhattan). Then, the source code of the used Fine kNN was generated, and the k-fold section was changed as 828 to calculate the LOOCV result of this classifier. UAR was used as an evaluation metric in previously presented SSC methods. However, we used UAR, unweighted average precision (UAP), F1 score using UAR and UAP, the geometric mean of the recall values, and classification accuracy to evaluate our proposed LDOP and RFINCA based SSC method comprehensively. The used procedure to calculate these performance metrics is shown in Fig. 4 [51–53].

With the performance procedure, which is shown in Fig. 4, accuracy, UAR, UAP, F1-score, and geometric mean values of the proposed LDOP and RFINCA based method were calculated, and the obtained results were listed in Table 3.

To validate these results, which are shown in Table 3, we demonstrated the confusion matrix of our SSC method was shown in Table 4.

6. Discussions

This paper proposes a novel LDOP and RFINCA based SSC method. Automated SSC is crucial to detect sleeping activities. Therefore, we presented a novel automated classification method, and this classification method was tested on the MPSSC database. Many methods were used this database to test their models. A new feature generation function is presented and it is named LDOP. LDOP and DWT feature extraction network generated 4096 features to obtain high, medium, and low levels features. RFINCA selected the most informative features.

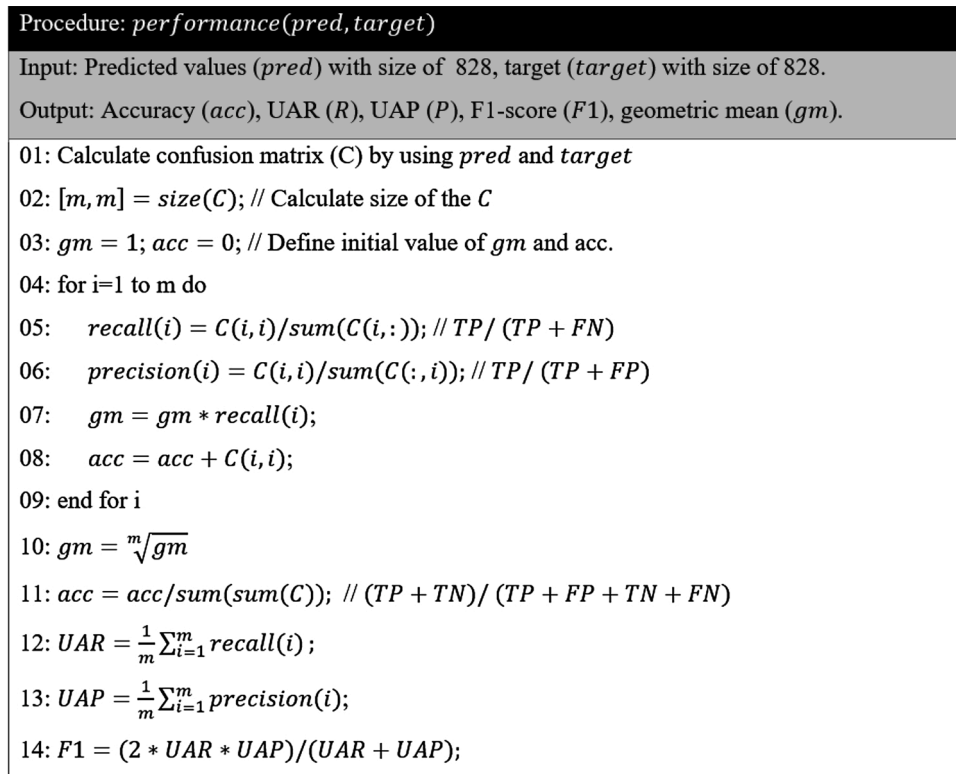


Fig. 4. The procedure of the performance metrics calculations.

Table 3
Results (%) of the proposed LDOP and RFINCA based SSC method.

Performance metric	Result
Accuracy	95.53
UAR	94.65
UAP	95.84
F1-score	95.24
Geometric mean	94.61

Table 4
Confusion matrix of the proposed LDOP and RFINCA based method.

Actual class	Output class				Recall (%)
	V	O	T	E	
V	474	8	1	1	97.93
O	19	195	1	1	90.28
T	2	0	37	0	94.87
E	3	1	0	85	95.51
Precision (%)	95.18	95.59	94.87	97.70	95.53

The size of the selected final feature vector is 95 in this work. MPSSC is a heterogeneous dataset. Especially, there are a fairly small number of observations in the T and E classes. Also, achieving high recall is very hard for V and E classes employed conventional feature extraction methods. Another problem of this dataset is to obtain 6 variable results using training, testing, and development partitions. To solve these problems, a LDOP and RFINCA based SSC method is presented, and results were obtained using LOOCV. Our feature extraction and selection methods are very powerful because we achieved 95.53% accuracy 94.65% UAR values using kNN classifier. Boxplot analysis was used and results shown in Fig. 5 to show the classification capabilities of these features.

Statistical attributes of the features are shown using boxplot. The

relationship of the features can be seen in Fig. 5. The statistical attributes of these features of each class are clearly denoted that these features are separable because they have different shapes.

The proposed LDOP and RFINCA based SSC method was also compared to other methods, and the obtained comparatively results were listed in Table 5.

The benefits of the proposed method are given below.

- A high accurate SSC method is presented. High classification accuracy and UAR were achieved using the proposed LDOP, and RFINCA based SSC method (See Table 3 and Table 4).
- The proposed LDOP and RFINCA based SSC method uses hand-crafted features. It has a multileveled feature generation network, but the computational complexity of this feature generation network is $O(n \log n)$. Also, a feature range was used to decrease the time cost in the RFINCA. Therefore, this method is a lightweight method.
- Any metaheuristic optimization methods for instance genetic algorithm, particle swarm optimization, artificial bee colony were not used to increase the success of the proposed method.
- The automatic optimal feature selection problem was solved with RFINCA.
- We used LOOCV as a training and validation strategy to solve the low-performance problem on the MPSSC. LOOCV is the most robust training and validation strategy because there is no random assignment in the LOOCV. Therefore, our SSC method is robust.
- The proposed LDOP and RFINCA based SSC method outperformed. Table 5 denoted that our SSC method reached approximately 22% higher UAR than the best of others. Also, we achieved higher classification rates than deep learning methods without set millions of parameters.
- The results were given comprehensively using five performance metrics.

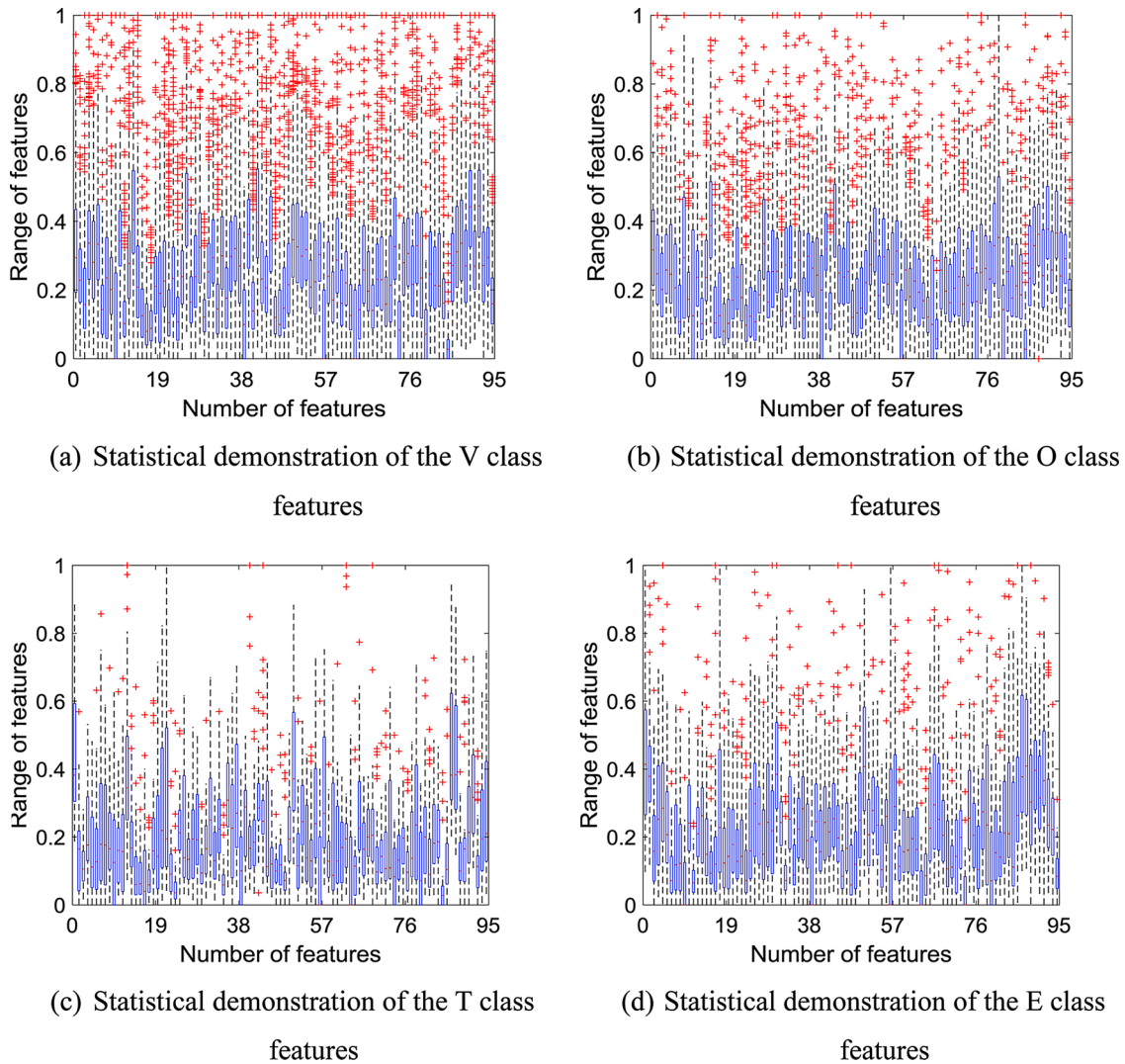


Fig. 5. Graphical illustration of the statistical attributes of the extracted and selected 95 most informative features according to classes. Here, blue boxes represent differences of quartile 3 (Q3) and quartile 1 (Q1), red line denotes mean value, red pluses are upper or lower values of [Q1, Q3] range.

Table 5
UAR results (%) of the proposed method and other state-of-art methods.

References	Year	Method	UAR
[17]	2017	MFCC, ELM, SVM	49.38
[18]	2017	CNN and Alexnet, VGG19	67.0
[19]	2018	LBP and HOG	66.5
[20]	2017	Deep CNN	72.6
[14]	2018	SVM, MFCC	55.8
[22]	2017	SVM	49.58
[23]	2017	GMM, SCAT and DNN	69.71
[25]	2018	CNN- Dual Conv. GRU	63.8
[26]	2019	Conditional Generative Adversarial Networks	67.4
[27]	2019	Wavelet Features	69.4
Our method		LDOP, multilevel DWT, RFINCA and kNN with LOOCV	94.65

7. Conclusions

To achieve high classification performance on the MPSSC dataset is very hard because it was collected from many subjects in several medical centers. A novel SSC method was presented to overcome this problem. This SSC method has a feature generation, feature selection, and classification phases. We inspired by the Covid-19 contamination rate to propose a feature extractor. Therefore, we used 17 sized overlapping

windows to extract 512 features. As it known from the literature, DWT is one effective decomposition method for sounds. Therefore, the proposed feature generation network was created using the proposed LDOP and DWT together. RFINCA selected optimal features automatically, and these features were classified using kNN with LOOCV. We used five performance metrics to evaluate the proposed method comprehensively. Accuracy, UAR, UAP, F1-score, and geometric mean values of our SSC method were calculated as 95.53%, 94.65%, 95.84%, 95.24%, and 94.61% respectively. The achieved results compared to other methods and approximately 22% higher classification rate was reached than the best of others (See Table 5). Results clearly demonstrated that the performance of the MPSSC database classification problem was increased incredibly.

8. Future directions

Our future directions are;

- Novel automated SSC applications can be presented/developed using the proposed LDOP and RFINCA method. Sleep activities and quality can be detected using this application. Sleep apnea can also be diagnosed with this automated SSC application.

- The proposed LDOP and RFINCA based method can be used to solve other signal processing and sound classification problems.
- Nonparametric (automatic) new generation feature selectors can be presented.
- Bigger snore sounds dataset can be collected to automated diagnose some diseases.

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Intellectual property

We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing we confirm that we have followed the regulations of our institutions concerning intellectual property.

Research ethics

We further confirm that any aspect of the work covered in this manuscript that has involved human patients has been conducted with the ethical approval of all relevant bodies and that such approvals are acknowledged within the manuscript.

Approval was obtained (required for studies and series of 3 or more cases)

Authorship

All listed authors meet the BIOMEDICAL SIGNAL PROCESSING AND CONTROL criteria. We attest that all authors contributed significantly to the creation of this manuscript, each having fulfilled criteria as established by the BIOMEDICAL SIGNAL PROCESSING AND CONTROL.

One or more listed authors do(es) not meet the BIOMEDICAL SIGNAL PROCESSING AND CONTROL criteria.

We confirm that the manuscript has been read and approved by all named authors.

We confirm that the order of authors listed in the manuscript has been approved by all named authors.

CRedit authorship contribution statement

Turker Tuncer: Conceptualization, Methodology, Software, Validation, Visualization, Supervision. **Erhan Akbal:** Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing. **Sengul Dogan:** Conceptualization, Investigation, Resources, Data curation, Project administration.

Declaration of Competing Interest

No conflict of interest exists.

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