ISSN 2278-3091
Volume 10, No.3, May - June 2021
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse511032021.pdf
https://doi.org/10.30534/ijatcse/2021/511032021

Screening of COVID-19 using Cough Audio Frequencies

Farrukh Sadiq[1], Dr. Khalid Masood[2], Muhammad Azeem[3], Anas Riaz Khan[4]
[1]Department of Computer Science, Lahore Garrison University, Pakistan, farrukhsadiq6@gmail.com
[2]Department of Computer Science, Lahore Garrison University, Pakistan, khalid.masood@lgu.edu.pk
[3]Department of Computer Science, Lahore Garrison University, Pakistan, azeemzulfiqarcs@gmail.com
[4]Department of Computer Science, Lahore Garrison University, Pakistan, anasriaz@gmail.com

ABSTRACT

Clinicians routinely use biomedical and audio signals (e.g. sighs, breathing, pulse, digestion, sounds of vibration) as markers to diagnose diseases or to evaluate the progression of diseases. Until recently, these signals were normally obtained during scheduled visits by manual auscultation. With the advancement of technologies, digital methods are used to collect the body sounds for cardiovascular or respiratory testing (e.g. digital stethoscopes to predict the progression of diseases. A few early studies showed promising results for the detection of COVID-19 using voice and diagnostic signals. In the proposed model, an effective analysis is performed through the collection of large, multi-group, airborne acoustic sound data to perform the screening of COVID-19. The technique uses cough and breathing patterns to show the distinctive features of COVID-19 and it is reported that the cough patterns of COVID-19 are identifiable from asthma cough patterns. Using machine learning algorithms, an efficient classification model is developed for the screening of COVID-19.The area below the curve (AUC) of our proposed model exceeds 80%. The present study also explores the analysis of air patterns that can be recorded using the breathing styles of the infected persons to enhance the efficiency of the proposed screening techniques.

Key words: Audio Signal, COVID-19, Deep Learning, Machine Learning

1. INTRODUCTION

Audio signals (i.e. sighs, breath, pulse, digestion, sounds) from the human body of the vibration) were used extensively by physicians and clinical researchers to diagnose and track diseases. However, until recently such signals were normally obtained during scheduled visits through manual auscultation. Study now begins using digital technologies to capture body sounds (for example, optical stethoscopes) and data analyses[24] are performed automatically, for example, asthma wheeze detections[18, 23]. In addition, researchers use human voice to help diagnose a certain variety of disorders early on: Parkinson's disease is associated with voice loss[6, 12], coronary artery frequency[19] and voice of sound, pitch, rhythm, variations in speed and amplitude. The use of humanly produced audio as a bioparticle for diverse diseases provides tremendous early warning potential and inexpensive solutions that can be implemented by masses when integrated in commodity systems. This is even truer if these solutions are able to unobtrusively track people in their everyday lives. Recent research has been initiated into the variations between respiration noise and healthy persons caused by positive COVID-19 devices such as hardness, respiration or voices. Lung auscultation Optical stethoscope figures serve as a signal for the detection of COVID-19. In comparison with other cough types, COVID-19 telephone detection was presented in [17] with 48 COVID 19 patients.

COVID-19 hospital patients' speech records are analyzed for automatically categorizing health conditions for patients. We study the use of crowd-based, uncontrolled human breathing sound data as diagnostic indicators for COVID-19. This paper describes precisely our initial results on a subset of our data collection, available Right now. Www.covid-19-sounds.org worldwide. Data was composed using a voice, toxin and respiratory application, and its history and symptoms (Android and Web). The app also asks whether the consumer has successfully examined COVID-19. For 10,000 samples, we have about 7,000 unique users to date. Although similar knowledge is tried otherwise, sometimes it is a limited range (e.g. collection of cough) or size (e.g., in a single area or facility, gather smaller samples). This is in our understanding the world's biggest unconfined and crowded compilation of COVID-19 sounds. In order to track the progress of diseases, the mobile app gathers information from people every two days. This is a basic feature of our set of data. Section 3 provides a complete overview of the data.

This paper addresses a section 3.3 of our knowledge and offers tentative proof of diagnostic signals that distinguish COVID-19 from healthy individuals; The COVID-19 cheering users of cough with healthy coughs and the users of asthma. More precisely, the contributions in the paper are:

- Description of the COVID-19 sound assemble method by applications and impression types assembled by the crowds. It is actually the largest collected sound form and one of the most inclusive. Sounds from around 7000 unique users are available (Over 200 of which registered a recent COVID-19 positive test).
- Starting results on discrimination in cough and breath sounds are discussed in COVID-19. We create three binary

assignments, one for the separation of COVID-19 from stable consumer. One distinguishes COVID-19 from positive cough consumers, and another distinguishes COVID-19 from positive cough users. The findings show that the score is below 80% for all tasks (AUC). In particular, strong and COVID-19 sounds can be correctly distinguished by 80 percent AUC (Task 1). We have an AUC of 82 percent while hard to differentiate A person who tested COVID-19 positive and who has a healthy cough from cough user (task 2) when trying to differentiate between users who caught for COVID-19 with asthma and coughing (Task 3) achieves a CAU of 80 percent.

• We show how the increase in audio can be used to increase the retrieval performance with less data for some of our tasks. Task 2 and Task 3 show a 5% and 8% change in outcomes.

• Discuss the results, their potential and illustrate a variety of future COVID-19 preliminary screening and progression detection guidelines for our research and diagnostics.

1.1 Spreading Coronavirus (SARS-Cov-2) From COVID-19 Biomedical Waste

Several study pieces have shown that the new disease COVID-19 is not only spreading due to historically direct contact[13], but also due to biomedical waste COVID-19. Ilyas Sadia et al. suggested the methods and procedures for treating biomedical waste in COVID-19 hospitals[14]. However, since the COVID-19 pandemic new biomedical waste techniques have emerged and disinfecting COVID-19 waste is necessary in order to handle the widespread use of COVID-19. Ramtek Shobhana and LS Bharat published[15] a study on the impacts of COVID-19 in the biomedical waste industry in India to monitor coronavirus transmission. The authors discussed the potential effects of the COVID-19 disease outbreak on waste management in healthcare and highlighted fundamental emphasis where optional working strategies or additional control measures are required.

Arghya Das et al. released the editor's letter[16] for COVID-19 on health-related waste issues and suggested recommendations for developing countries such as India. Other recommendations encourage the use of double-layered containers (using two or more bags), the obligatory labeling of containers and sackages as COVID-19 trash, the frequent disinfection of individual containers, the separate waste record keeping of isolation wards in COVID-19 hospitals.

Filimonau Viachaslau published [17] research on the future for the management of medical waste in the post-pandemic SARS-CoV-2 healthcare region, addressed the plastic waste crisis, and developed 'green' innovations in the healthcare industry. The authors proposed possible ways to improve the mitigation of this waste In the post-pandemic hospitality market. The hospitality industry should be incorporated into alternative, shorter-term food supply networks and food outlets to resolve the problem of food waste.

Kulakarni Bhargavi N and Anatharama V summarized [18] work of the municipality on problems and risks related to biomedical waste management in the circumstances of COVID-19 disease outbreaks. During the COVID-19 outbreak it discussed the global waste management context and examined various aspects of biomedical waste management. The discussion would allow determining parameters of infectious diseases through solid waste management, the effects for medical waste surgeons of current municipal waste treatment and disposal schemes. The authors suggested alternative waste management approaches to waste dumping and recommendations on potential scope to establish an appropriate waste management environment in and after the COVID-19 pandemic. Sharmas Hari Bhakta et al. presented a report [19] during and after the outbreak of SARS-CoV-2 on the possibilities, obstacles, and technologies for efficient and proper waste management and authors discussed the specific cases for plastic waste, pharmaceutical waste and food waste management as well as the need for the installation of solid distributed supply systems in the future.

Ganguly Ram Kumar and Chakraborty SK, behind the SARS-CoV-2 pandemic, proposed an integrated management mechanism for urban solid waste[20] and addressed the challenges of the existing waste management system to tackle mass waste generation. In light of an epidemic of new diseases, the authors tackled each newly generated problem by outlining strategies incorporating a variety of traditional, innovative, and newly proposed waste management strategies, in particular for collecting, sorting, disposing and recycling enormous quantities of municipal solid waste. Referring to the COVID-19 pandemic, Jean Philippe Adam et al. have reported[21] findings of the Center Hospital University Montreal hospital pharmacy (CHUM). They tackled the seven major issues: corporate relations, virtual organizations, risk management, time management, conflicts between workers, pharmacy reorganization and job reorganization. The COVID-19 biomedical waste management technology is challenging in reducing health effects and can be very useful in the development of new strategies to avoid and control the SARS-CoV-2 pandemic.

1.2 COVID-19 Sounds Taxonomy

In a variety of directions, the emerging information and communication technologies (ICT) sponsored the battle against COVID-19, including research efforts to:

1. Description of symptoms of COVID-19 with irregular respiratory patterns[2].
2. COVID-19 diagnosis and treatment with ML and DL technique[6]
3. Identification by mobile application of COVID-19 symptoms with cough data [8].
4. Crowd-sourced breathable sound data for COVID-19 diagnosis[9].
5. COVID-19 cough detection with the crowd sourcing dataset "COUGHVID" [22].
6. COVID-19 sound correlation study with MFCC system [23].
7. Diagnosis of COVID-19 by studying vocal fold

oscillations of the pulmonary voice[24].

8. Respiratory cough detection AI for COVID-19 [25],[26].
9. Structure for biomarkers for COVID-19 detection with language-production subsystems [27].
10. COVID-19 speech analysis with parameters [28].

The taxonomy of air COVID-19 sounds from crowd-sourced datasets can be seen in Fig.1, and data from crowd-sourcing datasets and data-driven techniques such as Artificial Inteligence Machine learning and profound learning techniques for diagnosing COVID19 disease have been obtained. These methods and techniques help diagnose the symptoms of COVID-19 from the crowded breathing sound data.. COVID-19 positive case symptoms can be detected by cough sound, a patient breath screening with voice findings, and a computer with Artificial Intelligence (AI) can feel COVID-19 symptoms from continuous speech and mental health.

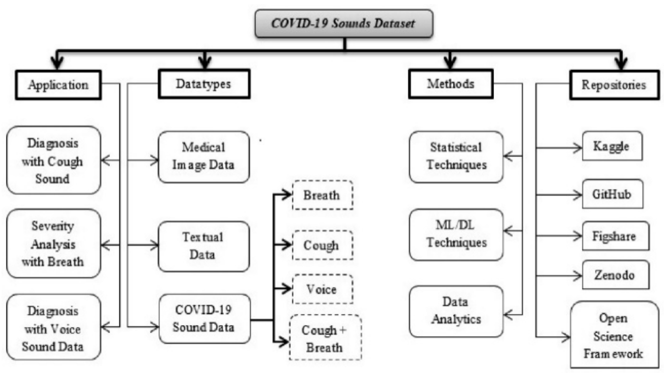


Figure 1: Taxonomy of respiratory COVID-19 sounds from crowd sourced datasets.

Artificial intelligence (AI) is a tool that could help to support that effort to evaluate COVID-19 prescreening researchers and scientists. This is the first review paper on the topic of this study to Our best information. This paper discusses briefly COVID-19 data and COVID-19 sound analysis. Section 1 includes the general taxonomy of sounds from COVID-19 data sets. Background work on COVID-19 data on respiratory sounds and the contribution of the work of each author, as defined in section 2. The results comparative study of each author and the quality of each data set is clarified in Section 3 and with the description and potential guidance, we have concluded our literary review analysis.

1.3 Motivation and Related Work

The utility of sound as an indicator for health and action was long recognized by researchers. For example, stethoscopes are used to detect heart or pulmonary sounds has been used with purpose-built external microphone recorders. These also involve the hearing and interpretation of highly trained professionals and are recently and swiftly replaced by a range of image technology such as MRI, sonography etc. are easier to analyze and interpret. Nevertheless, recent advances in audio automation and modeling will reverse this trend and make the best option. The microphone has recently been used for sound analyzing on commodities such as smartphones and wearables. In [8] microphone audio the user interface is understood and this information is collected to provide an overview of the surrounding environment in a group. In Emotion sense [27], Gaussian mixture models use telephone microphones as a sensor to detect user emotions in the wild.
In [22] the authors discuss the sleeping noises produced for sleep apnea episodes. Related works also detect the use of sound for The wheezing of asthma[18, 23]. Machine methods have been developed for the identification and diagnosis of safe respiratory diseases[24] and especially toxins: [4] uses neuronal cough-related convolution networks (CNNs) to identify cough in the atmosphere and diagnose three different diseases based on their distinct audio characteristics (bronchitis, bronchiolitis and pertussis). The clinical work focused on the use of voice analysis, for example in Parkinson's disease, to diagnose speech softness as a result of loss of vocal musculoskeletal synchronization [7, 12]. [6, 12].

The speakers also used the tone, pitch, rhythm, speed, and symptoms associated to immaterial conditions like post-trauma, trauma, and depression in bipolar disease[13]. Coronary artery disease has been linked to the frequency of speech (which may impair voicing as a result of hardening of the artery)[20]. [19]. [19]. Companies including Over and beyond Verbal and Mayo Clinic that in press releases they are driving certain approaches. Recent researchers have begun studying the potential of COVID-19 diagnosis of breathing sounds[10]. The digital stethoscope data in the pulmonary auscultation were used as a diagnostic signal in COVID-19[16]. The COVID-19 toxin detection analysis includes 48 COVID-19 patients and others who have been trained in a variety of models. COVID-19 analyzes the automated classification of patients' health status in four dimensions: seriousness, consistency of slumber, Patients' speech records The work differed because we have a thoroughly crowded data set to ensure that the fundamental true state of things is what the users say (in terms of signals and the COVID-19 test status), and information from various phones and microphones needs to be resolved in very different environments. Included in the diagnosis of bipolar disturbance were the sound, pitch, rhythm and volume of symptoms of invisible diseases such als post-traumatic strain[5], traumatic brains and depressions [13]. [13]. The voice frequency is associated with coronary artery disease (which may affect voice production by hardening of the artery)[19]. In press releases companies such as Beyond Verbal and Mayo Clinic announced that they are leading these approaches. Researchers have recently begun investigating the possibility that COVID-19 will be diagnosed in respiratory sounds [10]. Digital stethoscope data is used for diagnostic signal in COVID-19 in [16] lung auscultation. [29]. [29]. The COVID-19 cough detection research included 48 COVID-19 patients and other models of pathologic cough. [14] [14] [14] [14] COVID-19 analyzes the automated classification of patients' health status in four dimensions:

seriousness, consistency of slumber, Patients' speech records The study is different because we have a fully crowded dataset to ensure that the fundamental i.e what the persons state (in terms of COVID-19 signs and test status), and the data from the numerous phones and microphones must be solved in very different surroundings. The work is different. It is[17] that we differ in two ways from our work. Second, in a controlled setting, information is processed. In contrast, our data are crowded and the interpretation of the data is more difficult. Second, a deep learning model from end-to-end in its 100-sample data-sets; profound learning models usually override these very short datasets, but we've chosen another method. We use core AI models like SVM with different functions to solve such problems (handcrafted and obtained by means of transmission learning). There are also other crowdsourced approaches like this: a sound-collection web form that collects about 570 tests but not disclose COVID-19 examination is provided. With more than 200 COVID-19 positive users, our own app collects samples More than 7000 specific individuals, and enables users to share their progress in the app after a few days and add a new sample. In order to inform COVID-19 of automatic screening, we announced our pre-liminary results.

2. LITERATURE REVIEW

The utility of sound as a potential predictor of health and behavior has long been recognized by researchers and scientists. Digital stethoscopes have been used for example for the detection of heart or lung sounds through external microphone sensors designed for use. This also includes highly qualified listening and analytical experts and has been recently and rapidly replaced by more easily examined and interpreted novel technologies like a range of techniques for imaging (e.g. RID, sonography). Nevertheless, the latest developments in digital audio interpretations and modeling should reverse this trend and make sounds an affordable alternative that is easily transmitted. Recent microphones have been used on commodity devices like mobile phones and wearables for sound processing.

Wang Yunlu et al. proposed in [2] a framework for different classifications in broad screening of COVID-19 infected persons, which can be used to distinguish different breathing patterns and which we can use as a means of realistic application in the real world. This paper first presents a new and powerful RS-Model for filling the gap between a large number of training data and insufficient real-world knowledge in order to understand the characteristics of real respiratory signals. In order to classify six clinically significant respiratory patterns, bidirectional neural networks such as the GRU Network (BI at GRU) were implemented first (Tachypnea, Eupnea, Biots, Cheyne-Stokes, Bradypnea, and Central-Apnea). Research has shown that the proposed model can recognize six distinct breathing patterns with 94.5%, 94.4%, 95.1% and 94.8 percent, respectively, precision, accuracy, recall and F1. The BI at GRU acquired for the classification of respiratory trends in comparative studies exceeds the current modern models. The deep model and design principles proposed have immense potential for large-scale applications such as sleeping, public and business environments.

In [3], Jiang Zheng et al. suggested a portable non-contact device to track the health status of individuals with masks by observing the characteristics of the respiratory system. This computer comprises mainly a FLIR (forward-looking infrasound) thermal imaging camera and an Android. In practical conditions such as pre-screening, and this can help differentiate possible patients with COVID-19. In this work they carried out health check-ups by integrating thermal and RGB videos from DL cameras based on the architecture. First, pulmonary data analysis methods were used to distinguish people wearing a mask; to produce a health test result, a BI at GRU function is used for the results of lung disease; and, finally, 83,7 percent accuracy was obtained to classify the respiratory conditions of a diseased patient.

In [8] Imran Ali et al. introduced a screening solution based on AI (Artificial Intelligence) to detect COVID that was suggested, developed and ultimately tested using a smart mobile app. The mobile app called AI4 COVID-19 and sends three second cloud wheeze and comeback in two minutes to AI-based clouds. Cough is generally a simple symptom of over 30 non-COVID-19 medical conditions. This makes it extremely difficult to diagnose COVID alone in a multidisciplinary issue. By observing morphological path changes with variations in respiratory cough will achieve 88.76 percent accuracy.

In [9], Brown Chloe et al. propose an Android/iOS app for gathering COVID-19 sounds from over 200 positive respiratory sound data for COVID-19 from more than 7 k specific user names; Brown Chloe et al. has taken up several overall parameters and three main

I. COVID-19 sound-based tasks. Here are criteria,

II. COVID-positive/NO COVID/CUVID,

III. COVID positive for cough/NO COVID for cough,

asthma cough; for 220 cough breathing users the accuracy of 80 percent for task one; for 29 cough-only cough-offs 82 percent for task two; for 18 cough-only users the accuracy of task three is finally reached at 80 percent for modal 18 users; The recall feature (72 percent) is marginally less because of the non-specialist net to detect any cough of COVID-19.

Hassan Abdelfatah et al. [10] implemented a system to diagnose COVID positive by using the RNN model; authors illustrated the major impact of RNN (Recurrent Neural Network) with the use of SSP (Speech Signal Processing) to detect the disease and specifically, this LSTM (long short term memory) used to evaluate the hearing characteristics of patients' cough, respiration, and voice, Early detection and diagnosis of the COVID-19 virus. Compared to both coughing and breathing sound recordings, the model findings indicate poor precision in the speech test.

The "COUGHVID" crowdsourced dataset was introduced by Orlandic Lara et al. for cough analysis in the COVID-19 symptoms [22]; In the COUGHVID dataset, more than 20,000 cough crowdsourced records are provided act for a wide range of topics including gender, age, geography and COVID19 status. They have recorded 121 sounds of cough and 94 sounds from first hand in order to train the classification system, including speech, laughter, silence and various background sounds. They have taken self-reported status variables (25% of recording sounds with a safe value, 25% of COVID sound recordings, 35% of sound tele-records with a symbolic value and 15% of sound tele-records with a non-reported status; ensured the collection of the recordings that are to be marked by all three examiners with a 15% cough value). The number of positive COVIDs, COVID signs and stable individuals is 7.5 percent, 15.5 and 77 percent, respectively, of 65.5 percent men and 34.5 percent women. The results of 632 tagged COVID-19 cough records were hyperpnea(93.0%), whistling (90%), clash (98.7%), snoring (99.1%), or nasal clogging (99.2%).

Mohamed Bader et al. proposed in [23] a meaningful model for samples to be collected from non-COVID and COVID using the combination of the mel-frequency cepstral coefficients (MFCCs) and the SSP (Speech Signal Processing), and found the personal association of their relationship coefficients. These results show a high similarity between different respiratory sounds in MFCC and COVID cough, while MFCC speech is stronger between samples other than COVID-19 . In addition, these effects are preliminary and it is possible for future research to delete the multiple patient voices with COVID-19. Three women and four male voices were collected from seven stable patients, and two female and five male voices from seven COVID-19 were collected. Data from the Zulekha Hospital in Sharjah were collected from COVID-19 infected patients. The data is four times cough from each speaker, the numbers from 1 to 10 speakers, and each speaker's 4 to 5 times deep breath. Further, patients must sit with their heads relaxed when capturing their speech signals; in data collection, three captures are purchased for each speaker from smartphone devices, which may influence the quality of the voice.

Mahmoud Al Ismail and others [24] suggested a model with an examination of the vocal fold oscillation to detect COVID-19. Since most of these symptomatic patients have mild to severe respiratory impaired functions, we hypothesize that the signatures of COVID-19 could be observable by analysis of the movements of the vocal folds. Our aim is to confirm this hypothesis and to quantify the changes observed so as to make COVID-19 voice-based detection possible. We use a dynamic system model for the oscillation of voice folding and use our recent ADLES algorithm to solve it directly from recorded speech to produce vocal oscillation patterns. Experimental COVID-19 results show the characteristics of vocal fold oscillations related to COVID-19 in Topics good and bad on a scientifically-choose dataset. For our study, a set of data Collected and curated by Merlin Inc. under professional guidance, a independent company in Chile. The data-set included records of 512 individuals screened for COVID-19, which yielded either positive or negative results of COVID-19. We selected only recordings of those who were recorded in seven days after medical examination. Just 19 people met this requirement. Among these, ten women and nine men were. COVID-19 was diagnosed with negative testing in five women and four men. 91.20% is the logistic regression efficiency for extended vowels and their combinations. In their research ChaudhariGunavant et al. [25] show that crowd-sourced cough audio samples collected on smartphones worldwide; many groups have collected various COVID-19 cough recording data sets and consume them Training models for machine learning to detect the COVID-19. However, each model Data has been educated from a Various formats and configurations for recording; authors selectively collect cough recordings by collecting additional counting and vocal records. These datasets are also provided by various outlets, such as collection of data from clinical settings, crowdsourcing and extraction from mass media interviews. The AI algorithm, which properly COVID-19 predicts 77.1% (75.2 to 78.3%) ROC-AUC infection, which can then be used with COvID-19 status labels. This AI algorithm also generalizes Latin American and South Asian crowdsource samples with sufficient samples without further preparation.

LaguartaJord et al [26] proposed a cough sound recording AI (Artificial-Intelligence) model for the examination of COVID signs, enabling country-wide prescreening of COVID-18 sound samples at no expense. 97,1% precision is achieved to predict the positive COVID symptoms of tough sounds and 100% accuracy to detect asymptomatic sounds from 5 320 selected datasets.

Quatieri Thomas et al. [27] proposed a bodywork structure for identifying COVID's symptomatic condition with signals (SP) and speaking methods; the technology is based on the complexity of neuromatologic synchronization in articulation, breathing, and phonation over speech/sound respiratory subsystem within, guided by the existence of COVID symptoms with upper inflammation versus The research study of 5 patients with voice meetings provides well-growing evidence of COVID (pre-COVID) and post-COVID pre-exposure. This proposed approach provides the ability to demonstrate the dynamics of patient behavior in real life for advanced monitoring and alert of COVID in a versatile and continued analysis.

The study of the intelligent analysis of COVID-19 speech data is proposed by Jing Han et al. in [28], considering four parameters such as; i. sleep quality, ii. severity, iii. anxiety, iv. fatigue. Scientists and scientists from University Cambridge launched Jing Han et al. data obtained from the "COVID-19 sounds app," and researchers from Mellon University launched the "Corona Voice Detect App." After data collection, these individuals have collected a total of 378 segments; 260 records for future analyses have been taken from this preliminary sample. These 256 sound components were collected with 50 COVID-19 infected patients; poly pulses with a sample rate of 0.016MHz are converted for future testing. In this analysis, they considered two acoustic feature sets: ComParE & eGeMAPS; both feature sets were 69% exact.

Kota Venkata Sai Ritwik et al. [29] have suggested and researched the existence of signs on COVID-19 speech data, which closely supports speakers' approach. Each sentence of the Mel filter bank features are defined as support vectors for each phoneme. A two-class classifier is used to acquire the characteristics of normal COVID-19 expression. The limited size of video data was obtained from YouTube and showed that the SVM classification can achieve 88.6 percent accuracy and 92.7 percent F1-Score. Further research shows that the two classes can be better distinguished by some telephone classes than by others (stops, mid vowels, and nasals).

Brown Chloe et al. conducted COVID-19 data set PCA and SVM Classifier to detect COVID-19, and reached 80 percent 82 percent 80% of accuracies for 3 tasks (COVID Positive and Non-COVID, COVID Cough Positive/Non-COVID Cough, COVID cough/Non-COVID Asthma Cough). Jing Han et al. carried out an SVM diagnosis classification for COVID-19 disease with the Corona voice data application and the COVID patient's examination of sleep, exhaustion and anxiety conditions is reported 57%, 50%, 50%. Orlandic Lara et. al. performed PDS, down sampling, low pass filters, and COUGHVID labeling data methods and finally developed 632 labelling COVID-19 cough records that reported the accuracy of dyspnea (93%), whistling (90, 5%), clash (98,7%), choking (99,1%), nasal congestion (99,2%) and an 86,2% accuracy to be labeled mild.

Wang Yunlu et al. took the two-class fig share data set and conducted BI-ATGRU; achieved 94,5 percent breathing pattern accuracy. Imran Ali et al. using the ECS 50 data collection (for training) DTL-MC dependent classifier, the COVI Data App collected for diagnosis of COVID-19 by investigating the dysimilarities of the changes in morphological path in the respiratory system in two cough classes and in four sound wave classes with an overall accuracy of 88.76 percent. Jiang Zheng et al. conducted the Bidirectional Gated Recurrent Device with a mechanism for attenuating patient breathing and thermal video patients in Shanghai Ruijin Hospital, which achieves an accuracy of 83.69%. Mohamed Bader et al. performed MFCC technique on 14 patients (7 COVID and 7 non-COVID) data in two classes (NOVID vs. COVID, COVID vs. COVID); and achieved class 1 accuracy of 43%, with 42%, voice 79%, class 2 and 58%, cough 55% and voice 82%, respectively). Jiang X et al. conducted MFCC, Spectrum and Feature Extraction methods in public media for collected data from the clinical setting and obtained the precision of 72.1 percent for negative cough and positive cough. KotraVenkata Sai Ritwik et al. performed the YouTube Videos SVM Classifier to identify positive COVID patients with non-COVID and to achieve 88,66% accuracy.

LaguartaJord et al. carried out the MFCC, ResNet50 classifications, to identify both positive and negative patients in the MIT open-voice data model. LaguartaJord et al. achieved accuracy of 79.2%, 96.7% 97.1%, from personal assessment, doctor evaluation and official testing. LSTM (Long Short-Term Memorial) based on 14 patient data (7-positive and 7-negative), used by Hassan Abdelfatah et al. to distinguish Non-COVID-19 cough sound, with COVID-19 cough sound, achieves 84.4% precision for LSTM. The study of the results with precision, data and detection techniques for COVID-19 are shown in Table 1. Current research is not enough to diagnose COVID 19 disease using human respiratory sounds. In order to enhance the systemic efficiency to diagnose COVID 19 from respiratory sound data, researchers and scientists must suggest more advanced AI methods and techniques[31]. This review of literature will help researchers and clinical scientists move their research in this field.

3. RESEARCH METHODOLOGY

Normal recording and sound processing and modelling approaches have been followed for medical devices[25]. Due to the effect on public health of our activities, we have used realistic computer training and categories because of the limited size and background of the data set used. We describe the functionalities that we found and the approaches that we used to construct accurate classification models, taking into consideration the specific features of our findings (e.g., longitudinal mobile users and cross-validation). We examined two types of applications: handcrafting and transferring learning functions. We looked at issues such as logistic regression (LR), tree upgrading and vector support (SVMs). To evaluate the SVM classifier, a Radial Basic Function (RBF) kernel has been used. Parameter C and regularisation is considered for the following hyperparameter values.The data processing pipelines are shown in Figure 2.

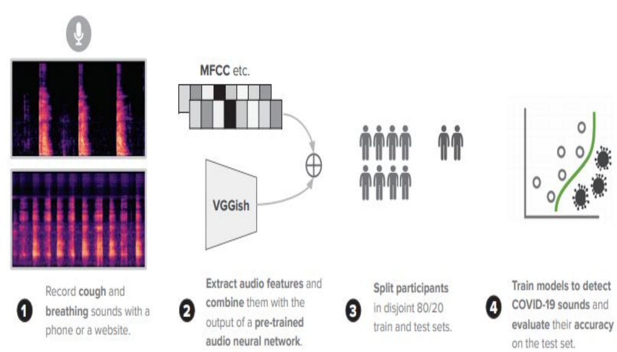


Figure 2: Description of the pipeline for our machine learning, description of the input of sounds, derived vector, training and tests of the users used for training classification models.

3.1 Feature Extraction

Handcrafted Features. A standard value of 22 kHz for audio tasks is reproved for the raw sound waveform recorded in applications. For audio processing, we have used booksa [20]. Various handmade features are derived from resampled audio at the frequency, structural, statistical and temporal attributes at frame level and segment level. A section is the whole audio recording instance and a photograph is a portion of all the audio records contained in a chapter. A full list is given here:

Duration: Max recording time following leading and trailing silence trimming.

- **Onset:** A starting count is calculated with signals which categorize peaks of a beginning intensity envelope obtained by summarizing any positive differences in the first order on each Mel strip[11].
- **Tempo:** Each recording, commonly used for music information retrieval[11], calculates a global acoustic tempo characteristic[12]. The rate of beats which occur at regular intervals in time is calculated. It is used in our sense for its highest detection ability.
- **Period:** The dominant signal envelope frequency. The FFT is measured on the cover and the frequency with the highest amplitude is indicated in 4th mode (as the envelope has non-zero mean).
- **RMS Energy:** The root center-square of the Fourier transformation provides short-term control.
- Spectral Centroid: Medium (centroid) derived by spectrogram magnitude frame.
- **Roll-off Frequency:** The spectrogram bin core frequency such that in this frame at least 85% of the spectrum energy is stored in this bin and bins below.
- **Zero-crossing:** Sign-change rate of the signal.
- **MFCC:** The melting frequency Cepstral Superior coefficients derived from the short power range, based on the transformation of the linear log power continuum on a non-linear Mel scale. Audio processing features include MFCCs[9] amongst the most common. There are the first 13 elements.
- **Δ-MFCC:** the temporal differential (delta) of the MFCC [1].
- **Δ2-MFCC:** the differential of the delta of the MFCC (acceleration coefficients) [1].

We extract a number of statistic features for time series features to capture distributions above the median levels (RMS Energy, Spectral Centroid, Roll-Off Frequency and any other variant of MFCC). The complete list consists of center, median, root, minimum, 1st, 3rd, interquartile, natural discrepancy. A total of 477 handmade features are the initial four-segment-level features, four fram-level functions represented by statistics for each frame, and three MFCC versions (4 + 4 €11 + 3 €13 = 477) represented by statistics for every piece.

Features from Transfer Learning. VGGish is used to automatically extract audio features in addition to handcrafted functions [15]. A convolution neuronal network performed a classification of raw audio inputs, training for the VGGish model using a broad YouTube dataset and a public release of the learned model parameters. The VGGish network is a It is used Turn raw waveforms into embedded components that are then transferred into a empty classification system as a feature extractor. The pre-exercised model VGGish divides the sample into 0.96 seconds and returns 128 dimensional vectors every 0.96 seconds without overlapping the sub-samples. The specimen rate is 16 KHz. The mean and norm difference are the final features of the entire 256-dimensional section (128 to 2). As VGGish is only focused on the input of the spectrogram, space which lack some important features of the temporal domain that inspire an additional use of the VGGish combination with handmade Functions. Functions. Section 5 reveals that the AUC is stronger than either VGGish or its manufactured features. We have a 477-dimension handmade vector for each modality (cough, breathing), a 256-dimensional vector based on VGGish, and various composite vectors of total dimensions up to 733. The concatenation of a subset of the characteristics of the handicraft and VGGish-based features is the common vector. The preservation of a portion of the original explicit variance in the main component analysis further reduces these vectors (PCA). Section 5 provides additional pre-processing information.

The word “data” is plural, not singular. The subscript for the permeability of vacuum μ_0 is zero, not a lowercase letter “o.” The term for residual magnetization is “remanence”; the adjective is “remanent”; do not write “remnance” or “remnant.” Use the word “micrometer” instead of “micron.” A graph within a graph is an “inset,” not an “insert.” The word “alternatively” is preferred to the word “alternately” (unless you really mean something that alternates). Use the word “whereas” instead of “while” (unless you are referring to simultaneous events). Do not use the word “essentially” to mean “approximately” or “effectively.” Do not use the word “issue” as a euphemism for “problem.” When compositions are not specified, separate chemical symbols by en-dashes; for example, “NiMn” indicates the intermetallic compound $Ni_{0.5}Mn_{0.5}$ whereas “Ni–Mn” indicates an alloy of some composition Ni_xMn_{1-x}.

Be aware of the different meanings of the homophones “affect” (usually a verb) and “effect” (usually a noun), “complement” and “compliment,” “discreet” and “discrete,” “principal” (e.g., “principal investigator”) and “principle” (e.g., “principle of measurement”). Do not confuse “imply” and “infer.”

Prefixes such as “non,” “sub,” “micro,” “multi,” and “"ultra” are not independent words; they should be joined to the words they modify, usually without a hyphen. There is no period after the “et” in the Latin abbreviation “*et al.*” (it is also italicized). The abbreviation “i.e.,” means “that is,” and the abbreviation “e.g.,” means “for example” (these abbreviations are not italicized).

An excellent style manual and source of information for science writers is [9].

4. EXPERIMENT AND RESULTS

Our assessment is now comprehensive on whether audio samples were classified as COVID-19 or whether their use is safe in section 4. Due to the high class disparity, a subsample of the initial dataset was used (described in Section 3.3). First, we show how data from various modalities have been combined and how the data set has been partitioned for experiments. In the later part of the portion, analysis and findings are covered.

4.1 Experimental setup

Classification tasks. Three clinically significant binary classification tasks will be discussed on the basis of data collection (Section 3):

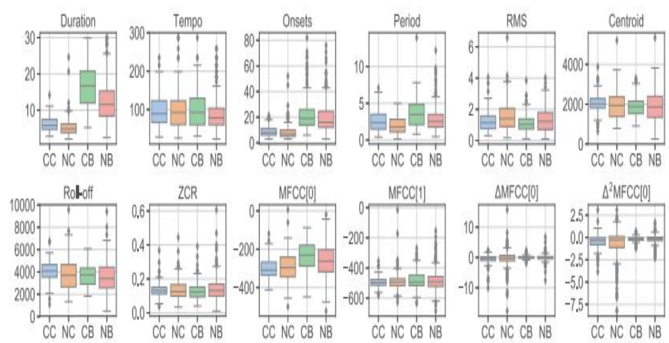
Task 1: Distinguished users, whose testing was positive, who had never smoked or symptoms and were in countries where COVID-19 was not common at that moment, as mentioned under Section 3, were not COVID-19 positive for users who had no positive medical record, who never had COVID-19 tested (non-COVID). Although we can't ensure they haven't been intoxicated, the chances are quite low.

Task 2: Distinguished users who decreed a COVID-19 positive and declared cough a symptom of users who declared no COVID-19 positive, who never smoken in countries where COVID-19 was not normal and who coughed (a common symptoms of COvic-19 patients as stated in Figure 3) (non-COVID with cough).

Task 3: A particular groups that declare that their COVID-19 is positive and declared that cough is a symptom (COVID-positive with cough) have registered asthma in their medical history and coughing as a symptom of COVID-19. A specific group of users did not declare their COVID-19 positive (non-COVID with cough). We investigate the differences between the distributions of the characteristics achieved by toux and breathing groups as a first step after functional extraction. Given the high dimensional characteristics, We cannot present all distributions but we just concentrate on the average statistical function of every family characteristic (e.g., Centroid is Centroid mean here).The graphs show that COVID positive users are starting up more, have higher times and have lower coughs and breaths of the RMS and feature less bottoms [1st part and deltas] for their MFCC. For both tasks, the COVID-positive samples are more orientated to the medium distribution while the overall (healthy) population exhibits a wider range (interquartile scope), which presupposes a (possibly forced) very different (healthy) toxicity and breathing. This also shows that cough and breath sounds are useful for COVID or Non-COVID consumer classification.

Feature ablation studies. We repeat experiments using three separate audio inputs: cough alone, breath alone and the audio modality (cough or breathing). The experiments are carried out to decide the best PCA cut-off value for the increasing dimensionality and equal comparison of the combined representation (see results in next section). The variance values explained vary from [70 percent, 80 percent, 90 percent and 95 percent]. In fact, this means that the classifiers use fewer feedback and have a less explicit variation. A combined picture can require a more compressed depiction than an image centred on toux or breaths to avoid overfitting.

User-based cross-validation. We generate instructions and test sets from different market segments that do not have the same customer in any of them. Since not all (non-COVID) grades were studied, that did not lead to complete matching class categories. The research selection balance has not improved. It is often difficult to guarantee that a division selects a representative test area so we use 10 times the cross validation on the outside circuit to choose disjoints (80%/20%division) and a check for hyperparameters on the interior circuit to identify the optimal parameters (using the 80 percent train-set in a 5-fold cross validation). This setup is close to an embedded cross-validation[7]. We carry out systemic experiments through the testing of 5400 models (3 operations / 3 modalities / 10 consumer breaks / 4 dimensional reduction - 3 forms of function / 5 super parameter cross-validation runs). The role of the receiver - ROC-AUC field, accuracy and reminder is one of the simple measurements we choose. The standard deviation and average outer folds output was seen (10 user split). We will address the results of our three assignments in the next segment. Demographic sensitivities Age and sex have no significant influence on or amplified results as one hot encoded features in our models (e.g. age: age: 40-49) (2 AUC).



Task	Modality	Samples (users)*	Feature Type	Mean ± std		
				ROC-AUC	Precision	Recall
1. COVID-positive / non-COVID	Cough+Breath	141 (62) / 298 (220)	1	0.71 (0.08)	0.69 (0.09)	0.66 (0.14)
			2	0.78 (0.07)	0.72(0.08)	0.67(0.11)
			3(A)	**0.80(0.07)**	0.72(0.06)	0.69(0.11)
2. COVID-positive with **cough** / non-COVID with **cough**	Cough	54 (23) / 32 (29)	1	0.65(0.22)	0.62(0.20)	0.69(0.14)
			2	0.82(0.16)	0.79(0.16)	0.71 (0.23)
			3(A)	**0.82(0.18)**	0.80(0.16)	0.72(0.23)
3. COVID-positive with **cough** / non-COVID **asthma cough**	Breath	54 (23) / 20 (18)	1	0.76(0.30)	0.64(0.29)	0.72(0.31)
			2	0.72(0.16)	0.77(0.22)	0.47(0.15)
			3(B)	**0.80(0.14)**	0.69(0.20)	0.69(0.26)

Figure 3: Box plots of the mean features of cough and breathing. CC: COVID Cough, NC: Non-COVID Cough, CB: COVID Breathing, NB: Non-COVID Breathing.

4.2 Distinguishing COVID-19 Users from Healthy Users

The outcomes of the classification for the above three tasks. We announce the best results for each task which could be obtained by either a single modality (tooth or breathing sounds) or a combination of the two. The first row reports the classification results for task 1: binary classification of discriminatory users who report positive tests for COVID-19 (COVID-positive) by users who replied no (non-COVID).
Classification of the three functions. * The number of samples before dividing into training/testing and down sampling. The logistic regression results for the first task are recorded, while the SVMs for the second two tasks. We report the best PCA modality and representation size for each role (the detailed results for each cut are shown in Figure).

Feature Form 1 = Craft with PCA = 0.8 for three tasks, Type 2= PCA = 0.95 for tasks 1 and 3, Type 3 = Cut + PCA VGGish = 0.95 for task 1, 0.9 for task 2, and 0.7 For task 3. Type 1 = PCA Handcrafted = 0.8 for three tasks. For type 3,

(a) indicates that we use VGGish-based feature plus time, tempo, beginning, and duration,

(b) in all features except for:

Any discriminatory figures show that short-breathing users may be a positive metric predictor for COVID-19 screening. The AUC for this job is 80%, although consistency and reminder amount to approximately 70%. Task 1 provides the lowest standard deviations from other features in all user splits, due to the higher data size (Tasks 2 and 3). We have only a very simple classifier (Logistic regression), and the data could be too small to filter out the noise and variety of our crowded data (e.g., differences in microphones, surrounding noises, ways of inputting the sounds). Despite these observations, we have confidence in the strength of the signal. We found that handmade features coupled with VGGish features have better outcomes than handmade or transfer learning, suggesting that transmission learning has potential in our study.

4.3 Distinguishing COVID-19 Coughs from Other Coughs

The second row of Table 1 explains the binary classification of users who announced positive testing for COVID-19, and also reported cough in the symptom survey, and related users who declared that they didn't test for COVID-19 positive but declared cough (Task 2). The best result is 82 percent AUC. The precision for this task is 80 percent, indicating that COVID-19 positive users can be very differentiated by cough sounds. Recall is marginally lower (72 percent), which means the model casts a good but more specialized net: not all COVID-19 coughs are detected but many of them. Nevertheless, this finding is tentative by the scale of the data as well as the relatively large standard deviations from Task 1. We also contrasted the above mentioned COVID-19 users with a cough with users who said they didn't get COVID-19 positive, but reported asthma and said a cough. The final row of Table 1 indicates an AUC of 80%. Although the reminder is appropriate, the accuracy for this task is as poor as for the other two tasks. It is important to note that breathing sounds act as more effective cues in this task to discriminate against users. We further assessed the usefulness of data increases for tasks 2 and 3 to boost efficiency (Section A.2)

5. CONCLUSION

We worked hard to produce crowd-source respiratory sounds and look at how this may aid in the diagnosis of COVID-19.. We currently only use a subset of the collected data to ensure that the proportion of positive COVID-19 users is as limited as practicable. Users in places where at the time there was no COVID-19 were equally likely to be genuinely well if they reported themselves as not ill. This requires a wider test, most certainly utilizing advanced machine learning techniques (e.g., deep learning). We will mix photo information with voice sounds for a hybrid model.

In addition to breathing and coughing, vocal patterns may provide useful additional classification functions. We also shown a limited analysis on the discrepancy between COVID 19 and asthma cough; but our dataset only includes consumers with other respiratory diseases, and we are eager to look into possible differences between COVID 19 and other diseases. The mobile app instructs users how to log measurements every day so that the sample size is large enough to provide more efficient training of deep learning algorithms. Finally, it is predicted that the proposed model is not only robust, but also useful in disease screening and that the AI screening model is a first obstacle to COVID-19 transmission [30].

REFERENCES

1. "**Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data**", DeepAI, 2021. [Online]. Available: https://deepai.org/publication/exploring-automatic-diagnosis-of-covid-19-from-crowdsourced-respiratory-sound-data. [Accessed: 07- Apr- 2021].
2. 2020. **coughvid**. https://coughvid.epfl.ch/about/, note= Accessed: 2020-05-30.
3. Fda.gov, 2021. [Online]. Available: https://www.fda.gov/media/134922/download. [Accessed: 07- Apr- 2021].
4. Charles Bales, Muhammad Nabeel, Charles N. John, Usama Masood, Haneya N. Qureshi, Hasan Farooq,

Iryna Posokhova, and Ali Imran. **Can machine learning be used to recognize and diagnose coughs?** arXiv:2004.01495 [eess.AS] 10 pages 2020.

5. Debrup Banerjee, Kazi Islam, Keyi Xue, Gang Mei, Lemin Xiao, Guangfan Zhang, Roger Xu, Cai Lei, Shuiwang Ji, and Jiang Li. **A deep transfer learning approach for improved post-traumatic stress disorder diagnosis. Knowledge and Information Systems** 60, 3 (2019), 1693–1724. 2019
6. L Brabenec, J Mekyska, Z Galaz, and Irena Rektorova. **Speech disorders in Parkinson's disease: Early diagnostics and effects of medication and brain stimulation.** Journal of Neural Transmission 124, 3 (2017), 303–334 .
7. Gavin C Cawley and Nicola LC Talbot. **On over-fitting in model selection and subsequent selection bias in performance evaluation.** Journal of Machine Learning Research 11 (2010), 2079–2107.
8. Yohan Chon, Nicholas D. Lane, Fan Li, Hojung Cha, and Feng Zhao. **Automatically characterizing places with opportunistic crowdsensing using smartphones.** In Proceedings of the ACM Conference on Ubiquitous Computing (UbiComp). Pittsburgh, Pennsylvania(2012), 481–490.
9. Steven Davis and Paul Mermelstein. **Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences.** IEEE Transactions on Acoustics, Speech, and Signal Processing 28, 4 (1980), 357–366.
10. Gauri Deshpande and Björn Schuller. **An overview on audio, signal, speech, & language processing for COVID-19.** arXiv preprint arXiv:2005.08579 (2020). 5 pages.
11. Daniel PW Ellis. **Beat tracking by dynamic programming.** Journal of New Music Research 36, 1 (2007), 51–60.
12. **Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data** | Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining", Dl.acm.org, 2021. [Online]. Available: https://dl.acm.org/doi/10.1145/3394486.3412865. [Accessed: 07- Apr- 2021].
13. Maria Faurholt-Jepsen, Jonas Busk, Mads Frost, Maj Vinberg, Ellen M Christensen, Ole Winther, Jakob Eyvind Bardram, and Lars V Kessing. 2016. **Voice analysis as an objective state marker in bipolar disorder.** Translational Psychiatry 6, 7 (2016), e856. 8 pages.
14. Jing Han, Kun Qian, Meishu Song, Zijiang Yang, Zhao Ren, Shuo Liu, Juan Liu, Huaiyuan Zheng, Wei Ji, Tomoya Koike, Xiao Li, Zixing Zhang, Yoshiharu Yamamoto, and Björn Schuller. **An early study on intelligent analysis of speech under COVID-19: Severity, sleep Quality, fatigue, and anxiety.** arXiv:2005.00096 [eess.AS] 5 pages.
15. S. Hershey, S. Chaudhuri, D. P. W. Ellis, J. F. Gemmeke, A. Jansen, R. C. Moore, M. Plakal, D. Platt, R. A. Saurous, B. Seybold, M. Slaney, R. J. Weiss, and K. Wilson. 2017. **CNN architectures for large-scale audio classification.** In Proc. IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). 131–135.
16. 2021.[Online].Available:https://www.researchgate.net/publication/342093744_**Exploring_Automatic_Diagnosis_of_COVID-19_from_Crowdsourced_Respiratory_Sound_Data.** [Accessed: 07- Apr- 2021].
17. Ali Imran, Iryna Posokhova, Haneya N. Qureshi, Usama Masood, Sajid Riaz, Kamran Ali, Charles N. John, Muhammad Nabeel, and Iftikhar Hussain. 2020. **AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an App**. arXiv:2004.01275 [eess.AS] 11 pages.
18. Shih-Hong Li, Bor-Shing Lin, Chen-Han Tsai, Cheng-Ta Yang, and Bor-Shyh Lin. **Design of wearable breathing sound monitoring system for real-time wheeze detection.** Sensors 17, 1 (Jan. 2017), 1–15.
19. Elad Maor, Jaskanwal D Sara, Diana M Orbelo, Lilach O Lerman, Yoram Levanon, and Amir Lerman. **Voice signal characteristics are independently associated with coronary artery disease.** Mayo Clinic Proceedings 93, 7 (2018), 840–847.
20. Brian McFee, Colin Raffel, Dawen Liang, Daniel PW Ellis, Matt McVicar, Eric Battenberg, and Oriol Nieto. librosa: **Audio and music signal analysis in python.** In Proceedings of the 14th Python in Science Conference. Austin(2015), TX, 18–24.
21. Cristina Menni, Ana M Valdes, Maxim B Freidin, et al. 2020. **Real-time tracking of self-reported symptoms to predict potential COVID-19.** Nature Medicine 10, 1038 (May 2020). 8 pages.
22. Rajalakshmi Nandakumar, Shyamnath Gollakota, and Nathaniel Watson. **Contactless sleep apnea detection on smartphones.** In Proceedings of the 13th Annual International Conference on Mobile Systems, Applications, and Services (MobiSys). Florence, Italy,(2015) 45–57.
23. Dinko Oletic and Vedran Bilas. **Energy-efficient respiratory sounds sensing for personal mobile asthma monitoring.** IEEE Sensors Journal 16, 23 (Dec. 2016), 8295–8303.

24. Renard Xaviero Adhi Pramono, Stuart Bowyer, and Esther Rodriguez-Villegas. **Automatic adventitious respiratory sound analysis: A systematic review.** PloS One 12, 5 (May 2017). https://doi.org/10.1371/journal.pone.0177926 43 pages.
25. Renard Xaviero Adhi Pramono, Syed Anas Imtiaz, and Esther Rodriguez-Villegas. **A cough-based algorithm for automatic diagnosis of pertussis.** PloS One 11, 9 (Sep. 2016). 20 pages.
26. Thomas Quatieri, Tanya Talkar, and Jeffrey Palmer**. A Framework for Biomarkers of COVID-19 Based on Coordination of Speech-Production Subsystems.** IEEE Open Journal of Engineering in Medicine and Biology (2020).
27. Kiran K Rachuri, Mirco Musolesi, Cecilia Mascolo, Peter J Rentfrow, Chris Longworth, and Andrius Aucinas. 2010. EmotionSense**: A mobile phones based adaptive platform for experimental social psychology research.** In Proceedings of the ACM Conference on Ubiquitous Computing (UbiComp). Copenhagen, Denmark, 281–290.
28. Jan Schlüter and Thomas Grill. **Exploring data augmentation for improved singing voice detection with neural networks.** In Proceedings of the 16th International Society for Music Information Retrieval Conference (ISMIR). Malaga, Spain(2015), 121–126.
29. Neeraj Sharma, Prashant Krishnan, Rohit Kumar, Shreyas Ramoji, Srikanth Raj Chetupalli, Nirmala R., Prasanta Kumar Ghosh, and Sriram Ganapathy. **Coswara – A database of breathing, cough, and voice sounds for COVID-19 diagnosis(2020).** arXiv:2005.10548 [eess.AS] 5 pages.
30. 2021. [Online]. Available: https://www.forbes.com/sites/marcwebertobias/2020/05/05/ai-and-medicaldiagnostics-can-a-smartphone-app-detect-covid-19-from-speech-or-a-cough/. [Accessed: 12- Apr- 2021].
31. Sri Harsha Tavidisetty Rajendra, Satish Anamalamudi, Muralikrishna Enduri, **Automated Detection of COVID-19 using Deep Learning.** International Journal of Advanced Trends in Computer Science and Engineering Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse511022021.pdf https://doi.org/10.30534/ijatcse/2021/511022021