



Automated asthma detection in a 1326-subject cohort using a one-dimensional attractive-and-repulsive center-symmetric local binary pattern technique with cough sounds

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Abstract

Asthma is a common disease. The clinical diagnosis is usually confirmed on a pulmonary function test, which is not always readily accessible. We aimed to develop a computationally lightweight handcrafted machine learning model for asthma detection based on cough sounds recorded using mobile phones. Toward this aim, we proposed a novel feature extractor based on a one-dimensional version of the published attractive-and-repulsive center-symmetric local binary pattern (1D-ARCSLBP), which we tested on a new cough sound dataset. We prospectively recorded cough sounds from 511 asthmatics and 815 non-asthmatic subjects (comprising mostly healthy volunteers), which yielded 1875 one-second cough sound segments for analysis. Our model comprised four steps: (i) preprocessing, in which speech signals and stop times (silent zones between coughs) were removed, leaving behind analyzable cough sound segments; (ii) feature extraction, in which tunable q-factor wavelet transformation was used to perform multilevel signal decomposition into wavelet subbands, allowing 1D-ARCSLBP to extract local low- and high-level features; (iii) feature selection, in which neighborhood component analysis was used to select the most discriminative features; and (iv) classification, in which a standard shallow cubic support vector machine was deployed to calculate binary classification results (asthma versus non-asthma) using tenfold and leave-one-subject-out cross-validations. Our model attained 98.24% and 96.91% accuracy rates with tenfold and leave-one-subject-out cross-validation strategies, respectively, and obtained a low-time complexity. The excellent results confirmed the feature extraction capability of 1D-ARCSLBP and the feasibility of the model being developed into a real-world application for asthma screening.

Keywords Asthma disease detection · Cough sounds · NCA · Biomedical engineering

1 Introduction

Asthma is a chronic recurring disease caused by an increase in airway sensitivity [1] that can affect both large and small airways [2, 3]. It is characterized by bronchial inflammation, which induces increased airway secretions, bronchial wall swelling, and smooth muscle contraction [4]. In 2019, asthma afflicted 262 million people globally and caused the death of 455,000 [5, 6]. Its incidence is increasing [7], which is exacerbated by rising obesity, stress, mood disorders, medication use, environmental exposure to pollen, pets, smoke, air pollution, and indoor allergens such as house dust mites [8–10]. Although

asthma can present at any age, 30% of cases occur in the first year of life. Indeed, asthma is the most common chronic disease in children. The risk of developing asthma is higher in those with a family history of asthma [11].

Asthmatic symptoms include recurrent coughing, wheezing, and shortness of breath, which can be triggered by dust, smoke, odor, and pollen. Asthma may be caused by allergies or it can develop independently of allergies [12]. In the presence of frequent cough episodes, day/night coughing, chest tightness, a family history of asthma, and allergic symptoms, asthma should be considered. Spirometry and peak expiratory flow rate (PEFR) measurement are diagnostic tests that can also quantify the severity of air-flow limitation caused by bronchial narrowing, which is proportional to the level of airway inflammation [13].

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Serial portable peak flow meter measurements can be used to track changes in airway narrowing, which is particularly useful for managing asthma in children [14]. Because allergens can cause asthma, adjunctive allergy tests may be performed to identify culprit allergens [15]. Avoiding asthma triggers can help reduce the frequency of asthmatic attacks [16]. With contemporary medical care, asthma can generally be well controlled with inhaled medications, allowing patients to lead normal lives. However, underdiagnosis and under-treatment, which are more pervasive in low- and middle-income countries, are still responsible for residual risks, including mortality, among asthma patients.

While the clinical symptoms and signs of asthma are well-known, the physical examination may neither be sufficiently sensitive nor specific. Various machine learning models have been proposed to detect asthma automatically using recorded respiratory sounds. Haider and Behera [17] developed an automated method for detecting asthma and chronic obstructive pulmonary disease based on Hurst analysis, empirical mode decomposition, and spectral subtraction methods. Trained and tested on a dataset of lung sounds acquired from 80 normal, 80 asthmatic, and 80 chronic obstructive pulmonary disease subjects, the model attained 99.30% accuracy using a decision tree classifier. Kilic et al. [18] proposed a new machine learning model called global chaotic logistic pattern to discriminate asthma from other lung conditions and a healthy control group. TQWT-based signal decomposition was applied and four different feature selectors were used for this purpose. The support vector machine (SVM) algorithm was used as a classifier in the model, and a classification success of 98.53% was reported. Iqbal et al. [19] used machine learning methods for asthma detection on a four-class lung sound dataset comprising 100 normal, 321 wheezes (typical of asthma), 98 stridor, and 73 rattle sounds and attained 100% accuracy. Iqbal et al. [20] proposed a forecasting technique for real-time asthma disease detection on a cough sound dataset of 18 asthma patients and attained 99.91% accuracy. Sen et al. [21] recorded lung sounds with a 14-channel device to discriminate between chronic obstructive pulmonary disease (COPD) and asthma. Multivariate autoregressive model, Gaussian mixture model and SVM were used together. In this study, 98% classification accuracy was achieved using sound samples from 50 subjects. Khan et al. [22] developed a real-time system for real-time asthma detection on lung sounds based on signal normalization and empirical mode decomposition embedded on Raspberry Pi. The model attained 9.40% accuracy. On a lung sound dataset of 64 pneumonia, 48 asthma, and 100 healthy subjects, Yahyaoui and Yumusak [23] applied machine learning to detect pneumonia and asthma with 95.00% accuracy using the

k-nearest neighbor classifier. Topaloglu et al. [24] proposed a ResNet18-based asthma detection model. For this purpose, a sound dataset was created using a digital stethoscope and these sound signals were converted into images using a Mel spectrogram. Next, features were extracted from these images using ResNet18 deep network architecture, and the most significant features were selected by iterative NCA algorithm. The selected features were classified using kNN and SVM algorithms. This model achieved a classification accuracy of 99.73%. Yue and Xu [25] developed an automated asthma and pneumonia detection model based on short-time energy and Mel-frequency cepstral coefficients. Their study of 850 cough sounds recorded from patients attained 93.34% accuracy using a SVM classifier. Tasar et al. [26] developed a piccolo pattern-based respiratory sound classification model. Three cases were created in the research. They classified 7 respiratory diseases including asthma. In the developed model, the kNN algorithm achieved the highest classification success and a classification performance of over 99% was obtained for each case. A small number of asthma detection studies were based on other signal inputs.

1.1 Motivation and our model

The main goal of our research is to design and implement an automated system dedicated to asthma screening. Based on a mobile-based machine learning model, our approach integrates a state-of-the-art feature extractor carefully tailored to the analysis of cough sounds. The ultimate goal is to achieve a higher level of accuracy in asthma detection, providing a solid foundation for the development of an efficient and reliable screening tool. We were motivated to develop an automated system to screen for asthma that is accessible and easy to implement, i.e., computationally lightweight. The reference standard for asthma diagnosis is formal pulmonary function tests, while PEFr measurement may be used for therapeutic monitoring in diagnosed patients. On clinical examination, lung auscultation may uncover wheezing sounds typical of acute asthma attacks, but stethoscopes are not readily available, and lung auscultation requires prior training. Many respiratory conditions, including asthma, present with cough, cough sounds, which can be readily recorded using mobile devices, may contain features that can be used to discriminate the underlying respiratory condition. To validate this hypothesis, a new cough sound-based machine learning model was proposed in this work and tested on a new dataset of cough sounds recorded from more than 1000 participants. We chose handcrafted machine learning over deep learning to economize on computational demands and running time. The proposed model comprised four steps: (i) preprocessing; (ii) feature extraction; (iii) feature selection; and (iv)

classification. Asthma classification using cough sound recordings is technically challenging as they inadvertently contain ambient noise like speech and are of variable duration with inutile time pauses between the actual coughs. Hence, preprocessing was obligatory to remove unwanted speech and ambient noise from the sound signal and segment the signal into standardized segment lengths containing analyzable cough sounds to optimize the fidelity and data efficiency of the input cough sound signals. We used a one-dimensional (1D) version of the popular attractive repulsive center-symmetric local binary pattern (ARCSLBP) image descriptor [27] to extract features from the cough sound signals. However, 1D-ARCSLBP is a handcrafted feature extractor that, by itself, can only generate features at a low level. To overcome this constraint, we applied tunable q-factor wavelet transformation (TQWT) [28] to deconstruct the energy of the cough sound signal effectively into multiple low- and high-frequency wavelet bands. Applying 1D-ARCSLBP to the cough sound input signal and the wavelet subbands could extract features at both low and high levels. A simple neighborhood component function (NCA) [29] feature selector was applied to the extracted features to select the most discriminative features. These were fed to a downstream standard shallow SVM [30, 31] for classification.

1.2 Novelty and contributions

Novel contributions of this work include:

- A new cough sound dataset was acquired from more than 1,000 subjects.
- New preprocessing method for efficient removal of ambient noise, speech, and unwanted pauses in cough sound recordings.
- Handcrafted 1D-ARCSLBP feature extraction enabled the model to inherit known advantages of ARCSLBP [27] for advanced signal processing without the need for parameter tuning.
- Efficient and accurate computationally lightweight architecture built on shallow models that required linear running time to attain excellent performance commensurate with deep models (> 96% classification accuracy) on robust tenfold and LOSO CV.

2 Proposed model

The handcrafted asthma classification model comprised four phases: (i) cough sound signal preprocessing; (ii) TQWT- and 1D-ARCSLBP-based feature extraction; (iii) NCA-based feature selection; and (iv) SVM-based

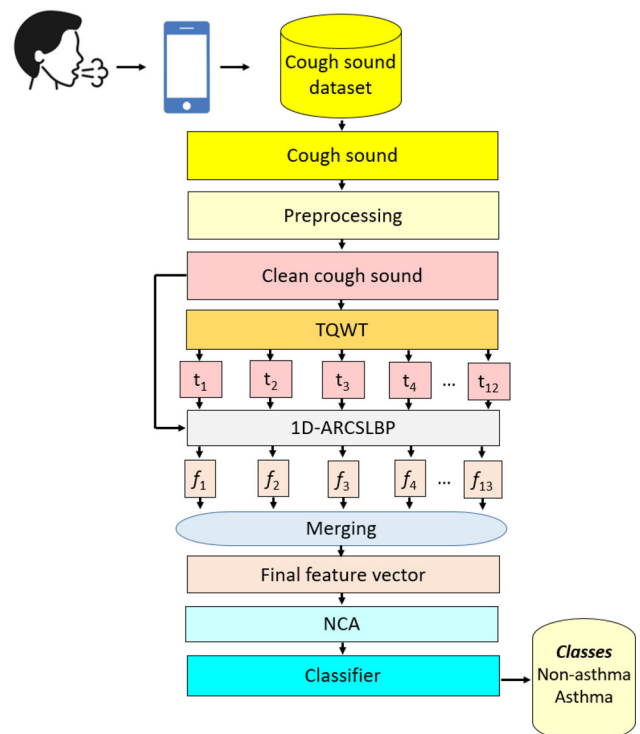


Fig. 1 Block diagram of the proposed 1D-ARCSLBP-based model for asthma classification using recorded cough sounds. First, cough sound signal input samples of variable time lengths were preprocessed to remove ambient speech and segment the samples into one-second segments that each contained an analyzable “clean cough sound”. Next, TQWT was applied to each one-second clean cough sound segment to generate 12 wavelet subbands ($t_1, t_2, t_3, \dots, t_{12}$). Next, 1D-ARCSLBP was applied to the clean cough sound segment and its 12 wavelet subbands to extract low- and high-level features. This yielded 13 feature vectors ($f_1, f_2, f_3, \dots, f_{13}$) each of length 256, which were concatenated into a final feature vector of length 3,328 ($= 13 \times 256$). From the latter, NCA selected the top 100 most discriminative features to feed to the SVM classifier for two-class classification of input cough sound samples into asthma versus non-asthma classes using tenfold and leave-one-subject-out cross-validation strategies

classification using tenfold and LOSO CV (Fig. 1). Details of the steps are explained in the following subsections.

2.1 Preprocessing step

First, the recorded cough sound signal input samples were preprocessed to remove ambient speech using power spectrogram-based classification [32]. This model was used to detect cough sounds. Next, one-second segments containing analyzable “clean cough sound” were sifted from the input samples, which varied in duration, by applying a predetermined threshold (the threshold value is selected as 0.01 dB for these sounds) to remove inutile stop sounds (pauses) between the coughs and a standardized one-second segment length. A result summarizing the effect (before/after) of the Preprocessing step applied to cough

sounds from asthma patients is given in Fig. 2. In addition, the steps of the preprocessing and the pseudocode (Algorithm 1) are given below:

As shown in Fig. 2, a preprocessing step was applied to remove the ambient and stop sounds from the raw signal. This step is effective in improving the accuracy of the proposed model. The steps of the preprocessing process are as follows:

Step 1 Obtain clean sounds from the collected sound samples by removing speech signals.

Step 2 Delete stop sounds (pauses) from the clean sound, retaining only usable cough sounds.

Step 3 Create one-second sound segments containing cough sounds to input into the model.

parameters to assign the wavelet filters: Q (Q -factor) defines the oscillatory value; R is the redundancy value; and J is the number of levels. A multileveled ($J + 1$) wavelet transform is created using J parameters. In this work, we selected Q , R , and J parameter values of 1 (non-oscillatory decomposition), 3, and 11, respectively, to perform 12 levels of signal decomposition to generate 12 wavelet subbands. The signal sampling frequency determined the choice of J parameter value (48 kHz, i.e., each one-second segment contained 48,000 values) and the length of the overlapping block (9) employed in 1D-ARCSLBP-based local textural feature extraction, based on the following calculation: number of levels = 12 ($= \log_2 \frac{48000}{9}$). The steps of the feature extraction are given below:

Step 4 Generate subbands from each sound segment using TQWT.

Algorithm 1 Pseudocode of cough sound preprocessing

<p>Input: Clean sound (S) with a length of len</p> <p>Output: Cough sound segments (cs) with a length of one second</p>
<pre> 01: Remove speech sound on the sound and obtain clean sound. 02: counter = 1; 03: for i=1 to L do // L is the length of the clean sound. 04: thr = $\frac{std(S)}{10}$; // To determine stop/pause sounds, we calculate the threshold (thr) using standard deviation (std(.)) of the signal. 05: if S(i) > thr then 06: CS(counter) = S(i); // Herein, CS is a cough sound. 07: counter = counter + 1; 08: end if 09: end for 10: for j=1 to counter step by fs do // fs is frequency 11: for i=1 to fs do 12: cs(i) = CS(j + i - 1); // Segment creation 13: end for i 14: end for j </pre>

2.2 Feature extraction step

TQWT was used to create wavelet subbands, from which low-and high-level features could be extracted. TQWT is a parametric signal transformation model that uses three

$$w = \phi(cs, 1, 3, 11) \quad (1)$$

where w represents the wavelet subband structure with 12 wavelet subbands; and $\phi(\cdot)$, the TQWT function.

Step 5 Extract features from wavelet subbands and cough segments.

$$f^1 = \varphi(cs) \tag{2}$$

$$f^{i+1} = \varphi(w^i), i \in \{1, 2, \dots, 12\} \tag{3}$$

where $\varphi(\cdot)$ represents the 1D-ARCSLBP function, the pseudocode of which is given below.

Algorithm 2 Pseudocode of 1D-ARCSLBP feature extraction function

```

Input: Signal (sgnl) with a length of ln
Output: Feature vector (fv) with a length of 256

01: Calculate the average value of the signal.  $o_1 = \frac{1}{ln} \sum_{j=1}^{ln} sgnl_j$ 
02: for i=1 to ln - 8 do
03:    $p = sgnl(i:i + 8)$ ; // Overlapping block creation
04:   Calculate the average value of the overlapping block (p).  $o_2 = \frac{1}{9} \sum_{k=1}^9 p_k$ 
05:   Find the median value of the p.  $m = median(p)$ 
// Attractive and repulsive bits' calculation.  $b^a$  and  $b^r$  define attractive and repulsive bits
respectively.
06:    $b_1^a = o_2 \geq p_5$ ;  $b_2^a = o_1 \geq p_5$ ;  $b_3^a = m \geq p_5$ ;
07:    $b_1^r = o_2 \leq p_5$ ;  $b_2^r = o_1 \leq p_5$ ;  $b_3^r = m \leq p_5$ ;
08:   for j=4 to 7 do
09:      $b_j^a = (p_{j-3} \geq p_5) \times (p_{13-j} \geq p_5)$ ;
10:      $b_j^r = (p_{j-3} \leq p_5) \times (p_{13-j} \leq p_5)$ ;
11:   end for j
12:    $map^1(i) = 0$ ;  $map^2(i) = 0$ ; // Map signal creation by deploying binary to decimal
13:   for j=1 to 7 do
14:      $map^1(i) = \sum_{j=1}^7 br_j^a \times 2^{7-j}$ ;
15:      $map^2(i) = \sum_{j=1}^7 br_j^r \times 2^{7-j}$ ;
16:   end for j
17: end for
18:  $h^1 = \delta(map^1)$ ;  $h^2 = \delta(map^2)$ ; //  $\delta(\cdot)$  is histogram extraction function.
19:  $feat = merge(h^1, h^2)$ ; //  $merge(\cdot)$  is concatenating/merging function.

```

From algorithm 2, it can be seen that 1D-ARCSLBP generated seven attractive and seven repulsive bits per run. Two map signals were generated from each bit by deploying these attractive and repulsive bits. By extracting the histograms of these map values, $2 \times 2^7 = 256$ features were obtained. A block diagram summarizing Algorithm 2 is given in Fig. 3.

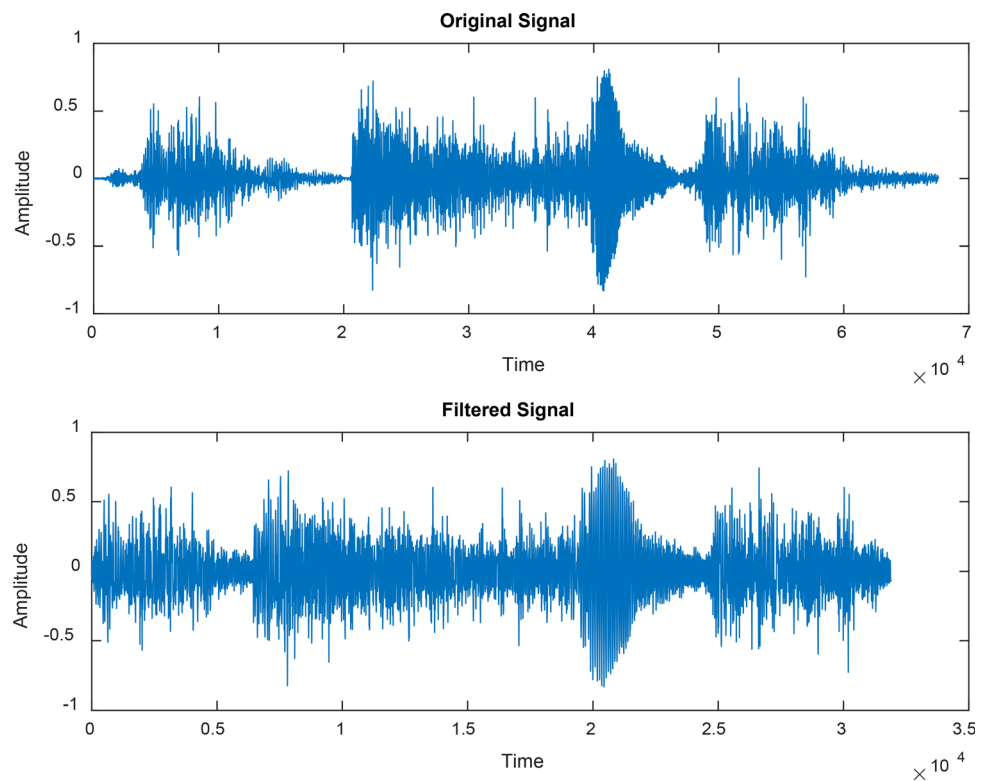
As can be seen in Fig. 3, the median value of both the main signal and the overlapping block is calculated. In addition, the mean value of the overlapping block is determined. These values are then compared with the

center value of the overlapping block. In this way, the first three bits of the attractive and repulsive bits are determined. The remaining four bits are obtained by sequential comparison. After this process, the attractive and repulsive

bits are converted to decimals and added to the map signal. Finally, histograms are extracted using the map signal, and the two histograms are combined to obtain the feature vector.

Step 6 Concatenate all features generated from the cough sound segment and its 12 subbands into a final feature vector.

Fig. 2 Before and after the preprocessing step



$$X(d, j + 256 \times (i - 1)) = f^i(d, j), d \in \{1, 2, \dots, \dim\}, \quad (4)$$

$$i \in \{1, 2, \dots, 13\}, j \in \{1, 2, \dots, 256\}$$

where X represents the final feature generated, and \dim is the dimension of the dataset (number of signals). The length of X is 3328 ($= 13 \times 256$).

2.3 Feature selection step

NCA, a simple but effective feature selector, was deployed to select the 100 most discriminative features from 3328 features in X based on the calculated individual feature weights, which represented the distinctive level of each feature. The main purpose of NCA is to bring together similar instances in the feature space and to remove instances belonging to different classes from each other. For this purpose, NCA optimizes an objective function. This function measures the similarity of a given pair of instances. In this research, the top 100 features were chosen on the qualified feature vector by sorting these features in descending order. Detailed steps of feature selection are given below:

Step 7 Apply NCA to the generated features to calculate 3,328 individual weights.

Step 8 Sort these weights and obtain sorted indexes.

Step 9 Choose the best 100 features.

2.4 Classification step

We used cubic SVM [33], a standard shallow classifier, for the two-class classification of input cough sound segments into asthma versus non-asthma classes. The main goal of SVM is to classify a dataset into two or more classes. In the case of binary classification, SVM tries to find a hyperplane that separates the classes as clearly as possible. In this paper, default hyperparameter settings were employed:

Kernel: polynomial;

Polynomial order: three;

Kernel scale: automatic;

Box constraint: one;

Validation: tenfold CV and LOSO CV.

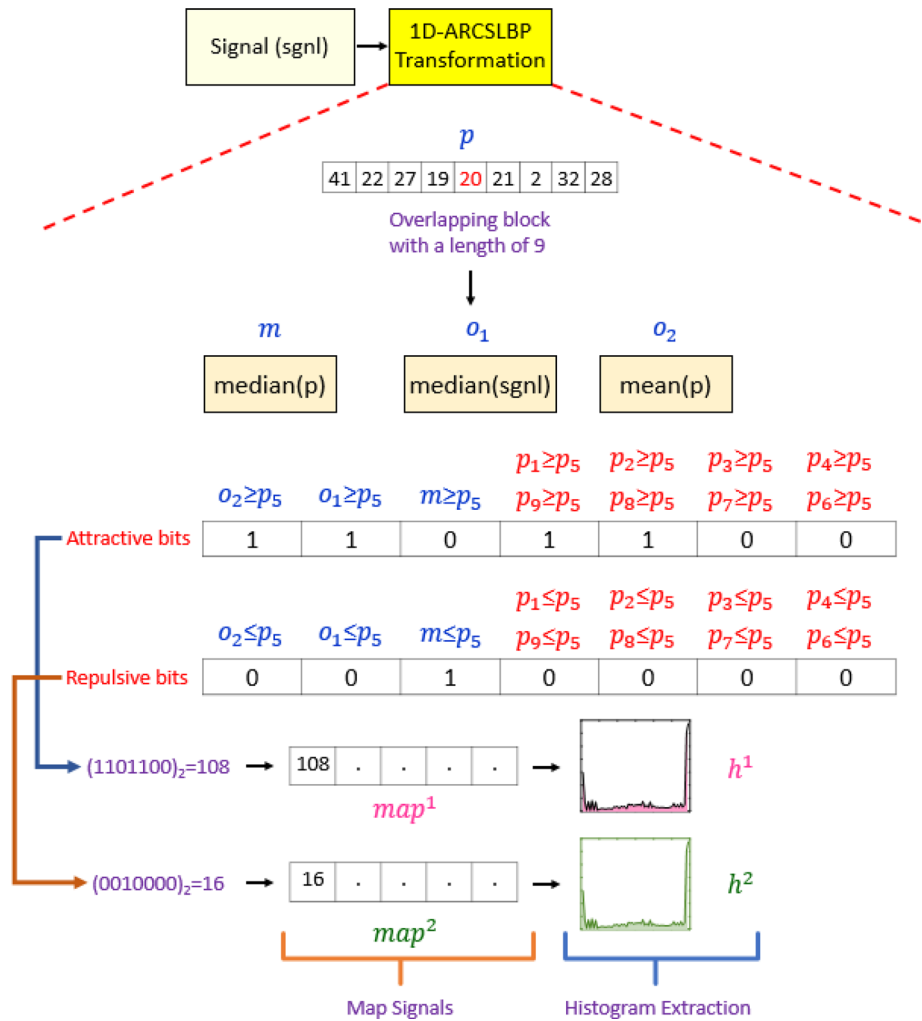
Step 10 Classify the top 100 features by deploying SVM with tenfold and LOSO CVs.

3 Experiments

3.1 Experimental setup

The model was implemented in central processing unit mode on a personal computer with the following specifications: 16 GB memory, 512 GB solid-state disk, Intel i7 processor with a 4.3 GHz clock, and Windows 11 operating system. MATLAB programming environment was used

Fig. 3 1D-ARCSLBP feature extraction method proposed in this work



in the model development process and the toolboxes, and libraries used in this process are listed in Table 1.

3.2 Dataset

The dataset comprised 994 and 881 cough sound recordings obtained from 511 asthmatics (103 male, 408 female; mean age 55.23 ± 14.97 years, range 10–2 years) and 815 non-asthmatic subjects (509 male, 306 female; most of the subjects in this group were healthy university students without a history of asthma), respectively. The cough sounds were recorded with varying durations in the hospital environment using a Samsung S6 Edge mobile phone. All recordings have a sampling frequency of 48 kHz. The duration of cough sound recordings obtained from 511 asthmatics ranges from a minimum of 0.5 s to a maximum of 6.59 s. Recordings from non-asthmatic subjects vary in length, ranging from 0.23 to 5.42 s. The cough sound recordings obtained from the subjects are in.wav file format. The hospital ethics committee had approved the retrospective collection of the cough sound dataset.

3.3 Performance evaluation metrics

For the evaluation of model performance for binary classification into asthma versus non-asthma classes, standard metrics were calculated: accuracy, sensitivity, specificity, precision, geometric mean (of sensitivity and specificity), and F1-score (harmonic mean of sensitivity and precision) [34, 35]. The mathematical equivalents of these performance metric values are given in Eqs. (5)–(10).

$$\text{Accuracy} = \frac{\text{TruePositives} + \text{TrueNegatives}}{\text{TotalExamples}} \tag{5}$$

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{TruePositives} + \text{FalseNegatives}} \tag{6}$$

$$\text{Specificity} = \frac{\text{TrueNegatives}}{\text{FalsePositives} + \text{TrueNegatives}} \tag{7}$$

$$\text{Precision} = \frac{\text{TruePositives}}{\text{TruePositives} + \text{FalsePositives}} \tag{8}$$

Table 1 Details of the programming platform

Features	Value
Programming platform	MATLAB
Version	2022a
Toolboxes	MATLAB Classification Learner Toolbox for classification step TQWT for signal decomposition step

$$\text{Geometricmean} = \sqrt{\text{Sensitivity} \times \text{Specificity}} \tag{9}$$

$$F1\text{score} = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \tag{10}$$

$$= c_1 + L \times (c_2 + c_3 + c_4 + c_5 + c_6) + c_2 + c_7 \times \text{cnt} + f \times (c_8 + c_9) + c_8 \tag{12}$$

$$= O(n) \tag{13}$$

3.4 Results

Our model attained excellent results for binary classification of cough sounds into asthma versus non-asthma classes, with 98.24% and 96.91% accuracy rates on tenfold and LOSO CV (Table 2).

These metrics highlight the robust performance of our model, showcasing its accuracy, sensitivity, specificity, precision, geometric mean, and F1-score across different cross-validation techniques. As shown in Table 2, the proposed method achieves a very high classification success for both cross-validation techniques (98.24% and 96.91%). In addition, when the F1-score result is analyzed, a very high-performance value is achieved. This result demonstrates the ability of the proposed model to strike a harmonious balance between precision and sensitivity.

3.5 Time burden

The time complexity of our model, shown for every layer using big O notation, is shown in Table 3,

As can be seen in Table 3, the approximate computational complexity of the proposed method is $O(n + k + d)$. Feature selection and classification steps are well-known methods in the literature, and their complexities are $O(k)$ and $O(d)$, respectively. The preprocessing and feature extraction steps consist of multiple phases. In this context, the time complexity of preprocessing (Algorithm 1) is analyzed in detail in Table 4.

When the analysis is performed using the cost and time information given in Table 4, the time complexity of the preprocessing step is given below:

$$\begin{aligned} \text{Total time cost} = & c_1 \times 1 + c_2 \times (L + 1) + c_3 \times L + c_4 \times L \\ & + c_5 \times L + c_6 \times L + c_7 \times \text{cnt} + c_8 \\ & \times (f + 1) + c_9 \times f \end{aligned} \tag{11}$$

Herein, c represents the cost and L represents the length of the signal. The values of cost, cnt and f are neglected in the algorithmic analysis. In addition, since $L \cong n$, the time complexity of the preprocessing step is $O(n)$. The next phase of the proposed model is feature extraction. In this phase, the signal is decomposed into 12 levels using the TQWT algorithm. Then, features are extracted from both the raw signal and the subbands using the 1D-ARCSLBP method. The pseudo code for this process is given in Algorithm 3, and the time complexity calculated using this algorithm is shown in Table 5.

As shown in Table 5, the proposed methods consist of TQWT-based signal decomposition and 1D-ARCSLBP. Since TQWT is a signal decomposition process, the computational complexity of this step is $O(\log n)$. In addition, an analysis of the computational complexity of the 1D-ARCSLBP method is given in Eqs. (14)-(19).

$$\begin{aligned} \text{Total time complexity} = & \text{number of levels(TQWT)} \times \text{1D} \\ & - \text{ARCSLBP} \end{aligned} \tag{14}$$

$$\text{TQWT signal decomposition complexity} \cong O(\log n) \tag{15}$$

Table 2 Performance of the 1D-ARCSLBP-based cough sound classification model for asthma detection

Performance metrics	Results (%)	
	Tenfold CV	LOSO CV
Accuracy (%)	98.24	96.91
Sensitivity (%)	98.19	96.08
Specificity (%)	98.30	97.84
Precision (%)	98.49	98.05
Geometric mean (%)	98.24	96.96
F1-score (%)	98.34	97.09

CV cross-validation, LOSO leave-one-subject-out

Table 3 Transition table of the proposed model

Steps involved	Time complexity
Preprocessing step	$O(n)$
Feature extraction	$O(n \log n)$
Feature selection	$O(k)$
Classification	$O(d)$

$$\begin{aligned}
 &= O(\log n) \times [(c_1 \times 1 + c_2 \times (\ln - 7) + c_3 \times (\ln - 8) \\
 &\quad + c_4 \times (\ln - 8) + c_5 \times (\ln - 8) + c_6 \times (\ln - 8) + c_7 \\
 &\quad \times (\ln - 8) + c_8 \times (4 \times (\ln - 8) + 1) + c_9 \times (4 \times (\ln - 8)) \\
 &\quad + c_{10} \times (4 \times (\ln - 8)) + c_{11} \times (\ln - 8) + c_{12} \times (7 \times (\ln - 8) + 1) \\
 &\quad + c_{13} \times (7 \times (\ln - 8)) + c_{14} \times (7 \times (\ln - 8)) \\
 &\quad + c_{15} \times 2 + c_{16} \times 1] \tag{16}
 \end{aligned}$$

$$\begin{aligned}
 &= O(\log n) \times [c_1 + \ln(c_2 + c_3 + c_4 + c_5 + c_6 + c_7 + 4 \\
 &\quad \times (c_8 + c_9 + c_{10}) + c_{11} + 7 \times (c_{12} + c_{13} + c_{14}) - 7 \\
 &\quad \times c_2 - 8 \times (c_3 + c_4 + c_5 + c_6 + c_7 + c_{11}) - 31 \\
 &\quad \times c_8 - 32 \times (c_9 + c_{10}) - 55 \times c_{12} - 56 \\
 &\quad \times (c_{13} + c_{14}) + c_{15} \times 2 + c_{16}] \tag{17}
 \end{aligned}$$

$$= O(\log n) \times O(n) \tag{18}$$

$$\text{Totaltimecost} = O(n \times \log n) \tag{19}$$

As shown in Eq. (19), the total computational complexity of the TQWT-based 1D-ARCSLBP method is $O(n \log n)$. In this context, considering all the steps performed, the preprocessing step is $O(n)$, feature extraction step is $O(n \log n)$, feature selection step is $O(k)$, and classification step is $O(d)$. As a result of these calculated values, the time complexity of the model developed in this research is $O(n \log n + k + d)$.

4 Discussion

In this work, we have presented a new 1D-ARCSLBP-based cough sound classification architecture that was tested on a new two-class asthma cough sound dataset collected from more than 1000 patients. We were motivated by the success of ARCSLBP-based feature extraction in computer vision applications to develop a novel asthma cough sound classification model using a one-dimensional version of this feature extractor (1D-ARCSLBP). TQWT was incorporated to generate multilevel wavelet subbands from which both low- and high-level features could be extracted, effectively surmounting 1D-ARCSLBP’s ability to extract only low-level features. As a result of our

conscious decision to employ only shallow functions, our model possessed a low-time burden (Table 3). Despite this, our handcrafted multileveled feature extraction-based architecture attained excellent performance with 98.24% and 96.91% accuracy rates on tenfold and LOSO CV, which is better than or commensurate with other state-of-art methods, including deep models (Table 6).

As shown in Table 6, the 1D-ARCSLBP and NCA-based model, which is a lightweight method proposed in this research, was validated by applying LOSO and tenfold CV strategies. In this context, a classification success of 96.91% for LOSO CV and 98.24% for tenfold CV was achieved. The dataset used in this research is larger than most of the state-of-the-art methods in the literature [21, 37, 39–41, 43]. In addition, two different validation strategies were used in this research. These strategies increase the reliability of the results obtained using the proposed method. The proposed method provides a lightweight solution according to the literature [24]. Tasar et al. [26] used 8 classes in their research. However, the computational complexity of the method used in this study is higher than our model. The LOSO strategy, which is used to ensure the generalizability of the results, has been used in only two studies [18, 43]. One of these studies, Singh et al. [43] achieved 94.52% classification success and the size of the dataset used in this study is quite small. Kilic et al. [18] achieved a higher classification success than our model. However, the computational complexity of the model developed in this research is higher than our model. In this context, when state-of-the-art methods are analyzed, the automatic asthma detection model presented in this research is more efficient in terms of both classification performance and computational complexity.

The model developed in this work uses the SVM algorithm as the classification method. In addition to this algorithm, some well-known classification algorithms in the literature were also tested. These are k-nearest neighbor (kNN), artificial neural network (ANN), decision tree (DT), and random forest (RF) algorithms. The SVM algorithm showed the best performance among these methods and the calculated classification accuracies (for tenfold CV) are comparatively given in Fig. 4.

As shown in Fig. 4, the best classification performance was obtained with the SVM algorithm. The DT algorithm showed the lowest classification performance with about 73%.

The advantages and limitations of our model are discussed below.

Advantages:

- A learning architecture was built using novel 1D-ARCSLBP and other shallow methods. While computationally lightweight, it was demonstrated to be highly

Table 4 Detailed computational complexity analysis of the preprocessing step

Input: Clean sound (S) with a length of L Output: Cough sound segments (cs) with a length of one second	Cost	Times
01: Remove speech sound on the sound and obtain clean sound.	-	-
02: $counter = 1$;	c_1	1
03: for $i=1$ to L do // L is the length of the clean sound.	c_2	$L + 1$
04: $thr = \frac{std(S)}{10}$;	c_3	L
// To determine stop/pause sounds, we calculate the threshold (thr) using standard deviation ($std(.)$) of the signal.	-	-
05: if $S(i) > thr$ then	c_4	L
06: $CS(counter) = S(i)$; // Herein, CS is a cough sound.	c_5	L
07: $counter = counter + 1$;	c_6	L
08: end if	-	-
09: end for	-	-
10: for $j=1$ to $counter$ step by fs do // fs is frequency	c_7	cnt
11: for $i=1$ to fs do	c_8	$f + 1$
12: $cs(i) = CS(j + i - 1)$; // Segment creation	c_9	f
13: end for i	-	-
14: end for j	-	-

accurate when tested on a new asthma cough sound dataset comprising 1,875 samples recorded from 1,326 hospitalized subjects.

- Over 96% accuracy rates for binary classification into asthma versus non-asthma classes were attained by deploying robust validation techniques. In particular, the LOSO CV results support the readiness of the model for implementation in real-world applications, e.g., in the clinic or hospital ward.
- Our proposed architecture has linear time complexity ($O(n \log n + k + d)$), is very simple, and can be coded by researchers/developers efficiently.

Limitations:

- The cough sounds were collected from a single center. The reliance on data from a solitary center may introduce potential biases and limit the generalizability of our findings. The specificity of the dataset to a particular demographic, environmental conditions, or healthcare setting raises concerns about the external validity of our model. The potential consequences of this constraint include the risk of model overfitting to

the characteristics unique to the single-center dataset. Variabilities in cough sound patterns influenced by regional accents, environmental factors, or demographic differences may not be adequately captured. Consequently, the model may exhibit reduced performance when applied to diverse populations or alternative healthcare environments. However, in future works, multiple centers can contribute to a common larger dataset. Collaboration with multiple institutions or leveraging existing databases with diverse samples could be instrumental in addressing this limitation.

- Cubic SVM was implemented with default settings. The use of default settings without hyperparameter optimization may result in suboptimal model performance. Cubic SVM has hyperparameters that, if left unoptimized, might not be well-suited for the specific characteristics of the dataset. This could lead to issues such as underfitting or overfitting, compromising the model's ability to generalize to new, unseen data. Hyperparameters can be further tuned using an optimizer to obtain better classification results. By optimizing hyperparameters, researchers can fine-tune the

Table 5 Detailed computational complexity analysis of the feature extraction step

Input: Signal (<i>sgnl</i>) with a length of <i>ln</i>	Cost	Times
Output: Feature vector (fv) with a length of 256		
00: TQWT	-	-
01: Calculate the average value of the signal. $o_1 = \frac{1}{ln} \sum_{j=1}^{ln} sgnl_j$	c_1	1
02: for $i=1$ to $ln - 8$ do	c_2	$(ln - 8) + 1$
03: $p = sgnl(i:i + 8)$; // Overlapping block creation	c_3	$ln - 8$
04: Calculate the average value of the overlapping block (<i>p</i>). $o_2 = \frac{1}{9} \sum_{k=1}^9 p_k$	c_4	$ln - 8$
05: Find the median value of the <i>p</i> . $m = median(p)$	c_5	$ln - 8$
// Attractive and repulsive bits' calculation. b^a and b^r define attractive and repulsive bits respectively.	-	-
06: $b_1^a = o_2 \geq p_5$; $b_2^a = o_1 \geq p_5$; $b_3^a = m \geq p_5$;	c_6	$ln - 8$
07: $b_1^r = o_2 \leq p_5$; $b_2^r = o_1 \leq p_5$; $b_3^r = m \leq p_5$;	c_7	$ln - 8$
08: for $j=4$ to 7 do	c_8	$4 \times (ln - 8) + 1$
09: $b_j^a = (p_{j-3} \geq p_5) \times (p_{13-j} \geq p_5)$;	c_9	$4 \times (ln - 8)$
10: $b_j^r = (p_{j-3} \leq p_5) \times (p_{13-j} \leq p_5)$;	c_{10}	$4 \times (ln - 8)$
11: end for j		
12: $map^1(i) = 0$; $map^2(i) = 0$; // Map signal creation by deploying binary to decimal	c_{11}	$ln - 8$
13: for $j=1$ to 7 do	c_{12}	$7 \times (ln - 8) + 1$
14: $map^1(i) = \sum_{j=1}^7 b_j^a \times 2^{7-j}$;	c_{13}	$7 \times (ln - 8)$
15: $map^2(i) = \sum_{j=1}^7 b_j^r \times 2^{7-j}$;	c_{14}	$7 \times (ln - 8)$
16: end for j	-	-
17: end for	-	-
18: $h^1 = \delta(map^1)$; $h^2 = \delta(map^2)$; // $\delta(\cdot)$ is histogram extraction function.	c_{15}	2
19: $feat = merge(h^1, h^2)$; // $merge(\cdot)$ is concatenating/merging function.	c_{16}	1

model to extract the best possible performance from the chosen algorithm, ensuring it aligns with the specific characteristics of the data.

Potential advantages and challenges in clinical applications:

- The successful translation of our proposed model from a research context to practical, real-world scenarios, such as clinics or hospital wards, holds significant

potential. The model's high accuracy in asthma screening can facilitate early detection of the condition. This, in turn, enables prompt intervention and treatment, potentially improving patient outcomes and reducing the burden on healthcare resources.

- By automating the screening process, the proposed model has the potential to optimize healthcare resources. Clinics and hospital wards can allocate personnel more efficiently, directing attention to

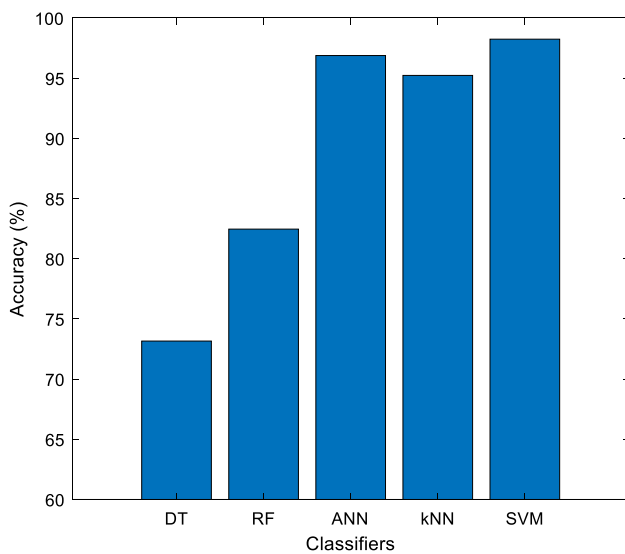
Table 6 Comparison of automated asthma detection models

Study	Method	Classifier	Subjects (n)	Split ratio	Classes(n)	Results (%)
Kilic et al. [18]	Global chaotic logistic pattern and four feature selector	SVM	815 non-asthma, 613 asthma; 1428 segments	LOSO	2	Acc 98.53 Pre 98.54 Sen 98.86 Spe 98.90 Gm 98.88 F1 99.14
Sen et al. [21]	Gaussian mixture model and multivariate autoregressive model	SVM	20 COPD, 30 asthma	tenfold CV	2	Acc 97.5
Topaloglu et al. [24]	Mel spectrogram conversion and attention ResNet18	SVM	767 asthma, 722 non-asthma; 1489 segments	tenfold CV	2	Acc 99.73
Tasar et al. [26]	Piccolo pattern and iterative NCA	kNN	458 URTI, 695 healthy, 1294 COPD, 320 Bronchiectasis, 740 Pneumonia, 260 Bronchiolitis, 20 Asthma 40 LRTI 3827 segments	tenfold CV	8	Acc 98.95 Pre 98.56 Sen 98.99 Gm 98.98 F1 98.77
Badnjevic and Pokvić [36]	ANN	Neural network	522 healthy, 728 asthma; 1800 samples	80:20	2	Acc 98.85 Sen 97.11 Spe 98.85
Islam et al. [37]	Welch's method, Z-score normalization, statistical features	ANN, SVM	30 healthy, 30 asthma	58:2	2	Acc 93.30 Sen 93.30 Spe 93.30
Naqvi et al. [38]	Spectral analysis	SVM	100 healthy, 100 asthma, 100 pneumonia; 3000 samples	fivefold CV	3	Acc 96.70
Nabi et al. [39]	Integrated power features	kNN	55 asthma (mild, moderate, severe); 775 samples	tenfold CV	3	Acc 100.0
Badnjevic et al. [40]	Neuro-fuzzy system	ANN	37 healthy, 170 asthma 248 pneumonia; 700 samples	80:20	3	Acc 99.41
Shaharum et al. [41]	Mel-frequency cepstral coefficients	kNN	30 mild asthma, 20 moderate asthma, 35 severe asthma	70:30	3	Acc 97.50
Khasha et al. [42]	Time-series feature extraction	Time-series ensemble learning	96 asthma; 2870 samples	tenfold CV	3	Acc 92.10 Sen 87.00 Spe 94.00
Singh et al. [43]	Quantitative analysis	SVM	43 healthy, 30 asthma	LOSO CV	2	Acc 94.52 Sen 97.67 Spe 90.00

Table 6 (continued)

Study	Method	Classifier	Subjects (n)	Split ratio	Classes(n)	Results (%)
Our method	1D-ARCSLBP- and NCA-based model	SVM	815 non-asthma, 511 asthma; 1875 segments	1. LOSO 2. tenfold CV	2	1 Acc: 96.91 Sen: 96.08 Spe: 97.84 Pre: 98.05 Gm: 96.96 F1: 97.09 2. Acc: 98.24 Sen: 98.19 Spe: 98.30 Pre: 98.49 Gm: 98.24 F1: 98.34

**ANN artificial neural network; CV cross-validation; kNN k-nearest neighbor; LOSO leave-one-subject-out; NCA neighborhood component analysis; SVM support vector machine

**Fig. 4** Summary of classification results obtained with tenfold CV

confirmed cases while streamlining the diagnostic workflow.

- Seamless integration with existing healthcare systems can enhance the model's adoption. Compatibility with Electronic Health Records (EHR) or other clinical databases ensures a smooth incorporation into routine medical practices.
- The challenges associated with diverse patient populations and varied cough sound characteristics across different clinical settings may affect the model's generalizability. Addressing this requires continuous

validation and adaptation of the model to accommodate diverse datasets.

- Ensuring regulatory compliance and adherence to healthcare standards are paramount. The proposed model must meet stringent regulatory requirements to guarantee patient safety and data security, adding an extra layer of complexity to implementation.

Clinician acceptance and training are crucial factors for successful integration. Clinicians may initially be skeptical of automated systems, and effective training programs must be implemented to familiarize healthcare professionals with the model's capabilities and limitations.

5 Conclusions

Using a novel 1D-ARCSLBP feature extractor, a new hand-modeled architecture was proposed and studied on a new large cough sound dataset that comprised 1875 cough sound segments acquired from 1326 participants. Our model attained excellent 98.24% and 96.91% accuracy rates using tenfold and LOSO CV, respectively. Moreover, the model possessed a low-time complexity of $O(n \log n + k + d)$. The excellent results confirmed the feature extraction capability of 1D-ARCSLBP on cough sound signals. In addition, the low-computational demands and ease of implementation position our model favorably against published state-of-the-art models, demonstrating that our model is ready to be developed into a real-world application.

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Data availability The data presented in this study are available on request from the corresponding author. The data are not publicly available due to restrictions regarding Ethical Committee Institution.

Declarations

Conflict of interest The authors of this manuscript declare no conflicts of interest.

Ethical approval This research has been approved on ethical grounds by the Non-Interventional Research Ethics Board Decisions, Firat University, on 7 June 2022 (2022/08–27).

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