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Exploiting optimum acoustic features in COVID-19 individual's breathing sounds

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Abstract **- The world is facing an extreme crisis due to the COVID-19 pandemic. The COVID-19 virus interrupts the world's economy and social factors; thus, many countries fall into poverty. Also, they lack expertise in this field and could not make an effort to perform the necessary polymerase chain reaction (PCR) or other expensive laboratory tests. Therefore, it is important to find an alternative solution to the early prediction of COVID-19 infected persons with a low-cost method. The objective of this study is to detect COVID-19 infected individuals through their breathing sounds. To perform this task, twenty-two (22) acoustic features are extracted. The optimum features in each COVID-19 infected breathing sound is identified among these features through a feature engineering method. This proposed feature engineering method is a hybrid model that includes; statistical feature evaluation, PCA, and k-mean clustering techniques. The final results of this proposed Optimum Acoustic Feature Engineering (OAFE) model show that breathing sound signals' Kurtosis feature is more effective in distinguishing COVID-19 infected individuals from healthy individuals.**

Keywords - acoustic features, COVID-19 breathing sounds, feature engineering, k-mean, PCA

I. INTRODUCTION

The word COVID-19 became familiar among every individual worldwide due to its adverse impact on daily routine life [1]. The first case is reported in a patient with severe respiratory syndrome with cough, fever and dizziness at Wuhan hospital in China [2]. The lung is the primary respiratory organ affected by this virus [3]. Lung auscultation is a method that plays a vital role in examining respiratory disorders by distinguishing normal respiratory sounds from abnormal sounds [4]. Abnormal breathing sounds are common in society, such as; bronchial breathing, stridor, wheeze, rhonchus, cackles, and pleural friction rub. The breathing sounds of patients with COVID-19 can be examined via lung auscultation methods [3].

The breathing sound waveforms of both COVID-19 infected individuals and healthy individuals are illustrated in Fig. 1. The normalised amplitudes of breathing sound signals are plotted against time. However, all characteristic differences and similarities may not be visualised via a waveform plot. Thus, further calibrations need to be done to identify significant signal characteristics to differentiate COVID-19 and healthy individual's breathing sounds.

The rest of the paper follows; Section II gives a background inspection and a literature review on audio signal processing applications to detect COVID-19 breathing sounds. Section III presents the proposed methodology, while Section IV presents the obtained results. The conclusions of this study are presented at the end of the paper

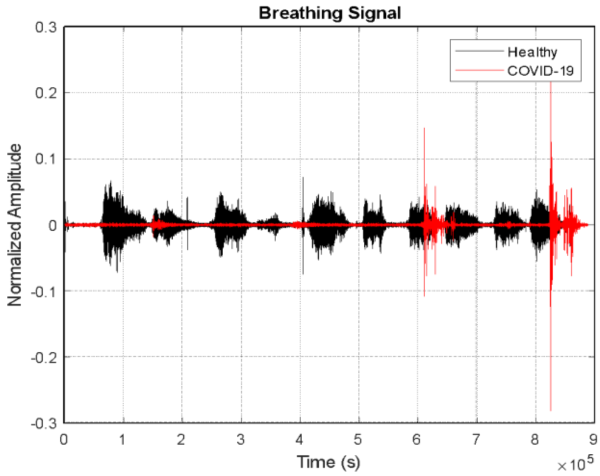


Fig. 1. COVID-19 and healthy breathing sounds in the time domain

II. LITERATURE REVIEW

Breathing is a chemical and mechanical process that includes inhaling and exhaling. In this process, Oxygen is inhaled in to the body, while Carbon Dioxide is exhaled [5]. Breathing is an essential process for all living creatures, including humans, because it impacts the whole body to regulate the functionalities of the organs. There are pathologies such as; asthma, pneumonia, and Chronic Obstructive Pulmonary Disease (COPD) that affect the breathing process [6]. Many of the pathologies undercover severe health problems that need proper treatment. Among many of these pathologies, the main problem facing the present society is detecting COVID-19 virus-infected persons. Thus, it is stated that the breathing process is the primary mode of transmission of the virus into the human respiratory system [7].

Many applications have already been presented for early diagnosis of various disorders that occur in different organs of the human body, mainly in the heart, brain, kidney, and lungs. Sound-based disorder identification techniques started to be experimented several years ago; thus, plenty of medical equipment was invented to hear and analyse these sounds of the human organs. The most significant sound analysis module is the stethoscope, which tends to listen to the inner sounds of hearts and lungs, including; murmurs, heart sounds, and breathing sounds. In the modern world, Artificial Intelligence (AI) is a popular engineering concept; hence many of these equipments are developed to perform various applications, including; developments of smartphone apps, telemedicine, medical and surgery tools. Acoustic sounds would be critical data for future developments of these applications to identify COVID-19 patients.

Among many applications, audio-based smartphone applications are widespread in research studies to detect COVID-19 patients. For example, Stasak et al. [8] proposed a smartphone-based speech analysis application to detect pathological effects relevant to COVID-19 screening. Similarly, Imran et al. [9] proposed an AI-based smartphone app to detect COVID-19 infected people through their cough sounds. Breathing sounds are also integrated to screen COVID-19 infected people via smartphone applications. In their study, Faezipour et al. [10] proposed an idea to develop a smartphone-based breathing sound simulation app that can self-test a person's breathing patterns and identify his/her breathing complications. The idea of this app is specifically proposed to detect COVID-19 patients. Despite these smartphone-based applications, Huang et al. [3] recorded breathing sounds via an electronic stethoscope and sent these recordings to a computer-based signal analysis method. They used a time-frequency distribution of the waveforms of both COVID-19 virus-infected and healthy individuals to examine the characteristics in the signal patterns. Then these visualising results are compared with clinically proven data to differentiate COVID-19 and healthy people. Apart from identifying COVID-19 infected people through breathing sounds, a few more applications were developed to diagnose other breathing disorders. Yañez et al. [11] proposed a breathing rate monitoring system to use at home. This system allows early prediction of exacerbation of Chronic Obstructive Pulmonary Disease (COPD).

Audio processing is a fast-growing method in medical diagnosis to categorise the most effective acoustic features. Many studies are conducted to find the best feature selection of the audio signals generated by the human body. For example, Milani et al. [12] examined both frequency and time domain acoustic features to identify normal and abnormal heart sounds. Nagasubramanian et al. [13] analysed multivariate vocal sounds and acoustic features with deep learning techniques to predict Parkinson disease. Chambres et al. [14] used mel-frequency cepstral coefficients (MFCC) of lung sounds to detect individuals with respiratory diseases. However, many research studies are conducted at the present day with a scope of early diagnosis of COVID-19 virus-infected people; but, many of these studies are still at the proposal stage. Therefore, in the near future, there could be successful outcomes from them. Nevertheless, this study would focus on identifying the most effective acoustic features to detach the breathing sounds of COVID-19 individuals and healthy individuals. Therefore, the findings of this study shall be proposed to apply in the future and ongoing COVID-19 breathing sound analysis application to invent and develop technical solutions for the COVID-19 pandemic.

III. PROPOSED METHODOLOGY

An acoustic feature-based clustering method which shows in Fig. 2, is proposed in this study. This proposed methodology carries four (4) stages; data collection, signal pre-processing, acoustic feature extraction, and optimum acoustic feature engineering. These four (4) stages conduct a particular task to obtain accurate outcomes in identifying COVID-19 and healthy individuals through their breathing sounds.

A. Data collection

The breathing sounds of COVID-19 and healthy individuals are collected from the Coswara open-access database [15], which contains various respiratory sounds, including; breath, cough, and voice [16]. However, only the breathing sounds are considered from the Coswara database to achieve the objective of this study. First, the sound quality is inspected manually before selecting the input sound recordings to the proposed methodology. All the sound recordings which are manually inspected (both visual and listening inspections) shows the sounds are incredibly in good condition. The sounds in the recordings are clear, and fewer background noises. A total number of forty (40) breathings sounds are taken for the training purpose, including twenty (20) sounds of each COVID-19 and healthy individuals. Then an additional four (4) sound recordings are selected to test the trained model. These four (4) recordings include; two (2) from COVID-19 and the remaining two (2) from healthy individuals, but they are considered as unknown in the testing process.

B. Signal pre-processing

The proposed signal pre-processing stage includes noise reduction and enveloping of the selected breathing sound signals. Breathing sounds can be considered as soft and low-pitched audio signals. A Finite Impulse Response (FIR) filter may be a better signal filtering solution to reduce the background noises and stabilise the signal [17]. These background noises may include the different sounds that are produced from internal organs of the body and other disturbances that occur during the sound recording process.

The filtered signal is then windowed with Hamming windowing method. The Hamming window has a fixed window function that can cancel the nearest side lobe of signals. Compared to other windowing methods, i.e. Hanning windowing, the performance speed and the noise cancellation is better in the Hamming windowing method [18].

In this study, each window of the filtered signal is designed for 30ms with a 10ms overlap. The proposed Hamming window is defined by:

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

where $'n'$ is the input sample number and $'N'$ is the total number of input samples [19]. Hence, this windowed signal will address the discontinuity of the actual breathing sounds by giving a smooth and soft waveform to obtain more reliable information from its features.

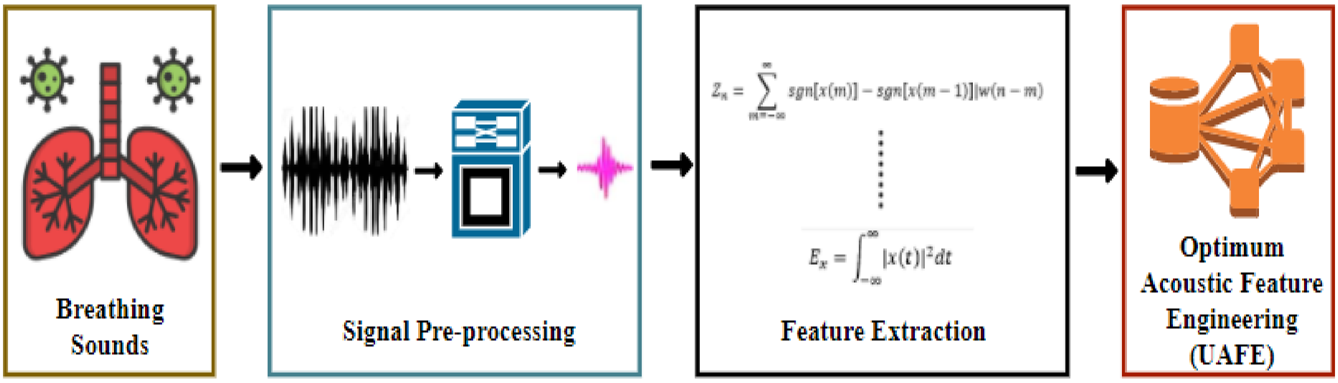


Fig. 2. Proposed methodology

C. *Acoustic feature extraction*

The information of each window of the breathing sound signals is extracted from the features of temporal, spectral, and frequency domains. These features are commonly used in different audio processing applications and provided acceptable results [20]. Twenty-two (22) multi-dimensional features are extracted from the selected three (3) domains. These extracted features may contain all key properties of the COVID-19 and healthy individual's breathing sounds. A summary of extracted features is dispatched in Table I.

TABLE I. EXTRACTED FEATURES

Feature Domain	Name of the Features	Nor of Features Extracted
Temporal	Zero-Crossing Rate, Energy, Entropy of energy	3
Spectral	Spectral Centroid, Spectral Spread, Spectral Entropy, Spectral Flux, Spectral Roll-off, Chroma Vectors	17
Frequency	Harmonic Ratio, Fundamental Period	2
Total number of features extracted		22

D. *Optimum Acoustic Feature Engineering*

A novel feature engineering-based learning algorithm is proposed to achieve the stated objective of this study. The proposed Optimum Acoustic Feature Engineering (OAFE) method requires only the extracted features of each selected input class, such as; COVID-19 individuals and healthy individuals. This proposed OAFE method may directly influence the final data prediction; thus, it may provide better and most influential acoustic features from the extracted twenty-two (22) features. Hence, this method will be an effective solution to avoid misleading features.

The statistical features such as; mean, standard deviation, variance, Skewness and Kurtosis are considered as the inter-dependent properties of each extracted twenty-two (22) acoustic features. These statistical features may emphasise the inherent nature of the extracted features to achieve better clustering performance with higher accuracy.

However, these features are in a multi-dimensional space which may make the final clustering process uneasy. Therefore, a feature dimensional reduction is conducted via Principal Component Analysis (PCA) to remove redundant features and keep the features in a low-dimensional space. Then, the final feature prediction is conducted through an unsupervised k-mean clustering algorithm to predict the class-based clustering to identify both COVID-19 and healthy individuals separately. The proposed OAFE process is illustrated in Fig. 3.

As of Fig. 3, the five (5) statistical features are calculated for each column of the input features matrix X. Thus, the columns represent twenty-two (22) extracted features, while rows of the matrix represent the number of input breathing sounds. Then the output feature matrix will become as $XStat$, which contains twenty-two (22) features as columns, while five (5) computed statistical features as rows. However, at the PCA dimensionality reduction stage, the feature matrix $XStat$ is turned $XPCA$ by having the first three (3) PCA values as columns and five (5) statistical features as rows. The reason for selecting only the first three (3) PCA values is because the PCA orders the eigenvectors in decreasing order, while the first three (3) PCAs may have a high impact on the feature clustering process.

To identify the optimum acoustic feature for the application of COVID-19 and healthy individual's breathing sound identification, the feature matrix $XPCA$ is transposed and sent to the proposed k-mean clustering algorithm. Through the k-mean algorithm, the computed statistical features of a total of twenty-two (22) extracted acoustic features are ranked as highest influenced feature to lowest influence feature. Hence, the firmness of these features depends on their ranks. Therefore, the best influential features are considered as an optimum feature for the stated objective of this study.

IV. RESULTS AND DISCUSSION

The performance of the proposed OAFE method is evaluated using four (4) unknown breathing sound recordings. Before inputting these unknown breathing sounds, the training performance of the computed $XPCA$ feature matrix is assessed via computing its accuracy. Hence, the proposed k-mean clustering model provided 80% of overall training accuracy for all forty (40) input sounds. After the training is done, the PCA-based feature matrices of unknown four (4) breathing sounds are fed into the training model. The final two class clustering outcomes of these four (4) breathing sounds are illustrated in Fig. 4.

It can be seen that all selected features in the transposed feature matrix of $XPCA$ of all four (4) unknown breathing sounds distinguish two clusters; COVID-19

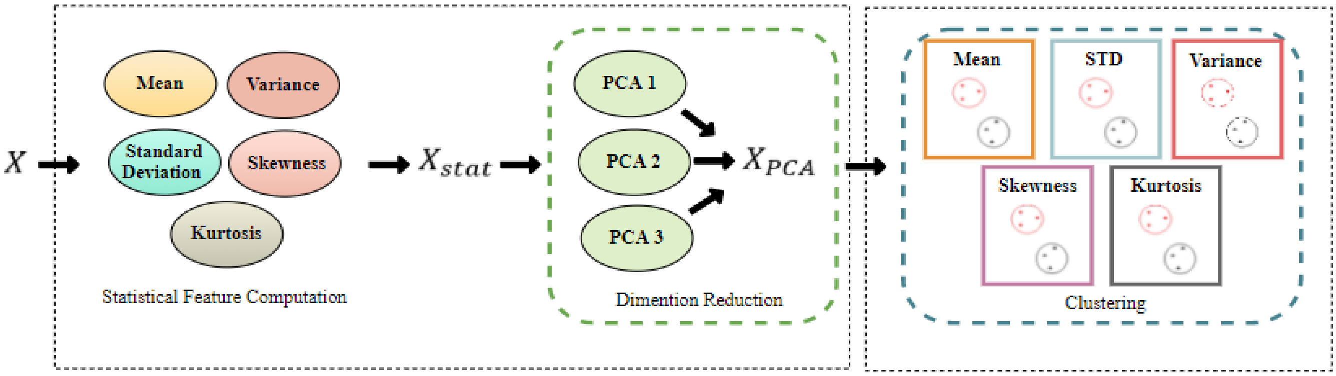
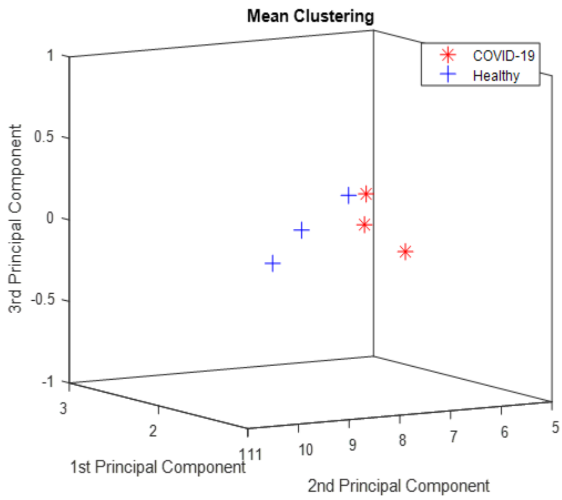


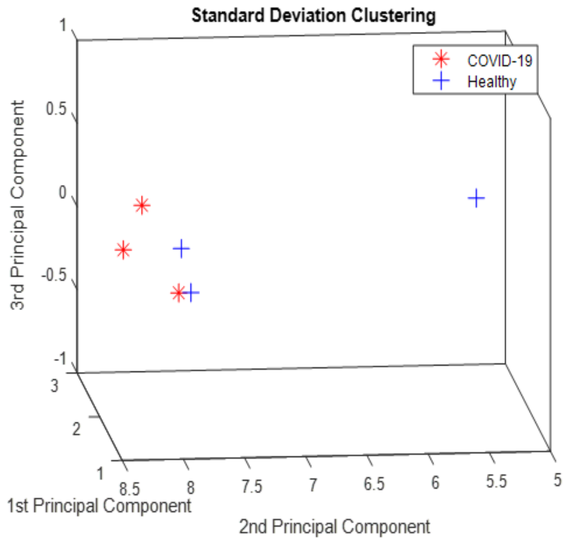
Fig. 3. Optimum acoustic feature engineering method

individuals and healthy individuals. However, PCA3 (third PCA value) in the Skewness predicted wrong. When further evaluating this wrongly predicted PCA, it is found that it belongs to a COVID-19 individual's breathing sound. Nevertheless, the overall performance of the executed statistical features of breathing sounds such as; mean, standard deviation, variance, Skewness, and Kurtosis indicated that these five (5) features extensively impact the stated purpose of this study.

The traditional way of feature clustering for two or more classes is carried out by inputting a feature matrix (X) containing extracted features in high dimensional or low dimensional space with a number of input samples/signals. However, the novelty of the proposed OAFE method is to find the optimum feature or a set of features through the originally extracted features. Therefore, another set of features (in this study, five (5) statistical features) are computed from the original set of features to narrow down the most reliable information. Hence, the OAFE method does not contain the number of samples/signals as its input, yet it only contains features of the samples/signals in both rows and columns. In other words, this method considers each feature vector of the matrix X to calculate the five (5) statistical features. Thus, the combination of each feature vector creates a feature matrix containing; five (5) rows (statistical features) and twenty-two (22) columns (original features) before the dimensional reduction.



(a)



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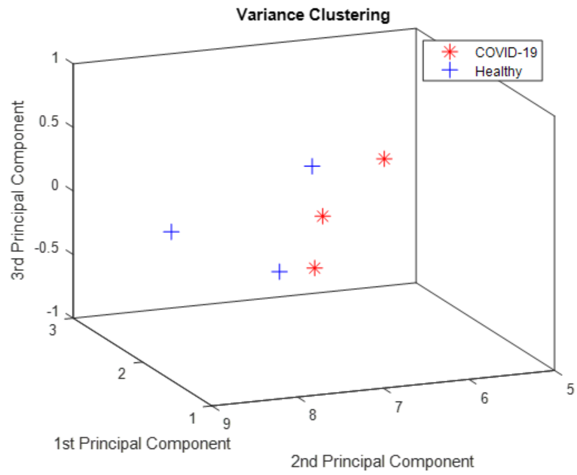

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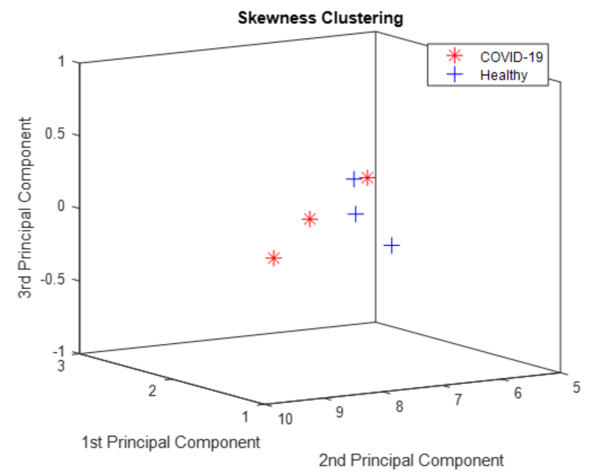

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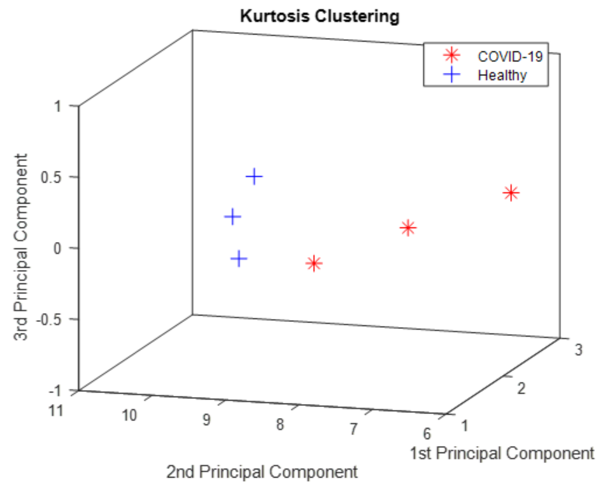

(e)

Fig. 2. Clustering results of both COVID-19 and healthy individual's breathing sounds: (a) Mean Clustering, (b) Standard Deviation Clustering, (c) Variance Clustering, (d) Skewness Clustering, (e) Kurtosis Clustering.

A cluster-based evaluation is implemented to find the most optimistic feature/features in the dimensionality reduced feature matrix $XPCA$. The results shown in Fig. 4 indicate that all five (5) statistical features effectively classify the breathing sounds of COVID-19 and healthy individuals.

TABLE II. OPTIMUM FEATURE RANKING

Ranking in Descending Order	**PCA**			**Reason for Ranking**
	1	***2***	***3***	
1) Kurtosis	✓	✓	✓	Distances between cluster points are longer.
2) Variance	✓	✓	✓	Distances between cluster points are less than Kurtosis.
3) Mean	✓	✓	✓	Distances between cluster points are close to each other, but the clusters can be clearly defined.
4) Standard Deviation	✓	✓	✓	Distances between PCA1 in both clusters are close to each other, yet the clustering is acceptable.
5) Skewness	✓	✓	X	PCA3 of COVID-19 class clustered as a feature in healthy class. Thus, it is a wrong prediction.

The computed features are ranked in descending order and dispatched in Table II based on the Euclidean distance between the cluster points. The results indicate that the most relevant optimum feature vector is Kurtosis.The obtained test results are further verified via a mix and match method that mixed up all the breathing signals used in training and testing. Subsequently, the trained model is again tested for the PCA1 to PCA3 of $XPCA$ matrix of randomly selected twenty (20) input breathing sounds. Remarkably, the final clustering observation of these features is identical to the results obtained for four (4) unknown breathing sound clustering results, which the Skewness predicted wrong for two (2) breathing sound signals of COVID-19 infected individuals. Hence, the results of Euclidean distance between the cluster points of this proposed mix and match method are identical to Table II. Therefore, it can be noted that the proposed method is well accurate to address the proposed issue of identifying the COVID-19 infected and healthy individual's breathing sounds.

V. CONCLUSION

Currently, the demand for an alternative PCR and other laboratory testing methods is higher to predict a COVID-19 positive individual in an early stage. This study displays a possible method to distinguish a COVID-19 individual from a healthy individual. The proposed method is based on the feature engineering technique examined via twenty-two (22) acoustic features. The proposed feature engineering model is a hybrid model that includes; model 1: computation of statistical features from original features and their dimension reduction, model 2: feature clustering. The novelty of this proposed feature engineering model is that it is altered from the traditional feature clustering method. The samples/signals are considered in the input feature matrix and the extracted features in the traditional method. However, the proposed acoustic feature engineering method relies only on the features of each sample/signal.

The proposed feature engineering model examines; which feature is better to be used in any COVID-19 breathing sounds related application. The early stage of this hybrid feature engineering method computes five (5) statistical features such as; mean, standard deviation, variance, Skewness, and Kurtosis from all originally extracted twenty-two (22) acoustic features. This hybrid feature engineering model is named Optimum Acoustic Feature Engineering (OAFE), narrowing down the most effective statistical features of the original acoustic features. Among these five (5) statistical features, the most relevant feature/features are ranked in descending order. As of the obtained results, the most to the least compelling features are Kurtosis, variance, mean, standard deviation, and Skewness, respectively.

The proposed OAFE method with the signal pre-processing and feature extraction stages can be used in many practical applications such as; developing smartphone applications or hardware implementation to detect COVID-19 infected persons in real-time. However, this OAFE method will be further expanded by integrating more features like cepstral, wavelet and more to improve its performance. Also, the proposed clustering method can be made more robust by adding more training and testing data.

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