2022-05-04

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Funder: King Abdulaziz City for Science and Technology, Riyadh, Saudi Arabia.

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***Abstract*— Coronavirus pandemic that has spread all over the world, is one of its kind in the recent past, that has mobilized researchers in areas such as (not limited to) pre-screening solutions, contact tracing, vaccine developments, and crowd estimation. Pre-screening using symptoms identification, cough classification, and contact tracing mobile applications gained significant popularity during the initial outbreak of the pandemic. Audio recordings of coughing individuals are one of the sources that can help in the pre-screening of COVID-19 patients. This research focuses on quantitative analysis of covid cough classification using audio recordings of coughing individuals. For analysis, we used three different publicly available datasets i.e., COUGHVID, NoCoCoDa, and a self-collected dataset through a web application. We observed that wet cough has more correlation with covid cough as opposed to dry cough. However, the classification model trained with wet and dry coughs, both, has similar test performance as that of the model trained with wet cough samples only. We conclude that audio-signal recordings of coughing individuals have the potential as a pre-screening test for COVID-19.**

Keywords—Coronavirus, COVID-19 detection, machine learning

I. INTRODUCTION

COVID-19 that is caused by Coronavirus has now spread all over the world and researchers, scientist, and engineers are working to aid the medical professionals in the process of testing, analysing, control and curing the disease [1]. There are more than 350 real-time polymerase chain reaction (RT-PCR) coronavirus disease-2019 (COVID-19) testing kits commercially available as a pre-diagnosis tool [2]. These testing kits have their own pros and cons [3,4]. Despite their commendable performance, some drawbacks of these kits are that they are not free of cost, laborious procedure, time taking results, false negative diagnosis and uncomfortable for patients [5,6]. A mobile application as a pre-diagnosis test can be a better approach in some aspects i.e., it is readily available and free of cost for all the users [7,8,9]. Most common symptoms of COVID-19 disease include cough, fever and fatigue [10,11,12]. In case of high severity of disease, a person can lose his life too [13,14]. So, it is a necessity to diagnose the disease at an early stage to start medication timely. Cough of a person can be a useful source for identification of virus [12,15,16].

Few studies have been caried out up till now which have used audio signals of cough events for the prompt detection of disease [17,18]. For diagnosis using cough voices, the major requirement is abundance of data. In a study of 2020, a dataset, called NoCoCoDa, for covid has been collected and used to declare the fact that majority (77%) of Covid coughs' pattern is more inclined towards wet cough [19]. In another study of 2020, CNN based audio classifier has been used to categorize Covid and Non-covid classes with a test accuracy of 70.58% [20]. A mobile application has been developed in 2020, named as AI4COVID-19, using the application the user records his cough voice and it is sent to the cloud [21] where an AI Engine produces the output within 2 minutes. ESC-50 [22] is the online available dataset, used for this research [21]. For AI Engine, three parallel classifiers are used to process the data, i.e., deep transfer learning-based multi class classifier (DTL-MC), classical machine learning-based multi class classifier (CML-MC) and deep transfer learning-based binary class classifier (DTL-BC) with 92.64%, 88.76% and 92.85% accuracy. Overall accuracy achieved for cough detection using this algorithm is 95.60%.

For classification of audio data, local discriminant bases (LDB), linear predictive coding (LPC) and mel-frequency cepstral coefficients (MFCC) are some of the commonly used features. MFCCs have proved to be more efficient [23]. Few researchers have used MFCCs for audio-based cough detection. Charles Bales [24] in his study has developed a diagnostic tool using convolutional neural networks (CNN) for identification of coughs for three types of diseases (i.e., bronchitis, bronchiolitis and pertussis) based on their unique MFCCs and achieved an accuracy of 90.17% for cough detection. Vipin Bansal [5] has also used MFCCs as features for his study. In the mobile application, AI4COVID-19, MFCCs have been extracted and then PCA has been applied to get the feature vector [6]. A classification algorithm [25],

This research is supported by King Abdulaziz City for Science and Technology, Riyadh, Saudi Arabia, Project grant number: 5-20-01-007-0033.

TABLE I. TYPES OF DATA DRIVEN DECISION MODELS [26].

	Rule-based	**Shallow Statistical**	**Deep Learning**
Model Type	Collection of rules or a decision tree based on common sense or experience	"Shallow" models such as linear or logistic regression plus probabilities	Many-layered classification, regression, and reinforcement models
Amount of data	No data or small data	"Medium" data—Thousands of records	"Big" data – millions of records
Features	"Smart" features	"Smart" features	Raw data / "dumb" features

xtreme gradient boosting (XGBoost) has been developed to categorize breathing patterns in COVID-19 patients using MFCCs. For labelling the lungs' sounds, another model has been developed using depth-wise separable convolution neural network (DS-CNN) as a classifier with short-time Fourier-transformed (STFT) feature, MFCC feature and their fusion, resulting in 82.27%, 73.02% and 85.74% accuracy, respectively.

There are 3 types of data driven decision making models, i.e., rule-based models, shallow statistical models and deep learning models as shown in Table I[26]. Deep learning models generally outperform rule-based and shallow statistical models, but they require huge amount of data [26]. In case of a pandemic like Covid-19, gathering huge amount of data in short time is very challenging. Most of the reported literature on covid detection has used deep learning models with limited amount of data.

The aim of this study is to analyse performance of rule-based and shallow statistical models with limited amount of cough data for covid detection. Quantitative analysis has been carried out using rule-based and shallow statistical classifiers with MFCCs as features.

Data used for this study is a blend of three datasets. First dataset has been collected using self-developed "Smart Cough" web application, other two datasets are publicly available datasets i.e., Novel Coronavirus cough database (NoCoCoDa) [19] and COUGHVID [27].

II. METHODOLOGY

A. Dataset

In this study, three datasets have been used. The first dataset is collected using a self-developed web application "Smart Cough". The dataset was collected from May 2020 to July 2020. A total of 1055 coughing subjects from Saudi Arabia participated in the experiment voluntarily. Amongst 1055 coughing subjects (742 male and 313 female), 22 subjects were covid positive and rest were covid negative. The web-application has a record button that starts recording audio from the microphone for up to 3 seconds. A small questionnaire is shown before recording to acquire details about participating subject i.e., age, gender, disease history, symptoms, covid status and recording method (phone/wired headset). The subjects recorded their cough audios on web-application. The sampling frequency for these audio signals is 48kHz. There is a lack of covid positive samples in this dataset as covid patients were reluctant due to their bad health. Hence, covid positive cough samples have been acquired from two publicly available datasets.

One is an online available dataset i.e., NoCoCoDa, containing 73 COVID-19 positive cough samples of 11 subjects [19]. The sampling frequency for this dataset is 44100Hz. Cough samples in NoCoCoDa were acquired from online interview videos with unknown recording methods. As the cough events have been recorded from online sources, there are periods where multiple individuals are speaking during the cough events and also music was overlaid over speech, hence most of the data was noisy. Therefore, only 28 recordings were selected for this study.

COUGHVID [27], the other publicly available dataset, contains cough samples of COVID-19 positive and negative subjects of 10 seconds duration each, collected through a web-application. After recording audio signal via microphone device, a small questionnaire is prompted to acquire subject's age, location, gender, respiratory condition and covid status. Since, this is an online and publicly available web-application, the data is being updated every day. This dataset has a sampling frequency of 48kHz. In our research, 30 Covid-19 positive cough samples were taken from this dataset.

B. Data Preprocessing

For noise removal from the audio signals, the data has been pre-processed. Initially, the region of interest has been extracted from all the audio samples where the cough event was significant in each signal. as the sampling frequency is different for all datasets, so all the audio signals have been resampled to a sampling frequency of 44100Hz to achieve a single pattern for all.

C. Feature Extraction

After preprocessing of data, the next step is feature extraction. MFCCs are widely used as features for audio signals, so for all audio samples, MFCCs have been acquired using Audio Toolbox in MATLAB.

<u>Mel Frequency Cepstral Coefficients (MFCCs) Extraction:</u>

Figure1 shows the flow diagram for extraction of MFCCs [28]. In the beginning, speech signal is passed through a pre-emphasis filter to flatten the signal spectrally. Then, the pre-emphasized signal is segmented into short frames, with a small overlap, to ensure stationarity. To lessen the edge effect caused by segmenting the data, a hamming window is applied to each frame [28]. Hamming Window is expressed mathematically as

$$H(n) = 0.54 - 0.46\cos\left(2\pi\frac{n-1}{N-1}\right) \quad (1)$$

where N = 160, i.e., the number of points in a frame and n varies from 1 to N [28]. The signal is then passed through the FFT block to achieve the frequency spectrum, which is then filtered through a filter bank. The centres of all frames are equally spaced in Mel scale. Conversion from linear frequency domain to Mel-frequency domain can be seen in equation 2 [12].

$$M(f) = 1127\, ln\left(1 + \frac{f}{700}\right) \quad (2)$$

Cepstrum is then calculated from the output power of the filter bank. Afterwards, in the Delta block, derivates are added to get delta coefficients, for better performance of the system [28].

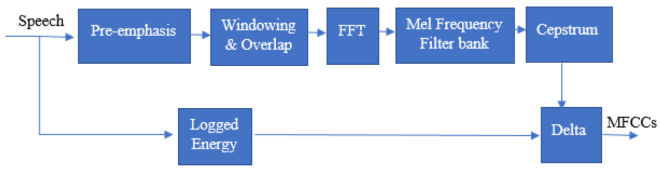

Fig 1. Flow diagram for MFCCs extraction method [28].

D. Dimensionality reduction of MFCCs matrix:

For each signal, MFFCs are a matrix of order m x n. Out of all these features, only significant ones are selected for this study. As it has been established through literature review that first 14 features are most significant for audio signals [20, 29], so first 14 columns from MFCCs' matrix are selected. Few techniques are tried and tested for features' representation. In the first method, the sum of these 14 columns is calculated to get a row vector of 14 features. The mean of these 14 columns is calculated to get a row vector of 14 features as second method. For third method, first 14 values from all the rows of the features' matrix are concatenated in a single vector to get the most significant features. The investigated classifiers' accuracies with this type of feature vector (method 3) outperformed the classifiers' accuracies with the first two feature vectors (method 1 and 2). For the sake of simplicity, the classification accuracies using this type of feature vector are reported only in the results section.

III. Classification

Next step is the classification of data to identify the COVID-19 patients. For this purpose, an extensive analysis has been done by applying various classification techniques including tree, linear discriminant analysis (LDA), logistic regression, naïve bayes, support vector machine (SVM), K-nearest neighbour (KNN), ensemble and neural network, on the features obtained by using the method 3 mentioned above.

For training the models, MATLAB's classification learner application is used with 70% of data and the best models are exported. Afterwards, the models are tested using 30% data from total dataset. Samples for training and testing are randomly selected.

A. Segregation of wet and dry COVID-19 positive samples:

In this research, for the purpose of extensive analysis, COVID-19 positive dry and wet cough samples are segregated. It has been proven in the research of NoCoCoDa [19] that COVID coughs mostly correlate wet coughs rather than dry coughs. This claim was based on a graph plotted using two features, i.e., number of peaks and power ratio as shown in figure 2 [4]. In this study, after resampling the other two datasets to NoCoCoDa's sampling frequency i.e 44100 Hz, number of peaks and power ratio is calculated for all Covid-19 positive cough samples and a similar plot has been obtained (see Fig. 3) as NoCoCoDa study [19,30]. Using the resulting plots, it can be verified that the features of COVID-19 cough samples, which are located in the vicinity of wet coughs depict wet coughs and outliers are dry coughs. After excluding the dry COVID cough samples, training has been caried out again with samples from all three datasets for further analysis.

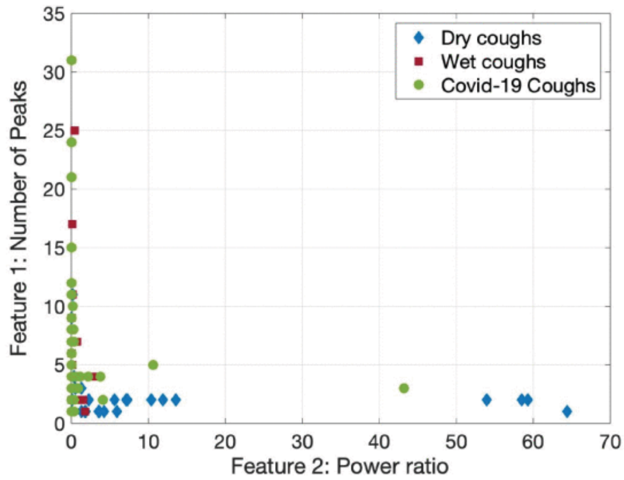

Fig 2: Comparison of COVID-19 coughs with dry and wet coughs with respect to number of peaks and power ratio [19]

IV. Results

Initially, 'Smart Cough' dataset has been used with 22 covid positive and 50 covid negative samples for training. Table II reports the cross-validation accuracies acquired for all the classifiers trained using third type of features vector. 5-fold cross-validation has been applied to build the models.

The model with highest accuracy i.e., neural network (73.6%), was selected and exported. The exported model has been tested using 40 (20 covid positive and 20 covid negative) cough samples. Test accuracy using neural network came out to be 55%. Test data for all three investigated cases is same.

Due to lack of positive COVID samples in our dataset, Covid-19 positive cough samples from other two public datasets have been used. 22 COVID positive cough samples are extracted from NoCoCoDa and 30 from COUGHVID. This combination of data consists of 80 COVID positive cough samples from all 3 datasets and 70 COVID negative samples from the self-collected dataset. For training and testing, 110 (60 Covid-19 positive and 50 Covid-19 negative) and 40 cough samples (20 Covid-19 positive and 20 Covid-19 negative) have been used, respectively. This combination of data consisted of both, dry and wet, COVID cough samples. Figure 3 shows the scatter plots for all dataset indicating wet cough samples and the outliers (dry cough samples).

TABLE II: VALIDATION ACCURACIES OF CLASSIFIERS USING MFCCS.

Sr No.	Classifier	Cross Validation accuracy (%)
1	Tree	58.3
2	Linear Discriminant	69.4
3	Logistic Regression	72.2
4	Naïve Bayes	63.9
5	SVM	70.8
6	KNN	69.4
7	Ensemble	70.8
8	Neural Network	**73.6**

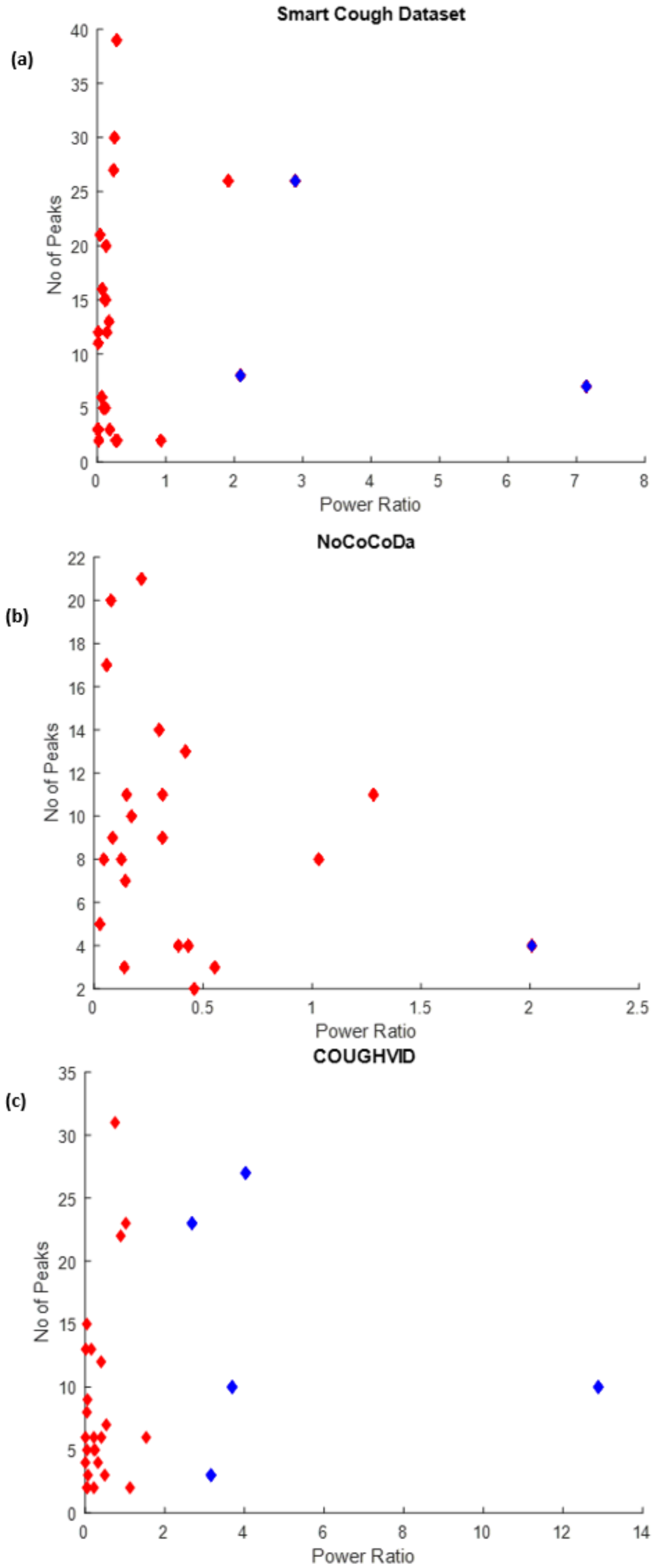

Figure 3. Scatter plot for COVID positive samples of (a) 1st dataset collected using "Smart Cough", (b) NoCoCoDa, (c)COUGHVID dataset

For further analysis, dry COVID cough samples are discarded from the combined dataset. For this combination of data, 101 cough samples, containing 50 Covid positive and 51 Covid negative samples, are used for training. Cross validation accuracies for both combinations, the one with dry cough samples and the one without dry cough samples, are depicted in Table III.

TABLE III: CROSS-VALIDATION ACCURACIES OF CLASSIFIERS USING COUGH DATASET WITH DRY SAMPLES AND COUGH DATASET WITHOUT DRY SAMPLES.

Sr No.	Classifier	Cross-validation accuracy of dataset with dry cough samples	Cross-validation accuracy of dataset without dry cough samples
1	Tree	72.7	74.3
2	Linear Discriminant	65.5	73.3
3	Logistic Regression	69.1	65.3
4	Kernel Naïve Bayes	82.7	80.2
5	SVM	**84.5**	**86.1**
6	KNN	83.6	**86.1**
7	Ensemble	82.7	80.2
8	Neural Network	80.9	85.1

Models with best validation accuracies are exported from the application. Test accuracy of 75% is achieved for SVM in case of data with dry cough samples. Similarly, for data without dry cough samples, test accuracy of 75% has been achieved SVM and KNN, respectively.

V. Observations and Discussion

We observed from the results that even after removing the dry cough samples from the dataset there is slight difference in the highest validation accuracy but no difference in the test accuracy (Table III).

The dataset was collected using a proper recording method via web-application, so the collected dataset is less noisy. The collected dataset has been made publicly available[31]

The proposed audio-based pre-test for COVID-19 disease is better than testing kits in some respects such as the result is provided to the patient within seconds. The test is free of cost and there is no need for the patient to visit a lab for the test. Unlike testing kits available, this test does not make the patient feel anxious or uneasy.

For the future work on this research there is scope for improvement in classification accuracy. This can be achieved using better pre-processing techniques as basic pre-processing methods have been employed on these datasets to achieve this result. The dataset used for this research has 80 COVID-19 patients' cough recordings. For further improvement in results, dataset can further be extended. Furthermore, a comparison between gender-based accuracy can be conducted by employing the proposed architecture on male and female cough samples.

VI. Conclusion

In this era of COVID-19 outbreak, burden on the hospitals has already increased and there exists several problems regarding testing kits as COVID-19 pre-test. As a solution to few of them, in this research audio recordings of coughing individuals have been used as a pre diagnosis for detection of COVID-19. Data from three sources has been used i.e., self-collected dataset, NoCoCoDa dataset and COUGHVID dataset. An extensive analysis has been performed using multiple classifiers for data containing dry cough samples and the one without dry cough samples. Test accuracies for both datasets have been achieved to be 75%. COVID-19 testing using cough samples can be advantageous for clinical diagnostic systems as well as for the patients. This research can be a step forward for a better pre-screening of COVID-19.

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