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Spectral features and optimal Hierarchical Attention Networks for Pulmonary abnormality detection from the Respiratory Sound signals

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Abstract: The most important concern in the medical field is to consider the analysis of data and perform accurate diagnosis. However, the analysis of pulmonary abnormalities may depend on the diagnostic experience and the medical skills of the physicians, and is a time-consuming practice. In order to solve such issues, an efficient Water Cycle Swarm Optimizer-based Hierarchical Attention Network (WCSO-based HAN) is developed for detecting the pulmonary abnormalities from the respiratory sounds signals. However, the developed optimization technique named WCSO is devised by incorporating the Water Cycle Algorithm (WCA) with Competitive Swarm Optimizer (CSO). Here, the pre-processing is performed using the Hanning window and Spectral gating-based noise reduction method in order to remove the falsifications or noises from the signal. Thereafter, the process of feature extraction is carried out to extract the significant features, such as Bark frequency Cepstral coefficient (BFCC) and the short term features, such as spectral flux and spectral centroid. Once the significant features are extracted, classification is performed using HAN where the training procedure of HAN is carried out using WCSO. Furthermore, the developed WCSO-based HAN obtained efficient performance using True Positive Rate (TPR), True Negative Rate (TNR) and accuracy with the values of 0.943, 0.913, and 0.923 using dataset 1, respectively.

Keywords: Water Cycle Algorithm (WCA), Bark frequency Cepstral coefficient (BFCC), Hierarchical Attention Network, Deep Neural Network (DNN)

1. Introduction

Pulmonary disease is a kind of sickness that affects the lungs and various parts of the respiratory system. Lung diseases are the third major reason for the occurrence of the death in world [1]. According to World Health Organization (WHO), the five main respiratory diseases, such as acute lower respiratory tract infection (LRTI), asthma, chronic obstructive pulmonary disease (COPD), tuberculosis, and lung cancer cause the death of more than 3 million people all over the world [5]. In addition, respiratory diseases may occur due to some environmental factors, namely genetic factors, infections, pollutions, seasonal variations, and human-induced factors, like utilization of tobacco, age and work-related factors. Meanwhile, the respiratory diseases contain curable and chronic phases for attaining healthy individuals, while COPD failed to overcome various symptoms. It is a chronic procedure that can be controlled and prevented from internal severities [7]. This type of respiratory diseases harshly affects the entire healthcare method and badly affects the life of human. Avoidance, earlier analysis and proper treatment are the chief factors for restricting harmful impact of these toxic diseases [5]. Moreover, respiratory sounds produced from the airways and the lungs offer essential information regarding their pathologies and physiologies [4] [21]. The respiratory sounds are categorized in two classes, like normal and abnormal based on acoustic

sound created from lungs. The normal and abnormal pulmonary sounds can be distinguished by the anomalies coming from the lungs. Several medical strategies and diagnostic tools are utilized by clinical experts for diagnosing the lung sound into pathological and normal one [20] [9].

Respiratory sounds offer significant information regarding the lungs of the patients. The auscultation of lung sounds is a primary module of diagnosing the pediatric lung disease, analogous to the diagnosis of bronchitis, sleep, and apnea pneumonia [16] [5]. Rhonchus, squawk, crackle, wheeze, stridor, and pleural rub are the frequently recognized anomalous lung sounds. These abnormalities can be differentiated from the normal lung sounds based on timbre, pitch, frequency, intensity, musicality, and energy [17] [5]. Rhonchi and crackles are the widespread adventitious sounds of lungs. Crackles are explosive sounds, which occur due to the watery bubbles in the bronchial tubes or tracheas, whereas rhonchis occur caused due to the blocked pulmonary airways as the air passes by the tubes. The assessment of crackles and rhonchis is very imperative in diagnosing the lung diseases [3]. Consequently, the sound from the lungs is important for identifying the particular respiratory diseases and thereafter analyzing its characteristics on the basis of chronic and non-chronic. However, the slight differences among the adventitious classes of lung sounds can be a tough job even for a medical expert, and hence established a subjectivity in the analytic interpretation [18] [5]. Moreover, the respiratory sounds are considered as the auscultated noninvasive feature sounds produced by breathing passage through the airways, and also by other respiratory systems by the exhalation and the inspiration process. The audible forms and adventitious forms of the respiratory sounds are not easy to hear with no diagnostic tools. Nowadays, respiratory sound auscultation remains as an important experimental tool, which is the most common, precise and necessary investigative instrument for several pulmonologist clinicians. Lung auscultation from diverse areas builds an insight for analysis and describing the disorder levels [7].

The auscultation relies very much on the diagnostic experience and the medical skills of the physician, which are more complicated to attain. Based on the computer-driven respiratory sounds, recognition of automatic lung sounds using machine learning has a vital experimental implication for diagnosing the abnormal activities in the lungs [11] [3]. Recently, deep learning approaches have attained significant attraction in biomedical engineering and clinical diagnostics due to its unparalleled success [12]. A major benefit of utilizing deep learning paradigms is that it is not necessary to craft the features from data manually as the network learns the abstract representations and functional features from data during training. Due to the progressive growth of convolutional neural networks (CNN) in image classification process, these networks are widely accomplished in biomedical research fields for anomaly recognition [13], image classification, image augmentation, computerized report generation, and image segmentation [14]. Moreover, there are various advanced applications of deep CNNs in analyzing the cardiac diseases, cancer, ophthalmic diseases, and neurological diseases. The existing natural language processing (NLP) techniques, speech and audio processing employ deep RNNs for learning temporal and sequential features [15][4]. With the potential of automated feature learning, deep learning approaches are more standard and can diminish boundaries of conventional ML-driven techniques, thereby exposed very much promising performance [19] [5].

The major contribution of this research is to devise a proposed WCSO-based HAN for detecting the pulmonary abnormalities. At first, the respiratory sound signal is acquired from the dataset, and then the input signal is pre-processed using the Hanning window and the spectral gating-based noise reduction. Thereafter, significant features, namely BFCC, spectral

flux and spectral centroid are effectively extracted. Finally, the pulmonary abnormality classification is performed using the HAN classifier. Furthermore, the training procedure of HAN classifier is carried out by developed WCSO algorithm, which is designed by the incorporation of WCA and CSO, respectively.

The key part of the research is illustrated as follows:

- ❖ **Developed WCSO-based HAN:** An effective pulmonary abnormality detection approach is devised using proposed WCSO-based HAN. Here, the HAN classifier is employed for the effective classification of pulmonary abnormalities where the training procedure of HAN is performed by the developed optimization algorithm, named WCSO technique, respectively.

The remaining sections of research paper are arranged as follows: section 2 presents the literature review and also the challenges faced by various existing abnormality detection techniques based on the respiratory sound signals, section 3 elaborates about the proposed WCSO-based HAN method, section 4 portrays the experimental outcomes of proposed technique, and the conclusion of research work is presented in section 5.

2. Motivations

This section presents the various abnormality detection techniques based on the respiratory sound signals along with their advantages and drawbacks, which motivate the researchers to design the proposed WCSO-based HAN method.

2.1 Literature Survey

The different existing abnormality detection approaches on the basis of respiratory sound signals are reviewed in this section as follows, Bruno M. Rocha *et al.* [1] devised a Public respiratory sound database for evaluating respiratory sound classification. This technique provided accurate clinical signals, but this technique failed to avoid confounding noises. Alfonso Monaco *et al.* [2] designed a multi-time-scale machine learning framework for classifying respiratory sounds like wheezes and crackles. This approach consists of three different phases, such as data standardization, multi-time-scale feature extraction, and categorization phase. This technique was capable of discriminating the well controls from the patients with the symptoms of respiratory issues. This technique was more suitable for large-scale applications. However, this technique failed to recognize the significant sounds at the respiratory cycle level. Fei Meng *et al.* [3] introduced a machine learning technique for detecting the respiratory sounds using wavelet coefficients. This technique effectively incorporated wavelet signal similarity with wavelet entropy and the relative wavelet energy. This approach achieved better classification accuracy. However, the normalization phase may leads to an accumulation of errors. Jyotibdha Acharyay, and Arindam Basu [4] developed deep CNN-RNN model for classifying the respiratory sounds using Mel spectrograms. Here, a local log quantization of trained weights is used for significantly reducing the memory requirements. This approach achieved substantial weight compression without any adjustments in the architectural model. However, this approach failed to minimize the cost of computation.

Samiul Based Shuvo *et al.* [5] devised a light weight CNN model for classifying the respiratory diseases using hybrid scalogram features. This technique achieved higher accuracy for classifying the ternary chronic diseases, but failed to implement this approach in real-world clinical applications. Hai chen *et al.* [6] designed an optimized S-transform and

deep residual networks for recognizing respiratory sounds, like crackles, wheezes, and normal sounds. This technique offered cost-effective telemedicine analysis of respiratory diseases. However, this technique failed to perform multi-classification in order to yield effective results. Gokhan Altana *et al.* [7] presented a Second order difference plot (SODP) approach for classifying respiratory sounds. It was a non-linear approach that analyzes the correlation among the consecutive data points in three dimensional spaces by utilizing the chaos theory. This technique was easily incorporated with the diagnostic tools for achieving effective results, and also offered detailed analysis with respect to the left and right lungs, but the computational cost was high in this method. Siddhartha Gairola *et al.* [8] introduced a Deep Neural Network (DNN) for finding the anomalous lung sounds accurately. This approach was easily incorporated with other frameworks to minimize the computational complexities. However, this model failed to utilize larger datasets in order to achieve effective results.

2.2 Challenges

The issues faced by various abnormality classification techniques based on the respiratory sound signals are described as follows,

- The major limitation in multi-scale machine learning framework developed in [2] is the lack of ability for recognizing the significant sounds at the phase of respiratory cycle. Moreover, deep learning techniques, such as Long Short-Term Memory (LSTM) and ResNet was failed to enhance the classification performance.
- The machine learning method employed in [3] achieved good performance, but it failed to incorporate the respiratory sounds with various medical parameters, like spirometry parameters for providing intellectual disease recognition system.
- The machine learning-based automatic classification approach is introduced in [9] efficiently classified the abnormal and the normal pulmonary sounds. However, it failed to remove the noises or the falsifications from the signals for enhanced filtration of the recorded signals.
- The classification method developed in [11] achieved enhanced outcomes for the categorization among the normal and abnormal respiration. However, this approach failed to devise an adaptive technique related to the detection rate of heart sounds for substantially the classification performance.
- The major limitation commonly found in detection of pulmonary abnormality is the incapability to avoid the occurrence of over-training and under-training data. In addition, ensuring the Eigen vector includes more absolute information of lung sounds before dimension reduction still poses a great challenge [10].

3. Proposed WCSO-based HAN for pulmonary abnormality detection

This section illustrates the process of designing and developing a method for the detection of pulmonary abnormality with the respiratory sound signal using proposed WCSO-based HAN. However, the newly proposed WCSO algorithm is devised by the integration of WCA [22] and CSO [23]. The proposed technique integrates the advantages of both the algorithms for obtaining enhanced performance outcomes. The various phases involved in this technique includes, pre-processing, feature extraction, and pulmonary abnormality detection. Initially, the respiratory sound signal is considered as an input signal, and is fed as an input to the pre-processing phase in order to remove the unwanted distortions and external calamities from the signal. Here, the pre-processing is performed using Hanning window [27] and spectral gating-based noise reduction model [28]. The result of pre-processed module will be

presented to the feature extraction phase such that the features, such as BFCC and short term features, like spectral flux and spectral centroids are effectively extracted from the respiratory sound signal. Finally, the pulmonary abnormality classification is carried out using HAN [29] to detect the pulmonary abnormality. However, the classifier is trained using the proposed WCSO for obtaining the classified outcomes. Figure 1 illustrates the schematic representation of the developed WCSO-based HAN for the pulmonary abnormality detection.

Figure 1. Schematic view of developed WCSO-based HAN for detecting pulmonary abnormality.

3.1 Input acquisition

Initially, the input respiratory signal is acquired from a dataset E with ω quantity of signals, which is formulated as,

$$E = \{R_1, R_2, \dots, R_h, \dots, R_\omega\} \quad (1)$$

where, R_h signifies h^{th} input signal in database, and ω indicates the overall signals. Here, the input respiratory signal R_h is presented to the pre-processing phase.

3.2 Pre-processing

After the acquisition of input respiratory signals, the pre-processing is carried out for the noises or the falsifications present in the input signals. The respiratory signal R_h is considered as an input for pre-processing where the process is carried out using Hanning window [27] and Spectral gating-based noise reduction technique [28]. The main aim of pre-processing is to improve the quality of input signals for the further processing.

3.2.1 Hanning window

Hanning window is a technique employed for pre-processing the respiratory input signal. The infinite signal streams are transformed to continuous stream of chunks known as frames. The key benefit of utilizing the Hanning window [27] is to attain the signals from the stationary conditions. In addition, Hanning window executes a progression of fine tuning by the frames, and hence the equation of Hanning window is expressed as,

$$H(w) = \begin{cases} 0.5 \left(1 - \cos \left[\frac{2\pi t}{D-1} \right] \right) \cong \sin^2 \frac{\pi t}{(D-1)} & ; 0 \leq t \leq D-1 \\ 0 & ; \text{Otherwise} \end{cases} \quad (2)$$

where, $H(w)$ represents the Hanning window function, and the segments are zero-padded. The output obtained by Hanning window is denoted as P_1 .

3.2.2 Spectral gating-based noise reduction technique

The spectral gating-based noise reduction approach [28] is an algorithm utilized for pre-processing in order to reduce the unwanted noises or distortions from the signals. The steps to be performed in the process of spectral gating-based noise reduction technique is illustrated as follows,

Step 1: An FFT is computed over the noise audio clip

Step 2: Statistics are computed over FFT of the noise in terms of frequency.

Step 3: A threshold value is measured on the basis of statistics of the noise (and the preferred sensitivity of the approach)

Step 4: An FFT is computed over the signal

Step 5: A mask is computed by comparing the signal FFT to the threshold value

Step 6: The mask is smoothed with a filter over frequency and time

Step 7: The mask is applied to the FFT of the signal, and finally made to invert.

As a result, the final output obtained for the pre-processing phase is denoted as P_δ .

3.3 Feature extraction

Once the pre-processing is done, the pre-processed signal P_δ is presented to the feature extraction module for extracting the features, such as BFCC, and the short term features, such as spectral flux and spectral centroid. The feature extraction process is very important for achieving higher accuracy rate, and also for performing effectual pulmonary abnormality detection.

3.3.1 BFCC technique

The BFCC [26] representation is utilized to extract the significant features from input pre-processed respiratory sound signal. BFCC distorts power spectrum in such a way that it matches with individual observation of intensity. Here, the frequencies are varied to bark scale by the equation given below as follows,

$$Bark(w) = 13 \arctan(0.00076w) + 3.5 \arctan\left(\left(\frac{w}{7500}\right)^2\right) \quad (3)$$

where, *Bark* signifies bark frequency, and *w* represents frequency in Hertz. Here, the mapped bark frequency is prearranged to 18 triangle band pass filters. Accordingly, BFCC feature is formed by DCT to bark frequency cepstrum, for that 10 DCT coefficients denotes amplitude of cepstrum. As a result, the output extracted using BFCC is denoted as f_1 .

3.3.2 Short term feature-based technique

Here, the short term features, such as spectral flux and spectral centroid are effectively extracted from the pre-processed input signal, and the extracted features are explained below as follows:

a) Spectral flux

The rate of the spectral information in respiratory sound signal is measured using spectral flux feature. The information is obtained on the basis of frequency-driven parameters in such a way that the difference value of the successive spectral frames is measured. The equation for spectral flux equation is computed below as follows,

$$f_a = \sum_{U=0}^{K/2-1} \left(|A_s(U)|^2 - |A_{s-1}(U)|^2 \right) \quad (4)$$

where, the term $A_s(U)$ signifies spectrum value of the respiratory sound signal, and f_a denotes the spectral flux feature.

b) Spectral Centroid

Spectral centroid feature is used to define spectrum center gravity, and it computes the spectral value and higher centroid values associated to improved signals with enhanced frequency. Moreover, this feature offers the information about the data variation, which is expressed as,

$$f_b = \frac{\sum_{o=1}^{\beta/2} W(o) S_r(o)}{\sum_{o=1}^{\beta/2} S_r(o)} \quad (5)$$

where, $S_r(o)$ defines a short-time Fourier transform, $W(o)$ signifies frequency of o^{th} frame, and β represents frame length. The output obtained from spectral centroid feature is denoted as f_b . As a result, the short term features are represented as f_2 .

Finally, the overall extracted features are integrated for generating a new feature vector for the effective process of pulmonary abnormality classification, and is represented as,

$$F = \{f_1, f_2\} \quad (6)$$

where, F signifies total feature vector, and it is given to the pulmonary abnormality classification process.

3.4 Proposed WCSO-based HAN for pulmonary abnormality detection

Here, the feature vector F is presented as an input for the pulmonary abnormality detection module. The pulmonary abnormality detection module is carried out using HAN. The training process of HAN is performed using proposed WCSO algorithm. The proposed WCSO-based HAN is used for detecting the pulmonary abnormalities from the respiratory sound signal in an accurate manner. However, the WCSO-based HAN is devised by the incorporation of WCA and CSO for training HAN, such that the optimal weights of HAN can be determined. The major advantage of using HAN classifier is that it generates optimal solution with least training time, thus HAN classifier is utilized for effective pulmonary abnormality detection. The structural design and the training procedure of HAN are described below as follows,

3.4.1 Architecture of HAN

The architectural depiction of HAN [29] is displayed in figure 2. The design of HAN contains various units, such as attention units, long short-term memory (LSTM), softmax, and self-attention units. The HAN classifier utilizes the extracted feature output F for performing the pulmonary abnormality detection.

Figure 2. Structural representation of HAN

A. Attention unit

The attention unit consists of three different modules, such as CNN, LSTM, and attention layer

CNN: In the CNN unit, feature layers of VGGNet are utilized in such a way that the feature maps are extracted. Here, the primary procedure is to perform image rescaling in 448×448 pixels. Therefore, the output obtained from feature layer VGGNet is $512 \times 14 \times 14$ size. Moreover, the 512×196 dimensions vector placed in the fully connected layer based on the tanh function converts it to the dimension vector with 1024×196 size.

$$I_{cd} = \tanh(O_d I_d + s_d) \quad (7)$$

where, I_d represents the feature vector of whole regions, I_{cd} represents each region. The dimensional extension enables the inclusion process in depth.

LSTM: LSTM contains various memory cells, and hence comprises of four different phases in updating the states of the cells. The primary phase formulates the result in order to determine the thrown information from different cell states, whereas the remaining phases makes the decision on the basis of new information that wants to be stored in the states, and then the equation is expressed as,

$$k_l = \sigma(O_k [b_{l-1}, q_l] + e_k) \quad (8)$$

$$d_l = \sigma(O_d [b_{l-1}, q_m] + e_d) \quad (9)$$

$$T_c = \tanh(L_T [b_{l-1}, q_l] + e_T) \quad (10)$$

where, T_c indicates the memory to be known, the input vector is signified as q_l , b_l denotes the hidden state, forget gate is represented as k_l , and d_l specifies the input gate.

The process of updating the older state T_{l-1} to new state T_l is indicated as,

$$T_l = k_l * T_{l-1} + d_l * T_d \quad (11)$$

$$J_l = \sigma(O_J (b_{l-1}, q_l) + e_J) \quad (12)$$

$$b_l = J_l * \tanh(T_l) \quad (13)$$

where, J_l represents the output gate.

Attention layer: At first, O_κ and O_ρ are presented to the fully connected layer and then combined with the tanh function. The attention distribution map is computed on the basis of the softmax function,

$$b_{att} = \tanh((O_{\rho, att} \cdot H_{cd} + e_{cd, att}) \oplus (O_\kappa + e_{\kappa, att})) \quad (14)$$

$$B_o = \text{Soft max}(O_v \cdot b_{att} + e_v) \quad (15)$$

where, O_p is 196×1024 denotes the dimension matrix, 1024 dimension matrix is specified as O_k , $O_{p,att}$ and $O_{k,att}$ represents the 1024×512 dimension matrix, O_v denotes the 512 dimension vector, and B_o represents the shape, and addition vector is signified as $\oplus$. The weighted sum is measured based on the attention distribution map, and the equation is expressed as,

$$H'_d = \sum v_d \cdot H_{cd} \quad (16)$$

B. Self-Attention unit

The self-attention is employed for gathering the global information, and the equation is formulated as,

$$\delta_d = q_d + \sum_{p=1}^{V_v} \frac{\eta(g_d, n_d)}{\varepsilon} (O_v, g_p) \quad (17)$$

where, $\eta(\cdot)$ signifies the function among d and p , O_v represents the linear transform, and the ε signifies the normalization factor.

Thus, the output obtained from HAN is denoted as J_τ that signifies the detected pulmonary abnormalities as normal and abnormal.

3.4.2 Training process of HAN using proposed WCSO

The training process procedure of HAN [29] is performed using the proposed WCSO algorithm. Here, the developed WCSA trains the weights of the classifier in order to achieve effective optimal solution. In addition, the developed WCSA is devised by the incorporation of the WCA [22] and CSO [23]. WCA [22] is a nature inspired algorithm that addresses constrained optimization issues. Typically, the major idea of WCA is the water cycle process in order to observe how streams and rivers pass into sea. The WCA theory starts with a primary population known as raindrops such that the optimal raindrop is regarded as a sea. Thereafter, the overall optimal raindrops are selected as a river, whereas left over raindrops are selected as the streams moving to sea and rivers. This kind of procedure is dependent on the magnitude of flow. On the other hand, CSO [23] utilizes competitive strategy, where the particle that loss the competition can update the location by learning the strategy of winner. It considers exploitation and the exploration capability for obtaining enhanced balancing policy. The proposed optimization approach showed effective and robust performance by attaining global optimal solution. The hybridization CSO with the WCA shows the effectiveness of the proposed mechanism by minimizing the computational complexity issues in an enhanced way. The algorithmic phases of the proposed WCSA is described below as follows,

a) Initialization: the population is initialized with Q raindrops, and it is given as,

$$Q = \{Q_1, Q_2, \dots, Q_n, \dots, Q_L\}; 1 \leq n \leq L \quad (18)$$

where, L signifies the overall raindrop solutions, and Q_n specifies n^{th} raindrop.

b) Compute fitness measure: The fitness measure is used for finding the best solution by computing the best value of fitness and the fitness equation is expressed as,

$$Fitness = \frac{1}{M} \sum_{\theta=1}^M [Z - J_{\tau}]^2 \quad (19)$$

where, Z denotes the classifier output of HAN, and J_{τ} implies the target output.

c) Compute the cost function:

The decision variables $(Q_1, Q_2, \dots, Q_{L_{var}})$ can be specified as floating point variables or can be defined as a predefined set for the discrete and continuous boundaries. Besides, the raindrop with the cost is computed on the basis of cost function assessment, which is expressed as,

$$N_z = Cost_z = a(R_1^z, R_2^z, \dots, R_{L_{var}}^z) \quad z = 1, 2, 3, \dots, L_{pop} \quad (20)$$

where, the overall raindrops is represented as L_{pop} and L_{var} signifies the overall design values.

For the major phase, L_{pop} raindrops are created. The quantity of L_{sr} from the optimum least values is regarded as sea and rivers. In addition, L_{sr} implies the summing up of the overall rivers, and the single sea. The left over raindrops forms the streams to join into the rivers or sea, and the equation is formulated as,

$$L_{sr} = \text{Total number of rivers} + \underset{sea}{1} \quad (21)$$

$$L_{Raindrops} = L_{pop} - L_{sr} \quad (22)$$

d) Calculate the intensity of flow: The process of assigning the raindrops to sea and rivers is done based on flow intensity, and the equation is expressed as,

$$L_u = \text{round} \left\{ \left\lfloor \frac{Cost_u}{\sum_{z=1}^{L_{sr}} Cost_z} \times L_{Raindrops} \right\rfloor \right\} \quad u = 1, 2, \dots, L_{sr} \quad (23)$$

where, L_u represents the streams passing to particular sea or rivers.

e) Evaluate the stream flow to the river or sea: The stream are produced from each raindrop, and then joins with each other to create new rivers. In addition, streams pass to the sea directly, in such a way that every streams and river meets in sea. A stream flowing to river besides fusion line amongst them by the randomly chosen distance is formulated as follows,

$$Q \in (0, N \times n), \quad N > 1 \quad (24)$$

where, N lies between the range 1 and 2, the present distance among the stream and river are signified as n . The N value being superior to 1 facilitates the streams to move in diverse directions over the rivers. This rule can be employed for passing rivers to sea. Hence, the present position of streams and rivers is expressed as,

$$Q_{stream}^{z+1} = Q_{stream}^z + rand \times N \times (Q_{river}^z - Q_{stream}^z) \quad (25)$$

$$Q_{river}^{z+1} = Q_{river}^z + rand \times N \times (Q_{sea}^z - Q_{river}^z) \quad (26)$$

$$Q_{river}^{z+1} = Q_{river}^z (1 - rand \times N) + rand \times N Q_{sea}^z \quad (27)$$

By incorporating the CSO with WCA, the optimization problems in WCA can be solved, and the standard equation of CSO is expressed as,

$$Q^{z+1} = Q^z + Y^{z+1} \quad (28)$$

$$Q^{z+1} = Q^z + X_1 Y^z + X_2 (Q_y^z - Q^z) + \phi X_3 (\bar{Q} - Q^z) \quad (29)$$

$$Q^{z+1} = Q^z (1 - X_2 - \phi X_3) + X_1 Y^z + X_2 Q_y^z + \phi X_3 \bar{Q} \quad (30)$$

$$Q^z = \frac{Q^{z+1} - X_1 Y^z - X_2 Q_y^z - \phi X_3 \bar{Q}}{1 - X_2 - \phi X_3} \quad (31)$$

Considering $Q^z = Q_{river}^z$ and then substituting equation (31) in (27),

$$Q_{river}^{z+1} = \frac{Q_{river}^{z+1} - X_1 Y^z - X_2 Q_y^z - \phi X_3 \bar{Q}}{1 - X_2 - \phi X_3} (1 - rand \times N) + rand \times N Q_{sea}^z \quad (32)$$

$$Q_{river}^{z+1} = \frac{Q_{river}^{z+1}}{1 - X_2 - \phi X_3} (1 - rand \times N) - \frac{X_1 Y^z + X_2 Q_y^z + \phi X_3 \bar{Q}}{1 - X_2 - \phi X_3} (1 - rand \times N) + rand \times N Q_{sea}^z \quad (33)$$

$$Q_{river}^{z+1} - \frac{Q_{river}^{z+1}}{1 - X_2 - \phi X_3} (1 - rand \times N) = rand \times N Q_{sea}^z - \frac{X_1 Y^z + X_2 Q_y^z + \phi X_3 \bar{Q}}{1 - X_2 - \phi X_3} (1 - rand \times N) \quad (34)$$

$$Q_{river}^{z+1} \left(1 - \frac{1 - rand \times N}{1 - X_2 - \phi X_3} \right) = rand \times N Q_{sea}^z - \frac{X_1 Y^z + X_2 Q_y^z + \phi X_3 \bar{Q}}{1 - X_2 - \phi X_3} (1 - rand \times N) \quad (35)$$

$$Q_{river}^{z+1} \left(\frac{1 - X_2 - \phi X_3 - 1 + rand \times N}{1 - X_2 - \phi X_3} \right) = rand \times N Q_{sea}^z - \frac{X_1 Y^z + X_2 Q_y^z + \phi X_3 \bar{Q}}{1 - X_2 - \phi X_3} (1 - rand \times N) \quad (36)$$

$$Q_{river}^{z+1} \left(\frac{rand \times N - X_2 - \phi X_3}{1 - X_2 - \phi X_3} \right) = rand \times N Q_{sea}^z - \frac{X_1 Y^z + X_2 Q_y^z + \phi X_3 \bar{Q}}{1 - X_2 - \phi X_3} (1 - rand \times N) \quad (37)$$

$$Q_{river}^{z+1} = \frac{1 - X_2 - \phi X_3}{rand \times N - X_2 - \phi X_3} \left[rand \times N Q_{sea}^z - \frac{X_1 Y^z + X_2 Q_y^z + \phi X_3 \bar{Q}}{1 - X_2 - \phi X_3} (1 - rand \times N) \right] \quad (38)$$

where, $rand$ denotes the uniformly distributed random number among 0 and 1, $X_1, X_2, X_3 \in [0,1]^n$, Y^z denotes the velocity of loser, Y_y^z represents the location of winner, and

N lies between the range 1 and 2, ϕ indicates the parameter that controls the influence of $\bar{Q}(j)$, the mean position value of every particles in $\ell(j)$ is signified as $\bar{Q}(j)$.

f) Evaluate the condition for evaporation: Evaporation is the chief factor to protect from immature convergence. The evaporated water is absorbed by the atmospheric region to generate clouds, and thereafter water gets condensed in colder atmosphere, thereby releasing water in the form of rain to earth. The rain produces new streams to flow into rivers, which then passes to sea. Besides, $n_{\max}$ is a least number closer to 0 and the $n_{\max}$ value decreases adaptively as,

$$n_{\max}^{z+1} = n_{\max}^z - \frac{n_{\max}^z}{\max iteration} \quad (39)$$

g) Raining process: After evaporation, raining process starts. Here, fresh raindrops forms the streams in various places such that the equation for indicating the new location of recently created streams is expressed as,

$$Q_{stream}^{new} = lb + rand \times (ub - lb) \quad (40)$$

where, lb represents lower bound, and ub signifies the upper bounds.

$$Q_{stream}^{new} = Q_{sea} + \sqrt{\mu} \text{ rand } u(1, L_{var}) \quad (41)$$

where, μ represents coefficient that denotes the limit of searching area nearer to the sea and the value is set to 0.1, $\text{rand } u$ denotes the frequently distributed random number.

h) Feasibility assessment: The assessment of solution feasibility is performed to find the optimal value. If the newly achieved solution has the best value, then the existing one is updated with the best value.

i) Termination: All the above mentioned procedures are iteratively performed until the optimal solution is achieved. Table 1 portray the pseudo code of developed WCSO-based HAN

Table 1. Pseudo code of developed WCSO-based HAN

Sl. No	Pseudo code of developed WCSO-based HAN
1	Input: Q
2	Output: Q_{river}^{z+1}
3	Begin
4	Initialize the parameters L_{sr} , $n_{\max}$, L_{pop}
5	Generate initial population randomly by equation (18)
6	Determine cost of each raindrop by equation (20)
7	Compute intensity of flow by equation (23)
8	Estimate the flow of stream to the rivers by equation (24)
9	For
10	if $N > 1$

11	Satisfy evaporation condition
12	Else
13	Replace the position of the river with sea
14	end if
15	if $ L_{sea}^z - L_{river}^z < n_{max}$
16	Replace the location of river with sea
17	Else
18	Satisfy evaporation circumstance
19	end if
20	Start raining procedure by equation (40) and equation (41)
21	Reduce the value of h_{max} by equation (39)
22	Validate the convergence criteria
23	Satisfies the convergence criteria
24	Stop
25	Else
26	Reiterate the procedure
27	end for
28	End

The proposed WCSO-based HAN of pulmonary abnormality detection is very effective in detecting the pulmonary abnormalities, which is then offered to the applications for the performance enhancement.

4. Results and Discussion

The experimental outcomes of the developed WCSO-enabled HAN with respect to various performance evaluation metrics is portrayed in this section.

4.1 Experimental set-up

The experimentation of the developed technique is performed in PYTHON tool by International Conference in Biomedical and Health Informatics (ICBHI 2017) (dataset-1) [25] and respiratory sound database (dataset-2) [24], and for the efficient pulmonary abnormality detection. Moreover, the developed technique requires PC with Windows 10 OS, Intel I3 processor, and 4 GB RAM.

4.2 Dataset description

This section describes the two various dataset utilized for the pulmonary abnormality detection.

Dataset1: This database [25] contains overall recording time of 5.5 hours with 6898 respiratory phases, of which 1864 includes crackles, 886 have wheezes, and 506 enclose wheezes and crackles in 920 annotated audio samples from different 126 subjects. Besides, cycles are annotated by respiratory experts containing wheezes, crackles, and a blend of crackles and wheezes, or without anomalous respiratory sounds. Moreover, heterogeneous equipments are used for acquiring the signals with the duration ranging from 10s to 90s. In addition, the location of the chest from where recordings are collected is also provided. The file names are categorized into 5 different elements, namely patient number, recording index,

chest location, acquisition mode, and recording equipment and are separated with underscores (_).

Dataset2: This dataset [24] was developed by two different research teams in Greece and Portugal. It contains annotated 920 recordings of different duration from 10s to 90s. The recordings are taken from 126 patients. The overall time of the recording is 5.5 hours with 6898 respiratory phases of which 886 include wheezes, 1864 enclose crackles, and 506 have wheezes and crackles altogether. The data contains noisy recordings and fresh respiratory sounds that imitate real life circumstances. The patients cover different groups of age, such as elderly, adults and children.

4.3 Evaluation metrics

The performance evaluation of the developed WCSO-based HAN is analyzed on the basis of the evaluation metrics, like TPR, TNR, and accuracy.

b) TPR

TPR is a metric used for calculating the truly positive results of the detected pulmonary abnormality, and the equation is formulated as,

$$TPR = \frac{S}{S + V} \quad (42)$$

c) TNR

TNR is utilized for computing the exact outcomes of the true-negatives of detected pulmonary abnormalities, which is formulated as,

$$TNR = \frac{T}{T + U} \quad (43)$$

c) Accuracy

Accuracy is a measure, which computes the true positives and the true negatives of the detected pulmonary abnormality, and the equation is formulated as,

$$ACC = \frac{S + T}{S + V + U + V} \quad (44)$$

where, the true positive is represented as S , T signifies the true negatives, U indicates false positives, and V specifies the false negatives.

4.4 Performance analysis

This section portrays performance analysis of the developed WCSO-based HAN using dataset-1 and dataset-2 with respect to training data values.

(i) Analysis using dataset 1

Figure 3 portrays the performance assessment of the developed WCSO-based HAN approach by considering TPR, TNR and accuracy metrics by varying the training data percentage. Figure 3a) presents the assessment using TPR. By considering the training data as 70%, the

TPR value measured by the proposed WCSO-based HAN for the iteration 10 is 0.906, iteration 20 is 0.912, iteration 30 is 0.918, and iteration 40 is 0.925. The assessment based TNR is portrayed in figure 3b). For the training data 80%, the proposed WCSO-based HAN computed a TNR value for the iteration 10, 20, 30, and 40 is 0.887, 0.893, 0.897, and 0.905. The analysis using accuracy metric is presented in figure 3c). When considering the training data as 60%, the accuracy value computed by the proposed WCSO-based HAN for the iteration 10 is 0.876, iteration 20 is 0.883, iteration 30 is 0.888, and iteration 40 is 0.894.

Figure 3. Performance assessment of the developed method using dataset-1 a) TPR b) TNR c) Accuracy

(ii) Analysis using dataset-2

The performance assessment of the developed WCSO-based HAN by varying the training data percentage based on TPR, TNR, and accuracy is illustrated in figure 4. The analysis using TPR measure is presented in figure 4a). When the training data is 60%, the proposed WCSO-based HAN approach measured a TPR value for the iteration 10, iteration 20, iteration 30, and iteration 40 is 0.907, 0.912, 0.918, and 0.924. Figure 4b) presents the analysis using TNR metric. The TNR value computed by the developed WCSO-based HAN technique for the iteration 10, 20, 30, and 40 is 0.857, 0.863, 0.868, and 0.874 for the training data 70%. The analysis using accuracy measure is portrayed in figure 4c). For the training

data 80%, the accuracy value measured by the proposed WCSO-based HAN for the iteration 10 is 0.901, iteration 20 is 0.906, iteration 30 is 0.912, and iteration 40 is 0.918.

Figure 4. Performance assessment of the developed method using dataset-2 a) TPR b) TNR c) Accuracy

4.5 Comparative methods

The comparative assessment of developed WCSO-based HAN is performed by comparing the proposed technique with the existing techniques, such as Random Forest classifier [2], Machine Learning [3], DNN [4], and CNN [5].

4.6 Comparative analysis

This section illustrates the comparative analysis carried out using dataset-1 and dataset-2 with respect to the performance metrics, such as TPR, TNR, and accuracy.

(i) Analysis using dataset-1

Figure 5 portrays performance assessment of developed WCSO-based HAN approach by considering the metrics, like TPR, TNR and accuracy by varying the training data percentage. Figure 5a) presents the assessment based on TPR. By considering training data as 70%, the TPR value measured by the proposed WCSO-based HAN is 0.912, whereas the TPR value measured by the existing techniques, such as Random Forest classifier is 0.751, Machine Learning is 0.819, DNN is 0.858, and CNN is 0.872. The performance gain computed by the developed WCSO-based HAN by comparing with the existing techniques is 17.65%, 10.13%, 5.858%, and 4.400%. The assessment using TNR is shown in figure 4b). For training data 80%, the proposed WCSO-based HAN computed a TNR value of 0.893, while the TNR value computed by the existing techniques, namely Random Forest classifier, machine learning, DNN, and CNN is 0.718, 0.771, 0.809, and 0.841. The performance gain achieved by the proposed WCSO-based HAN in comparison with other existing techniques, such as Random Forest classifier, Machine learning, DNN, and CNN is 19.60%, 13.61%, 9.375%, and 5.757%. The analysis using accuracy metric is given in figure 4c). The accuracy value measured by the Random Forest classifier is 0.710, Machine Learning is 0.755, DNN is 0.803, CNN is 0.847, and proposed WCSO-based HAN is 0.883 for training data 60%.The performance gain measured by developed WCSO-based HAN by comparing with the existing techniques is 19.58%, 14.49%, 9.062%, and 4.082%.

Figure 5. Assessment of developed method using dataset-1 a) TPR b) TNR c) Accuracy

(ii) Analysis using dataset-2

The analysis of the developed WCSO-based HAN by varying the training data percentage using TPR, TNR, and accuracy is presented in figure 6. The analysis using TPR is portrayed in figure 6a). By considering the training data as 60%, the proposed WCSO-based HAN approach measured a TPR value of 0.912, whereas the TPR value computed by the existing techniques, such as Random Forest classifier, Machine Learning, DNN, and CNN is 0.743, 0.782, 0.830, and 0.877. Figure 6b) presents the analysis using TNR metric. The performance gain computed by the developed WCSO-based HAN by comparing with the existing techniques is 18.54%, 14.24%, 9.020%, and 3.866%. The TNR value computed by the Random Forest classifier is 0.704, Machine Learning is 0.742, DNN is 0.807, and CNN is 0.842, while the developed WCSO-based HAN technique measured a TNR value of 0.863 for training data 70%. The performance gain achieved by the developed WCSO-based HAN in comparison with other existing methods, such as Random Forest classifier, Machine learning, DNN, and CNN is 18.49%, 14.01%, 6.532%, and 2.527%. The analysis using accuracy metric is presented in figure 6c). For training data 80%, the accuracy value measured by the Random Forest classifier, machine learning, DNN, CNN, and proposed WCSO-based HAN is 0.742, 0.787, 0.834, 0.876, and 0.906. The performance gain measured by the developed WCSO-based HAN by comparing with the existing techniques is 18.05%, 13.07%, 7.886%, and 3.264%.

Figure 6. Assessment of the developed technique based on dataset 2 a) TPR b) TNR c) Accuracy

4.7 Comparative discussion

Table 2 explains the comparative discussion of developed WCSO-based HAN technique on the basis of dataset-1 and dataset-2 for the training data 90%, with respect to the performance evaluation metrics, namely TPR, TNR, and accuracy. The TPR value measured by the proposed WCSO-based HAN is 0.943, whereas the TPR value measured by the existing techniques, such as Random Forest classifier is 0.775, Machine Learning is 0.845, DNN is 0.883, and CNN is 0.906. Likewise, the TNR value measured by the Random Forest classifier, machine learning, DNN, CNN, and proposed WCSO-based HAN is 0.731, 0.791, 0.817, 0.862, and 0.913. The proposed WCSO-based HAN computed an accuracy of 0.923, whereas the accuracy value computed by the existing techniques, namely Random Forest classifier, machine learning, DNN, and CNN is 0.751, 0.800, 0.847, and 0.882. Thus from the analysis, it is clearly shown that developed WCSO-based HAN approach achieved a maximal TPR value of 0.943, higher TNR value of 0.913, and maximum accuracy value of 0.923 using dataset 1.

Table2. Comparative discussion of the developed WCSO-based HAN technique

	Metrics	Random Forest classifier	Machine Learning	DNN	CNN	Proposed WCSO-based HAN
Dataset 1	TPR	0.775	0.845	0.883	0.906	0.943
	TNR	0.731	0.791	0.817	0.862	0.913
	Accuracy	0.751	0.800	0.847	0.882	0.923
Dataset 2	TPR	0.781	0.819	0.864	0.908	0.935
	TNR	0.735	0.770	0.822	0.861	0.902
	Accuracy	0.753	0.797	0.844	0.887	0.929

5. Conclusion

This research work presents a robust and effective pulmonary abnormality approach known as WCSO-based HAN for detecting the pulmonary abnormalities from the respiratory sound signals. The developed WCSO is newly designed by the incorporation of WCA and CSO algorithm. Initially, the Hanning window technique and the spectral gating-based noise reduction technique are employed for pre-processing the input respiratory signal. Thereafter, the significant features are extracted in feature extraction module for further processing. The extracted features are used to perform final pulmonary abnormality classification process, which is carried out using HAN classifier wherein the training procedure of HAN is performed by the newly devised optimization algorithm, called WCSO. The developed WCSO is derived by the integration of WCA and CSO. However, the performance assessment of the proposed WCSO-based HAN is done using the performance metrics, namely TPR, TNR, and accuracy with higher TPR of 0.943, maximum TNR of 0.913, and higher accuracy of 0.923. The future concern of this research would be the plan of developing

effective deep learning classifiers for improving effectiveness of pulmonary abnormality detection system.

6.Ethics approval and consent to participate

Approved by RDC of mansarovar Global University Madhya Pradesh India

7.Consent for publication

Yes

8.Availability of data and materials

Not applicable

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