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Research Article

An automated Covid-19 respiratory sound classification method based on novel local symmetric Euclidean distance pattern and ReliefF iterative MRMR feature selector

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ABSTRACT

Covid-19 is a new variety of coronavirus that affects millions of people around the world. This virus infected millions of people and hundreds of thousands of people have passed away. Due to the panic caused by Covid-19, recently several researchers have tried to understand and to propose a solution to Covid-19 problem. Especially, researches in machine learning (ML) have been proposed to detect Covid-19 by using X-ray images. In this study, 10 classes of respiratory sounds, including respiratory sounds diagnosed with Covid-19 disease, were collected and ML methods were used to tackle this problem. The proposed respiratory sound classification method has been proposed in this study from feature generation network through hybrid and iterative feature selection to classification phases. A novel multileveled feature generating network is presented by gathering multilevel one-dimensional wavelet transform and a novel local symmetric Euclidean distance pattern (LSEDP). An automated hybrid feature selection method is proposed using ReliefF and ReliefF Iterative Maximum Relevancy Minimum Redundancy (RIMRMR) to select the optimal number of features. Four known classifiers were used to test the capability of our approach for lung disease detection in respiratory sounds. K nearest neighbors (kNN) method has achieved an accuracy of 91.02%.

1. Introduction

An outbreak occurred in China Wuhan towards the end of 2019. This epidemic, which is transmitted from person to person very quickly, threatens the whole world. This virus was grouped as 2019 new coronavirus (2019-nCoV) and was named Covid-19 [1, 2]. Covid-19 is a virus belonging to the coronavirus family [3]. Coronaviruses are divided into 4 groups: gamma coronavirus, delta coronavirus, alphacoronavirus, and beta coronavirus [4, 5]. Alpha and beta coronaviruses infect the respiratory and central nervous functions of mammals. Gamma and delta coronavirus tend to infect birds. Alpha and Beta coronaviruses have different symptoms, especially in humans. There are some viruses such as HCoV-229E, HCoV-HKU1, HCoV-OC43 with milder symptoms [6-8]. However, viruses such as SARS-CoV and MERS-CoV can cause fatal infections [9, 10].

Covid-19 virus, which belongs to the beta coronavirus family, also causes deadly respiratory infection disease, pneumonia, and kidney failure [5, 11, 12]. The most common symptoms of Covid-19 can be presented as sore throat, cough, fever, and fatigue. Covid-19, which is transmitted to large masses by inhalation, is a newly encountered virus type, so our immune system does not know what to respond to this virus [13]. Every patient with low immunity and chronic illness could be more affected by this virus. This disease has an incubation period. Generally, the effects that start on the 2nd day can be carried until the 14th day and they vary from person to person [14, 15]. This newly encountered virus has been extensively studied in the literature to both minimize its effects and increase the

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recognition of the virus. Some of these studies are listed below.

Huang et al. [10] proposed a method to describe the respiratory sounds of Covid-19 patients. An electronic stethoscope was presented in the study. Separation of abnormal sounds and normal sounds was confirmed by the analysis of 6 doctors in the proposed method. Aykanat et al. [16] proposed a method for classifying respiratory sounds. In the proposed method, they studied the classification of sounds received from an electronic stethoscope. The main aim of the study is to measure and classify lung sounds through an easy-to-use and cost-effective electronic stethoscope. For this purpose, 1630 test subjects were used. Two machine learning techniques, convolutional neural network (CNN) and support vector machine (SVM) were used to evaluate and classify the obtained sounds. In the study, 86.0% accuracy rate was calculated. Son [17] proposed a method for classifying lung sounds. In the study, a dataset of 85 samples was collected to measure the performance of proposed feature selection methods. Support vector machine, k-nearest neighbor, naïve bayes have been implemented as classifier for this dataset. F-measure, recall, precision parameters were used to evaluate the performance of the study and were calculated as 94.1%. Bardou et al. [18] compared 3 different methods on the classification of lung sounds. The first proposed method was based on the Mel-frequency cepstral coefficients method. The local binary pattern was used in the second approach. In the third method convolutional neural network was used. A comparison of these methods is presented in the study. In the study, normal, coarse crackle, fine crackle, monophonic wheeze, polyphonic wheeze, squawk, and stridor classes were used. According to the obtained results, CNN has been observed to achieve more successful results than other methods. Naves et al. [19] developed a pattern recognition system. The main purpose of the study is to classify lung sounds. There are 5 different sounds in Dataset: normal, fine crackle, coarse crackle, polyphonic wheezes, and monophonic. The accuracy rate obtained in the study was calculated as 98.1%. Kandaswamy et al. [20] proposed a new method for classifying lung sound signals. Wavelet transform and artificial neural networks were used for the analysis of audio signals. In the study, 6 classes as normal, crackle, wheeze, stridor, rhonchus, and squawk were used. Ucar and Korkmaz [21] proposed a deep learning-based method using chest X-rays. Accuracy, completeness, specificity, correctness, Matthew correlation coefficient, and F1 score parameters were used for the evaluation of the study. In the study, 3 classes as Covid-19, Pneumonia, and normal were used. Obtained accuracy rates were calculated as 100.0% for Covid-19, 96.73% for Pneumonia and 98.04% for normal. Narin et al. [22] proposed a method for Covid-19 detection. Convolutional neural network is chosen in the proposed method. Chest X-Ray Images [23] dataset was used to evaluate the study. As the evaluation parameter, accuracy was selected and the accuracy rate was calculated as 98.0 for two classes (normal and Covid-19). Sethy and Behera [24] proposed a study for the diagnosis of Covid-19. In the study, the convolutional neural network method was used and the Kaggle Repository [3] dataset was chosen. The accuracy rate for normal and Covid-19 classes was calculated as 95.38%.

In the literature, many methods, research and ML (Machine Learning) methods have been proposed since Covid-19 is one of the hottest academic research areas. In general, researchers aimed to classify Covid-19 disease using normal or pneumonia chest X-ray images. But the characteristic of the respiratory sound of Covid-19 disease led to the idea of proposing Covid-19 diagnostic methods based on sound classification. Therefore, lung respiratory sounds belonging to 10 different classes, including Covid-19 were collected within the scope of this study and a new method is presented to help in the diagnosis of Covid-19.

2. Dataset

In this section, a data set was created by collecting lung respiratory sounds. These sounds, normally prepared for educational purposes, are used by medical professionals and healthcare providers. These respiratory sounds were shared by Medcool [25], EMTprep [26], Fouad [27] and Alhadapediatrics [28] on YouTube. These records were shared between 27.06.2018 and 10.04.2020. 657 sound recordings of 10 classes. Each of the 657 sound recordings consists of 2 or 3-second sounds. Firstly, each audio file was converted to wav file format. Then, the sounds carefully listened for segmentation. It was carefully checked that the same sound did not continue repeatedly during the fragmentation of the sound files. Table 1 demonstrates the attributes of the collected dataset.

3. Method

In this study, a new stable feature generation network and an automated iterative-hybrid feature selector is proposed. The proposed feature generation network uses a novel textural feature extractor and it is called LSEDP (Local Symmetric Euclidean Distance Pattern). In the proposed LSEDP, Euclidean distance is utilized for binary feature generation. As it is known from the literature, multileveled feature extractors have high performance for classification because they extract low, medium and high levels feature.

Therefore, 9-leveled DWT (Discrete Wavelet Transform) [29, 30] is considered to create levels and LSEDP extracts 256 features from each level and raw sound signal. RFIMRMR selects the most meaningful and informative features from the extracted 2560 features. Four shallow classifiers are used for classification and these are bagged tree (BT) [31], linear discriminant (LD) [32], kNN [33, 34] and support vector machine (SVM) [35].

Table 1. Type and Number of the collected Respiratory Sounds

ID	Sound Type	Number of observations	Number of videos
1	Vesicular Respiratory Sounds	83	7
2	Fine Crackles (Rales)	57	7
3	Wheezing (expiratory)	70	8
4	Rhonchi	72	8
5	Stridor	63	7
6	Coarse Crackles (Rales)	82	7
7	Bronchovesicular Respiratory Sounds	61	8
8	Bronchial Respiratory Sounds	65	5
9	Sounds of Coronavirus (Covid-19)	29	1
10	Healthy Person Respiratory	75	10
Total		657	68

The technical contributions are given below:

- A total of 657 new sound sets belonging to 10 classes were gathered from YouTube. The collected data set is presented publicly available for open access.
- A novel distance-based feature extractor (LSEDP) is presented. LSEDP and multileveled DWT are used together for presenting a multileveled feature generation network. This network generates low, medium, and high-level features. ReliefF [36] and MRMR (Maximum Relevancy Minimum Redundancy) are parametrical feature selectors. To select the best number of features, users/researchers generally set parameters one more time. The proposed RFIMRMR both uses the effectiveness of these feature selectors together and select the best number of features automatically. To obtain results comprehensively, four classifiers are used in 5 categories.
- A novel sound based Covid-19 detection method is presented and this method is a highly accurate method. The proposed method classified 10 respiratory sounds. Therefore, this method is a general diagnosis method, and it is demonstrated that this method could be used in medical applications.

3.1 The Proposed Respiratory Sound Classification Method

This study proposed a novel hand-crafted multileveled feature generation network and automatic features selector. A novel respiratory sound classification method is proposed by using four shallow classifiers. The schematically overview of the proposed method is shown in Figure 1.

To overview the proposed LSEDP and RFIMRMR based respiratory sound classification method, the procedure of this method is shown in Figure 2.

As can be seen from Figure 1 and 2, this method has three fundamental phases and these are explained in subsections.

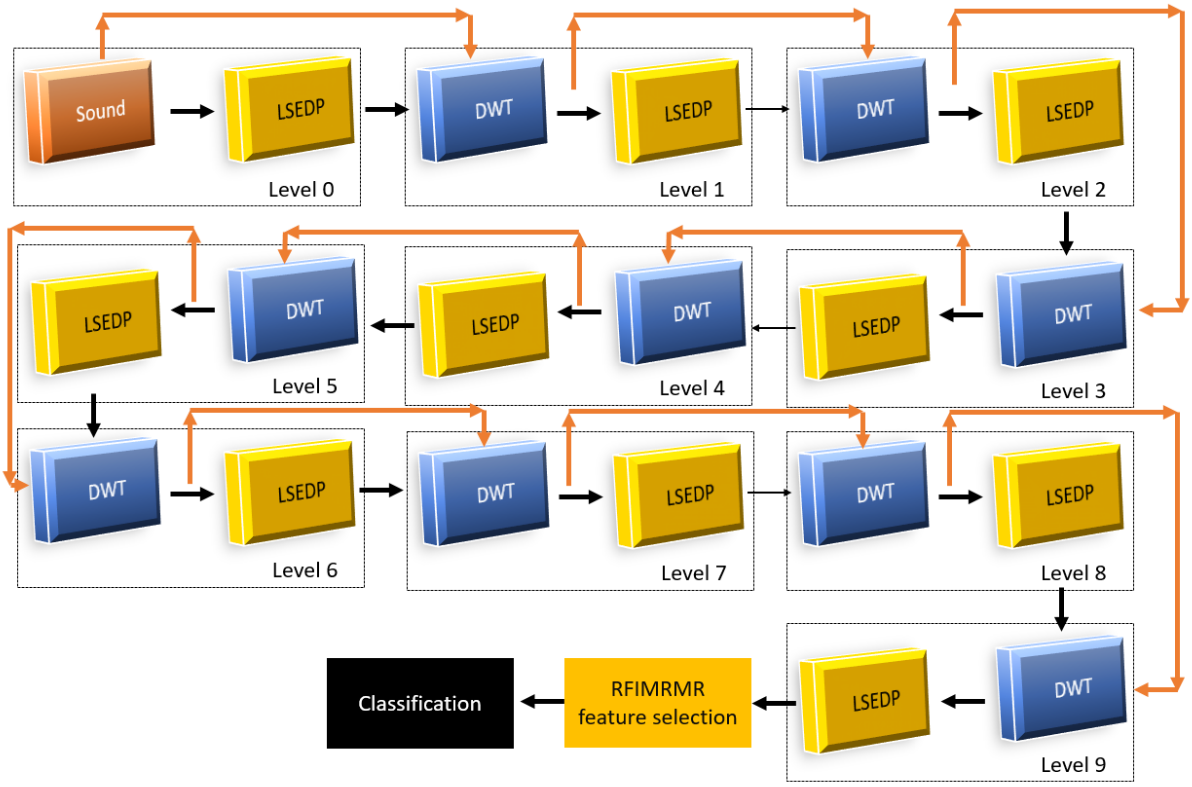

Figure 1. Graphical overview of the proposed method.

Procedure: $CovSoundDet(BS)$

$Input$: Breathing sound (BS) with size of L.

$Output$: Predicted values (pv).

```
Load breathing sound dataset.
for k=1 to num do // num is number of road sound
    Read each road sound (BS)
    for i=1 to 10 do // Apply TMP and LCSBP based feature generation network.
        X(k,(i − 1) ∗ 256 + 1: i ∗ 256) = LSEDP(BS)// In this line, LSEDP and feature concatenation are processed together.
        [BS, high] = dwt(BS, sym4); // Decomposition using DWT with Sym4 filter and update BS as low-pass sub-band.
    end for i
end for k
Normalize each feature.
Select 107 the most informative features by using RFIMRMR
pv = kNN(X_best, 10); // Classify final feature by using kNN and obtain pv.
```

Figure 2. The procedure of the proposed respiratory sound classification based Covid-19 detection method.

3.2 Multileveled discrete wavelet transforms and local symmetric Euclidean distance pattern based feature generation network

The proposed multileveled DWT [29, 30] and LSEDP based feature generation network is aimed to extract meaningful and discriminating features from respiratory sounds. Textural feature extractors which are local binary pattern (LBP) [37] and ternary pattern (TP) [38, 39] are very effective for feature extraction on both images and signals. LBP and TP use signum and ternary functions to generate binary features and these bits are utilized to construct feature vector. Signum function is a basic comparison function and the ternary function is a parametrical feature generator and parameter setting process of ternary function is hard (ternary function uses threshold value and optimal threshold value finding is a non-polynomial problem). As it is known from the literature, there are many distance-based classifiers like kNNs. Also, some feature selectors use distance metrics, for instance, ReliefF [36] and Neighborhood Component Analysis (NCA) [40]. Therefore, a novel feature generator (LSEDP) is presented to use effectiveness of both textural feature extractors and distance metrics. DWT has been widely preferred transformations for signal processing. In this study, Symlet 4 (sym4) which is one of the filter of DWT decomposition method was used to construct level. Because sym4 filter is used for both decomposition and noise reduction. The proposed feature generator is inspired by deep networks. Thus, multileveled architecture is used. According to our experimental study, 9-leveled DWT was given the best result. That is why, 9-levelled DWT was applied to sound signals. The proposed LSEDP extracts 256 features from raw sound and low-pass filter coefficients of each level DWT. In total, 2560 features are generated by using the proposed LSEDP and DWT based generator as seen from Figure 1. Steps of this feature generator are listed in below.

Step 1: Load raw breathing sound (BS).

Step 2: Calculate 9 low-pass filter sub-bands of the BS by applying 9-leveled DWT with sym4 filter.

$$[LowPass^1\ HighPass^1] = DWT(BS, sym4) \quad (1)$$

$$[LowPass^i\ HighPass^i] = DWT(LowPass^{i-1}, sym4), i = \{2,3, \dots, 9\} \quad (2)$$

where $LowPass^i$ and $HighPass^i$ are low-pass and high-pass filter coefficients of the i[th] level DWT, $DWT(.,.)$ is one dimensional DWT function and $sym4$ defines Symlet 4 filter.

Step 3: Generate features of the respiratory sound and low-pass filter of it by using the proposed LSEDP.

$$f^1 = LSEDP(BS) \quad (3)$$

$$f^{i+1} = LSEDP(LowPass^i), i = \{1,2, \dots, 9\} \quad (4)$$

In Eqs. 3-4, $LSEDP(.)$ defines the used fundamental feature extractor. The LSEDP procedure is defined in sub-steps.

Step 3.1: Divide BS into 33 sized non-overlapping windows.

$$p = BS(j: j + 32), j = \{1,2, \dots, L - 32\} \quad (5)$$

where p is window with size of 33 and L defines the length of the respiratory sound.

Step 3.2: Assign center as 17[th] value.

$$pc = p(17); \quad (6)$$

Step 3.3: Calculate distances of the symmetric values by using Euclidean distance, center value, and symmetric values.

$$d1(k) = \sqrt{(p(k) - pc)^2 + (p(33 - k) - pc)^2}, k\{1,2, \dots, 8\} \quad (7)$$

$$d2(k) = \sqrt{(p(17 - k) - pc)^2 + (p(17 + k) - pc)^2}, \quad (8)$$

where $d1$ and $d2$ express first and second distances.

Step 3.4: Extract binary features (8-bit) by using first and second symmetric distances.

$$bit(k) = \begin{cases} 1, d1(k) \geq d2(k) \\ 0, d1(k) < d2(k) \end{cases} \quad (9)$$

Step 3.5: Calculate map signal value by using the extracted

8-bit binary features.

$$map(j) = \sum_{k=1}^{8} bit(k) * 2^k \quad (10)$$

where map is constructed feature signal by using LSEDP.

Step 3.6: Calculate histogram of the map value to generate feature vector.

$$f(t) = 0, t = \{1,2, \dots ,256\} \quad (11)$$

$$f(map(j) + 1) = f(map(j) + 1) + 1 \quad (12)$$

where f is the calculated feature vector by applying LSEDP.

Step 4: Concatenate the extracted features from each level.

$$feat(i * 256 + t) = f^i(t), i = \{1,2, \dots ,10\}, t = \{1,2, \dots ,256\} \quad (13)$$

where $feat$ expresses final features with size of 2560. Eq. 13 denotes feature concatenation process mathematically.

3.3 ReliefF and iterative MRMR based feature selector

In this phase, a novel 2-leveled hybrid feature selector is presented. These feature selectors are ReliefF [36] and iterative MRMR. ReliefF is one of the distance-based feature selectors. It uses the Manhattan distance based fitness function and generates both positive and negative weights. Negative weighted features express redundant features. In the MRMR, sorted features indices are generated and it is called as idx. By using idx, features are selected parametrically. For automatic feature selection, a loss calculator should be used. As it is known from the literature, classifiers have been utilized as loss value generator. Four classifiers are used in this study, hence, variable tests are processed for feature generation.

Step 5: Generated ReliefF weights of the extracted 2560 features by using ReliefF weight generation function.

$$R^{Weight} = RF(feat, target) \quad (14)$$

where $RF(.,.)$ weight generation function of the ReliefF and R^{Weight} ReliefF weights with the length of 2560.

Step 6: Remove negative weighted features.

$$f^+(h) = feat(i), if\ R^{Weight}(i) > 0, h = h + 1, h \le i, i = \{1,2, \dots ,2560\} \quad (15)$$

where f^+ is selected positive weighted features.

Step 7: Calculate idx by using MRMR feature selection function and f^+.

$$idx = MRMR(f^+, target) \quad (16)$$

Step 8: Select features iteratively by using idx and f^+. To decrease the computational complexity of the proposed IMRMR, a range is defined. In this step, from 40 features to 500 features are used and loss values of these features are calculated. In this section, any classifier can be used as loss value generator.

$$X^{r-39}(i) = f^+\big(idx(i)\big), i = \{1,2, \dots , r\}, r = \{40,41, \dots ,500\} \quad (17)$$

$$loss^{r-39}(i) = kNN(X^{r-39}, target, Manhattan, 10) \quad (18)$$

where X^{r-39} is $(r-39)^{th}$ selected features, $loss^{r-39}$ expresses $(r-39)^{th}$ loss value of the selected features. $kNN(.,.,.,.)$ denotes kNN classification method. In here, Manhattan distance based Fine kNN with 10-fold cross-validation was used.

Step 9: Find minimum loss value and select the best number of features by using the founded index, idx and f^+.

$$[minimum, index] = \min(loss) \quad (19)$$

$$index = index + 39 \quad (20)$$

$$X_{best}(i) = f^+\big(idx(i)\big), i = \{1,2, \dots , index\} \quad (21)$$

where X_{best} is the selected optimal features. The proposed RFIMRMR method selects 107 features for this study.

3.4 Classification

In the classification phase, MATLAB Classification Learner (MCL) is utilized to apply classifiers. In this study, four different classifiers are used, such as LD, SVM, kNN, and BT. 10-fold CV is selected for the used validation and test strategy. This is the last phase of the proposed method and is shown below as Step 10.

Step 10: Classify selected features (X_{best}) by using any of the used four shallow classifiers to illustrate discriminative attribute of the X_{best}.

The attributes of the used four classifiers are listed in Table 2.

4. Experiments

MATLAB2019a programming environment and MCL tool of this programming environment was used to implement the proposed LSEDP and RFIMRMR based Covid-19 sound classification method. Four shallow classifiers and source code of these classifiers were generated to obtain numerical results. Classification accuracy (CAC), unweighted average recall (UAR), unweighted average precision (UAP), F1-score ($F1$), and geometric mean (GM) were used to obtain numerical results [41-43]. These performance measurements have been widely preferred to evaluate the classification methods. To calculate these measurements, number of true positives (TP), true negatives (TN), false negatives (FN) and false positives (FP) should be used. Mathematical notations of these performance criteria are shown as below:

$$UAP = \frac{1}{N} \sum_{i=1}^{N} \frac{TP_i}{TP_i + FP_i}, i = \{1,2, \dots ,10\} \quad (22)$$

$$UAR = \frac{1}{N} \sum_{i=1}^{N} \frac{TP_i}{TP_i + FN_i} \quad (23)$$

$$GM = \sqrt[N]{\prod_{i=1}^{N} \frac{TP_i}{TP_i + FP_i}} \tag{24}$$

$$F1 = \frac{2 * UAP * UAR}{UAP + UAR} \tag{25}$$

$$CAC = \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i} \tag{26}$$

In order to validate these results which are shown in Table 3, confusion matrices of the used four classifiers are shown in Figure 3 and 4.

5. Discussions

Covid-19 is a global problem and many people have suffered from this disease. Many treatment methods and vaccine studies have been proposed to solve Covid-19 problem. In this study, our aim is to detect Covid-19 with stethoscope sounds. Hence, 657 sounds with belonging to 10 classes were gathered from YouTube. A novel hand-crafted feature extraction network and an iterative 2-layer feature selector were proposed to classify these sounds automatically. A novel LSEDP feature extractor was presented to generate distinctive features from the collected sounds. The proposed LSEDP feature extraction network generated 2560 features. To select the most distinctive ones of the generated 2560 features, RFIMRMR feature selector was presented. The feature selection process of the RFIMRMR by using kNN was shown below.

Table 2. Attributes of the used four conventional classifiers

Classifier	Parameters and explanations
LD [32]	LD is a non-parametric classifier. In the MCL, we only can set covariance structure and it is set as Full.
SVM [35]	Kernel is 3rd degree polynomial (Cubic) function, box constraint level (C) is 1 (it is default setting), multilevel method is selected as one-vs-all.
kNN [33, 34]	k is selected as 1 and distance metric is city block
BT [31]	BT is one of the ensemble methods in the MCL. Bag is selected as ensemble method, learner type is decision tree (DT), maximum number of split is 656 and 30 learners are used in this classifier.

Table 3. Measurements (%) of the proposed LSEDP and RFIMRMR based Covid-19 classification method

Classifier	UAP	UAR	GM	F1	CAC
LD	87.46	86.36	86.22	86.89	86.45
SVM	88.63	88.65	88.39	88.62	88.28
kNN	91.36	91.22	91.06	91.29	91.02
BT	88.61	87.18	86.91	87.82	87.21

Predicted Class

True Class	1	2	3	4	5	6	7	8	9	10
1	71	2	1	0	0	2	0	7	0	0
2	1	47	0	1	0	6	0	0	2	0
3	2	1	59	1	0	5	0	2	0	0
4	0	3	2	61	0	2	2	2	0	0
5	0	0	2	1	59	0	0	0	1	0
6	4	7	0	1	0	68	0	2	0	0
7	1	3	0	7	0	1	49	0	0	0
8	3	0	3	0	0	2	0	56	1	0
9	0	0	1	1	0	0	0	2	25	0
10	0	0	1	1	0	0	0	0	0	73

LD

Predicted Class

True Class	1	2	3	4	5	6	7	8	9	10
1	75	3	0	0	0	3	0	2	0	0
2	3	46	1	0	0	6	0	0	1	0
3	0	0	57	4	0	5	0	3	1	0
4	2	1	2	61	0	4	1	0	1	0
5	0	0	1	1	59	0	2	0	0	0
6	3	5	2	0	0	68	1	2	1	0
7	1	1	0	0	1	0	56	1	1	0
8	1	1	2	1	0	2	0	57	1	0
9	0	1	0	1	0	0	0	0	27	0
10	0	0	0	0	0	1	0	0	0	74

SVM

Figure 3. The confusion matrices of the LD and SVM

Predicted Class

True Class	1	2	3	4	5	6	7	8	9	10
1	77	1	0	3	0	1	0	1	0	0
2	3	46	2	0	0	4	1	0	0	1
3	1	3	59	3	0	1	0	1	1	1
4	1	3	1	64	0	1	1	1	0	0
5	0	0	0	0	61	1	0	1	0	0
6	2	5	2	1	0	72	0	0	0	0
7	0	0	0	2	2	0	57	0	0	0
8	2	0	1	2	0	0	0	60	0	0
9	0	1	0	0	0	0	0	0	28	0
10	0	0	0	1	0	0	0	0	0	74

kNN

Predicted Class

True Class	1	2	3	4	5	6	7	8	9	10
1	79	1	1	0	0	1	0	1	0	0
2	6	43	1	0	0	5	2	0	0	0
3	6	3	50	6	1	4	0	0	0	0
4	2	2	2	60	0	3	2	0	0	1
5	0	0	0	0	60	1	1	1	0	0
6	1	3	5	2	0	69	0	1	0	1
7	0	1	0	3	0	0	57	0	0	0
8	5	1	1	1	0	1	0	56	0	0
9	0	0	1	2	0	0	0	1	25	0
10	0	0	0	0	0	1	0	0	0	74

BT

Figure 4. The confusion matrices of the kNN and BT

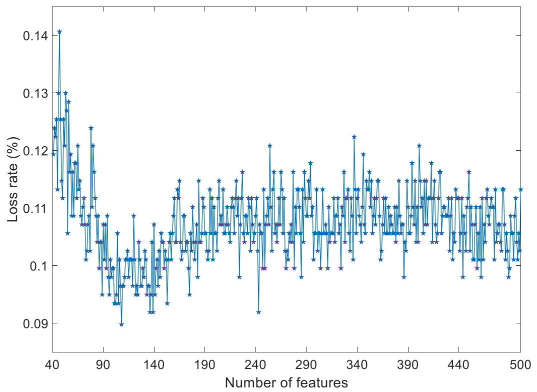

Figure 5. Graphical illustration of the proposed RFIMRMR feature selection process with a range of from 40 to 500 features

As can be seen from Figure 5, the best number of features can be selected automatically. The selected 107 features were forwarded to 4 conventional classifiers and 86.45%, 88.28%, 91.02, and 87.02% classification accuracies were calculated by using LD, SVM, kNN and BT classifiers respectively. To clear the demonstration of these results, confusion matrices of these classifiers were also shown. 9th class represents Covid-19 disease with belonging to 29 respiratory sounds. kNN classifiers reached 96.55% classification accuracy (there is only one misclassified observation) for Covid-19 detection. The kNN classifier is frequently preferred in different studies [44, 45]. LD, SVM and BT classifiers also achieved 86.21%, 93.10% and 86.21% classification accuracies for Covid-19 detection respectively.

When the confusion matrix of the kNN method is examined, it can be seen that some diseases are almost never confused with other diseases, but only a small portion of some diseases can be confused. However, since the number of these mixed samples is very small, it can be said to be insignificant. Similar to the study here, 97% successful detections were obtained in the study for the detection of Covid-19 from the cough sound [46]. In another study, Covid-19 disease was tried to be detected from coughing, breathing and speaking sounds and a successful classification of 66.74% was obtained [47]. In another study, 80.7% AUC value was obtained from breathing and coughing sounds [48]. The studies here have shown that the success rate in this study is higher than its counterparts.

The main contributions of this paper are feature generation and selection methods. To show the distinctiveness of generated and selected 107 features, boxplot analysis was used. Boxplot has been widely used the statistical demonstration to illustrate separable attributes of the features. It shows quartiles (Q3-Q1 is shown as blue boxes), arithmetic average value (red line), upper and lower bounds, and abnormal values (red plus). Boxplots of the selected 107 features according to classes were shown in Figure 6 and 7.

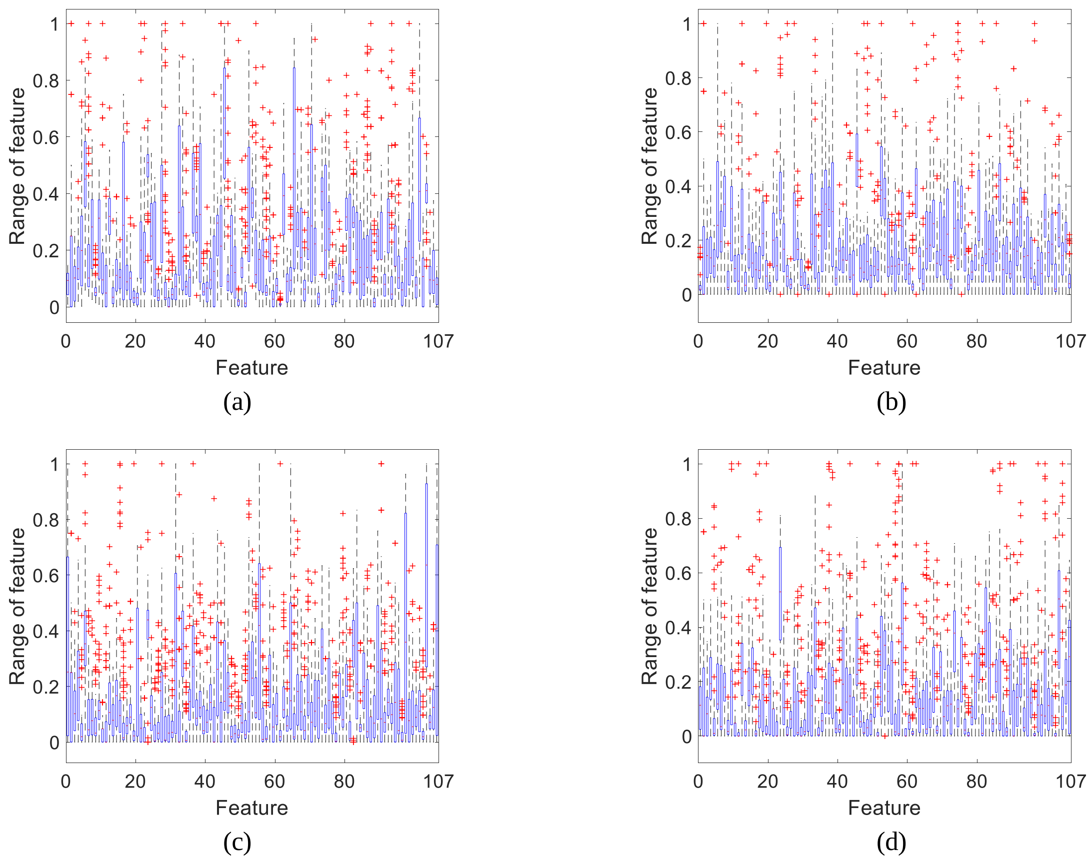

Figure 6. Boxplots of the extracted and selected 107 features by using the proposed LSEDP feature generation network and RFIMRMR feature selector. This figure shows statistical attributes of the (a) features of 1st class (b) features of 2nd class (c) features of 3rd class (d) features of 4th class

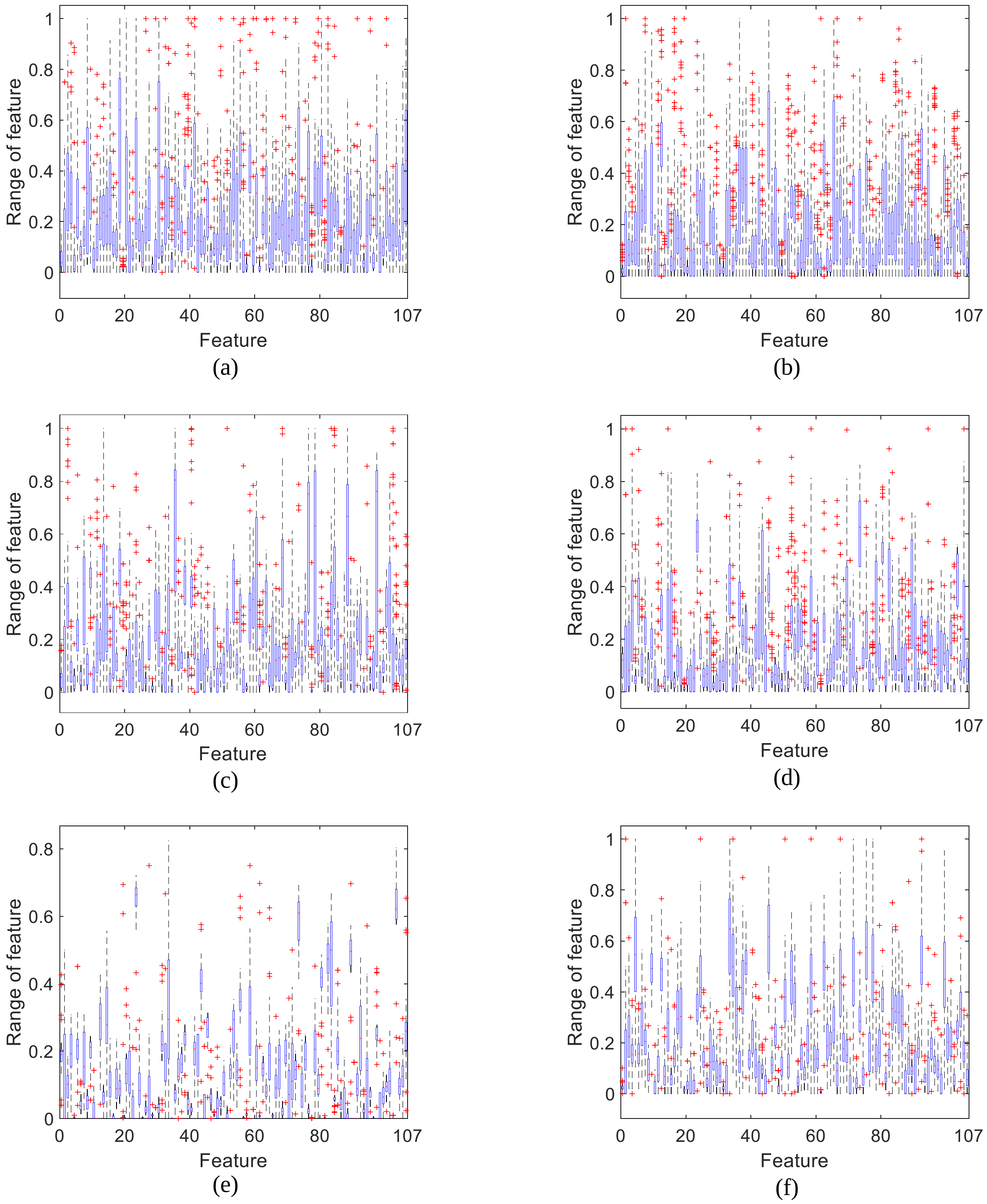

Figure 7. Boxplots of the extracted and selected 107 features by using the proposed LSEDP feature generation network and RFIMRMR feature selector. This figure shows statistical attributes of the (a) features of 5th class (b) features of 6th class (c) features of 7th class (d) features of 8th class (e) features of 9th class (f) features of 10th class

Figure 6 and 7 validated the obtained high success rates. The benefits of the proposed LSEDP and RFIMRMR based methods are shown below.

- A novel respiratory sound dataset was collected and it was publicly published. This dataset is heterogeneous.
- A novel textural and one-dimensional distance-based feature generator (LSEDP) was presented to extract salient features of the sounds. LSEDP and DWT were used together to provide a multilevel feature generation network, which is used the handcrafted method and a decomposition algorithm. The time complexity of this method was calculated as $O(nlogn)$.
- The problem of the most informative feature selection method was solved by this proposed method.
- The proposed LSEDP and RFIMRMR based feature generation and selection method is successful because four conventional/shallow classifiers achieved higher than 86% classification accuracies. By using the proposed methods, a high accurate respiratory sound classification method was presented.
- The proposed method classified of Covid-19 diagnosed respiratory sound with high performance.

In the literature, the lack of a publicly available respiratory sound data set is one of the limitations of the proposed method. However, experimental results have shown that Covid-19 disease can be classified with high performance by using the proposed method.

6. Conclusion

This study aims to diagnose Covid-19 disease by using respiratory sounds. Therefore, a new respiratory sound dataset was collected in the first step. Then, a novel hand-crafted feature generation network and an iterative hybrid feature selector were proposed. The proposed LSEDP uses Euclidean distance to generate binary features. LSEDP aimed to use positive effect of the Euclidean distance for feature generation. To generate low, medium, and high levels features, 9-leveled DWT was used in the proposed feature generation network. To use effectiveness both ReliefF and MRMR, RFIMRMR was proposed and it solved the most discriminating numbers of features selection problem automatically. The proposed LSEDP feature generation network extracted 2560 features and RFIMRMR selected 107 most discriminative of them. These features were used input as 4 conventional classifiers and the best-resulted classifier was found as kNN (See Table 3). kNN reached the rates of 91.36%, 91.22%, 91.06%, 91.29% and 91.02%, UAP, UAR, GM, F1 and CAC respectively. It also classified Covid-19 with 96.55% classification accuracy. These results imply the success of the proposed method. A novel intelligent stethoscope can be developed by using the proposed method and novel datasets can be collected in the future works.

Declaration

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article. The authors also declared that this article is original, was prepared in accordance with international publication and research ethics, and ethical committee permission or any special permission is not required.

Author Contributions

T. Tuncer developed methodology. E. Aydemir collected dataset. F. Ozyurt performed the analysis. S.B. Belhaouari supervised and improved the study. S. Dogan and E. Akbal write and made proofreading of manuscript.

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