frontiers | Frontiers in Signal Processing

REVIEW
published: 03 June 2022
doi: 10.3389/frsip.2022.759684

Automated Discrimination of Cough in Audio Recordings: A Scoping Review

Praveer Sharan *

MIT-Auto ID Laboratory, Cambridge, MA, United States

The COVID-19 virus has irrevocably changed the world since 2020, and its incredible infectivity and severity have sent a majority of countries into lockdown. The virus's incubation period can reach up to 14 days, enabling asymptomatic hosts to transmit the virus to many others in that period without realizing it, thus making containment difficult. Without actively getting tested each day, which is logistically improbable, it would be very difficult for one to know if they had the virus during the incubation period. The objective of this paper's systematic review is to compile the different tools used to identify coughs and ascertain how artificial intelligence may be used to discriminate a cough from another type of cough. A systematic search was performed on Google Scholar, PubMed, and MIT library search engines to identify papers relevant to cough detection, discrimination, and epidemiology. A total of 204 papers have been compiled and reviewed and two datasets have been discussed. Cough recording datasets such as the ESC-50 and the FSDKaggle 2018 and 2019 datasets can be used for neural networking and identifying coughs. For cough discrimination techniques, neural networks such as k-NN, Feed Forward Neural Network, and Random Forests are used, as well as Support Vector Machine and naive Bayesian classifiers. Some methods propose hybrids. While there are many proposed ideas for cough discrimination, the method best suited for detecting COVID-19 coughs within this urgent time frame is not known. The main contribution of this review is to compile information on what has been researched on machine learning algorithms and its effectiveness in diagnosing COVID-19, as well as highlight the areas of debate and future areas for research. This review will aid future researchers in taking the best course of action for building a machine learning algorithm to discriminate COVID-19 related coughs with great accuracy and accessibility.

Keywords: cough analysis, AI and health, COVID-19, datasets, neural network

OPEN ACCESS

Edited by:
Mohamed Elgendi,
ETH Zürich, Switzerland

Reviewed by:
Hamid Reza Marateb,
Universitat Politecnica de Catalunya, Spain
Naimul Khan,
Ryerson University, Canada

***Correspondence:**
Praveer Sharan
praveer35@gmail.com

Specialty section:
This article was submitted to Biomedical Signal Processing, a section of the journal Frontiers in Signal Processing

Received: *16 August 2021*
Accepted: *21 January 2022*
Published: *03 June 2022*

Citation:
Sharan P (2022) Automated Discrimination of Cough in Audio Recordings: A Scoping Review. Front. Sig. Proc. 2:759684. doi: 10.3389/frsip.2022.759684

1 INTRODUCTION

This paper will review the different approaches used to discriminate between types of coughs through the limited technology of a micro-phone from a smartphone, as well as the medical issues surrounding coughs around the world. It will first describe a systematic method to identify papers that are relevant to the fields of artificial intelligence, coughs, and cough discrimination, and therefore worthy of review. The following section will discuss our step-by-step process of using the Google Scholar, PubMed, and MIT library search engines to iden-tify relevant papers. Following that, we will provide an overview of the field, including information on the biology of coughing, the different types of coughs, cough recording datasets, and propose methods for cough detection and discrimination. Then, we discuss the research done on COVID-19 related cough discrimination.

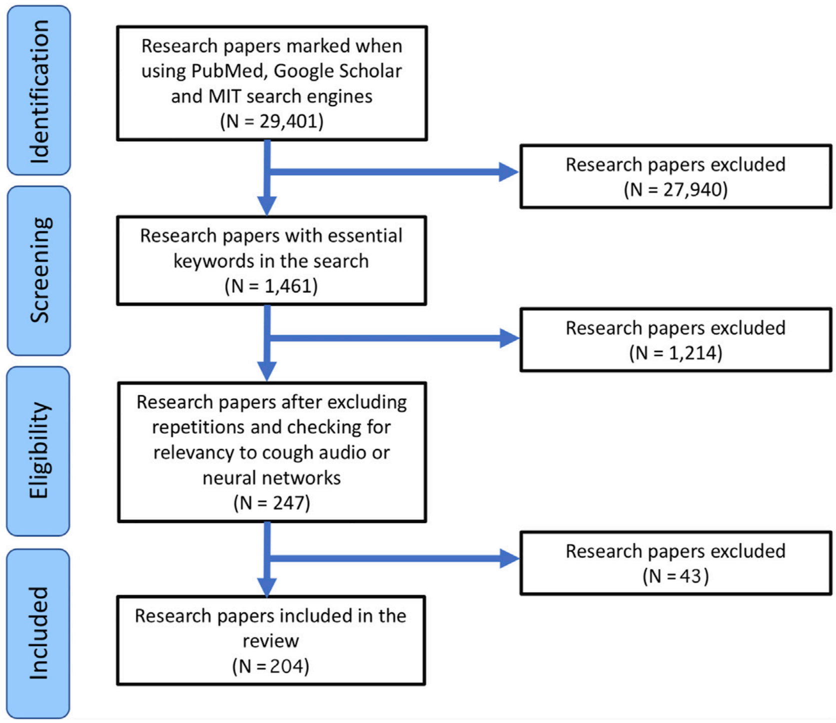

FIGURE 1 | Flowchart for methodology of reviewing papers.

After-wards, we describe other cough detection related techniques, such as principal component analysis (PCA) and loss change analysis (LCA) techniques, infection testing, pH monitoring, cough monitor-ing, and cough treatment. Finally, we discuss miscellaneous factors such as COVID-19 datasets, privacy, and applications. This review will provide insight into what can be done for early diagnosis of the COVID-19 cough through the rapid recognition of its symptomatic cough to lower the transmission of the virus.

2 REVIEW METHODOLOGY

The research papers chosen for this review had to meet the following criteria: they discuss a prototype or algorithm aiding in detecting coughs; they use artificial intelligence or neural networks to discriminate between types of coughs; they consist of information about the biological origin of a cough or the recorded audio of a cough; they discuss chronic cough and its treatments; or they discuss the difference between multiple types of coughs, such as those of COVID-19, the common flu, lung cancer, or others. All these papers ultimately help in computer recognition of various kinds of coughs. Many were found through reviewing papers on coughs and AI, and then examining the papers that cited them. The more cita-tions the research paper had, the easier it was to find other relevant papers. The keywords used were the following, ranked by useful-ness: "cough," "cough artificial intelligence," "cough sound analysis," "cough discrimination," "covid 19 cough," "chronic cough," "suppura-tive airway disease," "lower airway infection cough," "cancer cough," and "gastro oesophageal reflux cough."

As shown in **Figure 1**, we searched for ""cough" "artificial intel-ligence" symptom discrimination "detection" diagnosis" as well as ""cough" reflex larynx chronic wheeze "infection" "clinic"" and finally ""chronic cough" treatment unmet needs," finding a total of 1,461 hits.

We then selected the papers that had the most citations according to Google Scholar, reviewed them, and found 19 additional papers that were relevant. We selected the papers that matched the criteria set forth above.

A paper fit the criteria if it involved cough and treatment needs or cough and cough biology or cough and artificial intelligence or COVID-19 and cough.

All of these were filtered using the criteria described above, and a final list of the 204 most relevant papers was identified.

List 1 includes the reviewed papers on topics related to cough discrimination for various types of cough. List 2 includes the reviewed papers for various methods used for cough discrimination. References in bold fonts refer to papers that are primarily related to that topic, while references in italic fonts refer to papers that focus on coughing more than its detection. For each topic, the paper with the highest accuracy is listed.

List 1: Method used in cough analysis (8 topics).

We now present 8 topics organized in three categories in relation to how cough issues may be solved:

- Cough Detection.
  - PCA/LCA: (Ali et al., 2020), (Derraz, 2020), (Larson, 2011), (Spycher et al., 2008), (Khomsay, 2019) (Highest true positive rate: 92% (Larson et al., 2012))
  - Cough counting: (Vizel et al., 2010), (Smith et al., 2006), (Hsu et al., 1994), (Aerts et al., 2005), (Leconte et al., 2011) (Highest accuracy: 90% or higher (Vizel et al., 2010))
  - Cough recording techniques: (Ferrari et al., 2008), (Goldsmith, 2003), (Murata et al., 1998), (Salmi et al., 1988), (Doherty et al., 1997), (Aerts et al., 2005), (Drugman et al., 2013), (Moradshahi, 2013), (Smith et al., 2006), (Hsu et al., 1994), (Larson, 2011), (Rocha, 2017), (Birring et al., 2008), (Leconte et al., 2011), (Abaza et al., 2009), (Augustinov, 2020), (Orlandic, 2020), (Pinkas et al., 2020), (Bagad et al., 2020), (Balamurali, 2020), (Sharma et al., 2020a), (Chaudhari, 2020)
  - Cough monitoring: (Harle, 2006), (Birring et al., 2008), (Leconte et al., 2011), (Casaseca-De-La-Higuera, 2015), (Alsabek, 2020), (Seshadri et al., 2020) (Highest accuracy ranges from 75% to 93% (Leconte et al., 2011))
- Artificial intelligence in cough discrimination.
  - Pre-processing step (e.g. Spectral analysis): (Rocha, 2017), (Botha, 2018), (Vizel et al., 2010), (Monge-Alvarez et al., 2019b), (Ferrari et al., 2008), (Salmi et al., 1988), (Abaza et al., 2009), (Murata et al., 1998), (Hsu et al., 1994), (Doherty et al., 1997), (Amoh and Odame, 2016), (Monge-Alvarez et al., 2019a), (Moshou, 2001), (Abaza et al., 2009), (Guarino, 2005), (Belkacem, 2020), (Amrulloh et al., 2015), (Pramono et al., 2016), (Windmon et al., 2019), (Carpentier et al., 2018), (Sharan et al., 2019), (Casaseca-De-La-Higuera, 2015), (Rocha, 2020), (Dubnov, 2020), (Xu et al., 2020), (Orlandic, 2020), (Balamurali, 2020), (Chaudhari, 2020), (Subirana, 2020) (Highest accuracy: 94% for female and 97% for male coughs (Abaza et al., 2009))
  - Classification step (e.g. Neural networks): (Parker et al., 2013), (Charles, 2020), (Shi et al., 2018), (Monge-Alvarez et al., 2019b), (Moshou, 2001), (Shin et al., 2009), (Charles, 2020), (Abeyratne, 2013), (Amoh and Odame, 2016), (Monge-Alvarez et al., 2019a), (Kakabutr, 2017), (Swarnkar et al., 2013), (Ali et al., 2020), (Derraz, 2020), (Larson, 2011), (Rocha, 2017), (Botha, 2018), (Amrulloh et al., 2015), (Pramono et al., 2016), (Windmon et al., 2019), (Carpentier et al., 2018), (Sharan et al., 2019), (Larson et al., 2012), (Zhuang et al., 2010), (Casaseca-De-La-Higuera, 2015), (Barata, 2019), (Rocha, 2020), (Hoyos-Barcelo et al., 2018), (Dubnov, 2020), (Khomsay, 2019), (Belkacem, 2020), (Shuja, 2010), (Augustinov, 2020), (Pal and Sankarasubbu, 2020), (Xu et al., 2020), (Pinkas et al., 2020), (Bagad et al., 2020), (Balamurali, 2020), (Chaudhari, 2020), (Alsabek, 2020), (Subirana, 2020) (Highest accuracy: 99% for used model (Charles, 2020))
- Chemical tests in cough discrimination.
  - Infection testing: (Equi, 2001), (De Marco et al., 2007)
  - pH monitoring: (Blondeau et al., 2007), (Ing et al., 1991), (Palombini et al., 1999)

3 OVERVIEW OF THE FIELD

3.1 The Biology of Coughing

Unexplained chronic cough is a global issue, and the patients suffering from chronic cough are typically not given the necessary attention and treatment (Kang et al., 2019). Additionally, doctors cannot prescribe medicine without fear of tachyphylaxis (Doherty et al., 1997). Biologically, a cough originates from the sudden opening of the glottis after contraction, which creates a violent, explosive sound. The cough also originates from the larynx, as the larynx is responsible for cough reflex and dysfunction can cause coughing issues. For an acute cough, there are parainfluenza coughs which are more stable than influenza coughs. Coronavirus is clinically similar to the rhinovirus.

List 2: Cough-related topic to be solved (7 topics).

We now present 7 topics in relation to cough topics, organized in two categories:

- Cough types.
  - Acute cough: (Morice, 2002), (Wee-Yang and Boushey, 2008), (Ferrari et al., 2008), (Salmi et al., 1988)
  - Pertussis: (Parker et al., 2013), (Spycher et al., 2008)
  - Asthma: (Fujimura, 2003), (Hsu et al., 1994), (Birring, 2011)
  - Lung: (Chang et al., 2011), (Redding and Carter, 2017), (Harle, 2006), (Harle et al., 2020), (Botha, 2018), (Equi, 2001), (Abeyratne, 2013), (Chang et al., 2008), (Wee-Yang and Boushey, 2008), (De Marco et al., 2007), (Windmon et al., 2019), (Larson et al., 2012), (Abaza et al., 2009), (Dubnov, 2020), (Balamurali, 2020), (Sharma et al., 2020a)
  - Gastro-oesophageal: (Blondeau et al., 2007), (Ing et al., 1991)
  - COVID-19: (Ali et al., 2020), (Derraz, 2020), (Belkacem, 2020), (Dubnov, 2020), (Shuja, 2010), (Pal and Sankarasubbu, 2020), (Pinkas et al., 2020), (Bagad et al., 2020), (Sharma et al., 2020a), (Chaudhari, 2020), (Alsabek, 2020), (Subirana, 2020), (Seshadri et al., 2020)
- Unmet needs.
  - Chronic cough issues including Tachyphylaxis: (Hilton et al., 2015), (Gibson, 2016), (Chung, 2017), (Kang et al., 2019), (Mcgovern et al., 2018), (Chang et al., 2008), (Palombini et al., 1999), (Birring et al., 2008), (Birring, 2011), (Ryan et al., 2010), (De Marco et al., 2007), (Pavord, 2008), (Hsu et al., 1994), (Bowen et al., 2018), (Chang et al., 2011), (Redding and Carter, 2017), (Blondeau et al., 2007), (Ing et al., 1991), (Windmon et al., 2019), (Bowen et al., 2018), (Doherty et al., 1997), (Morice, 2002)

Irwin (Irwin and Curley, 1991) lists the types of coughs as: asthma related, lung related, and common cold related. Morice (Morice, 2002) lists the types of coughs as acute, chronic, pertussis related, lung related, influenza related, and gastro-oesophageal related. Given what was relevant in the papers, we used acute, pertussis, asthma, lung-related, gastro-oesophageal, COVID-19, and chronic coughs as categories.

3.2 Types of Coughs

The two main categories of coughs are acute cough, which is temporary, and chronic cough, which is typically more severe and lasts for a significant amount of time. Specific diseases that result in coughs include pertussis, COVID-19, gastro-oesophageal diseases, lung cancer, and bronchitis.

3.3 Cough Recording Datasets

The ESC-50 dataset (https://github.com/karolpiczak/ESC-50) can be used to train the computer as it has an array of natural sounds including coughs, which was used by Imran et al. (Ali et al., 2020) and John (Charles, 2020). FSDKaggle 2018 and 2019 have also been used as datasets, used by John (Charles, 2020). However, datasets such as these are not available to the public, and the ones that are accessible are not extensive and do not focus solely on coughs. This impedes progress as it is difficult for other scientists to use the existing databases already created. Therefore, more databases need to be made available to the public.

3.4 Cough Discrimination Techniques

Neural network based algorithms have been effective in discriminating cough. Some popular choices for these neural networks are k-NN, Feed Forward Neural Network, and RF. Classifiers such as Support Vector Machine and the naive Bayesian classifiers have been used frequently. Parker et al. (2013) used a classic approach with k-NN, Fast Forward Neural Network, and RF to detect paroxysmal coughing from pertussis cases. After feeding vectors into the neural networks, the evaluation of whether or not a cough was that of per-tussis was performed by averaging the results of the decision trees of the RF. They checked for overfitting by reserving data for cross-validation of the k-NN and RF. The Neural Network was trained 100 times, and the results were averaged. All algorithms functioned with relatively good accuracy. A drawback of the k-NN algorithm is that while it is accurate, it is also very time consuming to run. This can be improved through various spin-offs of the algorithm.

3.4.1 Convolutional Neural Networks (CNN)

Amoh et al. (Amoh and Odame, 2016) used CNNs as a method to classify coughs. The basis of their paper is that the same techniques and types of neural networks which are used in neural networks for imaging could be applied to coughs. Since CNNs are trained for imaging, they can again be used in helping with training for coughs. However, since imaging deals with fixed 2D images and sound processing deals with many frames of sound, the neural network must be slightly tweaked. Pre-segmentation ensures that spectro-temporal data are of a fixed dimension from the audio signal, which can then be fed into the network. The data can fit the fixed dimension by discarding segments or by being zero-padded. Additionally, the paper advised using deep Random Neural Networks (RNN) instead of Hidden Markov Models (HMMs). This was done because deep RNNs are more likely than HMMs to model long-term contexts, and are resistant to additional noise, making the RNN an ideal neural network for detecting coughs. In terms of spectral analysis, the 128-bin Short Time Fourier Transform is used to create 64 frequency points. By using this spectral data as input into the Convolutional Neural Network, using a stochastic gradient descent, training results are smooth. For this paper, a learning rate of 0.001, a batch size of 20, and a Nesterov's moment of 0.9 were used. The RNN was trained using the adadelta optimizer.

3.4.2 Evolved Cepstral Coefficient (ECC)—Hidden Markov Model (HMM) Hybrid

When testing different algorithms for machine learn-ing, Shin et al. (2009) found it best to use ECCs in place of MFCCs because MFCCs have problems with finding the optimal number of fillers. Additionally, an HMM with a first-order ergodic structure was chosen due to the original HMM's inherent issues. Coupled with the Hilbert transform to calculate the signal of a cough sound, this hybrid model achieved great accuracy and resilience. Spectral analysis is frequently performed on cough audios to analyze the audio of the cough and help discriminate between different types of coughs, and 23 of the papers focus on this. For example, coughs can differ in peak wavelength.

The paper described a cough, moan, and voice as the main iden-tifiers of cough abnormalities. It then delved into the science of a cough sound, its basic concept and its sample sounds, a proposed hybrid model to detect a cough sound, and then tested its proposed model using various SNRs. The artificial neural network model was used, as well as the hidden Markov model. However, due to the HMM's inherent issues, the discrete first-order HMM with an ergodic structure was chosen. Upon testing, it was seen that the hybrid model worked well in more noisier environments and im-proved recognition. While the standard HMM had a recognition percentage of 88% at 5 dB which plummeted to 3% at–10 dB, the hybrid model had a higher recognition percentage of 91% at 0 dB which was relatively unchanged at 82% at −10 dB.

3.5 Instruments Used for Cough Detection

Ferrari et al. (2008) discussed a proper method to set up a recording setup for maximum accuracy. When recording a pig farm for coughs, the microphones on the pig farm were connected via preamplifiers (Monacor SPR-6) to an 8-channel analog-to-TDIF (Tascam digital interface) unit (Soundscape SS8IO-3). All recordings were sampled at a rate of 44.1 kHz with a resolution of 16 bits. While counting the coughs and cough attacks did not provide an answer, it was seen that the non-infected pigs coughed with a higher peak frequency (750–1800 Hz) while the infected pigs coughed with a lower peak frequency (200–1,100 Hz). Another paper, Goldsmith (2003), proposed a novel instrument for analyzing cough sounds. The cough would be fed directly into a microphone, and minimal interference would be heard. However, the most common apparatus used for recording cough sounds was a smartphone.

Other papers relating to cough detection that were less relevant are: Alqudaihi et al. (2021) and Hoare et al. (1972).

3.6 Critical Review of Papers Based on Accuracy

We reviewed the papers if they included results for the accuracy of the used neural network algorithm. **Table 1** lists the 21 most accurate algorithms among the reviewed reports. High accuracies as shown in this table are produced from using a neural network algorithm.

Very few algorithms have been able to achieve an extremely high accuracy or success, and those that have in general, use simpler algorithms. Convolutional neural networks prove to do very well. However, there is general disagreement over which neural networks are more successful among scientists and how certain algorithms can be combined for maximum efficiency.

4 COUGH RECORDING TECHNIQUES

There have been many methods tested for recording coughs of the highest quality audio, but a microphone array has proven to be very successful. Salmi et al. (1988) analyzed the cough noise by a person on a static charge sensitive bed by passing it through a sampling rate of 30 Hz. The program used an algorithm where it calculated the mean noise levels of the signal. Then, the detection level was multiplied by 4 for acoustic signals and 3 for body movement signals. If both body movement and acoustic signals surpassed the threshold simultaneously, then a cough would be recognized. This algorithm can also be used for sleep and sleep-related apneas. Cough sounds are transients containing frequency components with a range of 80 Hz to around 4,000 Hz, at minimum. Therefore, high-pass filtering can cut off low-frequency noise, or different sounds. The results of recording the coughs over a long period of time with automatic analysis of cough has advantages in high sensitivity and specificity.

Murata et al. (1998) described an experiment used to discriminate between productive coughs, caused by excess airway secretions, and non-productive coughs. In the experiment, some subjects had chronic airway diseases and some were healthy. Coughs with spu-tum were described as productive coughs. The voluntary coughs, on the other hand, were compared with vowel sounds for recording. Then, a sound spectrogram and time-expanded waveform were cre-ated through the cough audio waves. The cough was analyzed in its second phase after the expulsion of sound from the cough. Phase 2 was the longest phase with a length of 105 msec, followed by phase 3 (the noise created by the vocal cords closing) with a length of 90 msec, and lastly by with phase 1 (the expulsion) in last with a length of 50 msec.

Doherty et al. (1997) analyzed the differences acoustically between healthy members when given an induced cough. By giving capsaicin to the set of subjects, a spontaneous cough will be produced. The researchers plotted the data on a spectrogram by overall spectral energy, and root means square pressure plots. The Root-Means-Square plots showed that the most common pattern is a cough with two energy peaks, at the beginning and end. Less common were a single peaked cough sound and more than three high energy peaks. The spectrograms varied greatly, as did the spectral energy chart. Capsaicin is able to produce reproducible cough noises without fear of tachyphylaxis.

Aerts et al. (2005) focused on cough detection in pig houses, where sound equipment was hooked up to the laboratory and recorded the number of coughs for the pigs. When doing this, underestimations of up to 94% in counting coughs were reported. The goal of Drugman et al. (2013) was to study different sensors for cough detection and then test them in an experiment with healthy subjects in a confined room. The performance of the ECG sensors, thermistor, chest belt, accelerometer, contact, and audio microphones outperformed the KarmelSonix system.

Drugman et al. (2013) studied different sensors for cough detection and then tests them in an experiment with healthy subjects in a con-fined room. The performance of the sensors ECG, thermistor, chest belt, accelerometer, contact and audio microphones outperformed the Karmelsonix system.

Moradshahi (2013) tested cough sound discrimination algorithms in noisy environments since reverberation can cause a great deal of inaccuracy in these algorithms. When white noise was added to the system, the success of the discriminator decreased significantly, and when the distance from the microphone was greater, the algorithm could not discriminate between two different cough types. When tested with varying volume of cough sounds, the success of the discriminator also changed. As the volume increased, the success of the discriminator increased, but when the volume reached a certain point, the saturation of the system was so high that the success of the discriminator dropped. To improve upon the single microphone, the researcher used a microphone array and beamforming techniques to improve the performance of the discriminator in these noisy scenarios. The success of the discriminator increased with these new adjustments.

Orlandic (2020) described methods for data collection that can be used for cough analysis algorithms around the world. Its first consideration was the best method for data collection, which asked the user to cough into an elbow with the microphone at arm's length since coughing is a potentially dangerous activity during a pandemic. Since this dataset uses crowdsourcing, it ran into the problem that many samples will be unrelated to the database's desired content. Classifiers were used for this database cleansing using power spectral density. This paper has public source code for the XGB classifier that performed this task.

Bagad et al. (2020) proposed an AI model that is able to predict the presence of COVID-19 from cough sounds alone, which have been recorded on a phone application. The data collection procedure can be described in the following steps: subject enrollment, where the users report their demographic information; cough-sound recording, where the users records three separate audio samples of themselves coughing; and testing. The main neural architecture described for this task was the CNN, and the training strategies described were augmentation, pre-training, and label smoothing. It turned out that the performance for this algorithm was similar for both male and female individuals.

Sharma et al. (2020a) discussed the differences between speech and cough noises for those with and without COVID-19 and for those without it. The sound of the cough, the pattern of breathing, the respiration rate, way of speech, and intervals of breathing are all subtle tells that could reveal a decently accurate diagnosis. In those with COVID-19, low pitches with popping and bubbling would be heard. There will be cough sounds for a continuous 30 min, with an episode lasting around half a minute or so. A

TABLE 1 | Critical review of papers based on accuracy.

Paper title	Year	Review
Diagnosis of COVID-19 and non-COVID-19 patients by classifying only a single cough sound Maleki (2021)	2021	The paper used a cost-effective algorithm based on computer-aided digital technolo-gies. The accuracy rate was extremely high: 98.33% for all patients and 97.20% for only COVID-19 patients. No errors or confidence intervals were reported. The authors used 6,737 recorded cough samples and 8,854 control sounds with 5 different recorders, with a total of 43 subjects
A generic deep learning based cough anal- ysis system from clinically validated sam- ples for point-of-need COVID-19 test and severity levels Andreu-Perez et al. (2021)	2021	The algorithm proposed combines a cough detection algorithm based in EMD and a recognition method known as DeepCough3D. This performance was high, with a sensitivity of 91% and a 10% margin of error. The Type I error for the DeepCough3D algorithm was 3.36%, and its respective Type II eror was 2.82%. No confidence intervals were reported. There were 8,380 clinically validated samples used. Classification was based on severity, such as borderline positive, standard positive, or high positive
COVID-19 artificial intelligence diagnosis using only cough recordings Laguarta et al. (2020)	2020	A screening test was proposed that discriminates an impressive 98.5% COVID-19 positives from a forced-cough recording. The algorithm uses CNNs. The model has a 97.1% discrimination accuracy if the subjects are diagnosed with an official test. It discriminates 100% of those who are asymptomatic, although the Type I error is high: 16.8%. No confidence intervals were reported. The dataset used was extremely large and balanced, as the same number of COVID-19 positive and negative samples were used. The sample set of two-second audio chunks was also balanced, used in training of the proposed model
Automatic detection and classification of cough events based on deep learning Augustinov (2020)	2020	The paper used deep neural learning with an automatic CNN. The reported accuracy was high at 92.5%, but with the 3-label model, the accuracy decreased to 81.2%. The dataset was fully balanced due to obtaining 50% of 1,602 spectrogram image samples that are cough holder segments. No errors or confidence intervals were reported. The network used contained 1,602 spectrogram images with half being cough holder segments and the other being healthy. Data acquisition was performed using the LEOSound Lung-Sound-Monitor. 48 patients were measured for 8 or more hours, and 100,507 samples of 30-s windows were used in data acquisition
Practical cough detection in presence of background noise and preliminary differ- ential diagnosis from cough sound using artificial intelligence Charles (2020)	2020	Special algorithm was used involving XGBoost database and CNNs. High accuracy of the used model was reported at 99%, with a loss of only 3%. Reported Type I errors are: 7%, 12%, and 25% while Type II errors are: 8%, 0%, and 0% for an artificial neural network, random forest, and k-NN, respectively. No confidence intervals were reported. All sounds were converted to spectogram using the Python librosa library, and were 44 kHz. The detection training dataset had roughly 35,000 images
Towards device-agnostic mobile cough detection with convolutional neural net- works Barata (2019)	2019	A simple convolutional neural network was used with a high success rate. The accuracy measured was high at 90.9%. There was no concrete value given for either Type I or Type II errors. However, it was shown that the highest rates for Type I errors are from the algorithm k-NN, followed by the random forest, then by the convolutional neural networks. No confidence intervals were reported
Efficient k-NN implementation for real- time detection of cough events in smart- phones Hoyos-Barcelo et al. (2018)	2018	This paper used vp-trees with k-NN search for an efficient algorithm. The classification accuracies were high, over 93%. No confidence intervals were reported
Automatic cough detection for bovine res- piratory disease in a calf house Carpentier et al. (2018)	2018	The paper proposed a complex algorithm with medium-high precision of 84.2% in certain circumstances to a high precision of 94.2% in others. However, the sensitivity of the overall algorithm was quite low: 41.4%. Type I and II errors varied throughout the batches, but no concrete average was given for either. Type II errors were higher than Type I errors. No confidence intervals were reported. The individual sound events were manually extracted, therefore making the ratio of non-cough to cough events balanced. Sounds were recorded over two time periods of 82 and 96 days, with 21 and 14 calves in each compartment. There were 664 different cough references, and 445 min total of sound data
A machine hearing system for robust cough detection based on a high-level rep- resentation of band-specific audio features Monge-Alvarez et al. (2019a)	2018	Real time cough monitoring was able to achieve high accuracy with a sensitivity of 92.71% and a specificity of 88.58%. No confidence intervals were reported
Dog cough sound classification using arti- ficial neural network and the selected rele- vant features from discrete wavelet trans- form Kakabutr (2017)	2017	An artificial neural network was used with a high accuracy of around 90% on average. No confidence intervals were reported
Deep neural networks for identifying cough sounds Amoh and Odame (2016)	2016	A convolutional neural network edged out a recurrent neural network in cough detection, with a specificity of 92.7% for the convolutional network and a specificity of 87.7% for the recurrent network. No confidence intervals were reported

(Continued on following page)

TABLE 1 | (*Continued*) Critical review of papers based on accuracy.

Paper title	Year	Review
Effect of downsampling and compressive sensing on audio-based continuous cough monitoring Casaseca-De-La-Higuera (2015)	2015	The paper used a simple cough detection system based on simple decision-tree classification, and had an extremely high performance with a 98% sensitivity and 97.13% specificity. No confidence intervals were reported
Automatic cough segmentation from non- contact sound recordings in pediatric wards Amrulloh et al. (2015)	2015	An algorithm using non-Gaussianity, Shannon entropy, and cepstral coefficients was used and showed high accuracy of 97.3%, a sensitivity of 92.8%, and specificity of 97.5%. No errors or confidence intervals were reported. The data set used contained 14 subjects with a sound recording length of 840 min
Automatic identification of wet and dry cough in pediatric patients with respira- tory diseases Swarnkar et al. (2013)	2013	A k-mean clustering algorithm was used with a logistic regression model to detect wet and dry coughs. The model was moderately accurate with a 88% specificity for wet coughs and a 76% specificity for dry coughs. A 95% confidence interval was reported, being 87%–88% for the training/validation dataset, and 76%–84% for the prospective dataset. The sounds were recorded using a bed-side non-contact microphone, and the data contained 78 patients. There were 310 cough events from 60 patients (the training/validation dataset), and 117 cough events from 18 patients (the prospective dataset)
Detecting paroxysmal coughing from per- tussis cases using voice recognition tech- nology Parker et al. (2013)	2013	There was a high rate of success and low error due to running the neural network hundreds of times. 90% of coughs correctly classified as pertussis, Type I errors ranged from 7–25%, and Type II errors ranged from 0–8%. More specifically, for a neural network: the success rate for detecting actual pertussis and a lack of one was 93% and 92%, respectively, with Type I and Type II errors of 7% and 8%. For random forest: the success rate for detecting actual pertussis and a lack of one was 88% and 100%, respectively, with Type I and Type II errors of 12% and 0%. For k-NN: the success rate for detecting actual pertussis and a lack of one was 75% and 100%, respectively, with Type I and Type II errors of 25% and 0%. No confidence intervals were reported. Pertussis sound files were collected from children and from YouTube, and were classified as either pertussis or non-pertussis
The objective assessment of cough fre- quency: accuracy of the LR102 device Leconte et al. (2011)	2011	The accuracy of the LR102 device was proven to be somewhat accurate, as the automatic counting and manual counting were closely correlated at r = 0.87 for occurrence of cough episodes per hour and r = 0.89 for the occurrence of a single cough per hour. Cough frequency was overestimated. Errors were not reported. For a single cough, the confidence interval at 95% was reported to be 0.75 to 0.92, and for an episode, the confidence interval at 95% was reported to be 0.78 to 0.93. In total, 40 h of recording were analyzed
Accurate and privacy preserving cough sensing using a low-cost microphone Larson (2011)	2011	This is extremely accurate system that used a PCA and a random forest classifier, resulting in an average true positive rate of 92% and a Type I error of 0.5%. No confidence intervals were reported. 17 subjects experiencing cough episodes were used in data acquisition. They were recorded with an Android G1 mobile phone, which was placed around their neck or in their shirt pocket.
Validation of an ambulatory cough detec- tion and counting application using vol- untary cough under different conditions Vizel et al. (2010)	2010	This was a highly successful algorithm with a consistent success of 90% or higher. Specificity for all cough events was 94% and the sensitivity was 96%. No errors or confidence intervals were reported. The data was acquired with the help of 12 volunteers, and the sounds were recording using the PulmoTrack hardware. Each recording was 25 min long for a total of 300 min
Automatic detection system for cough sounds as a symptom of abnormal health condition Shin et al. (2009)	2009	A successful and resilient hybrid model was created through combining attributes of ECCs, the artificial neural network, and the hidden Markov model. The model achieved a recognition percentage of 91% at 0 dB noises and a 82% at -10 dB noises, as well as performing equally well under noiser conditions. No confidence intervals were reported
Classification of voluntary cough sound and airflow patterns for detecting abnor- mal pulmonary function Abaza et al. (2009)	2009	The optimal classifier used in this algorithm resulted in an extremely high perfor- mance with 94% for female coughs and 97% for male coughs. No concrete error percentages or confidence intervals were reported. 52 healthy subjects were used in this study, as well as 60 subjects who had obstructive or restrictive lung disorders. These subjects performed three individual voluntary coughs
Establishing a gold standard for manual cough counting: video versus digital audio recordings Smith et al. (2006)	2006	This was an accurate method of counting coughs in either videos or through audio. The mean cough frequencies of each differed by 0.1 coughs/hour and the mean of cough frequency differences was 0.3 coughs/hour, with a standard deviation of 0.6 coughs/hour. The 95% limits of agreement were reported from -1.5 to +0.9 coughs/hour. 8 patients with chronic cough were studied through manual cough counting, as well as a video camera with infrared lighting and digital sound recording. Each cough recording was 8 h long

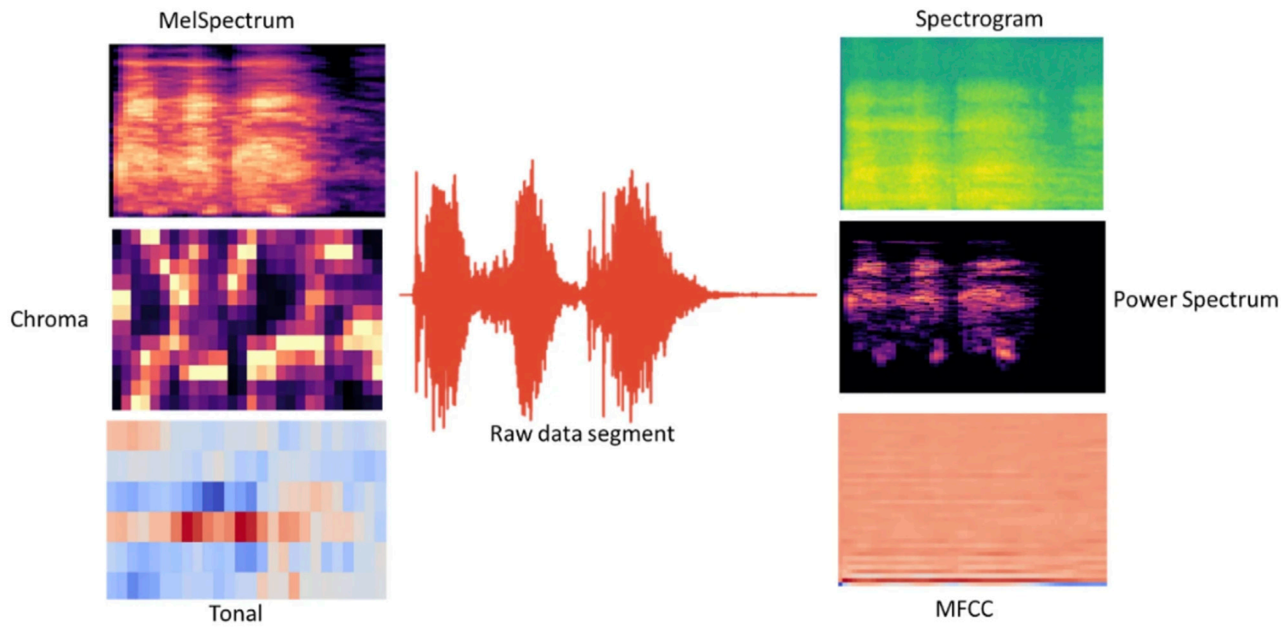

FIGURE 2 | A cough audio and its six representations: the MelSpectrum, chroma, tonal, spectrogram, power spectrum, and MFCC, according to Mohammed et al. (2021). The cough undergoes an audio splitting step, generating six frequency measures based on the Mel frequency scale. These are audio signal representations based on frequency. These representations are used in neural networks. MFCC stands for Mel Frequency Cepstral Coefficients.

trademark description of the COVID-19 cough is a dry, barking, hoarse sound. If lungs are injured, a wheezing sound could be heard.

Chaudhari (2020) talked about how datasets from crowdsourc-ing could be used with neural network algorithms to detect COVID-19 from cough audios with a reasonable accuracy. A deep neural net-work was used with the publicly available Coswara and Coughvid datasets of cough sounds. Datasets of smartphone-recorded coughs from South America were also used. MFCCs were used to extract audio features, and then an ensemble of Deep Neural Networks were used for classification. The accurate results of this algorithm demonstrates that crowdsourcing is a moderately accurate method of detecting COVID-19.

Other papers relating to cough detection that were less relevant are: Larson (2011).

5 RESEARCH ON COVID-19 RELATED COUGH DISCRIMINATION

In 2020, the main use of neural network architecture and machine learning algorithms for clinical diagnosis was to discriminate ac-curately whether a cough was caused by COVID-19 or some other lung-related disease, for example, through the method shown in **Figure 2**. Research papers already exist that generally use methods of spectral analysis combined with an array of neu-ral networks. However, the method of recording the data is also called into question, where the recording must be accurate enough to yield accurate results, and it must be affordable enough to be accessed by many around the globe in order to have a large scale impact. Papers Shuja (2010), Pinkas et al. (2020), and Chaudhari (2020) used smartphone applications for recording, which yield near 90% accuracy or above and are is accessible to millions of people around the world. Some of the classifiers that were used for these research papers are: DL-MC, CML-MC, DL-BC, logistic regression, gradient boosting trees, SVM, and RNN. Some of the datasets that were used include ESC-50, national COVID-19 data collection project, Koswara, and Coughvid.

Coppock et al. (2021) presented seven main concerns in using cough audio to train neural networks to detect whether or not one has COVID-19 or not. Firstly, the algorithms may not be specific to COVID-19 and may solely detect the general health of the subject. Secondly, the unfiltered environmental sounds in the background of the cough audio may tamper with the training of the neural networks and could introduce bias–perhaps a correct diagnosis for COVID-19 may be more likely indoors. Thirdly, the patient's knowledge of whether they have COVID-19 could corrupt neural network training if emotions leak into the voice. Fourthly, many datasets used for this training are not extremely reliable or valid. Fifthly, there are not many public codebases or datasets that can be used for neural network training. Next, demographic characteristics can introduce bias as disease prevalence is not consistent among all regions. Finally, the participant population is largely uncontrolled.

Therefore, reappearing participants will cause the model to function with higher accuracy, inflating the success scores.

5.1 Using Spectral Analysis

Moshou (2001) placed pigs in an isolated area with a microphone, and then recorded their coughs. The sample rate of the microphone was 22,060 Hz since a typical cough frequency is under 10,000 Hz. Thirty minutes of recording took 80 MB of disc space. To find the power spectra density of the sounds, a Fast Fourier Transform of 128 points was used on the cough audios. The MATLAB toolbox is commonly used for calculating PSD. The calculation yielded PSD vectors with 64 components, which were then used later in prob-abilistic neural network training. The Bayes decision rule can be applied to scenarios such as these, which have many different cate-gories; in this case, two. Probability density functions can be created using probabilistic neural networks, which had been used by Specht in 1966. The PNN was used with success to discriminate between cough sounds and other noises. The most challenging task was to separate the cough audio and the metal clanging as they have similar frequency content.

Monge-Alvarez et al. (2019a) proposed a machine that can detect cough solely based on audio recordings. First, the cough patterns were characterized using 29 short-term features adjusted for differ-ent noisy environments. Then, five frequency bands were defined to aid in the calculation of the spectrum properties of the acoustic cough audio. These spectrum properties were used to generate a long-term feature space using sample statistics that which were then fed into a series of SVMs, which were then trained for different noisy environments. The output to these SVMs was the detection of a presence of cough. Upon testing with patients, it was found that this machine outperforms many other methods in cough detection, and that it held well under the stress of three noisy environments. However, this method required a pre-processing step to eliminate other noises in the background.

Amrulloh et al. (2015) used an algorithm to identify cough segments from pediatric sound recordings using non-Gaussianity, Shannon entropy, and cepstral coefficient extractions from the cough. These characteristics were then fed into an artificial neural network.

Pramono et al. (2016) used a quick and easy neural network algo-rithm with three stages to identify specifically a pertussis cough. These three stages include sound event detection, feature extraction, and cough detection/classification.

Windmon et al. (2019) described a smart-phone app that can record and process cough audio to diagnose chronic obstructive pulmonary disease. The algorithm includes filtering noise, partitioning every cough into segments, extracting its features, removing biases, and then designing a two-level classification scheme based on Random Forests.

Carpentier et al. (2018) used an algorithm to discriminate between coughs in a calf house, using 664 different cough references. The algorithm worked well, with a precision of higher than 80%. Features such as spectral spread, entropy, and flux were used.

Sharan et al. (2019) used artificial intelligence to detect a croup cough using MFCCs which are used to capture features of automatically segmented cough sounds from test sets of patients. This algorithm was a significant improvement in automatically diagnos-ing croup automatically compared to previous methods.

Rocha (2020) aimed to create an algorithm that which could automatically detect explosive cough events that are related to pul-monary disease. Pre-processing included passing the audio signal through an 8-th order infinite impulse response high-pass filter with 80 Hz. Feature extraction was done with the help of STFT and MFCCs. Classification was done with the help of four classifiers: Naive Bayes for Bayesian, SMO for SVM, RIPPER for Propositional Rule Learner, and Bagging for Bootstrap Aggregation.

Dubnov (2020) proposed an algorithm that can automatically detect COVID-19 through a cough with the help of logistic regres-sion, SVM, Random Forest, Multilayer Perceptron, and CNN as methods of classification. They were used along with Fast Fourier Transformation for processing.

Balamurali (2020) proposed an algorithm for diagnosing children with asthma based on cough audios. The dataset was obtained by recruiting asthmatic children from clinics, with a mean age of 8 years. A smartphone was used for recording the children's ac-tive coughing. Vocalized sounds were also used because they can indicate whether there are any issues with throat inflammation or narrowing of pathways. MFCCs and CQCCs were used for audio feature extraction. The GM and UBM were used for classification, and the accuracy was reported to be the highest for the fused model (cough).

5.2 Other Methods

To detect the coughing noise, the online datasets ESC-50 and FSDKaggle 2018 and 2019 were used in the paper by John (Charles, 2020). All sounds were converted to spectrogram using the librosa library in Python. The Deep Residual Learning framework used a special algorithm that allowed for training of much deeper networks than other algo-rithms. XGBoost and Convolutional Neural Networks were used to determine the result and diagnosis. The accuracy of the used model was 0.99, and the loss was 0.03.

The sound of a cough can be divided into three parts based on audio, according to the paper by Shi et al. (2018). Through cough processing algorithms, a cough can be identified and determined whether it is a dry or wet cough. This is done through neural networks, SVM, and naive Bayesian classifier. Removing silence in a cough audio is important to preserving data. The endpoints of the cough can be calculated through the zero-crossing rate (ZCR), which is a ratio of the sign changes of a signal. Additionally, MFCCs that are used to convert the data into coefficients.

Abeyratne (2013) described an algorithm that could be used with high success to diagnose pneumonia. Pneumonia is a serious child-killer and diagnosing it in a hospital is difficult. It is possible, however, to diagnose pneumonia through the cough audio. The first step is to extract and augment the cough features. This can be done by computing many features from the cough and compiling them. The second step is to use an LRM as the pattern classifier. The leave-1-out cross validation technique can be used. The next step is to select a good model from the LRM which can be found through k-means clustering. The final step is to calculate the cough index for the disease, in this case, Pneumonic Cough Index (PCI). This can be calculated based on the previous information found. This index will ultimately determine if the cough is pneumonia related. The algorithm, when tested, resulted in a sensitivity and specificity of mostly greater than 90% when tested with various children. The re-search from this paper can provide a low-cost method of combating diseases such as pneumonia and will have great value in creating a vaccine for its related disease.

Kakabutr (2017) used artificial neural networks to classify cough sounds from dogs and to determine whether the dog is healthy, something that is difficult for many experienced practitioners. The artificial neural network is used to convert the raw cough audio from time domain into time frequency domain, additionally extracting the important features relating to the cough. Eight levels of decom-position were successfully used to classify this cough sound, and the optimal neural network model had 40 nodes in the hidden layer with 22 features. In the hidden nodes, a logistic function was used and in the output nodes, a hyperbolic tangent function was used. This model worked successfully, generating an average accuracy of 90% or higher with only using a quarter of all features.

Swarnkar et al. (2013) aimed to find a specific algorithm that could discriminate automatically between wet and dry coughs solely based on audio. This is useful because a wet cough can indicate lower respiratory tract bacterial infections while dry coughs could indicate other diseases. A logistic regression model was proposed to classify the coughs into wet and dry with the help of a k-means clustering algorithm. Upon testing with 78 patients, results showed that the sensitivity and specificity of the logistic regression model was near 88% with a 95% confidence interval for wet coughs and 84% with a 76% confidence interval for the next dataset with 18 patients. Therefore, this new algorithm can work successfully for cough monitoring without the need for professionals at a hospital setting.

Larson et al. (2012) could detect cough episodes through neural networks which can automatically identify tuberculosis. Recordings of 25.5 h were used with a large number of tuberculosis patients.

Zhuang et al. (2010) proposed using Acoustic Event Detection and extracting those discriminative features, which could result in higher rates of success. HMMs worked well, and the SVM-GMM-supervector was more successful at approximating the KL diver-gence between feature distributions for an audio segment.

Casaseca-De-La-Higuera (2015) proposed a simple and efficient algorithm for detecting coughs based on simple decision-tree classifications with spectral features and a smartphone audio sig-nal. Undersampling down to 400 Hz resulted in the sensitivity and specificity values remain above 90 percent.

Barata (2019) used a simple convolutional neural network to identify whether a cough event had occurred. The steps of the algorithm included extracting the audio event, preprocessing, and cough detection, which simplifies into two categories: cough or non-cough.

Hoyos-Barcelo et al. (2018) used local Hu moments through the audio signal from the device. Through pairing local Hu moments and a standard k-NN classifier, cough detection becomes more ac-curate, although it is more time-consuming. This study proposed a way to speed up the k-NN search, which would enable real-time performance on all smartphones.

Shuja (2010) demonstrated how in the battle to fight COVID-19 with artificial intelligence, the correct datasets and ways to use them are vital. It discussed three categories of datasets: medical im-ages, textual data, and speech data. In the section on speech data, the paper suggested that cough sounds, breathing rate, and stress can all be detected from smartphone applications and are relevant to diag-nosing the severity of COVID-19 symptoms. Some researchers have mentioned that the steps to determining a COVID-19 infection in-volve distinguishing those who are COVID-19 positive from healthy people, healthy people with a cough, and then finally those with asthma and a cough. Logistic regression, gradient boosting trees, and SVM classifiers were used in the study. Cough and breathing inputs, when combined, outputted the most accurate result.

Augustinov (2020) talked about how cough audios can be classified and categorized through deep learning, mainly for chronic ob-structive pulmonary disease. The Computerized Respiratory Sound Analysis group has developed a framework for classification of au-dios relating to the respiratory system, categorizing them as breath or adventitious respiratory sounds. The main issues with automatic detection of respiratory sounds are that there is not enough relevant data for extreme accuracy, and it brings ethical, privacy, and secu-rity issues into play. This paper described a network architecture that used CNNs as building blocks. The data had been acquired through using the LEOSound Lung-Sound-Monitor. For the binary classification model, the process was quite accurate, with a reported accuracy of 92.5%.

Pal and Sankarasubbu (2020) proposed a model neural architecture that would discriminate a COVID-19 cough based on examining the audio. This architecture included Symptoms Embeddings, which captures the hidden features of patient characteristics. TabNet was mostly used for this purpose. The second section of the architecture was Cough Embeddings, where it could capture deeper features when given a cough sound through its acoustic characteristics. Deep Neural Networks were mostly used for this. A High Pass Filter was also used to reduce the noise in the signal. This system would be useful because it would increase the breadth of COVID-19 screening while at the same time lowering the cost by using artificial intelligence.

Pinkas et al. (2020) described a deep machine learning model which was trained using recordings of coughs from those who tested for COVID-19, which can be used for screening through self-recording. The national COVID-19 data collection project provided the dataset used for this project, and the recordings consisted of coughs and counting verbally from 50 to 80. Counting is free of social or emo-tional bias, which makes it simple to examine. RNN-based expert classifiers were used, and the SVM was used to predict whether or not the audio indicated that the person was infected with COVID-19 or not. The dataset used for this project was self-recorded through a smartphone microphone, which demonstrated the feasibility for globally accessible data.

Alsabek (2020) primarily focused on how features of COVID-19 coughs and noises could be extracted and then compared through analyzing the audio signals. The data collection method asked each speaker to cough four times, take a deep breath, and count from one to ten. PRAAT was used for speech pre-processing, where silent portions of the recording are cut out. For the extraction of the fea-tures, MFCCSs were heavily used as they have broad applications in speaker and emotion recognition. The paper concluded that track-ing the coughing and breathing noises of the user was the best way to detect infection with COVID-19.

Here are some additional papers that touch on the subject of COVID-19 detection through neural networks and sound analysis: (Laguarta et al., 2020), (Sharma et al., 2020a), (Vijayakumar and Sneha, 2020), (Andreu-Perez et al., 2021), (Bansal, 2020), (Pahar, 2020), (Mouawad et al., 2021), (Coppock, 2021), (Manshouri, 2021), (Maleki, 2021), (Lella and Pja, 2021), (Jyothi, 2021), (Ramesh, 2021), (Desphande and Schuller, 2020), (Schuller, 2020), (Stasak et al., 2021), (Aly et al., 2021), (Chowdhury et al., 2021) (Harsharani, 2021), (Iqbal and Iqbal Faiz, 2020), (Khanzada et al., 2021), (Kranthi Kumar and Alphonse, 2021), (Meister et al., 2021), (Sharma et al., 2021), (Sharma et al., 2020b), (Tong et al., 2021), and (Usman, 2020).

Many of the research papers agree that the next step forward is that there must be more accessible datasets with far greater records than currently available. This would improve the accuracy of testing and therefore the accuracy of diagnosis through artificial intelli-gence.

6 PCA AND LCA TECHNIQUES

Commonly found with neural network techniques are PCA and LCA techniques, which aid in feeding the datasets into the neural network algorithms. Using these techniques correctly is vital in optimizing the performance of the deep learning algorithms. In general, PCA and LCA are used to convert data taken from the cough audio into a usable sequence of numbers that can then be used in a neural networking algorithm. For example, Imran et al. (Ali et al., 2020) created an app that predicts whether a user has COVID-19 based on the sound of their cough. PCA projections are used on the MFCC features from the audio to create feature vectors. Then, these feature vectors are fed into the neural networking algorithm to generate a diagnosis for the cough audio. This diagnosis will then tell the user of the app whether or not the user has COVID-19.

Derraz (2020) created a neural network that can classify a cough as one that is from COVID-19 or from another illness. A PNN, along with DSP and neural networks, was used to differentiate these coughs. However, PCA techniques were used to create feature vectors which are then fed into the neural networks.

Larson (2011) included a great example on how PCA can be used to optimize the deep learning algorithms. While this system used a lengthy random forest classifier, with the help of PCA, it could greatly optimize how the data was being fed into the neural network. In this example, the PCA used orthogonal components and eigenvectors to reduce dimensionality. Then, the components were ranked based on the amount of variation they could explain in the data. With this system, the data was being fed into a neural network in an efficient and relevant way.

Khomsay (2019) used deep learning networks and tensor flow for identifying coughs. However, it needed the help of PCA which performs feature extraction, then sending this data to the Deep Learning Network. LCA is important for statistical analysis and finding distinct subsets in a population with inherent heterogeneity. Spycher et al. (2008) used the LCA method on coughing children. It was able to group the children into various phenotypes based on their type of cough.

7 INFECTION TESTING

Equi (2001) conducted an experiment that compares cough swabs taken from children with cystic fibrosis and children with concomi-tant sputum. The cough swab was a strong predictor of sputum culture, while a negative result did not rule out infection.

The purpose of De Marco et al. (2007) was to discover whether chronic obstructive pulmonary disease (COPD) could be predicted by the presence of phlegm, chronic cough, and dyspnea. After a study was done, a correlation was found which showed that the presence of chronic cough or phlegm is linked with a high risk of developing COPD.

8 PH MONITORING

The aim of Blondeau et al. (2007) was to examine the association between cough and weakly acidic reflux by studying a large set of patients with unexplained chronic cough. After this study was done, a positive association was found between the two.

The purpose of Ing et al. (1991) was to examine the correlation between a chronic persistent cough and a gastro-oesophageal reflux. Subjects identified as having chronic cough underwent 24 h am-bulatory oesophageal pH monitoring. These results were compared with a matched control group.

Palombini et al. (1999) described an experiment where the plain chest radiographs of nonsmoking patients who complained of cough for over 3 weeks were examined. pH monitoring was also per-formed. Asthma, PNDS, and GERD were frequently found as culprits, earning them the expression “pathogenic triad of chronic cough.”

9 COUGH MONITORING

Harle (2006) conducted a study of the cough caused by lung cancer. The current treatments are not perfect, and there is not a lot of information about lung cancer and its associated cough. Cough is a big symptom and a frequently unmet clinical need. However, the study has the potential to improve the understanding of therapeutic options for the cough associated with lung cancer.

Birring et al. (2008) examined the effectiveness of the Leicester Cough Monitor (LCM). The LCM was used to measure cough fre-quency, with recordings of up to 6 h. The recording proved that the LCM is reliable enough to be trusted to assess cough frequency in patients for up to 24 h. It may even have the capabilities to work in clinics.

Leconte et al. (2011) examined the effectiveness of the LR102 device, which has the ability to identify cough episodes through a cough frequency meter with electromyography and audio sensors. The LR102 overestimated cough frequency, but still was relatively close and useful, and reduced the time needed for analysis.

10 COUGH TREATMENT

Mcgovern et al. (2018) explained where the mechanisms in a cough originate, as well as novel therapeutic ideas for a troublesome cough. Cough hypersensitivity syndrome exists among patients because the peripheral pathological process affects the activity and sensi-tivity of vagal primary afferent nerve fibers. Tissue inflammation can stimulate an increase in sensory neuron activity, which heightens cough reflex sensitivity. This sensitivity manifests from talking, laughing, or smelling perfumes. Neuroplasticity has an important relation with chronic cough and pain. Viruses cause inflammation in the respiratory system, which stands in the way of sensory neuron function, leading to cough. Plasticity is a contributor to the continuation of chronic cough and cough hypersensitivity syndrome among patients. Through understanding the neural pathways responsible for chronic cough, there are new methods of therapy emerging that could target the neural pathways such as targeting molecular pathways central to the development of excessive cough.

Kang et al. (2019) covered how Korean cough patients are not re-ceiving the required treatment that they need. After an observation of the Korean patients, half of them stated that there was a lack of treatment effects, and roughly 30% stated that they were given an unclear diagnosis. Other common unmet needs were that most patients reported difficulties in locating cough specialists or clinics, as well as wanting further information on cough treatment and pre-vention. This is a problem for Korean adult patients, as they describe their chronic cough as impairing their daily actions, frustrating their family and friends, and causing depression.

Fujimura (2003) examined the correlation between atopic cough and cough variant asthma through studying a set of patients with atopic cough and cough variant asthma, as well as the effectiveness of the treatment of inhaling beclomethasone dipropionate (BDP). In conclusion, the study demonstrated that the onset of typical asthma occurred significantly less frequently in those with atopic cough than in those with cough variant asthma. Additionally, the treatment significantly decreased the development of typical asthma in those with cough variant asthma. A significant number of patients with cough variant asthma end up developing typical asthma. Atopic cough has indeed been proposed as a cause of isolated chronic non-productive cough.

Gibson (2016) went into depth on the mistreatment of adult pa-tients with unexplained chronic cough (UCC). The research divided patients with UCC into cough categories of treatment-resistant, idio-pathic, and intractable. Another study divided them into refractory, unexplained, and idiopathic coughs. The paper offers some possible therapies, such as nonpharmacological therapies. An intervention included two to four sessions of education, cough suppression tech-niques, breathing exercises, and counseling, which resulted in a positive impact on cough severity. Inhaled corticosteroids (ICSs) targeted airway inflammation, also reducing cough severity in mul-tiple studies. However, if the patient tests negative for bronchial hyperresponsiveness and eosinophilia, then ICS's should not be prescribed.

Bowen et al. (2018) explained the causes of UCC, which is a chronic cough that has an unknown origin through a review of patients with UCC. Tachyphylaxis and dependence in pharmacotherapy are suspected to be the main problems, as they are frequently observed among patients with UCC. Clinicians are advised to use tricyclic antidepressants or gabapentin for treatment initiation. Although the chances of a successful treatment will diminish over time, most patients will be treated after several trials.

Redding and Carter (2017) showed the dangers of bronchiectasis and the effect that it can have on children. It is very likely that children who have this condition are underrepresented and untreated.

The aims of Harle et al. (2020) were to examine the cough, its impact, and its severity in the case of lung cancer. By using many cough-specific validated tools in the United Kingdom, a study can be done with lung cancer patients. This study demonstrated that there is an urgent demand for more potent antitussive treatments.

Birring (2011) discussed the treatment of chronic cough. It discussed whether asthma, gastroesophageal reflux, and upper air-way disorders are the causes or aggravants of chronic cough. There is a high demand to understand why a heightened cough reflex sensitivity exists for some patients, and whether genetic, molecular, or physiological concepts have a role to play in that.

The aim of Ryan et al. (2010) was to understand chronic cough and how speech language pathology could manage or improve the condition. Some outcome measures were capsaicin cough reflex sensitivity, automated cough frequency detection, and cough-related quality of life. Speech language pathology management may be able to intervene in the issues of refractory chronic cough.

11 COVID-19 DATASETS

The main public dataset for COVID-19 is the Coughvid dataset. The Coughvid crowdsourcing dataset contains over 25,000 recordings with 1,155 being those of COVID-19. These coughs originate from all around the world, and this is the largest known public cough dataset that is related to diagnosing COVID-19 in existence. This dataset can be accessed here: https://doi.org/10.6084/m9.figshare.14377019.

However, besides this dataset, there is a shortage of cough recordings that could be used to train neural networks that diagnose COVID-19 with a high accuracy.

12 PRIVACY

In terms of these studies done, publicizing a participant's name, email address, phone number, or any information that was irrelevant to the data of the study was prohibited. Therefore, every participant maintained privacy in cough recording, cough analysis, or cough treatment. The FDA prohibits use of any cough suppressants in children under the age of 18.

13 APPLICATIONS

The main commonalities within the research papers are that prepro-cessing is done to the cough audio, involving spectral analysis, and then a neural network is used. In this step, MFCCs and Fast Fourier Transforms are used to convert the audio into a suitable input for a neural network. These neural networks include CNN, Deep Neural Networks, k-NN, Random Forests, hybrids, and combinations of neural networks. In general, it appears that algorithms that use ensembles of neural networks or hybrids tend to be more accurate than those that solely use one type of neural network. It is clear that neural networks improve as the number and size of the datasets increase. Therefore, public datasets are a great help for training the neural networks. Researchers can use this information to cre-ate increasingly accurate neural network architecture that yields extremely accurate results. The more powerful and accessible the algorithm, the cheaper and more widespread an accurate diagnosis.

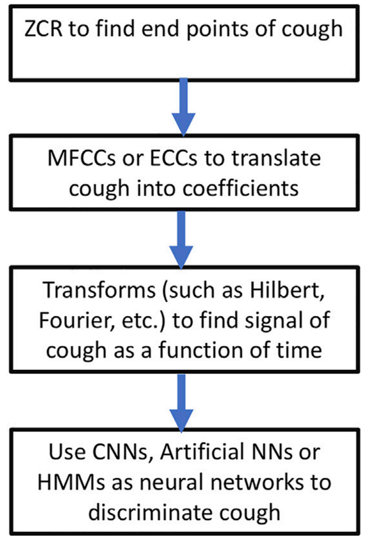

FIGURE 3 | Flowchart for Optimal Algorithm for Cough Discrimination, accord-ing to Amoh and Odame, 2016) and Shin et al. (2009) for COVID-19 would become, which is essential during a pandemic where millions are suffering across the globe.

14 RECOMMENDATIONS FOR FUTURE STUDIES

Public databases of cough recordings such as the one used in the Dicova challenge of this conference, the fkthecovid dataset, and the ESC-50 dataset exist. However, there is a shortage of data for training the neural networks.

1) More data is needed in the field to train the neural networks optimally.
2) Increase the accessibility of public datasets for researchers to use for training.
3) There must be a processing pipeline continuously gathering new data so that algorithms can adapt to new pandemics.

Beyond a need for larger datasets, all areas of the processing pipeline need to improve as we have seen throughout this review. In sum-mary, improvement areas include:

1) First and foremost, a need for larger datasets as we just dis-cussed
2) Increasing metadata when collecting coughs
3) Cough segmentation from surrounding noise
4) Pre-processing filter selection
5) Network architecture and algorithm selection
6) Testing and explainability
7) Detection of longitudinal metrics such as disease severity.

15 CONCLUSION

Much progress has been made in the detection and discrimination of cough based on neural networks, where optimal algorithms have been found such as shown in **Figure 3**. Machine learning algorithms have correctly diagnosed many that have been afflicted with all kinds of lung diseases. Further work is needed to bring neural networks into medical practice, which require more public data for training. This will likely be achieved in the near future. Cough discrimination, once performed at a high enough accuracy, can be applied to diag-nosing COVID-19 in clinics as well as in people's homes, which will greatly reduce the cost of screening as well as increase accessibility. Therefore, people will be able to test themselves faster and more conveniently than ever before. Since COVID-19 is incredibly con-tagious for a large part due to the lack of frequent testing, a more convenient, timely, method such as machine learning can improve testing and do its part in keeping COVID-19 under control.

Other papers that were instrumental to this literature review paper but were unrelated to cough specifically are: (Conference on Human Factors in Computing Systems, 2008), (Ablamowicz and Fauser, 2007), (Patricia, 2007), (Adya et al., 2004), (Akyildiz et al., 2002), (Akyildiz et al., 2007), (Using the amsthm Package, 2015), (Andler, 1979), (David, 2003), (Archer et al., 1984), (Bahl et al., 2004), (Bowman et al., 1993), (Braams, 1991), (Buss et al., 1987), (Clark, 1991), (Kenneth, 1985), (Cohen, 1996), (Cohen et al., 2007), (Conti et al., 2009), (CROSSBOW, 2008), (Dijkstra, 1979), (Douglass et al., 1998), (Dunlop and Basili, 1985), (Ian, 2007), (Simon Fear, 2005), (Gerndt, 1989), (Goossens et al., 1999), (Van Gundy et al., 2007), (Hagerup et al., 1993), (Harel, 1978), (Harel, 1979), (CodeBlue, 2008), (Heering and Klint, 1985), (Herlihy, 1993), (Hollis, 1999), (Hörmander, 1985a), (Hörmander, 1985b), (IEEE, 2004), (Kirschmer and Voight, 2010), (Knuth, 1981), (Knuth, 1981), (Knuth, 1984), (Knuth, 1997), (Kong, 2001a), (Kong, 2001b), (Kong and Thanasankit, 2002), (Kong and Thanasankit, 2003), (Kong, 2004), (Kong, 2005), (Kong, 2006), (Korach et al., 1984), (Jacob, 1994), (Kosiur, 2001), (Lamport, 1986), (Lee and Wexelblat, 1978), (Newton and Kinder, 2005), (Li et al., 2008), (McCracken and Golden, 1990), (Mullender, 1993), (Mumford, 1987), (Natarajan et al., 2007), (Nielson, 1985), (Novak, 2003), (Obama, 2008), (Petrie, 1986), (Poker- Edge .Com, 2006), (Reid, 1980), (SIGCOMM Comput, 1984), (Rous, 2008), (Sadiq et al., 2021), (Saeedi et al., 2010a), (Saeedi et al., 2010b), (Salas and Hille, 1978), (Joseph Scientist, 2008), (Smith et al., 2010), (Spector and Mullender, 1990), (Thornburg, 2001), (TUG, 2017), (Tzamaloukas and Garcia-Luna-Aceves, 2000), (Veytsman, 2022), (Wenzel, 1992), (Werneck et al., 2000), (Werneck et al., 2000), (Culler et al., 2004), (Geiger and Meek, 2005), (Zhou et al., 2008), (Zhou et al., 2010), (Anzaroot and McCallum, 2013), (Anzaroot et al., 2014), (Bornmann et al., 2019), and (R Core Team, 2019).

AUTHOR CONTRIBUTIONS

PS performed the extensive search and review of the papers, and compiled the manuscript. Brian Subirana was the originator of this project, who oversaw the review work and provided valuable feedback during the process.

REFERENCES

Abaza, A. A., Day, J. B., Reynolds, J. S., Mahmoud, A. M., Goldsmith, W. T., McKinney, W. G., et al. (2009). Classification of Voluntary Cough Sound and Airflow Patterns for Detecting Abnormal Pulmonary Function. *Cough* 5 (8), 8. doi:10.1186/1745-9974-5-8

Abeyratne, U. R. (2013). "Cough Sound Analysis - a New Tool for Diagnosing Pneu-Monia," in 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (IEEE), 5216–5219. doi:10.1109/embc.2013.6610724

Ablamowicz, R., and Fauser, B. (2007). Clifford: a Maple 11 Package for Clifford Algebra Computations, Version 11. Available at: http://math.tntech.edu/rafal/cliff11/index.html.

Adya, A., Bahl, P., Padhye, J., Wolman, A., and Zhou, L. (2004). "A Multi-Radio Unification Protocol for IEEE 802.11 Wireless Networks," in Proceedings of the IEEE 1st Inter-national Conference on Broadnets Networks (BroadNets'04) (Los Alamitos, CA: IEEE), 210–217.

Aerts, J.-M., Jans, P., Halloy, D., Gustin, P., and Berckmans, D. (2005). Labeling of Cough Data from Pigs for On-Line Disease Monitoring by Sound Analysis. *Trans. ASAE* 48 (1), 351–354. doi:10.13031/2013.17948

Akyildiz, I. F., Melodia, T., and Chowdhury, K. R. (2007). A Survey on Wireless Multimedia Sensor Networks. *Comput. Netw.* 51 (4), 921–960. doi:10.1016/j.comnet.2006.10.002

Akyildiz, I. F., Su, W., Sankarasubramaniam, Y., and Cayirci, E. (2002). Wireless Sensor Networks: A Survey. *Comput. Netw.* 38 (4), 393–422. doi:10.1016/s1389-1286(01)00302-4

Ali, I., Posokhova, I., Qureshi, H. N., Masood, U., Riaz, S., Ali, K., et al. (2020). *AI4COVID-19: AI Enabled Preliminary Diagnosis for COVID-19 from Cough Samples via an App*. Kharkiv, Ukraine: arXiv preprint arXiv:2004.01275.

Alqudaihi, K. S., Aslam, N., Almuhaideb, I. U., Almuhaideb, A. M., Rahman Ibrahim, S. J., Ibrahim, N. M. A. R., et al. (2021). Cough Sound Detection and Diagnosis Using Artificial Intelligence Techniques: Challenges and Opportunities. *IEEE Access* 9, 102327–102344. doi:10.1109/access.2021.3097559

Alsabek, M. B. (2020). *Studying the Similarity of COVID-19 Sounds Based on Correlation Analysis of MFCC. 2020 International Conference on Communica-Tions, Computing, Cybersecurity, and Informatics*. Sharjah, United Arab Emirates: CCCI.

Aly, M., Rahouma, K. H., and Ramzy, S. M. (2021). *Pay Attention to the Speech: Covid-19 Diagnosis Using Machine Learning and Crowdsourced Respira-Tory and Speech Recordings*. Alexandria Engineering Journal.

Amoh, J., and Odame, K. (2016). Deep Neural Networks for Identifying Cough Sounds. *IEEE Trans. Biomed. Circuits Syst.* 10 (5), 1003–1011. doi:10.1109/tbcas.2016.2598794

Amrulloh, Y. A., Abeyratne, U. R., Swarnkar, V., Triasih, R., and Setyati, A. (2015). Automatic Cough Segmentation from Non-contact Sound Recordings in Pediatric Wards. *Biomed. Signal Process. Control* 21, 126–136. doi:10.1016/j.bspc.2015.05.001

Andler, S. (1979). "Predicate Path Expressions," in Proceedings of the 6th. ACM SIGACT-SIGPLAN Symposium on Principles of Programming Languages, POPL '79 (New York, NY: ACM Press), 226–236. doi:10.1145/567752.567774

Andreu-Perez, J., Perez-Espinosa, H., Timonet, E., Kiani, M., Giron-Perez, M. I., Benitez-Trinidad, A. B., et al. (2021). A Generic Deep Learning Based Cough Analysis System from Clinically Validated Samples for Point-Of-Need COVID-19 Test and Severity Levels. *IEEE Trans. Serv. Comput.* 1, 1. doi:10.1109/tsc.2021.3061402

Anzaroot, S., and McCallum, A. (2013). UMass Citation Field Extraction Dataset. Available at: http://www.iesl.cs.umass.edu/data/data-umasscitationfield.

Anzaroot, S., Passos, A., Belanger, D., and McCallum, A. (2014). *Learn-ing Soft Linear Constraints with Application to Citation Field Extraction*. arXiv:1403.1349.

Archer, J. E., Jr., Conway, R., and Schneider, F. B. (1984). User Recovery and Reversal in Interactive Systems. *ACM Trans. Program. Lang. Syst.* 6 (1), 1–19. doi:10.1145/357233.357234

Augustinov, G. (2020). *Automatic Detection and Classification of Cough Events Based on Deep Learning*. Current Directions in Biomedical Engineering.

Bagad, P., Chancre, R., and Dungeon, J. (2020). *Cough against COVID: Evidence of COVID-19 Signature in Cough Sounds*. Wadhwani Institute for Artificial Intelligence.

Bahl, P., Chancre, R., and Dungeon, J. (2004). "SSCH: Slotted Seeded Channel Hopping for Capacity Improvement in IEEE 802.11 Ad-Hoc Wireless Networks," in Proceeding of the 10th International Conference on Mobile Computing and Networking (MobiCom'04) (New York, NY: ACM), 112–117.

Balamurali, B. T. (2020). Asthmatic versus Healthy Child Classification Based on Cough and Vocalised/a:/Sounds. *J. Acoust. Soc. Am.* 148 (3).

Bansal, V. (2020). "Cough Classification for COVID-19 Based on Audio MFCC Features Using Convolutional Neural Networks," in 2020 IEEE International Conference on Computing, Power and Communication Technologies (GUCON) (IEEE). doi:10.1109/gucon48875.2020.9231094

Barata, F. (2019). "Towards Device-Agnostic Mobile Cough Detection with Con-Volutional Neural Networks," in 2019 IEEE International Conference on Healthcare Informatics (ICHI) (IEEE). doi:10.1109/ichi.2019.8904554

Belkacem, A. (2020). *End-to-end AI-Based Point-Of-Care Diagnosis System for Classifying Respiratory Illnesses and Early Detection of COVID-19*. Cornell.

Birring, S. (2011). Controversies in the Evaluation and Management of Chronic Cough. *Am. J. Respir. Crit. Care Med.* 183 (6), 708–715. doi:10.1164/rccm.201007-1017ci

Birring, S., Fleming, T., Matos, S., Raj, A. A., Evans, D. H., and Pavord, I. D. (2008). The Leicester Cough Monitor: Preliminary Validation of an Automated Cough Detection System in Chronic Cough. *Eur. Respir. J.* 31 (5), 1013–1018. doi:10.1183/09031936.00057407

Blondeau, K., Dupont, L. J., Mertens, V., Tack, J., and Sifrim, D. (2007). Improved Diagnosis of Gastro-Oesophageal Reflux in Patients with Unexplained Chronic Cough. *Aliment. Pharmacol. Ther.* 25 (6), 723–732. doi:10.1111/j.1365-2036.2007.03255.x

Bornmann, L., Wray, K. B., and Haunschild, R. (2019). Citation Concept Analysis (CCA): a New Form of Citation Analysis Revealing the Usefulness of Concepts for Other Researchers Illustrated by Exemplary Case Studies Including Classic Books by Thomas S. Kuhn and Karl R. Popper. *Scientometrics* 122, 1051–1074. doi:10.1007/s11192-019-03326-2

Botha, R. (2018). *Detection of Tuberculosis by Automatic Cough Sound Analysis*. Physiological Measurement.

Bowen, A. J., Huang, T. L., Nowacki, A. S., Trask, D., Kaltenbach, J., Taliercio, R., et al. (2018). Tachyphylaxis and Dependence in Pharmacotherapy for Unexplained Chronic Cough. *Otolaryngol. Head. Neck Surg.* 159 (4), 705–711. doi:10.1177/0194599818788062

Bowman, M., Debray, S. K., and Peterson, L. L. (1993). Reasoning about Naming Systems. *ACM Trans. Program. Lang. Syst.* 15 (5), 795–825. doi:10.1145/161468.161471

Braams, J. (1991). Babel, a Multilingual Style-Option System for Use with Latex's Standard Document Styles. *TUGboat* 12 (2), 291–301.

Buss, J. F., Rosenberg, A. L., and Knott, J. D. (1987). *Vertex Types in Book-Embeddings*. Amherst, MA, USA: Technical report.

Carpentier, L., Berckmans, D., Youssef, A., Berckmans, D., van Waterschoot, T., Johnston, D., et al. (2018). Automatic Cough Detection for Bovine Respiratory Disease in a Calf House. *Biosyst. Eng.* 173, 45–56. doi:10.1016/j.biosystemseng.2018.06.018

Casaseca-De-La-Higuera, P. (2015). "Effect of Downsampling and Compressive Sensing on Audio-Based Continuous Cough Monitoring," in 2015 37th Annual Interna-Tional Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (IEEE). doi:10.1109/embc.2015.7319816

Chang, A. B., Byrnes, C. A., and Everard, M. L. (2011). Diagnosing and Preventing Chronic Suppurative Lung Disease (Csld) and Bronchiectasis. *Paediatr. Respir. Rev.* 12 (2), 97–103. doi:10.1016/j.prrv.2010.10.008

Chang, A. B., Redding, G. J., and Everard, M. L. (2008). Chronic Wet Cough: Protracted Bronchitis, Chronic Suppurative Lung Disease and Bronchiectasis. *Pediatr. Pulmonol.* 43 (6), 519–531. doi:10.1002/ppul.20821

Charles, N. (2020). *Practical Cough Detection in Presence of Background Noise and Preliminary Differential Diagnosis from Cough Sound Using Artificial Intelligence*. DSpace software, 1–35.

Chaudhari, G. (2020). *Virufy: Global Applicability of Crowdsourced and Clinical Datasets for AI Detection of COVID-19 from Cough Audio Samples*. Virufy AI Research Group.

Chowdhury, M. E. H., Ibtehaz, N., Rahman, T., Qibalwey, Y., Mahmud, S., Ezeddin, M., et al. (2021). *Qucoughscope: An Artificially Intelligent Mobile Application to Detect Asymptomatic Covid-19 Patients Using Cough and Breathing Sounds*. arXiv preprint arXiv:2103.12063.

Chung, K. F. (2017). Advances in Mechanisms and Management of Chronic Cough: the Ninth London International Cough Symposium 2016. *Pulm. Pharmacol. Ther.* 47, 2–8. doi:10.1016/j.pupt.2017.02.003

Clark, M. (1991). "Post Congress Tristesse," in TeX90 Conference Proceedings (TeX Users Group), 84–89.

CodeBlue, H. (2008). CodeBlue: Sensor Networks for Medical Care. Available at: http://www.eecs.harvard.edu/mdw/proj/codeblue/.

Cohen, S., Nutt, W., and Sagiv, Y. (2007). Deciding Equivalences Among Conjunctive Aggregate Queries. *J. Acm* 54 (2), 5. doi:10.1145/1219092.1219093

Cohen (1996). *Special Issue*. Digital libraries.

Conference on Human Factors in Computing Systems (2008). *CHI '08: CHI '08 Extended Abstracts on Human Factors in Computing Systems.*New York, NY, USA: ACM.

Conti, M., Pietro, R. D., Mancini, L. V., and Mei, A. (2009). Distributed Data Source Verification in Wireless Sensor Networks. *Inf. Fusion* 10 (4), 342–353. doi:10.1016/j.inffus.2009.01.002

Coppock, H. (2021). *End-2-end COVID-19 Detection from Breath Cough Audio*. Cornell University.

Coppock, H., Jones, L., Kiskin, I., and Schuller, B. (2021). Covid-19 Detection from Audio: Seven Grains of Salt. *Lancet Digital Health* 3 (9), e537–e538. doi:10.1016/s2589-7500(21)00141-2

CROSSBOW (2008). XBOW Sensor Motes Specifications. Available at: http://www.xbow.com.

Culler, D., Estrin, D., and Srivastava, M. (2004). Guest Editors' Introduction: Overview of Sensor Networks. *Computer* 37 (8), 41–49. doi:10.1109/mc.2004.93

David, A. (2003). *Optimal Motion Control of a Ground Vehicle*. Stockholm, Sweden: Royal Institute of Technology (KTH).

De Marco, R., Accordini, S., Cerveri, I., Corsico, A., Antó, J. M., Künzli, N., et al. (2007). Incidence of Chronic Obstructive Pulmonary Disease in a Cohort of Young Adults According to the Presence of Chronic Cough and Phlegm. *Am. J. Respir. Crit. Care Med.* 175 (1), 32–39. doi:10.1164/rccm.200603-381oc

Derraz, M. (2020). Remotely Diagnose Coronavirus by Recognizing and Counting of Coughs during Phone Calls. *Open Access J.* 3 (3), 1–8.

Desphande, G., and Schuller, B. (2020). *An Overview on Audio, Signal, Speech, Language Processing for COVID-19*. Cornell University.

Dijkstra, E. (1979). "Go to Statement Considered Harmful," in *Classics in Software Engineer-Ing (Incoll)* (Upper Saddle River, NJ, USA: Yourdon Press), 27–33.

Doherty, M. J., Wang, L. J., Donague, S., Pearsdn, M. G., Downs, P., Stoneman, S. A. T., et al. (1997). The Acoustic Properties of Capsaicin-Induced Cough in Healthy Subjects. *Eur. Respir. J.* 10 (1), 202–207. doi:10.1183/09031936.97.10010202

Douglass, B. P., Harel, D., and Trakhtenbrot, M. (1998). "Statecharts in Use: Structured Analysis and Object-Orientation," in *Lectures on Embedded Systems, Volume 1494 of Lecture Notes in Computer Science*. Editors G. Rozenberg and F. W. Vaandrager (London: Springer-Verlag), 368–394. doi:10.1007/3-540-65193-4_29

Drugman, T., Urbain, J., Bauwens, N., Chessini, R., Valderrama, C., Lebecque, P., et al. (2013). Objective Study of Sensor Relevance for Automatic Cough Detection. *IEEE J. Biomed. Health Inf.* 17 (3), 699–707. doi:10.1109/jbhi.2013.2239303

Dubnov, T. (2020). *Signal Analysis and Classification of Audio Samples from Individuals Diagnosed with COVID-19*. UC San Diego.

Dunlop, D. D., and Basili, V. R. (1985). Generalizing Specifications for Uniformly Implemented Loops. *ACM Trans. Program. Lang. Syst.* 7 (1), 137–158. doi:10.1145/2363.2708

Equi, A. C. (2001). Use of Cough Swabs in a Cystic Fibrosis Clinic. *Archives Dis. Child.* 85 (5), 438–439. doi:10.1136/adc.85.5.438

Ferrari, S., Silva, M., Guarino, M., and Berckmans, D. (2008). Analysis of Cough Sounds for Diagnosis of Respiratory Infections in Intensive Pig Farming. *Trans. ASABE* 51 (3), 1051–1055. doi:10.13031/2013.24524

Fujimura, M. (2003). Comparison of Atopic Cough with Cough Variant Asthma: Is Atopic Cough a Precursor of Asthma? *Thorax* 58 (1), 14–18. doi:10.1136/thorax.58.1.14

Geiger, D., and Meek, C. (2005). "Structured Variational Inference Procedures and Their Realizations (As Incol)," in Proceedings of Tenth International Workshop on Artificial Intelligence and Statistics, the Barbados (The Society for Artificial Intelligence and Statistics).

Gerndt, M. (1989). *Automatic Parallelization for Distributed-Memory Multipro-Cessing Systems*. Bonn, Germany: University of Bonn. PhD thesis.

Gibson, P. (2016). Correction to Reference in: Treatment of Unexplained Chronic Cough: CHEST Guideline and Expert Panel Report. *Chest* 149 (5), 1353.

Goldsmith, W. T. (2003). Method and Apparatus for Cough Sound Analysis. *J. Acoust. Soc. Am.* 113 (3), 1203. doi:10.1121/1.1566365

Goossens, M., Rahtz, S. P., Moore, R., and Sutor, R. S. (1999). *The Latex Web Companion: Integrating TEX, HTML, and XML*. 1st edition. Boston, MA, USA: Addison-Wesley Longman Pub-lishing Co., Inc.

Guarino, M. (2005). *Cough Analysis and Classification by Labelling Sound in Swine Respiratory Disease*. ISCA, 77–80.

Hagerup, T., Mehlhorn, K., and Munro, J. I. (1993). "Maintaining Discrete Probability Distributions Optimally," in Proceedings of the 20th International Colloquium on Automata, Languages and Programming, Volume 700 of Lecture Notes in Computer Science (Berlin: Springer-Verlag), 253–264. doi:10.1007/3-540-56939-1_77

Harel, D. (1979). *First-Order Dynamic Logic, Volume 68 of Lecture Notes in Computer Science*. New York, NY: Springer-Verlag. doi:10.1007/3-540-09237-4

Harel, D. (1978). *Logics of Programs: Axiomatics and Descriptive Power*. Cambridge, MA: MIT Research Lab Technical Report TR-200, Massachusetts Institute of Technology.

Harle, A., Molassiotis, A., Buffin, O., Burnham, J., Smith, J., Yorke, J., et al. (2020). A Cross Sectional Study to Determine the Prevalence of Cough and its Impact in Patients with Lung Cancer: a Patient Unmet Need. *BMC Cancer* 20 (1), 9. doi:10.1186/s12885-019-6451-1

Harle, A. s. m. (2006). Cough in Patients with Lung Cancer. *Lung Cancer* 83 (1), 32–39.

Harsharani, P. (2021). *Covid-19 Artificial Intelligence Diagnosis Using Only Cough Recordings*. IEEE.

Heering, J., and Klint, P. (1985). Towards Monolingual Programming Environments. *ACM Trans. Program. Lang. Syst.* 7 (2), 183–213. doi:10.1145/3318.3321

Herlihy, M. (1993). A Methodology for Implementing Highly Concurrent Data Objects. *ACM Trans. Program. Lang. Syst.* 15 (5), 745–770. doi:10.1145/161468.161469

Hilton, E., Marsden, P., Thurston, A., Kennedy, S., Decalmer, S., and Smith, J. A. (2015). Clinical Features of the Urge-To-Cough in Patients with Chronic Cough. *Respir. Med.* 109 (6), 701–707. doi:10.1016/j.rmed.2015.03.011

Hoare, C. A. R. (1972). "Chapter Ii: Notes on Data Structuring," in *Structured Programming (Incoll)*. Editors O. J. Dahl, E. W. Dijkstra, and C. A. R. Hoare (London, UK, UK: Academic Press), 83–174.

Hollis, B. S. (1999). *Visual Basic 6: Design, Specification, and Objects with Other*. 1st edition. Upper Saddle River, NJ, USA: Prentice Hall PTR.

Hörmander, L. (1985). "The Analysis of Linear Partial Differential Operators," in *IV, volume 275 of Grundlehren der Mathematischen Wissenschaften [Fundamental Principles of Mathematical Sciences]* (Berlin, Germany: Springer-Verlag). Fourier integral operators.

Hörmander, L. (1985). "The Analysis of Linear Partial Differential Operators," in *III, volume 275 of Grundlehren der Mathematischen Wissenschaften [Fundamental Principles of Mathematical Sciences]* (Berlin, Germany: Springer-Verlag). Pseudodifferential operators.

Hoyos-Barcelo, C., Monge-Alvarez, J., Zeeshan Shakir, M., Alcaraz-Calero, J.-M., and Casaseca-de-la-Higuera, P. (2018). Efficient K-NN Implementation for Real-Time Detection of Cough Events in Smartphones. *IEEE J. Biomed. Health Inf.* 22 (5), 1662–1671. doi:10.1109/jbhi.2017.2768162

Hsu, J. Y., Stone, R. A., Logan-Sinclair, R. B., Worsdell, M., Busst, C. M., and Chung, K. F. (1994). Coughing Frequency in Patients with Persistent Cough: Assessment Using a 24 hour Ambulatory Recorder. *Eur. Respir. J.* 7 (7), 1246–1253. doi:10.1183/09031936.94.07071246

Ian (2007). *The Title of Book One, Volume 9 of the Name of the Series One*. 1st. edition. Chicago: University of Chicago Press. doi:10.1007/3-540-09237-4

IEEE (2004). "Ieee Tcsc Executive Committee," in Proceedings of the IEEE International Conference on Web Services, ICWS '04 (Washington, DC, USA: IEEE Computer Society), 21–22. doi:10.1109/ICWS.2004.64

Ing, A. J., Ngu, M. C., and Breslin, A. B. (1991). Chronic Persistent Cough and Gastro-Oesophageal Reflux. *Thorax* 46 (7), 479–483. doi:10.1136/thx.46.7.479

Iqbal, M. Z., and Iqbal Faiz, M. F. (2020). "Active Surveillance for Covid-19 through Artificial Intelligence Using Real-Time Speech-Recognition Mobile Application," in 2020 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-Taiwan) (IEEE), 1–2. doi:10.1109/icce-taiwan49838.2020.9258276

Irwin, R. S., and Curley, F. J. (1991). The Treatment of Cough. *Chest* 99 (6), 1477–1484. doi:10.1378/chest.99.6.1477

Jacob, K. (1994). *Mapping Powerlists onto Hypercubes. Master's Thesis*. The University of Texas at Austin. (In preparation).

Joseph Scientist (2008). *The Fountain of Youth*. Patent No. 12345.

Jyothi, N. M. (2021). An Intelligent Model for Assessment of Cough in COVID-19 Infected Patients Based on Sound to Predict Their Clinical Criticality Using XGB Algorithm. *Int. J. Emerg. Trends Eng. Res.* 9 (1), 1–5.

Kakabutr, P. (2017). "Dog Cough Sound Classification Using Artificial Neural Network and the Selected Relevant Features from Discrete Wavelet Transform," in 2017 9th International Conference on Knowledge and Smart Technology (KST) (IEEE), 121–125. doi:10.1109/kst.2017.7886118

Kang, S.-Y., Won, H.-K., Lee, S. M., Kwon, J.-W., Kim, M.-H., Jo, E.-J., et al. (2019). Impact of Cough and Unmet Needs in Chronic Cough: a Survey of Patients in Korea. *Lung* 197 (5), 635–639. doi:10.1007/s00408-019-00258-9

Kenneth, L. (1985). *Clarkson. Algorithms for Closest-Point Problems (Computational Geometry)*. Palo Alto, CA: Stanford University. PhD thesisUMI Order Number: AAT 8506171.

Khanzada, A., Hegde, S., Sreeram, S., Bower, G., Wang, W., Mediratta, R. P., et al. (2021). *Challenges and Opportu-Nities in Deploying Covid-19 Cough Ai Systems*. Journal of Voice.

Khomsay, S. (2019). "Cough Detection Using PCA and Deep Learning," in 2019 Inter-national Conference on Information and Communication Technology Convergence (ICTC) (IEEE). doi:10.1109/ictc46691.2019.8939769

Kirschmer, M., and Voight, J. (2010). Algorithmic Enumeration of Ideal Classes for Quaternion Orders. *SIAM J. Comput.* 39 (5), 1714–1747. doi:10.1137/080734467

Knuth, D. E. (1981). *Seminumerical Algorithms, Volume 2 of the Art of Computer Programming*. 2nd edition. Reading, MA: Addison-Wesley.

Knuth, D. E. (1997). *The Art of Computer Programming, Vol. 1: Fundamental Algo-Rithms*. 3rd. ed. Addison Wesley Longman Publishing Co., Inc.

Knuth, D. E. (1984). *The $T_EX$book*. Reading, MA. Addison-Wesley.

Kong, W-C. (2002). "Chapter 9," in *E-commerce and Cultural Values (Incoll-W-Text (Chap 9) 'title')*. Editor T. Thanasankit (Hershey, PA, USA: IGI Publishing), 51–74.

Kong, W-C. (2004). *E-commerce and Cultural Values - (InBook-Num-In-Chap), Chap-Ter 9*. Hershey, PA, USA: IGI Publishing, 51–74. Available at: http://portal.acm.org/citation.cfm?id=887006.887010.

Kong, W-C. (2006). *E-commerce and Cultural Values (Inbook-Num Chap), Chapter (In Type Field) 22*. Hershey, PA, USA: IGI Publishing, 51–74.

Kong, W-C. (2005). *E-commerce and Cultural Values (Inbook-Text-In-Chap), Chapter: The Implementation of Electronic Commerce in SMEs in Singapore*. Hershey, PA, USA: IGI Publishing, 51–74.

Kong, W-C. (2001). *E-commerce and Cultural Values, Name of Chapter: The Im-Plementation of Electronic Commerce in SMEs in Singapore (Inbook-w-chap-w-type)*. Hershey, PA, USA: IGI Publishing, 51–74.

Kong, W-C. (2001). "The Implementation of Electronic Commerce in Smes in Singa-Pore (As Incoll)," in *E-commerce and Cultural Values* (Hershey, PA, USA: IGI Publishing), 51–74.

Kong, W.-C. (2003). "The Implementation of Electronic Commerce in SMEs in Singapore," in *E-commerce and Cultural Values*. Editor T. Thanasankit (Hershey, PA, USA: IGI Publishing), 51–74. doi:10.4018/978-1-59140-056-1.ch003

Korach, E., Rotem, D., and Santoro, N. (1984). Distributed Algorithms for Finding Centers and Medians in Networks. *ACM Trans. Program. Lang. Syst.* 6 (3), 380–401. doi:10.1145/579.585

Kosiur, D. (2001). *Understanding Policy-Based Networking*. 2nd. edition. New York, NY: Wiley.

Kranthi Kumar, L., and Alphonse, P. J. A. (2021). *Automatic Diagnosis of Covid-19 Disease Using Deep Convolutional Neural Network with Multi-Feature Channel from Respi-Ratory Sound Data: Cough, Voice, and Breath*. Alexandria Engineering Journal.

Laguarta, J., Hueto, F., and Subirana, B. (2020). COVID-19 Artificial Intelligence Diagnosis Using Only Cough Recordings. *IEEE Open J. Eng. Med. Biol.* 1, 275–281. doi:10.1109/ojemb.2020.3026928

Lamport, L. (1986). *LAT_EX: A Document Preparation System*. Reading, MA. Addison-Wesley.

Larson, E. C. (2011). "Accurate and Privacy Preserving Cough Sensing Using a Low-Cost Microphone," in Proceedings of the 13th International Conference on Ubiquitous Computing (IEEE), 375–384. doi:10.1145/2030112.2030163

Larson, S., Comina, G., Gilman, R. H., Tracey, B. H., Bravard, M., and López, J. W. (2012). Validation of an Automated Cough Detection Algorithm for Tracking Recovery of Pulmonary Tuberculosis Patients. *PLoS ONE* 7 (10), e46229. doi:10.1371/journal.pone.0046229

Leconte, S., Liistro, G., Lebecque, P., and Degryse, J.-M. (2011). The Objective Assessment of Cough Frequency: Accuracy of the LR102 Device. *Cough* 7 (1), 11. doi:10.1186/1745-9974-7-11

Lee, J. (1978). "Transcript of Question and Answer Session," in *History of Programming Languages I (Incoll)*. Editor R. L. Wexelblat (New York, NY, USA: ACM), 68–71. doi:10.1145/800025.1198348

Lella, K. K., and Pja, A. (2021). Automatic COVID-19 Disease Diagnosis Using 1D Convolutional Neural Network and Augmentation with Human Respiratory Sound Based on Parameters: Cough, Breath, and Voice. *AIMS Public Health* 8 (2), 240–264. doi:10.3934/publichealth.2021019

Li, C.-L., Buyuktur, A. G., Hutchful, D. K., Sant, N. B., and Nainwal, S. K. (2008). "Portalis," in *CHI '08 Extended Abstracts on Human Factors in Computing Systems* (New York, NY, USA: ACM), 3873–3878. doi:10.1145/1358628.1358946

Maleki, M. (2021). *Diagnosis of COVID-19 and Non-COVID-19 Patients by Classi-Fying Only a Single Cough Sound*. Cornell University.

Manshouri, N. (2021). *Identifying COVID-19 by Using Spectral Analysis of Cough Recordings: A Distinctive Classification Study*. Karadeniz Technical University.

McCracken, D. D., and Golden, D. G. (1990). *Simplified Structured COBOL with Microsoft/MicroFocus COBOL*. New York, NY, USA: John Wiley & Sons.

Mcgovern, A. E., Short, K. R., Kywe Moe, A. A., and Mazzone, S. B. (2018). Translational Review: Neuroimmune Mechanisms in Cough and Emerging

Therapeutic Targets. *J. Allergy Clin. Immunol.* 142 (5), 1392–1402. doi:10.1016/j.jaci.2018.09.004

Meister, J. A., Nguyen, K. A., and Luo, Z. (2021). *Audio Feature Ranking for Sound-Based Covid-19 Patient Detection*. arXiv preprint arXiv:2104.07128.

Mohammed, E. A., Keyhani, M., Sanati-Nezhad, A., Hejazi, S. H., and FarFar, B. H. (2021). An Ensemble Learning Approach to Digital Corona Virus Preliminary Screening from Cough Sounds. *Sci. Rep.* 11 (1), 15404–15411. doi:10.1038/s41598-021-95042-2

Monge-Alvarez, J., Hoyos-Barcelo, C., San-Jose-Revuelta, L. M., and Casaseca-de-la-Higuera, P. (2019). A Machine Hearing System for Robust Cough Detection Based on a High-Level Representation of Band-specific Audio Features. *IEEE Trans. Biomed. Eng.* 66 (8), 2319–2330. doi:10.1109/TBME.2018.2888998

Monge-Alvarez, J., Hoyos-Barcelo, C., Lesso, P., and Casaseca-de-la-Higuera, P. (2019). Robust Detection of Audio-Cough Events Using Local Hu Moments. *IEEE J. Biomed. Health Inf.* 23 (1), 184–196. doi:10.1109/jbhi.2018.2800741

Moradshahi, P. (2013). "Cough Sound Discrimination in Noisy Environments Using Microphone Array," in 2013 IEEE International Instrumentation and Measurement Technology Conference (IEEE). doi:10.1109/i2mtc.2013.6555454

Morice, M. A. H. (2002). Epidemiology of Cough. *Pulm. Pharmacol. Ther.* 15 (3), 253–259. doi:10.1006/pupt.2002.0352

Moshou, D. (2001). Neural Recognition System for Swine Cough. *Math. Comput. Simul.* 56 (4-5), 475–487. doi:10.1016/s0378-4754(01)00316-0

Mouawad, P., Dubnov, T., and Dubnov, S. (2021). Robust Detection of COVID-19 in Cough Sounds. *Nat. Public Health Emerg. Collect.* 21, 34. doi:10.1007/s42979-020-00422-6

S. Mullender (Editor) (1993). *Distributed Systems*. 2nd Ed. (New York, NY, USA: ACM Press/Addison-Wesley Publishing Co.).

Mumford, E. (1987). "Managerial Expert Systems and Organizational Change: Some Critical Research Issues," in *Critical Issues in Information Systems Research (Incoll)* (New York, NY, USA: John Wiley & Sons), 135–155.

Murata, A., Taniguchi, Y., Hashimoto, Y., Kaneko, Y., Takasaki, Y., and Kudoh, S. (1998). Discrimination of Productive and Non-productive Cough by Sound Analysis. *Intern. Med.* 37 (9), 732–735. doi:10.2169/internalmedicine.37.732

Natarajan, A., Motani, M., de Silva, B., Yap, K., and Chua, K. C. (2007). "Investigating Network Architectures for Body Sensor Networks," in *Network Architectures*. Editors G. Whitcomb and P. Neece (Dayton, OH: Keleuven Press), 322–328. doi:10.1145/1248054.1248061

Newton, L., and Kinder, B. (2005). Interview with Bill Kinder. *Comput. Entertain.* 3 (1), 4. doi:10.1145/1057270.1057278

Nielson, F. (1985). Program Transformations in a Denotational Setting. *ACM Trans. Program. Lang. Syst.* 7 (3), 359–379. doi:10.1145/3916.3917

Novak, D. (2003). "Solder Man," in *ACM SIGGRAPH 2003 Video Review on Animation Theater Program: Part I - Vol. 145* (New York, NY: ACM Press), 4. doi:10.1145/1006091.1006096

Obama, B. (2008). *A More Perfect Union*. Video.

Orlandic, L. (2020). *The COUGHVID Crowdsourcing Dataset: A Corpus for the Study of Large-Scale Cough Analysis Algorithms*. Embedded Systems Labarotory.

Pahar, M. (2020). *COVID-19 Cough Classification Using Machine Learning and Global Smartphone Recordings*. Cornell University.

Pal, A., and Sankarasubbu, M. (2020). *Pay Attention to the Cough: Early Diagnosis of COVID-19 Using Interpretable Symptoms Embeddings with Cough Sound Signal Processing*. Saama AI Research.

Palombini, B. C., Villanova, C. A. C., Araújo, E., Gastal, O. L., Alt, D. C., Stolz, D. P., et al. (1999). A Pathogenic Triad in Chronic Cough. *Chest* 116 (2), 279–284. doi:10.1378/chest.116.2.279

Parker, D., Picone, J., Harati, A., Lu, S., Jenkyns, M. H., and Polgreen, P. M. (2013). Detecting Paroxysmal Coughing from Pertussis Cases Using Voice Recognition Technology. *PloS one* 8 (12), e82971. doi:10.1371/journal.pone.0082971

Patricia, S. (2007). Abril and Robert Plant. The Patent Holder's Dilemma: Buy, Sell, or Troll? *Commun. ACM* 50 (1), 36–44. doi:10.1145/1188913.1188915

Pavord, I. (2008). Prevalence, Pathogenesis, and Causes of Chronic Cough. *Lancet* 371 (9621), 1364–1374. doi:10.1016/s0140-6736(08)60596-6

Petrie, C. J. (1986). *New Algorithms for Dependency-Directed Backtracking*. Austin, TX, USA: Technical report. master's thesis.

Pinkas, G., Karny, Y., Malachi, A., Barkai, G., Bachar, G., and Aharonson, V. (2020). SARS-CoV-2 Detection from Voice. *IEEE Open J. Eng. Med. Biol.* 1, 268–274. doi:10.1109/ojemb.2020.3026468

Poker-Edge.Com (2006). Stats and Analysis. Available at: http://www.poker-edge.com/stats.php.

Pramono, R. X., Imtiaz, S. A., and Rodriguez-Villegas, E. (2016). A Cough-Based Algorithm for Automatic Diagnosis of Pertussis. *PLoS ONE* 11 (9), e0162128. doi:10.1371/journal.pone.0162128

R Core Team (2019). R: A Language and Environment for Statistical Computing. Available at: https://www.R-project.org/.

Ramesh, G. (2021). *COVID or Just a Cough? AI for Detecting COVID-19 from Cough Sounds*. KDnuggets.

Redding, G. J., and Carter, E. R. (2017). Chronic Suppurative Lung Disease in Children: Definition and Spectrum of Disease. *Front. Pediatr.* 5, 30. doi:10.3389/fped.2017.00030

Reid, B. K. (1980). "A High-Level Approach to Computer Document Formatting," in Proceedings of the 7th Annual Symposium on Principles of Programming Languages (New York: ACM), 24–31. doi:10.1145/567446.567449

Rocha, B. (2020). "Personalized Detection of Explosive Cough Events in Patients with Pulmonary Disease," in 2020 IEEE 20th Mediterranean Electrotechnical Conference (MELECON) (IEEE).

Rocha, B. M. (2017). "Detection of Explosive Cough Events in Audio Recordings by Internal Sound Analysis," in 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (IEEE), 1–5. doi:10.1109/embc.2017.8037429

Rous, B. (2008). The Enabling of Digital Libraries. *Digit. Libr.* 12 (3).

Ryan, N. M. M., Vertigan, A. E., Bone, S., and Gibson, P. G. (2010). Cough Reflex Sensitivity Improves with Speech Language Pathology Management of Refractory Chronic Cough. *Cough* 6 (1), 5. doi:10.1186/1745-9974-6-5

Sadiq, F., Masood, K., Azeem, M., and Khan, A. R. (2021). Screen-ing of Covid-19 Using Cough Audio Frequencies. *Int. J.* 10 (3).

Saeedi, M., Zamani, M. S., Sedighi, M., and Sasanian, Z. (2010). Syn-thesis of Reversible Circuit Using Cycle-Based Approach. *J. Emerg. Technol. Comput. Syst.* 6 (4). doi:10.1145/1877745.1877747

Saeedi, M., Sedighi, M., and Saheb Zamani, M. (2010). A Library-Based Synthesis Methodology for Reversible Logic. *Microelectron. J.* 41 (4), 185–194. doi:10.1016/j.mejo.2010.02.002

Salas, S. L., and Hille, E. (1978). *Calculus: One and Several Variable*. New York: John Wiley & Sons.

Salmi, T., Sovijärvi, A. R. A., Brander, P., and Piirilä, P. (1988). Long-term Recording and Automatic Analysis of Cough Using Filtered Acoustic Signals and Movements on Static Charge Sensitive Bed. *Chest* 94 (5), 970–975. doi:10.1378/chest.94.5.970

Schuller, B. (2020). *COVID-19 and Computer Audition: An Overview on what Speech Sound Analysis Could Contribute in the SARS-CoV-2 Corona Crisis*. Cornell University.

Seshadri, D. R., Davies, E. V., Harlow, E. R., Hsu, J. J., Knighton, S. C., Walker, T. A., et al. (2020). Wearable Sensors for Covid-19: a Call to Action to Harness Our Digital Infrastructure for Remote Patient Monitoring and Virtual Assessments. *Front. Digit. Health* 2 (8), 8. doi:10.3389/fdgth.2020.00008

Sharan, R. V., Abeyratne, U. R., Swarnkar, V. R., and Porter, P. (2019). Automatic Croup Diagnosis Using Cough Sound Recognition. *IEEE Trans. Biomed. Eng.* 66 (2), 485–495. doi:10.1109/tbme.2018.2849502

Sharma, A., Baldi, A., and Kumar Sharma, D. (2021). How to Spot Covid-19 Patients: Speech & Sound Audio Analysis for Preliminary Diagnosis of Sars-Cov-2 Corona Patients. *Int. J. Clin. Pract.* 75 (6), e14134. doi:10.1111/ijcp.14134

Sharma, A., Baldi, A., and Kumar Sharma, D. (2020). *How to Spot Covid-19 Patients: Speech Sound Audio Analysis for Preliminary Diagnosis of SARS-COV-2 Corona Patients*. ISF College of Pharmacy.

Sharma, N., Baldi, A., and Kumar Sharma, D. (2020). Coswara–a Database of Breathing, Cough, and Voice Sounds for COVID-19 Diagnosis. *Cornell Univ.* 1, 275–281.

Shi, Y., Liu, H., Wang, Y., Cai, M., and Xu, W. (2018). Theory and Application of Audio-Based Assessment of Cough. *J. Sensors* 2018, 1–10. doi:10.1155/2018/9845321

Shin, S-H., Hashimoto, T., and Hatano, S. (2009). Automatic Detection System for Cough Sounds as a Symptom of Abnormal Health Condition. *IEEE Trans. Inf. Technol. Biomed.* 13 (4), 486–493. doi:10.1109/titb.2008.923771

Shuja, J. (2010). COVID-19 Open Source Data Sets: a Comprehensive Survey. *Expert Rev. Respir. Med.* 4 (5).

SIGCOMM Comput (1984). Acm Sigcomm Computer Communication Review. *Commun. Rev.* 13-14 (5-1).

Simon Fear (2005). Publication Quality Tables in LATEX. Available at: http://www.ctan.org/pkg/booktabs.

Smith, J. A., Earis, J. E., and Woodcock, A. A. (2006). Establishing a Gold Standard for Manual Cough Counting: Video versus Digital Audio Recordings. *Cough* 2 (6), 6. doi:10.1186/1745-9974-2-6

Smith, S. W. (2010). "An Experiment in Bibliographic Mark-Up: Parsing Metadata for Xml Export," in Proceedings of the 3rd. Annual Workshop on Librarians and Computers, Volume 3 of LAC '10. Editors R. N. Smythe and A. Noble (Milan Italy: Paparazzi Press), 422–431.

Spector, A. Z. (1990). "Achieving Application Requirements," in *Distributed Systems*. Editor S. Mullender. 2nd. edition (New York, NY: ACM Press), 19–33. doi:10.1145/90417.90738

Spycher, B. D., Silverman, M., Brooke, A. M., Minder, C. E., and Kuehni, C. E. (2008). Distinguishing Phenotypes of Childhood Wheeze and Cough Using Latent Class Analysis. *Eur. Respir. J.* 31 (5), 974–981. doi:10.1183/09031936.00153507

Stasak, B., Huang, Z., Razavi, S., Joachim, D., and Epps, J. (2021). Automatic Detection of COVID-19 Based on Short-Duration Acoustic Smartphone Speech Analysis. *J. Healthc. Inf. Res.* 5 (2), 201–217. doi:10.1007/s41666-020-00090-4

Subirana, B. (2020). *Hi Sigma, Do I Have the Coronavirus?: Call for a New Artificial Intelligence Approach to Support Health Care Professionals Dealing with the COVID-19 Pandemic*. Cornell University.

Swarnkar, V., Abeyratne, U. R., Chang, A. B., Amrulloh, Y. A., Setyati, A., and Triasih, R. (2013). Automatic Identification of Wet and Dry Cough in Pediatric Patients with Respiratory Diseases. *Ann. Biomed. Eng.* 41 (5), 1016–1028. doi:10.1007/s10439-013-0741-6

Thornburg, H. (2001). Introduction to Bayesian Statistics. Available at: http://ccrma.stanford.edu/~jos/bayes/bayes.html.

Tong, X., Spathis, D., Grammenos, A., Han, J., Hasthanasombat, A., Bondareva, E., et al. (2021). *Covid-19 Sounds: A Large-Scale Audio Dataset for Digital Covid-19 Detection*. OpenReview.

TUG (2017). Institutional Members of the TEX Users Group. Available at: http://wwtug.org/instmem.html.

Tzamaloukas, A., and Garcia-Luna-Aceves, J. J. (2000). *Channel-hopping Multiple Access*. Berkeley, CA: Technical Report I-CA2301, Department of Computer Science, University of California.

Using the amsthm Package (2015). American Mathematical Society. Available at: http://www.ctan.org/pkg/amsthm.

Usman, M. (2020). *On the Possibility of Using Speech to Detect COVID-19 Symptoms: An Overview and Proof of Concept*. Biomedical speech signal processing.

Van Gundy, M., Balzarotti, D., and Vigna, G. (2007). "Catch Me, if You Can: Evading Network Signatures with Web-Based Polymorphic Worms," in Proceedings of the First USENIX Workshop on Offensive Technologies, WOOT '07 (Berkley, CA: USENIX Association).

Veytsman, B. (2022). Acmart—Class for Typesetting Publications of ACM. Available at: http://www.ctan.org/pkg/acmart.

Vijayakumar, S., and Sneha, M. (2020). Low Cost COVID-19 Preliminary Diag-Nosis Utilizing Cough Samples and Keenly Intellective Deep Learning Approaches. *Alexandria Eng. J.* 60 (1), 549–557.

Vizel, E., Yigla, M., Goryachev, Y., Dekel, E., Felis, V., Levi, H., et al. (2010). Validation of an Ambulatory Cough Detection and Counting Application Using Voluntary Cough under Different Conditions. *Cough* 6 (1), 3. doi:10.1186/1745-9974-6-3

Wee-Yang, P., and Boushey, H. A. (2008). "Cough in Lower Airway Infections," in *Cough: Causes, Mechanisms and Therapy* (John Wiley & Sons), 81–96.

Wenzel, E. M. (1992). "Three-dimensional Virtual Acoustic Displays," in *Multimedia Interface Design (Incoll)* (New York, NY, USA: ACM), 257–288. doi:10.1145/146022.146089

Werneck, R., Setubal, J., and da Conceicão, A. (2000). Finding Minimum Congestion Spanning Trees. *ACM J. Exp. Algorithmics* 5 (11), 11. doi:10.1145/351827.384253

Windmon, A., Minakshi, M., Bharti, P., Chellappan, S., Johansson, M., Jenkins, B. A., et al. (2019). TussisWatch: A Smart-Phone System to Identify Cough Episodes as Early Symptoms of Chronic Obstructive Pulmonary Disease and Congestive Heart Failure. *IEEE J. Biomed. Health Inf.* 23 (4), 1566–1573. doi:10.1109/JBHI.2018.2872038

Xu, W., Chen, R., and Chen, X. (2020). A Review of Disorder Voice Processing toward to Applications. *J. Phys. Conf. Ser.* 1624 (3), 032012. doi:10.1088/1742-6596/1624/3/032012

Zhou, G., Lu, J., Wan, C.-Y., Yarvis, M. D., and Stankovic, J. A. (2008). *Body Sensor Networks*. Cambridge, MA: MIT Press.

Zhou, G., Wu, Y., Yan, T., He, T., Huang, C., Stankovic, J. A., et al. (2010). A Multifrequency Mac Specially Designed for Wireless Sensor Network Applications. *ACM Trans. Embed. Comput. Syst.* 9 (4), 1–41. doi:10.1145/1721695.1721705

Zhuang, X., Zhou, X., Hasegawa-Johnson, M. A., and Huang, T. S. (2010). Real-world Acoustic Event Detection. *Pattern Recognit. Lett.* 31 (12), 1543–1551. doi:10.1016/j.patrec.2010.02.005

Conflict of Interest: The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.