COVID-19 Detection Using Audio Processing: A Systematic Literature Review

Arifa Fauziya*[1] and Armein ZR Langi[2]

Bandung Institute of Technology, Bandung, Indonesia
23522053@std.stei.itb.ac.id

Abstract. This paper reports a systematic literature review regarding (i) datasets, (ii) processing algorithms, and (iii) their corresponding performance of cough audio processing based on COVID-19 disease detection. Early detection of respiratory diseases that is fast, practical, non-intrusive, and affordable is needed to prevent such diseases from turning into pandemics, such as in the recent COVID-19 case. We have proposed such a detection system using cough audio processing, as coughing is a recognizable sign of many respiratory illnesses, such as pulmonary edema, tuberculosis, pneumonia, whooping cough, and asthma, with future COVID-19 variants as a prime target. This study finds that theCoswara dataset is the most widely used, the Mel Frequency Cepstral Coefficient (MFCC) is the most popular extraction method, and SVM is the most common classifier. Overall, the accuracy that has been obtained is quite high, therefore the implementation of this cough detection system is convincing enough to continue. A cough detection system can then be designed to use several algorithms as plugins, capable of executing an optimal algorithm trained using a particular dataset.

Keywords: Cough Detection, COVID-19, Systematic Literature Review

1 Introduction

COVID-19 pandemic has been declared over, its new virus variants are expected to mutate, and without proper measures and preparations, they may develop into a full-blown pandemic. Such measures include prescreening systems for early detection, that is accurate, easy to administer, fast results, and affordable.

The most widely used testing method for COVID-19 is reverse transcriptase polymerase chain reaction (RT-PCR). It is highly accurate but has limited capacity, due to the necessity for laboratory testing of samples. Its low sensitivity of ribonucleic acid makes it less able to detect patients in early stages [1]. The PCR test also involves risky contact procedures, taking many hours to complete, and exposing medical staff to the viruses.

Recently detections based on cough sound processing have been studied extensively. Coughing, among others, is a recognizable sign of many respiratory illnesses, and AI-

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based models have been used to identify specific on such as pulmonary edema, tuberculosis, pneumonia, whooping cough, and asthma based on cough symptoms [4].

We then propose such a detection system using cough audio processing to take advantage of widespread mobile phones, accurate performances, fast, non-intrusive, affordable, as well as safe process. We intend to use a collection of processing algorithms to adapt it to a variety of respiratory diseases.

As in any detection system, we are concerned with a population parameter contained in healthy cough sound, \mu_0, and assumed to be altered into \mu1 by the diseases. We are interested in cough processing algorithms that produce samples, to estimate both parameters unbiasedly and efficiently. A statistical test is then applied to predict accurately the presence of the diseases.

Consequently, we need answers to a basic question: given a population of cough sounds, what kind of treatment is given by a disease to alter the population parameter, and what kind of algorithm for estimating altered parameter to be able to reject H0 significantly.

This paper reports a systematic literature review (SLR) to answer the questions. Section 2 describes the SLR methodology and its implementation, specific to this study. Section 3 describes the answers to those questions. Finally, Section 4 provides concluding remarks and discusses future work to utilize the results.

2 Research Methodology and Implementation

2.1 Methodology Review

A systematic literature review (SLR) was employed in this study as a research methodology. SLR differs from traditional reviews in that it uses a methodical approach and adheres to specific criteria [5]. The objective of SLR is to scope and deepen evaluation data using a trustworthy and responsible technique. SLR consists of three steps: planning, implementation, and reporting [6]. The study begins by formulating research questions, followed by identifying reliable database sources and searching for relevant papers. After acquiring an extensive collection of papers as references, the author went on to establish article selection criteria.

2.2 Research Questions

This research is based on the research questions (RQs) that had the purpose of focusing the research and keeping it systematic. The Population, Intervention, Comparison, Outcomes,and Context (PICOC) structure is used to make the structure of RQs[7]. The PICOC structure of this study is described in Table 1. This research focused on cough detection, especially as one of the symptoms of COVID-19. According to the previously explained PICOC structure, the research questions for this study are listed in Table 2.

2.3 Search Strategy

In order to find relevant papers, this research studies an inquiry based on a number of criteria. In order to conduct a pertinent inquiry for this study, the researchers used a number of keywords in the AND-OR pattern, including: (cough*) AND (detect*) AND (audio OR signal) AND (COVID OR COVID-19) AND (Mobile OR Smartphone) For implementing keywords in ScienceDirect that do not support wildcard signs (*), the following keywords are used: (cough OR coughs AND (detect OR detecting) AND (audio OR signal) AND (COVID) AND (Mobile OR Smartphone).

Table 1. PICOC Structure

Structure	Components
Population	Cough Detection, COVID-19 detection, Pre-screening Application, Cough Signals.
Intervention	Signal Process, Characterization Process
Comparison	Feature Extraction
Outcomes	Cough Detection System
Context	Research in COVID-19 cough detection

Table 2. Research Questions

ID	Research Questions	Motivation
RQ1	What dataset is used to detect COVID-19 cough?	Learn about the cough dataset used to detect COVID-19.
RQ2	What technology is used to detect COVID-19 cough?	To know the technology used in cough detection.
RQ3	How is the performance of the implemented algorithm?	To know the best algorithm for cough detection.

The digital libraries used in this research to implement these search strings are IEEE Xplore (https://ieeexplore.ieee.org), ScienceDirect (https://www.sciencedirect.com), SpringerLink (https://www.link.springer.com), and ACM Digital Library (https://dl.acm.org).

Table 3. Keywords

Term	Keywords and Alternative Words
Cough*	Coughs, coughing
Detect*	Detects, detecting, detector
Audio	Signal
COVID	COVID-19
Mobile	Smartphone

Table 4. Search Result

Digital Libraries	Number of Paper
IEEE Xplore	21
ScienceDirect	583
SpringerLink	354
ACM Digital Library	327
Total	1285

Table 5. Criteria Study

	ID	Description
Inclusion	I1	English Paper Written
	I2	Publication in 2020-2022
	I3	Relevant to the topic
	I4	Match the strings and search keywords
	I5	Journal, conferences, and proceeding pub-
	I6	Reputable journal
Exclusion	E1	Out of COVID-19 topic
	E2	Duplicating paper
	E3	Non-English Paper Written
	E4	The journal is not accredited
	E5	Does not use audio to detect cough

2.4 Study Selection

After using keywords to locate a number of journals, a filtering process was used to identify sources that met the research criteria. Based on Table 3, the requirements were determined. Keywords, time periods, and language restrictions were also applied during the title search process. Papers were restricted based on abstracts after meeting the inclusion and exclusion criteria, and the best publications were acquired using the current procedures.

The filtering process used in the Systematic Literature Review (SLR) method is illustrated in Fig. 1. Initially, keywords are created and applied to the search feature of a number of digital libraries, resulting in 1285 papers. These papers undergo a filtering process based on their titles' relevance to the study topic. After this step, the abstracts are carefully reviewed, and a study selection is made to produce a final list of literature to be studied.

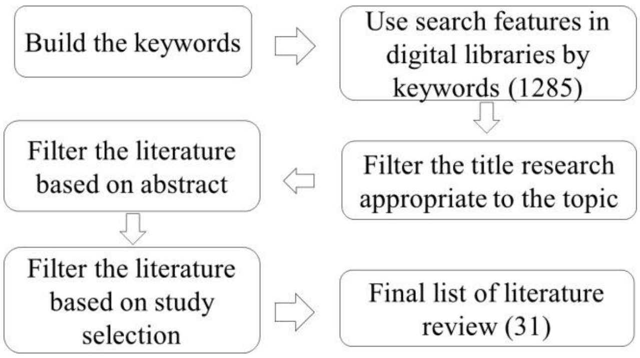

Fig 1. Filtering Process

2.5 Data Mapping

According to the investigation, there are 31 (thirty-one) articles discussing this topic between 2020 and 2022. Due to the pandemic's significant societal impact, as depicted in Fig. 2, the volume of research can support the development of this cough detection system. After analyzing it using study criteria, it was determined that three publication sources would be reviewed for this study, as shown in Fig. 3.

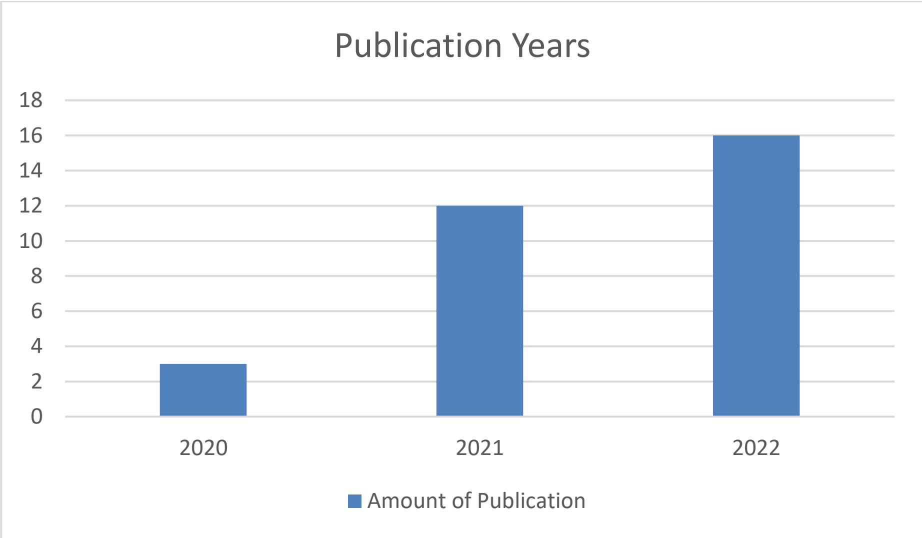

Fig 2. Publication Years

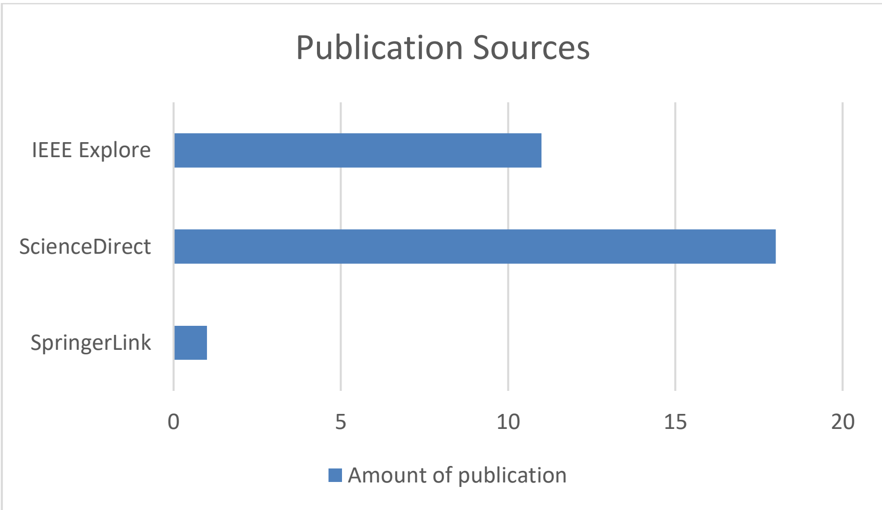

Fig 3. Publication Source

3 Research Result

Generally, there are main processes used in the research of evaluating methods for cough detection. According to Fig. 4, the process begins using a dataset to test the models of machine learning. The dataset that has been collected usually needs preprocessing because it contains other noises, such as breath, speech, etc. This preprocessing will differentiate between a cough and other noises to increase the quality of the audio processing model. Afterward, the data will be extracted to find the features of the selected disease, in this case, COVID-19 disease.

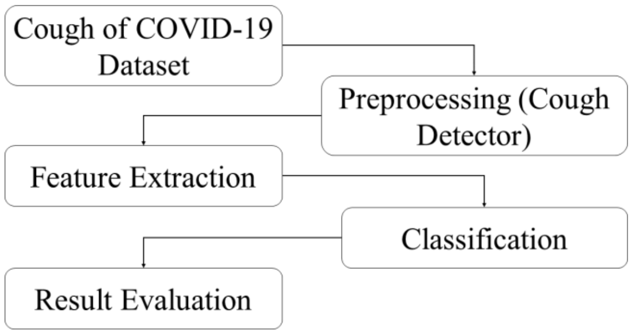

Fig 4. The method evaluation process of COVID-19 detection

The features found in the research were classified with a selected classifier to find the best classification to be implemented. This classification will produce the result of every piece of data that has been extracted.

Machine learning models use datasets both for training and testing processes. After the model goes through the training process, the rest of the data is used in the testing model to clarify the accuracy and other aspects of the evaluation. The cough model's overall performance was evaluated using validation and testing for accuracy, sensitivity, and specificity.

3.1 What dataset was used to detect COVID-19 cough?

Finding a trustworthy and well-balanced dataset is a must for building and testing machine learning models. Based on the research that has been done, several COVID-19 cough datasets are accessible online, including COUGHVID, COSWARA, Sarcos, Virufy, a Russian dataset, etc. This dataset is helpful for building effective and efficient cough detection models. A list of COVID-19 datasets, including access information, is described in Table 6. According to the table, the COSWARA dataset was the most used in cough detection [2] [4] [7] [8] [9] [10] [11] [12] [13] [14].

Table 6. COVID-19 Datasets

Datasets	Access	Confirmation	References
COUGHVID	Public	Verbal confirmation – PCR verified for COVID-19 positive samples	[2] [15] [16]
COSWARA	Public	PCR-tested verified	[2] [4] [7] [8] [9] [10] [11] [12] [13] [14]
Sarcos	Public	PCR-tested verified	[10]
Virufy	Public	PCR-tested verified	[2] [4] [6] [7] [13] [14] [17]
NoCoCoDa	-	-	[4]
Russian dataset	Public	-	[10]
Cambridge University dataset	Public	-	[1] [3] [5] [17] [28]
Environmental Sound Classification(ESC-50)	Public	-	[22] [2] [11] [24]
Firat University Hospital, Elazıˇg, Turkey	Limited	-	[16]
DCASE2016	Public	-	[22]
University of Lleida	Limited	-	[28]

3.2 What technology is used to detect COVID-19 cough?

A cough is a reflex action that expels inhaled compounds or objects from the respiratory tract (trachea). Cough is therefore an essential indicator that helps physicians diagnose disease [27]. Consequently, respiratory symptoms can serve as a screening strategy after undergoing pre-processing as depicted in Fig. 1. The obtained data then undergoes the processes of feature extraction and feature classification. As shown in Table 7, Mel Frequency Cepstral Coefficient (MFCC) is the most popular method for identifying coughs using audio.In addition, as shown in Table 8, several classifiers are commonly used to process the extracted features during the classification process. However, research indicates that SVM is the most popular classifier for classifying features.

Table 7. Features/Technology in Cough Detection

Features/Technology	Reference
L3-Net	[1]
Random Frog	[2]
UVE	[2]
VIP	[2]
Mel-Frequency Cepstral Coefficients (MFCC)	[3] [11] [13] [14] [17] [24] [26] [27]
Mel-Scaled Spectrogram	[3]
Tonal Centroid	[3]
Chromagram	[3]
Spectral Contrast	[3]
ResNet	[5] [18] [20]
ReliefF algorithm	[7]

Table 8. Classifier in Cough Detection

Classifier	**Reference**
SVM	[2] [3] [7] [14] [20][24] [26] [28]
Extremely Randomized Trees (Extra-Trees)	[3] [8] [9] [14]
Random Forest (RF)	[3] [8] [26] [28]
Adaptive Boosting (AdaBoost)	[3] [26]
Multilayer Perceptron (MLP)	[3] [20]
Extreme Gradient (XGBoost)	[3] [8] [26]
Gradient Boosting (GBoost)	[3] [26]
Logistic Regression (LR)	[3] [9] [20] [26] [28]
k-Nearest Neighbor (k-NN)	[3] [8] [16] [20] [26]
Histogram-based Boosting (HGBoost)	[3] [26]
Na¨ıve Bayes	[9] [28]
Deep Transfer Learning-based multi class classifier (DTL-MC)	[11] [24]
Classical Machine Learning-based Multi Class classifier (CML-MC)	[11] [24]
Deep Transfer Learning-based Binary Class classifier (DTL-BC)	[11] [24]
DNN	[13] [22]
Neural Network	[14]
Long short-term memory (LSTM)	[20]
ViT	[25]

3.3 How is the performance of the implemented algorithm?

Table 9 consists of evaluation information from the reviewed research. When analyzing the performance of an algorithm, various factors are considered, including AUC, precision, recall, accuracy, and F1 score. The numbers in Table 9 are of a statistical form; many evaluation results offer sufficient numbers to be classified as outstanding. However, this statistic cannot be used in its complete form because not all studies utilize the same dataset.

Table 9. Performance of Implemented Algorithm

References	AUC	Precision	Recall	Accuracy	F1-score
[1]	69	74	61	-	-
[2]	94.9	97.1	93.1		95
[3]	95	1	97	-	-
[5]	93	88	93	93	90
[7]	-	-	-	98.4	98.6
[8]	79.7	-	-	79.86	-
[9]	-	-	-	97.87	-
[10]	94	-	-	94	-
[11]	-	-	-	88.76	-
[13]	-	-	-	97.5	-
[17]	-	-	-	95.45	-
[18]	-	-	-	94.9	-
[19]	-	93.1	97.1	94.9	95
[21]	95	1	-	97	-
[20]	92.57	-	-	-	-
[22]	-	-	-	98.4	98.6
[23]	-	-	-	79.86	-
[24]	-	-	-	97.87	-
[25]	94	-	-	91	-
[26]	-	-	-	97.5	-
[27]	-	-	-	96.49	-
[28]	-	-	-	99.39	-
[29]	-	-	-	95.45	-

4 Conclusion and Future Work

This paper describes a method for identifying COVID-19 cough using audio processing. Previous studies used public datasets to develop popular cough detection models, particularly Coswara, the most popular public dataset used in several of the reviewed studies. Using various algorithms, AI technology has been implemented and continues to be developed to improve its accuracy. Mel Frequency Cepstral Coefficient (MFCC) is a technique that is more commonly used to extract features based on the reviewed literature, coupled with SVM as a classifier that is commonly used in a number of studies in this review. Overall, the accuracy that has been obtained is quite high, therefore the implementation of this cough detection system is convincing enough to continue. Nonetheless, the number according to Table 9 is still statistical and cannot be standardized because it is derived from various datasets. For further testing, evaluating applications from previous research with the same dataset is necessary.

Employing previously conducted research, the results of this study are extremely useful for continuing the development of the system into a pre-screening system, which can serve as a preventative measure against the spread of highly infectious diseases. The cough detection system can be used as a preliminary screening instrument to provide early treatment for diseases with high transmission rates, particularly those transmitted through cough droplets. The development of API standards for cough detection systems can facilitate the identification of the algorithm that best matches the processed dataset. A cough detection system may be designed as a plug-in capable of executing the optimal algorithm for a given dataset.

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