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Review of Cough Classification for COVID-19

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Abstract-*COVID-19 was declared a global epidemic on February 11, 2020, with the help of the World Health Organization (WHO). For the old COVID-19 prediction it is necessary to analyze the cough and respiratory noise. This paper focuses on obtaining exposure to COVID-19 in cases where the process of analyzing cough samples is performed using different audio output methods and different machine learning phases. The main focus of the paper is the classification of cough-related audios. It attempts to summarize the key lessons won in the cough discovery area and link diseases based on quantity, duration, and intensity of sound cough samples.*
Keywords-*COVID-19, cough classification, audio analysis, RNN, MFCC, LSTM, and machine learning.*

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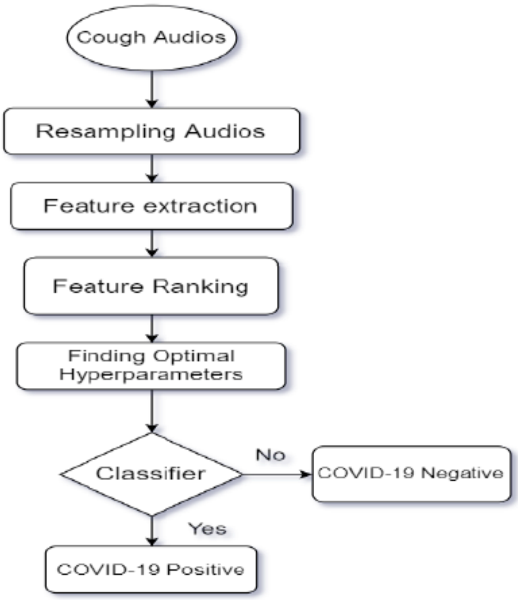
I. INTRODUCTION

COVID-19 (Corona virus Disease of 2019), caused by Acute Respiratory Syndrome 2 (SARS-CoV2), was declared a global epidemic on February 11, 2020, by the World Health Organization (WHO). The new corona virus, however, compared to different coronaviruses, bears SARS-CoV (severe acute respiratory pattern coronavirus) and MERS-CoV (Middle East Respiratory Pattern coronavirus) which caused outbreaks in 2002 and 2012, independently. [1, 2]. Common symptoms of COVID-19 fever, fatigue, and dry cough [3]. Other symptoms include shortness of breath, general pain, muscle aches, abdominal symptoms, and loss of smell or taste [4]. Many attempts have been made to identify the early symptoms of COVID-19 using artificial intelligence. Coughing is one of the most serious signs and symptoms of COVID-19 [5] and is a symptom of more than a hundred different conditions, and its effect on the respiratory tract is understood to vary [6]. COVID-19 is an encyclopedia, with 3 million deaths, while the USA has reported the highest number of cases (31.7 million) and deaths [7]. The spread of this epidemic has surpassed other health systems in need of experimental and operational cases [8]. Coughing has always been a symptom of many conditions. It is possible to distinguish between a cough and a diagnosis by examining logical features using a multidisciplinary approach [12, 37]. A review of Covid-19 acquisition methods can be planted in [11, 38]. Neuromotor interactions of respiratory speech, voice sounds, and speech are altered when a person is infected with Covid-19. Therefore, our audio processing models are introduced [39] to track both Covid-19. Sound processing of respiratory or cough sounds can also be monitored with Covid-19 ideas [11, 40-41]. In the case of COVID-19, which is a high-risk plant, early detection plays an important role as affected cases can be classified as early as opinion [10] Considering the need for COVID-19 interaction between COVID-19 and non-COVID-19 cases with pattern analysis cough. Coughing is a normal kick in the immune system that clears the airway and prevents harmful substances from entering the respiratory system [10]. Dry cough is one of the major symptoms of COVID-19 and high body temperature can therefore be used as a diagnostic tool. Coughing is associated with the noise of the feature and in this paper, the cough / pattern of COVID-19 is linked to causing congenital malformations of various points. Although other methods include laboratory tests of aging tar, nasal tar, and natural blood tests and the results take up to 2 days with advanced Rear Recap Polymerase Chain Response (RTCRT) tests and other tests such as Antigen testing. give a result in the case of 30 blinks. To reduce stress in chemical labs and to avoid the production of chemical waste and toxins, the construction of a bracket algorithm and a tight grip can process coughing sounds, and the results can be displayed in a matter of seconds with the help of DSP chipset and equipment. . literacy bracket algorithms. In this paper, we introduce the concept of cough noise analysis in conditions and classify waves according to different parameters to distinguish sound from that of COVID-19 or a healthy person [10]. The data series in COVID-19 cases is complex and data sets are usually non-existent without difficulty in detection. However, a lot of research has been done to find comparable data sets.

Brief flowchart of the proposed system [10]:

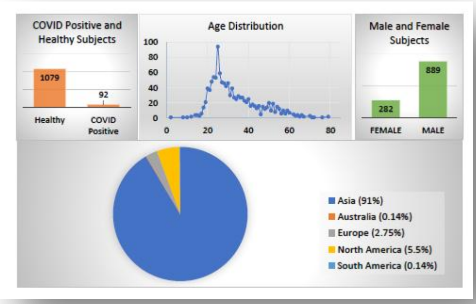


II. METHODOLOGY

1. Data: Several data sets are considered for testing: Coswara data set and Sarcos data set, audio files from SoundSnap, Speech Corpus, and sputum audio samples from the University of Cambridge.

A. The Coswara Dataset:

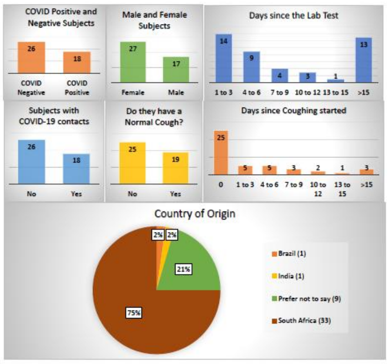
The Coswara project was aimed at developing a COVID-19 diagnostic tool based on breathing, coughing, and speech [8,14]. Here, participants were asked to donate a cough recording with a web-based data collection platform using their smart phones (https://coswara.iisc.ac.in). Collected audio data includes rapid and slow breathing, deep and deep coughs, strong vowel sounds, and spoken digits [8].



Coswara data set during the test: There are 1079 healthy and 92 studies with COVID-19 in the previously analyzed area, used to extract features and phase training. Most studies are between 20 and 50 years old. There are 282 women and 889 men and most of them are from Asia. Studies come from five continents: Asia (Bahrain, Bangladesh, China, India, Indonesia, Iran, Japan, Malaysia, Oman, Philippines, Qatar, Saudi Arabia, Singapore, Sri Lanka, United Arab Emirates), Australia, Europe (Belgium, Finland, France, Germany, Ireland, Netherlands, Norway, Romania, Spain, Sweden, Switzerland, Ukraine, United Kingdom), North America (Canada, United States), and South America (Argentina, Mexico) [8].

B. The Sarcos Dataset:

A similar program was recommended for South African participants to voluntarily allow themselves to record their cough using an online forum (https://coughtest.online) under the name of the research project: ‘COVID-19 test for cough noise analysis. This database will be called 'Sarcos' (SARCOVID-19 South Africa). Only coughs were collected as audio samples, and recently tested studies in the SARS-CoV laboratory were requested to participate [8].



Sarcos data set during the test: There are 26 COVID-19 negative articles and 18 COVID-19 positive articles on the site under review. Unlike the Coswara website, there are courses for more women than men. Most studies have been tested in the laboratory within two weeks of participation. Only 19 studies reported coughing as a symptom, and in these reported cases the cough symptoms were different. There were 33 studies from Africa (South Africa), 1 from South America (Brazil), 1 from Asia (India), and some refused to specify their location [8].

C. Speech Corpus:

Speech corpus are staffed by 60 healthy speakers (12 men and 8 women), as well as 20 patients from COVID-19 (12 men and 8 women). Each participant was asked to record a sample of coughing sounds, breathing sounds, and voice. Therefore, three samples were obtained from each participant [12]. This was how signal samples were downloaded from various websites, which helped the authors identify the symptoms associated with COVID-19 cough in their research activities.

III. EXTRACTION OF FEATURES

Sound waves have a set of parameters called speech features [12]. Determining these features is an important step that will affect system accuracy. At work, various features are extracted from the captured database. A list of excluded features is provided below:

• **Spectral Centroid (SC) :** Definition of spectral power, indicating changes in signal frequency and signal content over time. Also, SC allows us to find the exact location of the dominant format in each sub-band [12], [15], [16].

• **Spectral Roll-off (SR) :** Definition of spectral power, indicating changes in signal frequency and signal content over time. Also, SC allows us to find the exact location of the dominant format in each sub-band [12], [15], [16].

• **Zero-Crossing Rate (ZCR) :** The number of times a signal changes from positive to negative and vice versa. ZCR can measure a fraction of the prominent signal frequency [12], [18], [19].

• **Mel-Frequency Cepstral Coefficients (MFCC) :** MFCC is an important factor used in the field of emotional awareness because it provides a high level of visual perception of a person's [20], [21], [22], [23]]. In addition, MFCCs are computerized using a brain-stimulating filter followed by logarithmic compression and Discrete Cosine Transform (DCT) [12].

• **Δ MFCC :** Initial order period from MFCC. To combine different coefficients, we use the following expressions [12], [24], [25]:

$Dt = \Sigma\,(ct + n - ct - n\ Nn)\ Nn = 12\Sigma\, n2\ Nn = 1$ (2)

and the delta coefficient of independent t, and ct + to ct-n static coefficients.

• **Δ2 MFCC:** Out of the second-order of the MFCC. These features can be obtained from Δ MFCC using Eq. (2).

• **Log Independent Strength:** Improves performance of voice separation functions [8, 26].

• **Zero Crossing Rate (ZCR):** The level of crossing equals the number of times in a specified time frame when the amplitude of the signal exceeds the zero value [10].

Designed to keep timeline patterns in all coughs. Feature removal is considered an important step as one of the goals is to find an appropriate removal method that improves the accuracy of our system [12].

IV. NETWORK ARCHITECTURE

Shown below are the few classifiers listed:

A. Recurrent Neural Network (RNN)

RNN is mainly used to predict future data sequences using previous data samples. RNN is widely used to model sequential data as speech or text. However, these networks were not widely used as they were considered difficult to train, so they took a long-term dependence [12, 27].

B. Long Short-Term Memory (LSTM)

The RNN suffers from a perishable gradient problem, which increases with the length of the training sequence. Therefore, LSTM is used to overcome this problem. LSTM retains data for a long time, and it is easy to remember past data in memory [12].

C. Convolution Neural Network (CNN)

It is a well-known structure of the deep neural network, which is used primarily for image separation [28]. For example, in the last two decades, CNN has successfully used complex tasks such as facial recognition [29]. It also works well in isolating the air with the expression of COVID-19 [30].

D. K-Nearest Neighbour (KNN)

The KNN section based on its decision of class labels neighbors in the training and past setting were able to detect both [31, 32, 33] and distinguish [34, 35, 36] sounds such as coughing and snoring effectively [12].

E. Support Vector Machine (SVM):

(C = 50, gamma = 'default', kernel = rbf). C is a familiar parameter and tells SVM how much to avoid separating each training model [10].

V. CONCLUSION

After going through all the research papers, we understood in what ways the cough samples could be analyzed and what methodology can be utilized for the best way of detecting COVID-19. Hence, we came to a conclusion that an extensible sound processing platform was described which analyzed and classified cough sounds in different categories. Several parameters of the sound processing platform can be configured which includes different feature extraction and classifier methods. The findings of this paper have provided a new perspective and insights for cough classification. The objective is to improve the current testing system.

Future work will focus on testing the different platforms for the classification of COVID-19 cough sounds [11].

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