Exploration of Cough Recognition Technologies Grounded on Sensors and Artificial Intelligence

S. R. Preethi, A. R. Revathi, and M. Murugan

Abstract Artificial intelligence is ruling all industrial sectors and has its hand on the medical and healthcare field too. Cough is a symptom of divergent respiratory disorder diseases from a common cold to the current coronavirus disease. Cough is not only extant in humans, but it similarly found to be existing in numerous animals primarily in pigs [1]. Cough is generally a good self-reaction of the body to prevent secretions and its blockages in the upper airway. The frequency, sequence and pattern of the cough reveal the disease along with its severity. Thus, sensing platform and artificial intelligence are used intensively for cough analysis. This chapter is to explore about cough detection and throws light on the various cough detection methodologies, the artificial intelligence algorithms implemented, features involved in cough detection and constraint existent in implementation. In architectural analysis of cough detection; divergent types of the sensors, auxiliary equipment and neural network sustenance instruments deployed are entailed. Cough detection is enacted by voluminous machine and deep learning algorithms using classifiers such as random forest, decision tree, logistic regression, support vector machine, feed forward artificial neural network, convolutional neural network hidden Markov model, multiclass classifier with multilayer perceptron model, and validation is achieved through K-cross validation. The chapter also articulates about the dataset availability of various patterns of cough, the visualizing of sound pattern in frequency and time domain.

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Further cough is found to have two set of features namely superordinate and subordinate sound features. Superordinate features include Mel-frequency cepstral significant, non-Gaussianity score, Shannon entropy, energy, zero intersection ratio, spectral centroid, spectral bandwidth and spectral roll-off. Subordinate feature covers cough sequence type and duration, bouts occurred in a sequence, cough sequence number in prescribed interval time. The chapter also includes extensive analysis of above feature sets of cough sound. Hence, cough detection using artificial intelligence helps doctors to diagnose early and at ease. At times, it also overcomes the misdiagnosis of the disorders. The chapter also discusses in detail about the various datasets used for cough detection. Finally, includes the constraint of deployment of cough detection that covers the challenges in computational cost, size, budget and ease of deployment with ubiquitous computing.

Keywords Cough detection · Sensors · Machine learning · Deep learning algorithms · Classifiers · Superordinate features · Subordinate features

1 Introduction to Sick Sound—COUGH

One of the most important sickness indicating sounds is cough. Cough occurs due to the presence of disturbance in respiratory track. Based on the presence of liquid, airway passages and lasting time period, the cough can be classified on types, patterns and endurance. The cough along with its acoustic quality sound can be as wet or dry cough types. Wet cough is due to the presence of the disturbance at times due to occurrence of secretions such as mucus and pus. Dry cough is due to inflammations without any fluid secretions [2].

Cough occurring pattern may be obstructive and restrictive based on the nature of airway [3, 4]. In obstructive pattern, airway is widened or narrowed than the normal size. In restrictive pattern, fluid occupied air sacs are present. At time, there is a presence of combined pattern including both the patterns of obstructive and restrictive [5]. Endurance of the cough denotes the time period of existence of the cough as acute, subacute and chronic [6]. Acute coughs are durable for maximum three weeks, and subacute exists more than three weeks up to eight weeks. Chronic cough is serious infections lasting for a longer time period than 8 weeks. In terms of sound signal, the cough possesses two sorts namely airflow and acoustic signal. The airflow signal is plotted as graph between flow in L/sec and time period in second measured in patients mouth. Acoustic cough signal represents sound graph between amplitude and time in seconds generally tested at sternal manubrium. The taxonomy of cough based on types, pattern and endurance is given in Fig. 1 and Table 1.

Cough is a symptom of respiratory medical, non-respiratory medical and environment condition as described in Fig. 2. In case of respiratory medical condition, the reason could be upper respiratory tract infection, lower respiratory tract infect, pneumonia, bronchitis, influenza, asthma, whooping cough, post nasal drip, tuberculosis and corona.

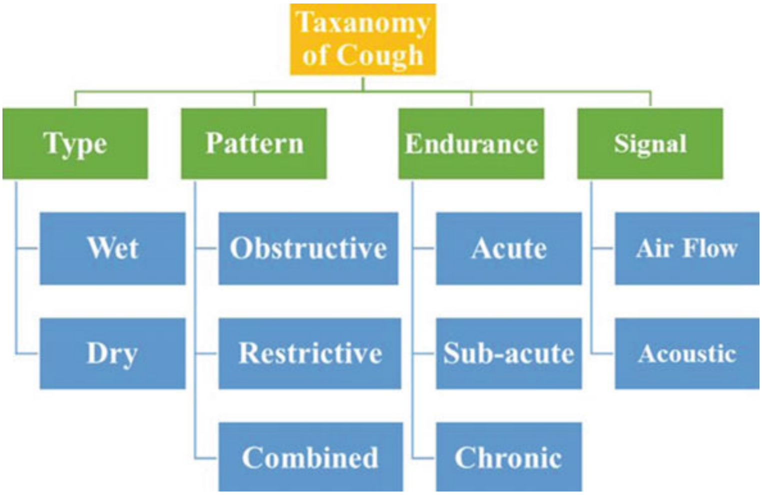

Fig. 1 Taxanomy of cough

Table 1 Details of cough taxanomy

Authors and year	Cough taxonomy	Subclassification	Indications
Mannino David M et al. 2003	Type	Wet	With the presence of acoustic sounds
		Dry	No presence of acoustic sounds
Jaclyn A Smith et al. 2006	Pattern	Obstructive	Widened or narrowed airways
Swarankar Vinayak et al. 2013		Restrictive	Air sacs filled with fluid
Gowrisree Rudraraju et al. 2020		Combined	Together forms of obstructive and restrictive
De Blasio et al. 2011	Endurance	Acute	Enduring less than 21 days
		Subacute	Existing for 3–8 weeks
		Chronic	More than 8 weeks existence
Yan Shi et al. 2018	Signal	Airflow	Represents air movement through mouth
		Acoustic	Denotes tussis echo

Non-respiratory medical conditions are gastroesophageal reflux, heart failure and tumors. Environment conditions like cooking fumes, smoking, air pollutants cause cough.

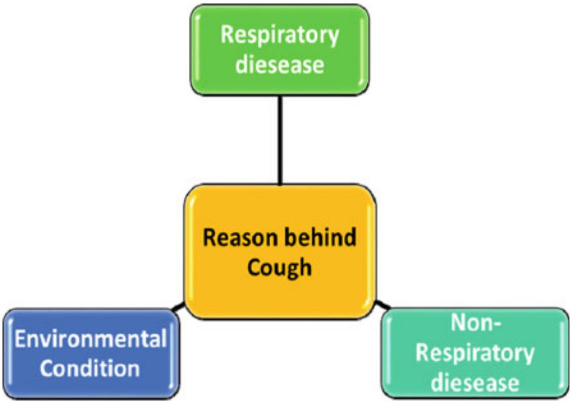

Fig. 2 Cough causing conditions

Fig. 3 Phases of cough

2 Cough Pattern Phases

Cough pattern has three phases as shown in Fig. 3, namely volatile expiration, intermediary and voiced phase [7]. At times, the cough possesses only two phases intermediary and voiced phase due to the nature of disease that causes cough.

3 Features of Cough

Generally, in case of clinical trials, cough has found to consist of many features such as Mel-frequency cepstral significant, explosive cough sounds, cough seconds, cough breaths, cough epochs, cough intensity, cough pattern, zero intersection ratio, spectral centroid, spectral bandwidth, and spectral roll-off as shown in Fig. 4 and Table 2.

Mel-frequency cepstral significant (MFCS) feature enables to recognize characteristics of human auditory [8], and hence, it is used in large scale for cough detection [9–11]. A 13 dimensional MFCS obtained through the Mel filter is processed through amplitude and zero crossed coupled first-order and second-order differentiator to enhance to 41 dimensional MFCS [12]. Along with cough frequency; explosiveness of cough sounds, the duration seconds, respiration rate inclusive of least cough and number of repeated cough sounds with less interval (epochs) are also important

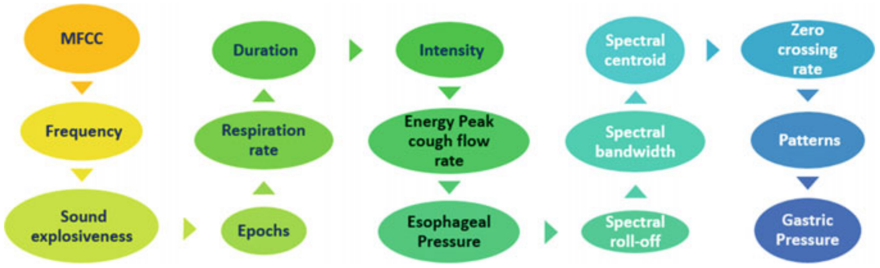

Fig. 4 Vital cough features

Table 2 Details of cough features

Author	Year	Feature
V. Tiwari et al.	2010	Mel-frequency cepstral significant
D. Parker et al.	2013	
Y. Yin et al.	2012	
Y. Chung et al.	2013	
Bowen Dua et al.	2017	
Y. Shi et al.	2016	Cough frequency
		Cough sound impulsiveness
		Cough duration
		Cough respiration rate
		Epochs
L. Pavesi et al.	2001	Cough intensity
K. K. Lee et al.	2012	
G. J. Gibson et al.	2002	Energy peak cough flow rate, Esophageal pressure, Gastric pressure
Y. Shi et al.	2017	
A. A. Abaza et al.	2009	Cough patterns
Gowrisree Rudraraju et al.	2020	Zero intersection ratio, Spectral centroid, Spectral bandwidth, Spectral roll-off

features [13]. Cough intensity is also taken into account by considering peak and mean energy [14, 15]. Along with energy peak cough flow rate, esophageal pressure and gastric pressure are also thrown light for voluntary, induced and spontaneous cough [16, 17]. Cough patterns also form an important end point for disease identification [18]. Zero intersection ratio indirectly implies the frequency of the cough sound generated. Spectral centroid is used to characterize the spectrum, and further, the extent of spectrum data is provided by spectral bandwidth. Spectral roll-off is used to distinguish between voice-related sounds with nonvoice-related sounds [5].

4 Methods and Algorithms Deployed for Cough Detection

Cough detection is performed by many researchers using two main methods namely instinctive cough segmentation and instinctive cough classification as shown in Fig. 5. In instinctive cough segmentation method, the cough-related audio sounds are riven into fragments to identify the features of interest for cough detection.

In case of instinctive cough classification, classifiers are used to analyze and detect the cough sounds. In Instinctive cough segmentation, the fragmenting is done automatically, whereas in instinctive cough classification, manual segmentation is performed before the classification [19].

Many algorithms are deployed by researchers for cough detection animal houses, cough-related diseases and up to detection of COVID-19 through cough. A cough device for recording the ambulatory cough with help of electromyography (EMG), electrocardiogram (ECG) and microphone was devised [20]. A Holter monitor with EMG and audio signal for based ambulatory cough meter [21].

Semi-automated device utilizes audio and EMG signal for cough detection in children [22]. Automated tagging of EMG and audio signal for objective cough monitoring in infants [23]. Accelerometer portable device with no programmed examination software for nocturnal cough and to study the sleep patterns for children with cough [24]. Lifeshirt [25] is programmed scrutiny of an amalgamation of EMG, ECG and plethysmography for quantification of cough frequency in chronic disorder patients.

A spontaneous instrument, hull instinctive cough summer [26], is devised using linear predictive coding significant and predictable neural Web. Hidden Markov model (HMM) is deployed for MFCS characteristic avulsion [27]. Device performing audio recording and physical totaling of sound of interest was performed in chronic obstructive pulmonary disease [28]. Decision tree-based discriminator is used to

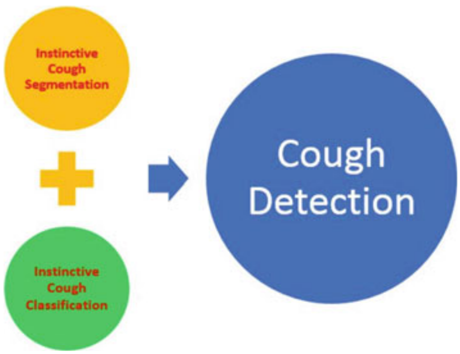

Fig. 5 Methods of cough detection

segment intended coughs and dialogue to extract rate of recurrence and entropy features [29].

Leicester cough monitor (LCM) [30] built using HMM also depends on audio recordings to pre-fragment probable cough events. Cough monitor [31] to observe chronic cough delivers evaluation of respirational sickness. An amalgamation of artificial neural network (ANN) and support vector machine (SVM) classifiers to monitor cough detection of tuberculosis patients by extracting MFCS [32]. Random forest classification [33] identifies cough segments in audio recordings with capability to reconstruct the cough sounds. Simple threshold method [34] differentiates numerous phases of dry and wet coughs and found that dry coughs posed low energy.

VITALOJAK—a cough observing structure [35] applied semi-automated recognition by means of physical corroboration. An aural introverted structure [36] based on Artificial Neural Network (ANN) for recognition of cough. Neural network [37] intended for cough recognition with sorts such as MFCS, formant rate of recurrence, kurtosis and B score. Support vector machine (SVM) with Gammatone cepstral coefficient (GMCC) feature for cough signal recognition [38].

Differentiation of wet and dry coughs in pediatric patients with logistic regression model (LRM) classifier with features such as MFCS, formant frequencies, kurtosis, zero crossing and B score. First cough classification for pertussis uses three classifiers namely ANN, random forest and K-nearest neighbor algorithm (KNN) with MFCS feature and energy level extraction. The tool significance for automatic cough detection was reported in 2013 [39].

Voluntary cough detection [40] was achieved with fast Fourier transform (FFT) coefficient using KNN. Automatic childhood pneumonia detection [41] uses LRM classifier with interest on features such as MFCS, wavelet and non-Gaussian. Non-contact pediatric ward cough segmentation deployed with ANN [42].

The acquired data exploited with ANN supporting accurate cough duration and cough detection with mutual information from sensors [43]. Mobi Cough [44] amalgamates Gaussian mixture model and universal background model (GMM-UBM) for forecasting cough sounds. Smart watch [45] records sounds and performs conformal prediction analysis to detect cough or sneezing events. HMM grounded on cough revealing [46] using univariate and multivariate time series cough data. Convolutional neural network (CNN) is deployed for cough detection [47] with mathematical model for sound analysis.

Asthma cough sound detection [48] through GMM-UBM deals with features such as MFCS and constant-Q cepstral coefficients. WheezeD [49] perceives respiration stage and installs CNN with acoustic in 2D spectro temporal image for breathless recognition. Power spectral density of cough sounds in different air quality conditions is tested by recognition algorithm deployed with principal component analysis (PCA) and SVM [50].

AI4COVID-19 [51] is artificial intelligence (AI) deployed for COVID-19 initial symptoms recognition with novel multipronged mediator centered risk averse architecture. FluSense [52] is innovative edge computing technology for crowd behavior and influenza indicators—cough. The exhaustive detail explaining the methods and their purpose is tabulated in Table 3, and important algorithms are highlighted in Fig. 6.

Table 3 Methods deployed for cough recognition at a glance

Author	Year	Methods deployed
Munyard et al.	1994	Ambulatory cough footage mechanism with assistance of EMG, ECG pulses
Chang et al.	1997	Holter observer-based tussis observer
Hamutcu et al.	2002	Cough monitoring with EMG and audio signal in children with cystic fibrosis
Corrigan et al.	2003	Automated tagging of EMG and audio signal for objective cough monitoring in infants
Paul et al.	2004	Accelerometer portable device with no programmed examination software
Coyle et al.	2005	Lifeshirt [25] is programmed scrutiny of a amalgamation of EMG, ECG and plethysmography
Barry et al.	2006	Hull instinctive cough summer using linear predictive coding significant and predictable neural Web
Matos et al.	2006	HMM for MFCS
Smith et al.	2006	Physical totaling of sound of interest was performed in chronic obstructive pulmonary disease
Martinek J et al.	2008	Intentional cough and speech discriminator based on decision tree
Birring S et al.	2008	Leicester cough monitor using HMM
Smith, J et al.	2010	Cough observer to observe chronic cough
Tracey et al.	2011	An amalgamation of artificial neural network (ANN) and support vector machine (SVM) classifiers for tuberculosis patients
Larson et al.	2011	Random forest classification cough identification
Chatrzarrin et al.	2011	Simple threshold to differentiate phases of coughs
McGuinness K. et al.	2012	VITALOJAK—a cough monitoring system
Drugman T et al.	2012	ANN based on acoustic solitary system
Swarnkar et al.	2013	Neural network-based cough detection
Liu et al.	2013	SVM for cough recognition
Swarnkar et al.	2013	LRM classifier for pediatric patients
Parker et al.	2013	Pertussis cough classification using ANN, random forest and KNN
Drugman T et al.	2013	Automatic cough detection tool significance
Lucio et al.	2014	Voluntary cough detection using KNN
Kosasih et al.	2014	Pneumonia detection with LRM classifier
Amrulloh et al.	2015	ANN automatic cough segmentation
Drugman T et al.	2016	ANN with accurate cough duration and detection
Pham C. et al.	2016	Mobi cough using Gaussian mixture model

(continued)

Table 3 (continued)

Author	Year	Methods deployed
Nguyen et al.	2018	Smart watch with Android app and conformal prediction analysis
Teyhouee et al.	2019	HMM grounded on cough revealing
Kvapilova et al.	2019	Cough detection using CNN
Hwan Ing Hee	2019	GMM-UBM asthma cough detection
Soujanya Chatterjee et al.	2019	WheezeD—CNN-based wheezing detection
Wang et al.	2019	PCA and SVM for cough recognition
Imran et al.	2020	AI4COVID-19—AI-based COVID-19 initial diagnosis.
Hossain et al.	2020	FluSense based on edge computing

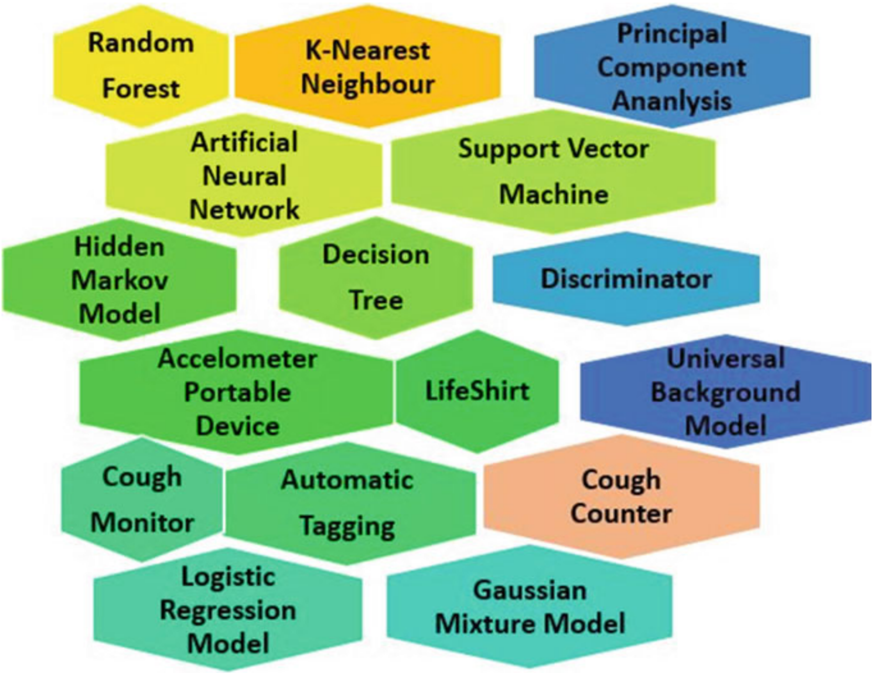

Fig. 6 Highlighted procedures of cough revealing

5 Instruments Organized in Cough Detection

In deploying, Internet of things six building blocks such as deployment types, sensor time, sensor types, architecture, application types and data requirements are considered [53]. Generally, IoT is used for automation of various devices for specific applications such as light controls and video surveillance [53, 54]. In this section, the instruments utilized for cough detection is discussed.

Multiparametric cough monitoring system [20] monitors cough along with activity and heart rates. Accelerometer, electrodes and microphone are deployed to record ECG, ECG and cough signal, respectively. Cough monitor [21] achieved with deployment of Holter monitor, a computer-based cough processor with selected filters and tape recorders used overnight. Cystic fibrosis-based cough is monitored with Logan Research (LR) 100 cough recording device. In addition, conventional tape recorder is used in first or second day of hospitalization for the duration of chest physiotherapy period.

Infant cough monitor was through LR100 cough monitor, infrared sound and video recorder [23]. Accelerometer portable device with no programmed examination software for nocturnal cough and to study the sleep patterns for children with cough [24]. Lifeshirt [25] was prepared of a A peripatetic cardiorespiratory observing structure, adapted unimaneuvering, touching base microphone, videoing in pseudo organized circumstance. Hull instinctive cough summer [26] is simulated by a computing device with MATLAB 6.1 version with LS_Toolbox version 2.1.1, signal processing toolbox version 5.1, neural network toolbox version 4.0.1 and Voicebox.

HMM for cough signals in audio recordings [27] deployed digital sound recorder and microphone placed in chest of the patient. Portable digital voice recorder with miniature omnidirectional condenser microphone wrapped in plastic foam for distinction of voluntary coughs [29]. LCM was inserted with unrestricted arena necklace microphone and digital sound recorder [30].

Cough sensing deployed with microphone present in mobile phone [33], T-Mobile G1 mobile phone platform was used. VITALOJAK [35] implemented with lapel microphone connected to trained manual cough counter, which compresses the signal with three distinct levels. Karmelsonix system, a commercially obtainable cough counter, used with two microphones namely audio and contact microphone for cough detection [36]. For pediatric patients, couch sideways contactless microphone is implemented for cough recognition [4]. Study of sensor significance [39] exploited the part of ECG, thermal resistor, trunk strap, acceleration sensor, touching base and acoustic microphones in cough finding. Rode NT3 a bed side microphone was placed in two directions for cough detection [41]. Non-contact detection in pediatric ward [42] was deployed with Rode NT3 microphone, preamplifier, A/D converter and mobile pre USB. Sensor-based automatic cough detection system [43] enacted ECG, thermistor, chest belt, accelerometer, oximeter, contact and audio microphones, sensors, analog signal conditioning circuit (front-end), analog-to-digital conversion, communication and storing functional blocks. Mobicough [45] consisted of wireless low-cost microphone connected through Bluetooth to mobile phone. Smart watch

[46] for cough detection with low power accelerometer sensor and audio recorder with support of Android app. Asthmatic voluntary sound [48] deployed with computing system supported with MATLAB 2017b and adobe audition CS6. AI4COVID-19 [51] used AI engine for performing cough symptom of COVID-19. FluSense [52] for influenza like illness sensing deployed squat rate microphone, thermal imaging information, Raspberry Pi and Intel Movidius neural engine. The details of instruments utilized for various cough detection work are summarized in Table 4, and important instruments list is highlighted in Fig. 7.

6 Parameters Achieved in Cough Detection Deployment

In cough detection deployment, the main parameters measured as in Fig. 8 are confidence interval, correlation coefficient, positive predictive value or positive foretelling rate, positive rate or optimistic ratio, negative rate, sensitivity or susceptibility, specificity or selectivity, recall, precision, accuracy and F1 score. Confidence interval denotes the sort of value with in which the correct rate lies.

Generally, it is used for comparison between verbal descriptive scores and visual analogue scales [55]. Correlation coefficient gives the strength of relationship with two methods of cough detection mainly video and audio. Positive predictive value indicates the possibility of the focuses with an affirmative screening examination ensuring a sickness. The interlinking connection between positive, negative rate, sensitivity, specificity and predictive value is portrayed in Fig. 9. Supplementary a comprehensive representation about mathematical assessment of parameters is presented in Table 5.

Sensitivity and specificity refer, respectively, to the actual positive cases and actual negative cases predicted appropriately. Positive predictive value and negative predictive value refer the correctness of predicted value is true positive or negative correspondingly.

7 Dataset Details for Cough Detection

For cough detection, numerous data are recorded, created, and existing data bases are used. Data are collected directly from patients [20], and at times, in certain situations, the recordings from subjects were carried out [21]. Mixed sounds from both healthy and ill patients [23], male and female [29] were collected. Sounds from cough due to various illness such as pneumonia, asthma, chronic disorder, tuberculosis and as well as COVID-19 were used [41], [51].

Cough sounds from adults, pediatric [42] and infants [23] are gathered. Already existing YouTube recordings [9], RALE repository [49], environmental sound classification dataset [45], health mode cough dataset [47], sounds from Freesounds.org

Table 4 Instruments list deployed for cough detection

Author	Year	Instruments installed
Munyard et al.	1994	Accelerometer, positive and negative electrode, microphone, conventional tape recorders and multiparametric cough monitoring system
Chang et al.	1997	Holter monitor, cough processor and tape recorder.
Hamutcu et al.	2002	LR100 cough recording device and conventional tape recorder.
Corrigan et al.	2003	LR100 cough monitor, infrared sound and video recorder
Paul et al.	2004	Accelerometer portable device with no programmed examination software
Coyle et al.	2005	A peripatetic cardiorespiratory observing structure, adapted unimaneuvering, touching base microphone, videoing in pseudoorganized circumstance.
Barry et al.	2006	Hull automatic cough counter using computing system with MATLAB 6.1
Matos et al.	2006	HMM deployed with digital sound recorder and microphone.
Smith et al.	2006	Digital acoustic footage
Martinek J et al.	2008	Portable digital voice recorder, a miniature microphone and plastic foam
Birring S et al.	2008	Leicester cough observer expending allowed arena choker microphone and digital sound tape recorder.
Larson et al.	2011	T-Mobile G1 mobile phone platform
McGuinness K. et al.	2012	VITALOJAK with lapel microphone, trained manual cough counter with compression software
Drugman T et al.	2012	Karmelsonix system, audio and contact microphone
Swarnkar et al.	2013	Couch side contactless microphone
Drugman T et al.	2013	ECG, thermal resistor, trunk strap, acceleration sensor, touching base and acoustic microphones
Kosasih et al.	2014	Two bed side microphone Rode NT3
Amrulloh et al.	2015	Rode NT3 microphone, preamplifier, A/D converter and mobile pre USB.
Drugman T et al.	2016	ECG, thermistor, chest belt, accelerometer, oximeter, contact and audio microphones, sensors, analog signal conditioning circuit (front-end), analog-to-digital conversion, communication and storing functional blocks.
Pham C. et al.	2016	Mobi Cough using wireless low cost microphone, mobile phone and Bluetooth.
Nguyen et al.	2018	Smart watch with accelerometer and audio recorder

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Table 4 (continued)

Author	Year	Instruments installed
Kvapilova et al.	2019	Health mode cough application in smart phone
Hwan Ing Hee et al.	2019	Computing system with MATLAB 2017b and adobe audition CS6
Imran et al.	2020	AI4COVID-19 in AI engine.
Hossain et al.	2020	FluSense with squat rate microphone, thermal imaging information, Raspberry Pi and neural engine Intel Movidius

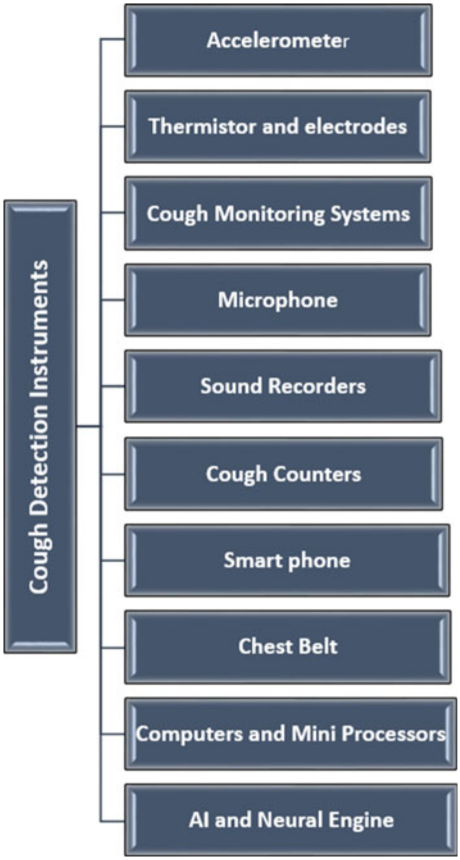

Fig. 7 Imperative implements used for cough recognition

[45], non-speech audio snippets [52] were utilized. In addition, more group of recordings such as Huawei W1 smart watch recordings [45], sounds from weaners [50] were congregated. Cough sound depending on aerial factors was gathered [50]. Sounds from hospital waiting room in recent for influenza like flu symptom checking were also done [52]. A detailed description of data collection is tabulated in Table 6, and the significant data collection depiction is presented in Fig. 10.

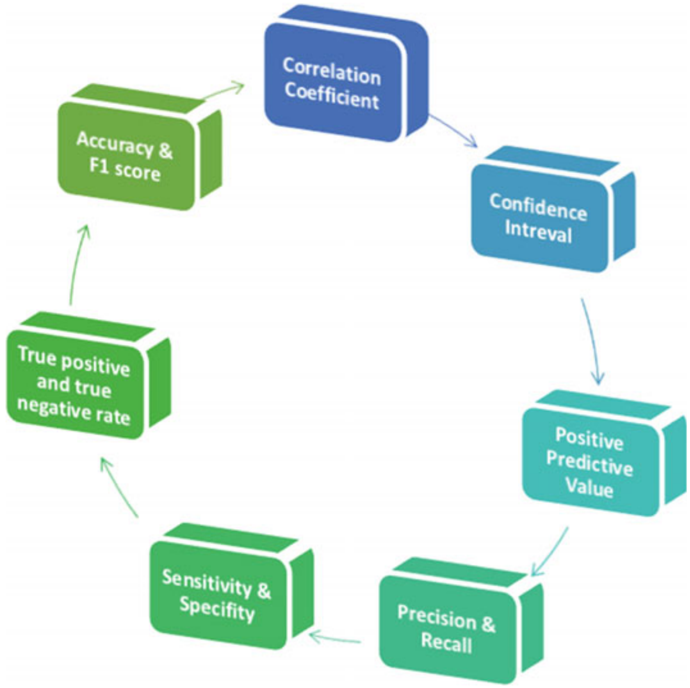

Fig. 8 Parameters list measured in cough detection

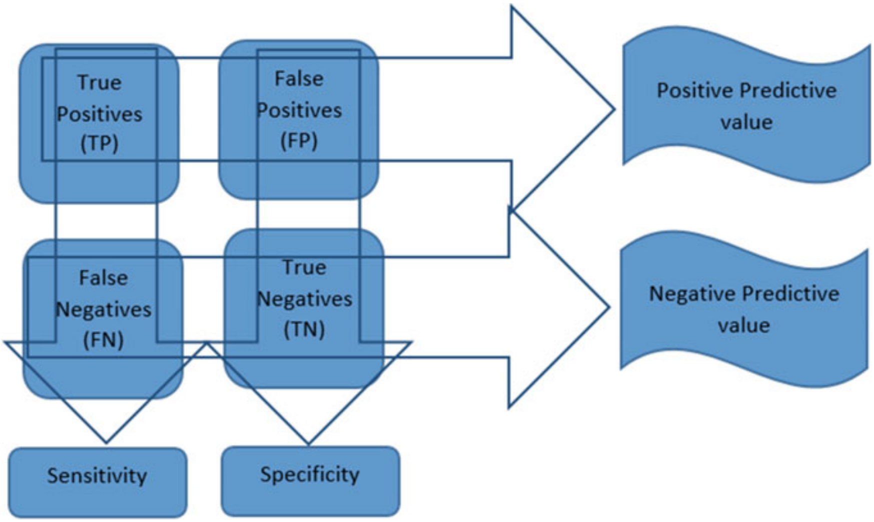

Fig. 9 Interlinking connection of parameters

Table 5 Parameter values and details for cough detection

Author	Year	Parameters description
Munyard et al.	1994	Confidence Interval—95%,
		Correlation coefficient—0.99
Corrigan et al.	2003	Susceptibility 81%
		Positive foretelling rate—0.8
Paul et al.	2004	Confidence Interval—95%
Coyle et al.	2005	Sensitivity—78.1%,
		Specificity—99.6%
Barry et al.	2006	Sensitivity of 80%
		Specificity of 96%
Matos et al.	2006	Sensitivity 82%
Smith et al.	2006	Confidence interval—95%
Martinek J et al.	2008	Sensitivity of 100%
		Specificity of 95%
Birring S et al.	2008	Sensitivity of 91%
		Specificity of 99%
Tracey et al.	2011	Sensitivity 81%
Larson et al.	2011	Susceptibility 92%,
		Mean true optimistic ratio of 92%
		False optimistic ratio of 0.5%.
Chatrzarrin et al.	2011	Accuracy 100%
McGuinness K. et al.	2012	Sensitivity higher than 99%
Drugman T et al.	2012	Sensitivity 95%
		Specificity 95%
Swarnkar et al.	2013	Sensitivity 94.5%
		Specificity 93.4%
Liu et al.	2013	Sensitivity 91%
		Specificity 95%
Swarnkar et al.	2013	Wet tussis susceptibility 84%
		Dry tussis susceptibility 76%
Parker et al.	2013	False positive fault 7%
		False negative fault 8%
Drugman T et al.	2013	Sensitivity 94.5%
		Specificity 94.5%
Lucio et al.	2014	Sensitivity 87.5%
		Specificity 84%
		Recall 86.6%

(continued)

Table 5 (continued)

Author	Year	Parameters description
		Precision 84.3%
Kosasih et al.	2014	Sensitivity (without wavelets) 94%
		Specificity (without wavelets) 63% Sensitivity (with wavelets)
		94%
		Specificity (with wavelets) 88%
Amrulloh et al.	2015	Sensitivity 93%
		Specificity) 97.5%
Drugman T et al.	2016	Sensitivity 94.7%
Pham C. et al.	2016	Recall 91%
		Precision 91%
		Subject independent training 81%
Nguyen et al.	2018	Accuracy 98.75% uncertainty 93.75%
Teyhouee et al.	2019	Region governed by acceptor operating characteristic curvature 92%
Kvapilova et al.	2019	Cough recognition sensitivity determined by human listeners was 90 and 75 at 99.5% specificity preset and 99.9% specificity preset, respectively
Hwan Ing Hee	2019	Sensitivity 82.81%
		Specificity 84.76%
Soujanya Chatterjee et al.	2019	Susceptibility 96.08%
		Selectivity 97.96%
		Exactness 96.99%
Wang et al.	2019	Average recognition rate 95%
Imran et al.	2020	Accuracy 90%
Hossain et al.	2020	Recall 92.26
		Precision 92.26
		F1 Score 92.25

8 Conclusion

In this chapter, an extensive exploration of cough detection methods implemented for various prevailing diseases such as tuberculosis, asthma, wheezing, chronic disorder to newly developed disease coronavirus infection disease in 2019 (COVID-19) is analyzed in a detailed manner. A classic introduction about the famous sick sound is given along with its taxonomy to gather a deep understanding about cough.

Cough-associated medical, non-medical and environment condition are presented. Important features of cough sound such as Mel-frequency cepstral significant, explosive cough sounds, cough seconds, cough breaths, cough epochs, cough intensity,

Table 6 Data collection description list for cough detection

Author	Year	Detailed description of data collection and datasets
Munyard et al.	1994	Collected from 20 subjects
Chang et al.	1997	21 occasions in 18 children aged between six and 15 years
Hamutcu et al.	2002	Recordings collected from 14 children
Corrigan et al.	2003	38 recordings from 30 infants; in which 13 with coughing illness and 17 healthy ones
Paul et al.	2004	Question survey from parents of 100 children with upper respiratory disorder
Coyle et al.	2005	Eight subjects with history of chronic pulmonary disorder which includes six women
Barry et al.	2006	33 fuming observant with twenty male and thirteen female in peer group of 20–54
Matos et al.	2006	Dataset consists of 2155 tussis from nine observants
Smith et al.	2006	Digital recordings from 21 patients
Martinek J et al.	2008	20 health subjects with 15 female aged between
		18 and 56 years and 5 male with age ranging from 26 to 66 years
Birring S et al.	2008	Footages from 15 patients with chronic cough extent beyond 21 days
Tracey et al.	2011	Ten subjects are used
Larson et al.	2011	2500 cough sounds from 17 subjects and recordings from 12 persons
Chatrzarrin et al.	2011	Set of eight highly dry and wet cough was used,
McGuinness K. et al.	2012	Ten patients echoes were documented which comprise six enduring cough, two asthma, one chronic cough and I healthy. In ten patients, four were female.
Drugman T et al.	2012	Two clusters of people were noted. Cluster A consists of 22 subjects. Cluster B comprised of ten supplementary focuses
Swarnkar et al.	2013	13395 separation entailing of cough and supplementary echoes. Further 342 coughs from three subjects
Liu et al.	2013	Designed cough dataset followed by 10 fold cross validation
Swarnkar et al.	2013	536 recorded pediatric cough from 78 patients against validation of 310 recordings from 60 patients and 117 cough events from 18 patients.
Parker et al.	2013	YouTube representing children coughs is utilized
Drugman T et al.	2013	32 healthy subjects are noted
Lucio et al.	2014	411 tussis echoes from 50 characters
Kosasih et al.	2014	815 cough sounds from 91 patients with illnesses as pneumonia, asthma and bronchitis
Amrulloh et al.	2015	1400 cough sounds from 14 pediatric subjects

(continued)

Table 6 (continued)

Author	Year	Detailed description of data collection and datasets
Drugman T et al.	2016	Two clusters of people were noted. Cluster A consists of 22 subjects. Cluster B included ten supplementary focuses.
Pham C. et al.	2016	1000 cough events and numerous noises
Nguyen et al.	2018	Environmental sound classification dataset with 2000 training samples. 40 recording samples in Huawei W1 smart watch in different ambient noise environments. We sampled another 40 sneezing recordings from Freesound.org.
Kvapilova et al.	2019	Health Mode Cough a public dataset with 22 subjects
Hwan Ing Hee	2019	1192 asthma cough sounds from 89 children and healthy 1140 cough sounds from 89 children
Soujanya Chatterjee et al.	2019	RALE repository consisting of 26 lung recordings of newborn to 78 years
Wang et al.	2019	Cough sounds from 84 weaners with aerial factors such as air temperature, relative humidity, ammonia concentration and dust concentration were measured
Imran et al.	2020	Environmental sound classification 50 dataset along with 993 cough sounds and non-cough sounds.
Hossain et al.	2020	21,230,450 non-speech audio snippets from hospital waiting rooms

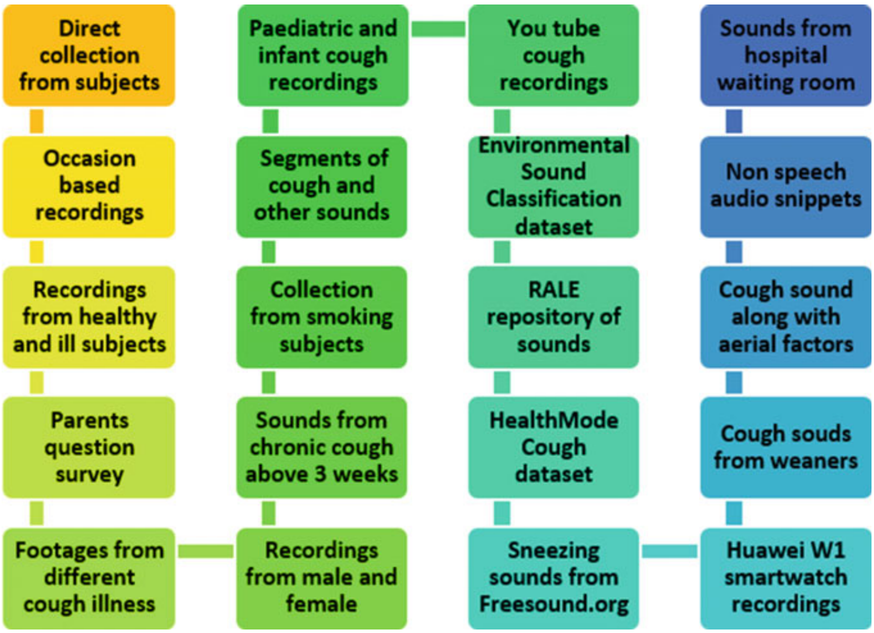

Fig. 10 Significant data collection depiction for cough detection

cough pattern, zero intersection ratio, spectral centroid, spectral bandwidth and spectral roll-off are discussed.

An extensive study of classification and segmentation algorithms such as random forest, KNN, principal component analysis, ANN, SVM, HMM, decision tree, discriminator, accelerometer portable device, universal background model, cough monitor, automatic tagging, cough counter, LRM and GMM deployed is highlighted.

A scrutiny of instruments such as accelerometer, thermistor, cough monitoring systems, microphone, sound recorders, cough counters, smart phones, chest belt, computers, mini processors and AI neural engine utilized in cough detection from conventional stage to the latest edge computing stage is investigated.

The important parameters like correlation coefficient, confidence interval, positive predictive value, precision, recall, sensitivity, specificity, true positive rate, true negative rate, accuracy and F1 score that plays a major role in cough detection are analyzed. Further, dataset involved and created in cough detection such as direct collection from subjects, occasion-based recordings, mixed healthy and ill recordings, cough footages, cough segments, smoking subject collections, environmental sound classification dataset, RALE repository, health mode cough sets, sneezing sounds, non-speech audio snippets, aerial factor cough, weaner cough sounds and Huawei cough sounds is also studied.

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