18th International Learning & Technology Conference 2021

AI-based Power Screening Solution for SARS-CoV2 Infection: A Sociodemographic Survey and COVID-19 Cough Detector

Sadhana S[a], Pandiarajan S[a], Sivaraman E[b,*], Daniel D[c]

[a]Department of CSE, Kalaignarkarunanidhi Institute of Technology, Coimbatore, India
[b]Department of CSE, PES University, Bangalore, India
[c]Department of CSE, Christ (Deemed to be University), Bangalore, India

Abstract

Globally, the confirmed coronavirus (SARS-CoV2) cases are being increasing day by day. Coronavirus (COVID-19) causes an acute infection in the respiratory tract that started spreading in late 2019. Huge datasets of SARS-CoV2 patients can be incorporated and analyzed by machine learning strategies for understanding the pattern of pathological spread and helps to analyze the accuracy and speed of novel therapeutic methodologies, also detect the susceptible people depends on their physiological and genetic aspects. To identify the possible cases faster and rapidly, we propose the Artificial Intelligence (AI) power screening solution for SARS-CoV2 infection that can be deployable through the mobile application. It collects the details of the travel history, symptoms, common signs, gender, age and diagnosis of the cough sound. To examine the sharpness of pathomorphological variations in respiratory tracts induced by SARS-CoV2, that compared to other respiratory illnesses to address this issue. To overcome the shortage of SARS-CoV2 datasets, we apply the transfer learning technique. Multipronged mediator for risk-averse Artificial Intelligence Architecture is induced for minimizing the false diagnosis of risk-stemming from the problem of complex dimensionality. This proposed application provides early detection and prior screening for SARS-CoV2 cases. Huge data points can be processed through AI framework that can examine the users and classify them into "Probably COVID", "Probably not COVID" and "Result indeterminate".

Keywords: Artificial Intelligence; Coronavirus (SARS –CoV2); Machine Learning; Pathomorphological Variations; Power Screening Solutions

1. Introduction

Novel and emerging pathogens play a crucial issue in public health. The proficiency for scalable, proactive and agile testing has arisen as a significant differentiator in some nation's ability to reverse and handle the pandemic curve. The

---

* Corresponding author.
 E-mail address: sivaraman.eswaran@gmail.com

partnership of researchers and Allen Institute for AI delivered the open-source SARS-CoV2 datasets [1]. These datasets are updated weekly and continuously referred in SARS-CoV2 related research articles to give the fast-track to innovative projects in real-time data. Trace, Test and Treat are the succeeded methodology for leveling the curve of the pandemic in its early stages [2]. However, the pandemic has rapidly spreading all regions in the world. So this methodology is not showing more appropriate [3]. Recent surveys proved that it is a kind of virus that often spreads through undiagnosed coughs [4]. Data demonstrates that 81% of SARS-CoV2 carriers don't develop serious indications to seek medical aid, however they perform as active spreaders [5]. Some people receive symptoms after several days of being affected. They seek medical help. These verdicts attain a new technique based on the "Pre-Screening test, self-isolation, medical care and treatment" for many critical cases.

In this article, we propose the Artificial Intelligence and Machine Learning algorithm to enhance the identification of possible SARS-CoV2 more rapidly using a mobile-based smart application. Moreover, we examine the pathomorphological variations caused by the virus in respiratory tracts. The cough sound of COVID-19 patients is different from other viral and common bacterial infections. Hence the deep study of relevant pathomorphological variations prefers that it can be probable. So, we need to apply the first principle-based methodology [6]. Further, we detect and list the non- SARS-CoV2 respiratory syndromes which are comparatively common and need to analyze a similar cough sound like that of SARS-CoV2 Patients. With the help of the database, this method examines the hypothesis using different kinds of data scrutiny and pre-processing methods.

The various form of data analysis techniques demonstrates that COVID-19 cough does have different attributes while comparing to bronchitis, normal cough and pertussis [7]. To build the perceptiveness from the analysis of cough data and knowledge of the medical domain, we formulate an Artificial Intelligence engine for the initial analysis of COVID-19 from the distinct attributes of cough sounds. This system processes on the front-end cloud-server that acts as the user-friendly application. This application observes the cough sound and transfers that data to the Artificial Intelligence engine. The Artificial Intelligence Engine tracks the sound, and examine whether it is a sound of a cough or not. If the noted audio (recorded sound) is not cough, it instructs the app to indicate to rerecord the cough sound. If the noted audio (recorded sound) is cough, it transfers that cough data to the AI engine diagnosis part. After the analysis, the application gives the outcomes in three possible factors: They are Probably COVID-19, Probably not COVID-19, Result indeterminate. To get reliable results with limited data, the AI risk-averse architecture was proposed. It contains three parallel classifications. Automated mediator consolidated the results of the classifier. In case all the three classifiers do not agree with the terms, the application returns 'Result indeterminate'. It reduces the misdiagnosis rate and offers the 2nd opinion practice.

2. Literature Survey

Medical Industry is seeking for novel and effective methodologies to screen and control the SARS-CoV2 pandemic. Artificial Intelligence is one of the technologies which helps to monitor the viral spread and detects the high-risk patients, also helpful in controlling this infection in real-time [8]. By analyzing the previous cases of data, itcan also forecast the mortality risk. Artificial Intelligence assists us to fight this virus by medical help, notification, population screening and giving suggestions about infection control [9 - 10]. It helps to enhance the treatment, planning and reported results of COVID-19 cases.

An Intelligent platform was built for automatic monitoring and forecast the transmission of SARS-CoV2 cases. A neural network can be developed for visual feature extraction of this disease and this would help for appropriate monitoring and treatment of infected persons [11]. Several surveys [12 - 19] suggests that different hidden attributes in cough sounds can be used for Artificial Intelligence-based successful diagnosis of more respiratory problems, so we hypothesize that "The sound of cough can help at least initial analysis of COVID – 19 for accomplishing various examinations of its unique hidden attributes which related to other non-COVID -19 Coughs".

According to the guidance of the World Health Organization (WHO), Nucleic Acid Amplification Tests (NAAT) should be used for the confirmation of SARS-CoV2 patients by identifying distinctive orders of viral Ribonucleic Acid (RNA). Currently, this is the standard approach but it is not sufficient to control the pandemic, because for the following reasons.

- Due to temporal and geographical factors, there is limited testing availability.

- There is a need for in-person visits to clinics, laboratories, and hospitals. Such visits help us to increase the testing rate of the public. Recent surveys show how SARS-CoV2 is highly stable and highly transmissible. The SARS-CoV2 aerosol stability is up-to 3 hours to 7 days on various surfaces.
- The approximate period for existing tests takes more days. In some countries, it expands up to 10 days due to overwhelmed cases in the labs [20 - 21]. At the time, the patient is under-examined but the virus might have started to spread to many persons within this period.
- The in-person testing methods have only limited protection but they have a high risk to spread the infection.

The United States Food and Drug Administration (FDA), permitted a rapid test that gives outcomes within 15 to 20 minutes for making the test more readily available [22]. The test acts the same as Polymerase Chain Reaction (PCR) by detecting a part of SARS-CoV2 Ribonucleic Acid in Oropharyngeal and nasopharyngeal swab. Recently the FDA permitted the Rapid Molecular dependent test, which brings positive results in 5 minutes and negative results in thirteen minutes [23]. But the FDA alerts that the chance of false-negative results is high [24] while using that test. But, still there is a need for that test in an office visit and to avoid the rupturing of self-isolation and social distancing. Though the newly permitted test requires more solutions for the above-mentioned problems.

To prevent others from this infection, the FDA permitted to collect the samples at home [25]. Though, if a nasal sample of patients is collected, they have to shift it to a specialized lab to process the specific examination on the medical kit. Hence this methodology is also delayed and compromised the quality of the samples (in case the sample stockpiled for too long). Besides, it gives a high probability of errors, while the sample collection is done by the patients, not by the trained health care professionals or doctors. Now two alternative methodologies for SARS-CoV2 infection leveraging analysis of either Computed Tomography (CT) scan images [26 - 31] or X-ray images [32 - 37] have been developed in literature surveys.

These methodologies are combined with Artificial Intelligence based Image Processing which helps to diagnosis the COVID-19 with higher accuracies. Sometimes it is comparatively better than Reverse Transcription Polymerase Chain Reaction (RT-PCR) based test. Recent surveys display the pooled-sensitivity rate of 94% (i.e., the confidence interval of 95% cases have 91% to 96%), but low specificity-rate of 37% (i.e., the confidence interval of 95% cases have 26% to 50%) for CT- dependent analysis [38]. Hence, CT- dependent analysis might use to solve the suboptimal PCR test sensitivity rate [39]. Though these methods minimize the problem on radiologists to do the analysis, but still there is a need to visit a well-furnished clinical facility. It is significant because there is a need to examine huge swaths of populations safely, rapidly and cost-efficiently.

3. Proposed Work

The recent pandemic COVID -19 implies stress on World Health-Care Sector. It is an important need to evaluate innovative patents for attempting to resist the fast-spreading SARS-CoV2. Technologies can provide the rapid detection of COVID-19 cases. To reduce the time for detecting the affected individual, we proposed an innovative method to collect the basic data of an individual such as their travel history, age, gender, common symptoms and signs with the assistance of their mobile application. Also, we collect the data of their cough sound for AI dependent diagnosis. These data analyses can help in the primary screening process and early detection of probable COVID-19 cases. Artificial Intelligence processes these millions of data that examine humans and separate them into safe, low risk, moderate and high-risk groups. It helps to detect the high-risk cases and quarantine them early, thus helps to reduce the viral spread (Table 1).

3.1 Data Collection Through Mobile Application

Based on the Center for Disease Control and Prevention Flowchart [40], we established our data collection norms to detect and evaluate novel SARS-CoV2 and we include some additional attributes for enhanced usage of detecting infected cases and resist the spread [41]. Table 1. shows the steps of data collection.

3.2 Steps for Identification of Possible Cases:

Let D_1, D_2, D_3, D_4 and D_5 be the data reported in the data collection system. D_2 contains the three datasets that are mentioned in (1)

$$D_2 = \{D_{2A}, D_{2G}, D_{2H}\} \tag{1}$$

And the 9 sets of Data within D_5 are mentioned in (2)

$$D_5 = \{ \begin{array}{c} (D_{5A}, T_{5B}), (D_{5B}, T_{5B}), (D_{5C}, T_{5C}), \\ (D_{5D}, T_{5D}), (D_{5E}, T_{5E}), \\ (D_{5F}, T_{5F}), (D_{5G}, T_{5G}), (D_{5H}, T_{5H}), (D_{5I}, T_{5I}) \end{array} \} \tag{2}$$

Here the set of (D_{5I}, T_{5I}) for $I = A, B, C, \ldots I$ denote the response of the user based on the existence and non-existence of i_{th} symptom and sign of D_{5i} and T_{5i} denotes the time duration of the specific symptom and sign.

(1) If the Identifier set I_1 in (3) is denoted as
$$I_1 = \{D_3, D_{5A}, D_{5B}, D_{5C}\} \tag{3}$$

is similar to any one of the features in the dataset X_1

$$X_1 = \begin{Bmatrix} (1,0,0,1) \\ (1,0,1,0) \\ (1,0,1,1) \\ (1,1,0,0) \\ (1,1,0,1) \\ (1,1,1,0) \\ (1,1,1,1) \end{Bmatrix} \tag{4}$$

for a user, then send it to Health Check Recommended for Coronavirus (HCRC) or Mobile Health Check Recommended for Coronavirus (MHRC). If I_1 is not similar to any one of the features in the dataset X_1 then test norms (4) can ensue.

(2) If the Identifier set I_2 in (5) is denoted as
$$I_2 = \{D_4, D_{5A}, D_{5B}, D_{5C}\} \tag{5}$$

is similar to any one of the features in the dataset X_1, then send Health Check Recommended for Coronavirus (HCRC) or Mobile Health Check Recommended for Coronavirus (MHRC) to the user else test norms can ensue.

(3) If I_1 is similar to one of the features of the dataset X_2 in (6) are

$$X_2 = \begin{Bmatrix} (1,0,0,1) \\ (1,0,1,0) \\ (1,0,1,1) \\ (1,1,0,0) \\ (1,1,0,1) \\ (1,1,1,0) \\ (1,1,1,1) \end{Bmatrix} \tag{6}$$

Then the user will be directed to an NCRC (non- identified respondents or No Health Check Recommended for Coronavirus).

(4) If I_2 is similar to one of the features of the dataset X_2, then the user will be directed to NCRC alert.

Table 1. Demographic Survey for COVID – 19 Cases through Mobile Application

Question number	Questions	Answer Field		
1	Enter your Current location details			
2	Enter the demographic data like Age (A), Gender (Male/ Female/ Transgender) and Health Complexions (Yes/ No). If "Yes" then mention that.	**Age**	**Gender**	**Health Complexions**
3	Did you travel outside of the country or any COVID-19 affected places in the prior 14 days?	**Yes** (Yes=1)		**No** (No =0)
4	Did you have close contact with the identified COVID- 19 patients in the prior 14 days?	**Yes** (Yes=1)		**No** (No =0)
5	Enter the symptoms and signs listed below a) Cold	**Yes** (Yes=1) Duration		**No** (No =0)
	b) Fever	**Yes** (Yes=1) Duration		**No** (No =0)
	c) Cough	**Yes** (Yes=1) Duration		**No** (No =0)
	d) Sore Throat	**Yes** (Yes=1) Duration		**No** (No =0)
	e) Respiratory Illness	**Yes** (Yes=1) Duration		**No** (No =0)
	f) Difficulty in Breathing	**Yes** (Yes=1) Duration		**No** (No =0)
	g) Fatigue	**Yes** (Yes=1) Duration		**No** (No =0)
	h) Body Pain	**Yes** (Yes=1) Duration		**No** (No =0)

The above steps help to detect the probable COVID cases and send an alarm to the nearby Healthcare clinic. If a user doesn't have any signs and symptoms of SARS-CoV2 viral infection, then Artificial Intelligence-based health alert can notify them that "Currently there is no COVID – 19 risk". Moreover, we collect the cough sound from the user for an AI-based Cough diagnosis that helps to make the result more accurate.

3.3 AI-Based Cough Diagnosis for COVID-19

Cough is the frequent and common symptom over a lot of diseases caused by viral or bacterial respiratory infection that not only belongs to the SARS-CoV2 or COVID – 19 [42 - 44]. Cough can also be caused by many non- respiratory conditions. Table 2. shows the medical condition of non-COVID-19 but that can be the reason for the cough. By using the cough sound, trained physicians execute various analyses among respiratory infections such as asthma, laryngitis, pneumonia and Tracheitis [45 - 50].

The location and nature of the primary irritant in the respiratory tract are slightly different, which leads to produce the unique cough sound. Sometimes, it is difficult for AI to differentiate the unique latent attributes in the COVID-19 patient's cough sound. The risk exists in AI-based Cough Diagnosis for the COVID-19 tool to obscure the cough that occurred by any identified disease shown in Table 1 with the COVID-19 cough. To estimate this risk, a brute force-dependent technique is used for collecting cough datasets from huge patients for each of the status mentioned in Table 2.

Table 2. Types of Cough Related to Respiratory or Non – Respiratory Illness other than COVID-19

Cough Related to Respiratory Illness	Cough Related to Non- Respiratory Illness
Asthma and allergies	Air pollutants
Chronic obstructive pulmonary disease (chronic bronchitis, emphysema)	Congestive heart failure
Croup	Drugs (beta-blockers, angiotensin changing enzyme inhibitors)
Cystic fibrosis, Early interstitial fibrosis	Foreign body
Interstitial lung disease	Gastro-esophageal reflux
Laryngitis	Idiopathic cough
Lower respiratory tract infection (bronchiolitis, bronchitis, pneumonia)	Laryngopharyngeal reflux
Lung abscess	Left-ventricular failure
Lung tumor	Mediastinal tumor
Para pertussis, Pertussis	Obstructive sleep apnea
Pleural diseases	Psychogenic cough
Postnasal drip	Smoking
Tracheitis	Somatic cough syndrome
Tuberculosis	Tic cough
Upper airway cough syndrome	Tracheoesophageal fistula
Upper respiratory tract infection	Vocal cord dysfunction

This massive dataset can help to train the powerful AI engine to distinguish the COVID-19 cough from other coughs which mentioned in Table 2. This methodology is difficult at this pandemic movement because it is hard to incorporate all the data which is time consuming. So, we developed a methodology of Domain-cognizant AI-design. It means that the Proposed Artificial Intelligence Engine doesn't simply depend on blind big data churning. But it depends on deep domain knowledge of medicinal scientists, researchers and scholars trained in infectious and respiratory illness to evaluate and short down the hypothesis testing scope. Also helps to reduce the data amount required to test for our hypothesis. The aim is to examine the pathomorphological variations occurred by SARS-CoV2 are unique from another cough mentioned in Table 2. Artificial Intelligence-based Cough Diagnosis for the COVID-19 tool will pick the idiosyncratic attribute of COVID – 19 coughs and give a consistent diagnosis.

3.4 Solution for Data Description and Practical Possibility

Collecting such massive data in this pandemic is difficult at this time because COVID -19 pandemic requires a fast response. To attain good results in this pandemic situation, we put domain knowledge instead of looking for big data. We select some of the indistinct cough causing conditions from Table 2 to complicate our Artificial Intelligence Engine due to the same pathomorphological variations in respiratory tracts as SARS-CoV2 and the same sign in cough. The shortlist consists of asthma, bronchitis, croup, bronchiolitis, pneumonia and influenza. With the help of previous surveys, we use verdicts to minimize the scope of differential analysis and data collection campaign to the respiratory infections. The unanalysed coughs (bronchitis and pertussis) have a distinct feature.

To make the active mobile application for COVID- 19 in a public place or with the existence of different background noises, we design an AI dependent cough detector. This tool of cough detector turns as a filter before the cough analysis and an ability to separate the cough sound from environmental noises. The open-source Environmental Sound Classification - 50 (ESC-50) datasets are used to train and validate this cough detector [51]. This ESC – 50 dataset gives the massive collection of human, social and environmental sounds. It is classified into fifty classes. One of the classifications is coughs. In our work, we took 1900 cough sounds and 3600 environmental sounds (non -

cough sounds) for the training and validating process. And we took the datasets from Virufy open-source cough Dataset for COVID -19 cough analysis. These datasets are original and collected at the hospital. Also, we took datasets from Kaggle open-source data and Hernanmd open-source Cough Datasets.

In the solutions of Artificial Intelligence, the theoretical viability does not assure the result based on the data quality. Moreover, the machine learning algorithm is used. The audio files (recorded cough sound) used in our method are 16-bit uncompressed Pulse Code Modulation format with a sampling rate of 44.1 kHz and 3-sec fixed length. For more process, we convert the audio samples of cough sound into the Mel scale. The Mel scale is a pitch classification technique. It is intended to create alterations in frequency (i.e., spectrogram with more closely replicate sound variations). Mel spectrogram is used over the typical frequency because it generates lower resolution in higher frequencies and vice versa, also it is related to the frequency bands of uniformed space in standard spectrogram [52 - 53]. In lower frequencies, cough sounds contain higher energy, thus the Mel spectrogram is suitable for recognizing the cough sound. Here (7), we transform the frequency F_q into Mel Scale M_s as:

$$M_s = 2595 * (1 + \frac{f_q}{700}) \tag{7}$$

To evaluate the Cepstral Coefficients, Cepstral analysis was performed on the Mel Spectrum of cough audio (recorded sound) samples is called Mel Frequency Cepstral Coefficients (MFCC) [54]. The extracted attributes of MFCC for all sample outcome in the M*N matrix, where each row denotes the feature extraction and each column denotes one signal frame of MFCC for a particular frame. Frames can differ from one sample to another sample. There are many methods to practice the extracted attributes for the data classification process. In our proposed method, *M*N* MFCC dependent attribute vectors are extracted for every cough samples input and concatenate them into a final single attribute vector of *2M*1*.

This method yields the mean of MFCC attributes parallel to every frame for the first attribute vector. Also, this method grabs the top Principle Component Analysis (PCA) *PM*1MFCC* attribute projections [55 - 56] across every edge and concatenates them into a single vector *M*1* by picking their magnitude. Then we combine *2M*1* single attribute vector and attribute vector. This method is demonstrated in Fig. 3.

Since the extracted cough audio attribute is multidimensional for visualizing the attributes, a reduction nonlinear dimensionality method named t-SNE (t- distributed Stochastic Neighbor Embedding) is used. It is appropriate for implanting the high dimensional data in two dimensions. In specific, this strategy designs a high dimensional object by two-dimensional points. This visualization permits feature interpretation in classes or clusters formation associated with classification decision limits. It can be monitored that different types of coughs hold unique features from each other. Hence, COVID-19 features are unique from other types of coughs. Thus, this observance implies the practical feasibility of Artificial Intelligence dependent cough based primary verdict for COVID-19 boosting us to move towards the strategy of Artificial Intelligence Engine for highly efficient and accruable implementation to permit mobile application dependent deployment.

The two phases of the solution for our proposed method: The first phase is the cough sound recognition from non-cough, noisy sounds and mixed cough. The other one is the COVID- 19 diagnoses from the cough sound. After trained the models for COVID 19 diagnosis and Cough detection, it deployed at the cloud server. The user interface provided by the application with pre-trained models. Cloud dependent implementation has the advantage of refining the model constantly until the data becomes obtainable.

3.5 The Architecture of the System

The entire architecture of the system is shown in Fig. 1 and the overall emphasizing steps are articulated in Fig. 2. The mobile application takes the sociodemographic and demographic survey. After completing the survey, it records the cough sound when incited by the voice recognition button. After clicking the diagnosis button, the noted audio is progressed to the server. In the server-side, the audio is nourished into a cough detector. If the audio file doesn't have a cough sound or the poor sound quality, then the server guides the application to re-record the cough sound. If the audio file has a cough sound, then the audio is progressed to three parallel and distinct classifier system. They are Classical Machine Learning dependent Multi-Class Classifier (CML- MC), Deep Transfer Learning dependent Multi-Class Classifier (DTL-MC) and Deep Transfer Learning dependent Binary-Class Classifier (DTL-BC).
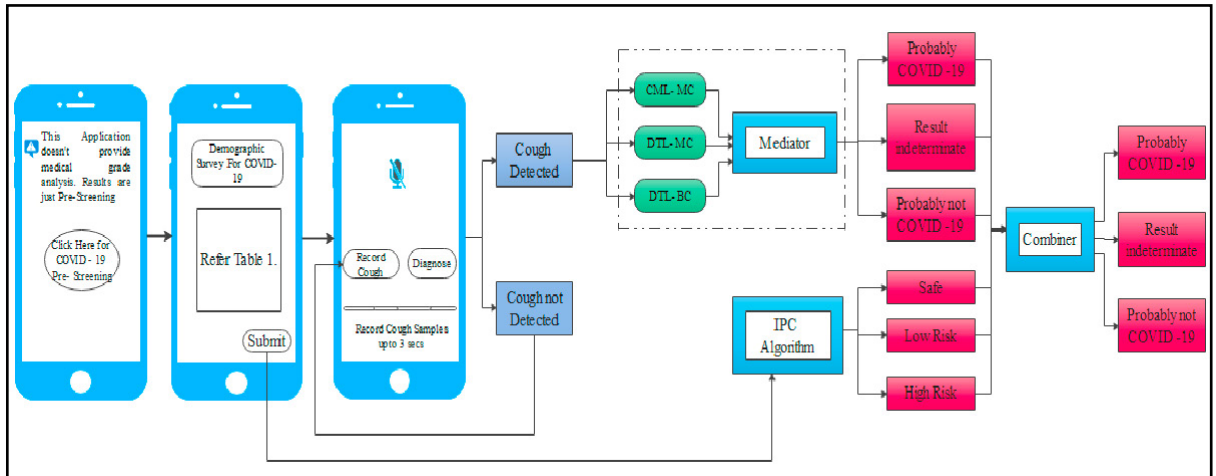
Fig. 1.   Architecture of the Proposed System

The outcome of the classifiers is prompted onto the mediator. The application will show the diagnosis results only if all the three classifier yields similar classification results. If the results are dissimilar, the application yield the text of "Result indeterminate". To reduce the possibility of misdiagnosis, this centered tri-pronged mediator system is developed. Here, the opinions of the three diagnosis classifiers are taken with veto power. This technique helps to minimize the total rate of misdiagnoses (False positive and False-negative rate) of the COVID -19 cough detector application.

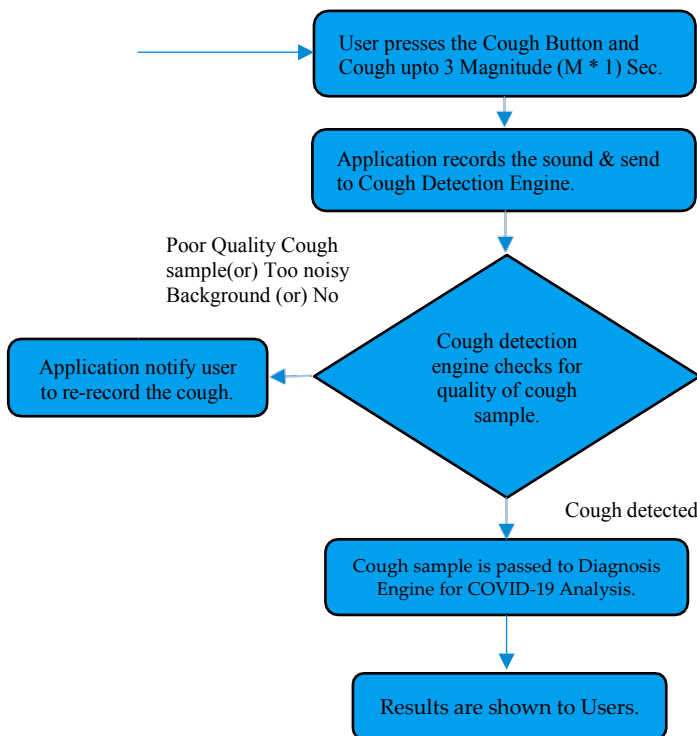### 3.6 Detection of Cough Sound

Fig. 2.   Overall Emphasizing Steps of Cough Detector

The noted audio (recorded cough sound) is progressed to a cloud-dependent server. Initially, the cough detector system evaluates its Mel spectrogram with 128 Mel components. Then it resized the image and changed into the grayscale image to merge the scaling intensity and minimize the image dimension resultant in a 320*240*1 dimensional image. The outcome of the image is nourished into Convolutional Neural Network (CNN) centered classifier to choose if the recorded audio input sample is cough sound or not. The high dimensional input of the Mel Spectrogram image is first forwarded through 2*2 max-pooling layer for minimizing the total complexity of the system. Then the two blocks of layers are progressed, each block consists of 2 Convolutional layers (CL) followed by 2 *2 max-pooling layer and 00.15 dropouts.

The first block of CL uses 16 filters and 5*5 kernel size while the CL of the second block uses 32 filters. To prevent the overfitting, the trained complex attributes from this 4 CL are compressed and transmitted to 256 Fully Connected Layer neurons followed by 00.30 dropouts. Finally, "Cough" and "not Cough" is classified by the softmax activation function and output layer. The detection model is fulfilled by the binary cross-entropy loss-function.

3.7 Diagnosis of COVID-19

After detecting the cough sound from Cough Detector System, it is passed to Artificial Intelligence dependent centered tri pronged mediator for the COVID-19 cough diagnosis process. Here we used three classifiers for producing the output with high reliability [57].

3.7.1   CLASSICAL MACHINE LEARNING DEPENDENT MULTI-CLASS CLASSIFIER (CML- MC)

With the Mel spectrogram image as input, this is the first solution that influences a CNN-dependent 4 class classifier. The 4 classes of cough occurred by 1) Normal cough (no infection in respiratory tracts) 2) bronchitis 3) pertussis 4) COVID – 19. The same type of CNN system is applied for detecting the cough but with a little variation to create a four-class classifier by altering the neuron number in the output-layer to 4 neurons for categorizing the input amongst 4 probable resultant classes. It helps to extenuate the overfitting of data. PCA based feature extraction techniques are applied here. These attributes are nourished into Multi-class SVM for data classification. Sampling attained the class balance from each class. With the help of Combined Attribute matrices as input, the k-fold SVM validation technique is performed for 1,00,000 iterations. This method is shown in Fig. 3.

3.7.2   Deep Transfer Learning dependent Multi-Class Classifier (DTL-MC)

This is a 2nd parallel diagnosis test that contains deep- learning strategy instead of Classical Machine Learning. To shift the knowledge trained by the cough detection system by the same kind of diagnosis model Deep Transfer Learning model is used. This permit to train deep architecture using restraint amount of trained data as the primary attribute of Mel spectrogram input which classifies the pre-trained cough and it needs to be fine-tuned for more-subtle attributes. Here, we fixed the initial weights of the 1st convolutional layer as a preliminary layer and train low-level latent attributes. For fine-tuning the weights, it permits the other layers. This method gives better performance than Scratch training of disease data.

3.7.3   Deep Transfer Learning dependent Binary-Class Classifier (DTL-BC)

This is a 3rd parallel diagnosis test that contains deep transfer learning-dependent Convolutional Neural Network with an input of Mel spectrogram image. But only the binary classification is performed by it with similar input. It is used by CNN structure in Cough Detector System.

4. Experimental Results

To compute the model performance, we use the metrics of F1-score, specificity, sensitivity, overall accuracy, precision, and recall on validate and cross-validate set models. K-Fold cross-validation technique is performed to

compute the machine learning model's performance [58]. From Cross-Validation, Mean Confusion matrices are performed to compute these approaches.

Table 3. Confusion Matrix for 5-Fold Cross-Validation

		Cough	No Cough
Cough		96.22	3.78
No Cough		4.70	95.30

Moreover, Regularization methodology is used to prevent overfitting issues. Different hyper-parameters tuning such as dropout rate, activation functions, learning rate, number of latent layers are the functions reliant on deep neural network models that are computed based on cross-validation accuracy. Besides, to prevent the probability of overfitting, we evaluate the epochs numbers versus model delay.
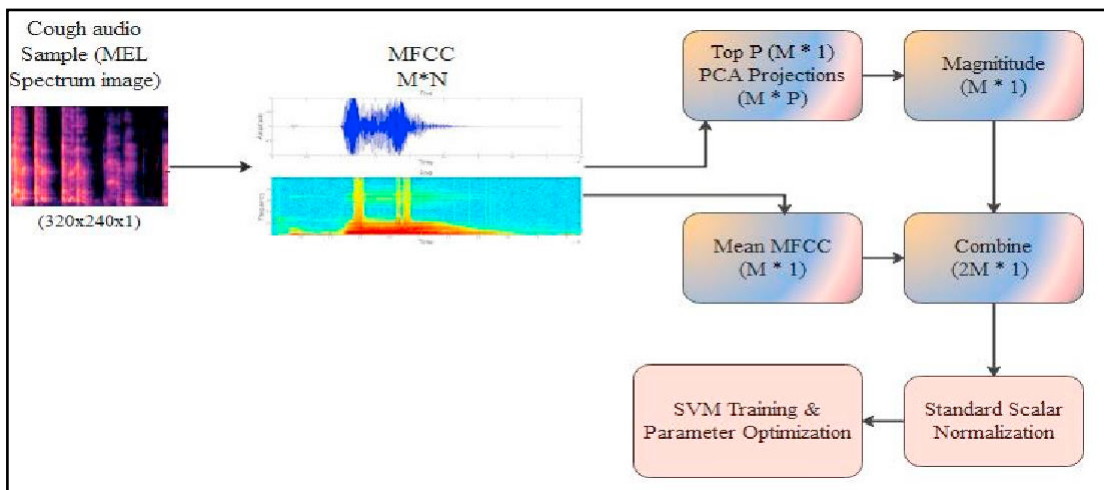
4.1 Detection of Cough

Fig 3. Classical Machine Learning-dependent Multi-class Classifier (CML-MC)

Table 3 and Table 4 show the detection algorithm of Confusion Matrix and Cough Detection Performance Metrics respectively. Results showed that this method can separate cough and non-cough with total accuracy of cough detection is 95.76%. Fig. 4 shows the error graph of epochs of neural network dependent model versus mean loss for training data sets and validating the data sets. This approach has not been over-fitted because of the decay curve in training and testing data sets.

Table 4. Cough Detection Performance Metrics

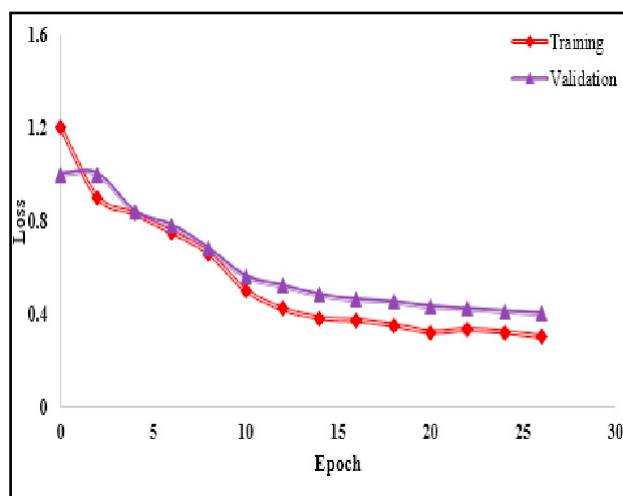| F1- Score	Specificity	Sensitivity	Precision	Accuracy
95.64	95.30	96.22	95.12	95.76

Fig 4. Error graph of epochs for 5-fold Cross Validation

4.2 Diagnosis of COVID- 19

Table 5 reports about the 1st classifier of CML-MC classifier. It shows the 5- fold cross-validation of the standardized mean confusion matrix. Fig. 5 denotes the overall accuracy of the Cumulative Distribution Function (CDF) with different k's in k-fold cross validation datasets. Data availability and Performance matrices of this system are demonstrated in Table 6. The outcome of total accuracy is 88.13%.

Table 5. Confusion Matrix of CML- MC Using 5-Fold Cross Validation

	Normal Cough	Bronchitis	Pertussis	COVID – 19
Normal Cough	83.23	3.98	5.97	6.82
Bronchitis	4.44	90.87	4.61	0.08
Pertussis	7.42	4.81	86.56	1.21
COVID – 19	4.91	0.34	2.86	91.89

Table 6. Performance Matrices of CML-MC classifier

Types of Cough	F1- Score	Specificity	Sensitivity	Precision	Accuracy
Normal Cough	85.52	95.32	83.23	86.62	-
Bronchitis	89.23	95.34	90.87	89.78	-
Pertussis	87.21	95.43	86.56	89.29	-
COVID-19	89.93	95.82	91.89	86.32	-
Overall	-	-	-	-	88.13

Table 7. Performance Matrices of DTL-MC classifier

Types of Cough	F1- Score	Specificity	Sensitivity	Precision	Accuracy
Normal Cough	94.52	98.32	93.12	95.82	-
Bronchitis	90.27	95.14	92.68	88.71	-
Pertussis	93.20	97.43	92.76	93.91	-
COVID-19	89.32	96.89	89.89	89.42	-
Overall	-	-	-	-	92.11

Table 8. Confusion Matrix for DTL-Mc Using 5-Fold Cross Validation

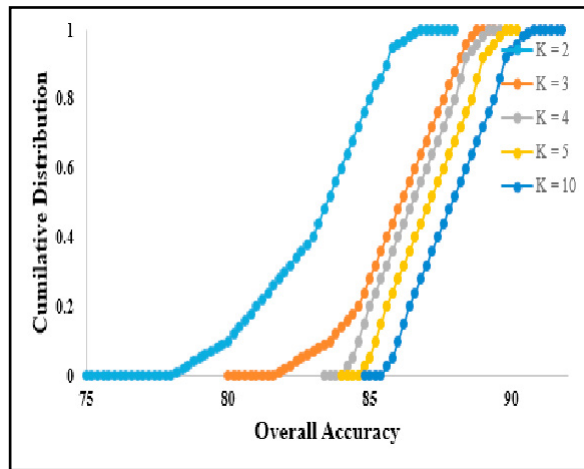|	Normal Cough	Bronchitis	Pertussis	COVID – 19
Normal Cough	93.12	1.81	1.73	3.34
Bronchitis	0.95	92.68	1.75	4.62
Pertussis	3.83	1.26	92.76	2.15
COVID – 19	2.1	4.25	3.76	89.89

Fig. 5.   Error graph of epochs for CML-MC using 5-fold Cross Validation

Table 7 shows the 2nd classifier DTL-MC performance metrics. Here, the total accuracy of the DTL-MC classifier is 92.11%. Table 8 shows the outcome of the normalized mean of the confusion matrix. For training and validating the datasets, the epochs vs mean loss of the DTL-MC classifier is reported in Fig. 6. After completing approximately 25 epochs, both curves are initiated to saturate that specifies the sensible learning time. Also indicates that it doesn't have overfitting.
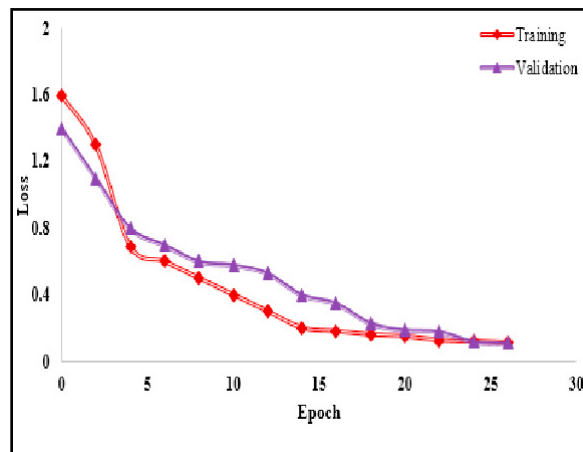

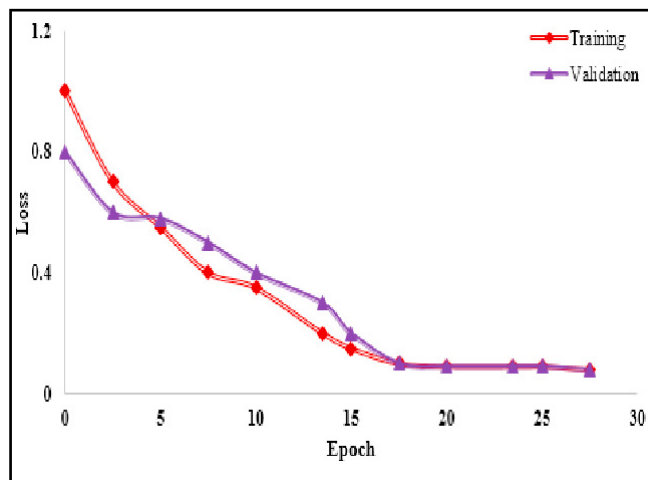Fig. 6. Error graph of epochs for DTL-MC using 5-fold Cross Validation

Fig 7.   Error graph of epochs for DTL-BC using 5-fold Cross Validation

Table 9 shows the 3rd classifier DTL-BC performance metrics. Table 10 reports the normalized mean of the confusion matrix. 92.77% is the classification accuracy of this method. Fig. 7 illustrates the epochs vs mean loss of the DTL-BC classifier. After completing 20 epochs, both curves are initiated to saturate that specifies the sensible learning time. Also indicates that it doesn't have overfitting. While choosing the binary classification technique, the amount of non-COVID-19 cough sound samples is more than the COVID-19 cough sound samples.

Table 9. Performance Metrics of DTL-BC

F1- Score	Specificity	Sensitivity	Precision	Accuracy
92.96	91.16	94.38	91.32	92.77

Table 10. Confusion Matric for DTL-BC Using 5 Fold Cross-Validation

	COVID -19	No COVID -19
COVID -19	94.38	5.62
No COVID -19	8.84	91.16

The outcome of DTL-BC and DTL-MC (deep learning-dependent classifier) is higher than CML-MC (manual attribute extraction dependent classifier). If the amount of data will increase, the classification accuracy for CML-MC classifiers will become increased.

4.3 Analysis of Overall Performance

After the performance analysis of 3 different kinds of classifiers, currently we examine the total performance of Artificial Intelligence (AI) power screening solution for SARS-CoV2 infection System with the help of mediator dependent architecture. This architecture gives the best performance when the classifier is entirely independent. Here, these 3 classifiers are not entirely independent but almost they are independent because it performs a unique training and testing process. Now we examine the overall performance of the methodology under the assumption of independent architecture. For comparison of the misdiagnosis rate of individual classifier vs mediator results, this needs to be performed.

Let P1, P2, and P3 are the predicted class labels for CML-MC, DTL-BC and DTL-MC respectively. And Pf is the predicted analysis outcome of the mobile application. The probable values of Pf can yield are 'Probably COVID-19 (C_{p1})', 'Probably not COVID -19 (C_{p0})', 'Result indeterminate (C_I)'.

Then the possibility that the application predicts 'Probably COVID-19 (C_{p1})' when the case is infected by SARS-CoV2 can be evaluated in (8)

$$P(P_f = C_{p1}|C_{p1}) = P(P_1 = C_{p1}|C_{p1}) * P(P_2 = C_{p1}|C_{p1}) * P(P_3 = C_{p1}|C_{p1}) \tag{8}$$

= 0.918 * 0.898 * 0.943 = 0.777

Then the possibility that the application predicts 'Probably not COVID -19 (C_{p0})' when the case is not infected by SARS-CoV2 can be evaluated in (9)

$$P(P_f = C_{p0}|C_{p0}) = P(P_1 = C_{p0}|C_{p0}) * P(P_2 = C_{p0}|C_{p0}) * P(P_3 = C_{p0}|C_{p0}) \tag{9}$$

= 0.958* 0.968* 0.911 = 0.844

Then the possibility that the application predicts 'Probably COVID -19 (C_{p1})' when the case is not infected by SARS-CoV2 is shown in (10)

$$P(P_f = C_{p1}|C_{p0}) = P(P_1 = C_{p0}|C_{p1}) * P(P_2 = C_{p0}|C_{p1}) * P(P_3 = C_{p0}|C_{p1}) \tag{10}$$
= 0.041 * 0.031 * 0.084 = 1.184 $\times10^{-4}$

Then the possibility that the application predicts 'Probably not COVID -19 (C_{p0})' when the case is infected by SARS-CoV2 is shown in (11)

$$P(P_f = C_{p0}|C_{p1}) = P(P_1 = C_{p0}|C_{p1}) * P(P_2 = C_{p0}|C_{p1}) * P(P_3 = C_{p0}|C_{p1}) \tag{11}$$
= 0.081 * 0.101 * 0.056 = 4.581$\times10^{-4}$

The prominence of the tri pronged mediator in this proposed method shows how the low-risk model can minimize the total false positive and false negative rate of Artificial Intelligence (AI) power screening solution for SARS-CoV2 is shown in equation (4) and (5). Here the rate of misdiagnosis of the total model is nearly zero. Tri pronged mediator counts over-sensitivity or under-sensitivity of each classifier by screening it with 'Result indeterminate (C_I)'.

The possibility that the application predicts 'Result indeterminate (C_I)' when the case can either infected by SARS-CoV2 or not infected by SARS-CoV2 is evaluated in (12) and (13).

$$P(P_f = C_I|C_{p1}) = 1 - [\begin{matrix} P(P_f = C_{p1}|C_{p1}) + \\ P(P_f = C_{p1}|C_{p0}) \end{matrix}] \tag{12}$$

1-[0.777+4.581$\times10^{-4}$] = 0.222

$$P(P_f = C_I|C_{p0}) = 1 - [\begin{matrix} P(P_f = C_{p1}|C_{p0}) + \\ P(P_f = C_{p0}|C_{p0}) \end{matrix}] \tag{13}$$

1-[0.844+1.184 $\times10^{-4}$] = 0.155

Now, the application would forecast the indeterminate result of 37.7% of the time of $P(P_f = C_I) = [P(P_f = C_{pl}|C_{p0}) + P(P_f = C_{pl}|C_{p1})]$. By shifting the mediation approach for minimizing the percentage where the outcome of the application reflects a simple or weighted majority with M number of classifiers. Table 6 summarizes the outcome. The dependency factor can be captured by introducing the co-efficient factor.

4.4 Function of the Combiner

To get the results more accurate, Combiner evaluates the results of the IPC algorithm and Cough Detector, and generates the outcome as "Probably COVID-19" or "Probably not COVID-19" or "Result indeterminate" is shown in Table 11.

Table 11. Function of Combiner

Cough Detector	IPC Algorithm	Outcome
Probably COVID-19	High Risk	Probably COVID -19
Probably COVID-19	Low Risk	Probably COVID - 19
Probably COVID-19	Safe	Result Indeterminate
Probably not COVID-19	High Risk	Result Indeterminate
Probably not COVID-19	Low Risk	Probably not COVID-19
Probably not COVID-19	Safe	Probably not COVID-19
Result Indeterminate	High Risk	Probably COVID - 19
Result Indeterminate	Low Risk	Result Indeterminate
Result Indeterminate	Safe	Result Indeterminate

5. Conclusion

This paper proposed the Artificial Intelligence (AI) power screening solution for SARS-CoV2 infection with the help of Socio-Demographic Survey and Cough Detector through Mobile Application. The proposed method can help to detect the patient who might have any mild signs and symptoms. Also, acts as the test medium for COVID-19 cough diagnosis from different types of cough. We reported that COVID-19 cough contains the distinct latent attributes from other coughs. We evaluated the algorithm by latent attribute in COVID-19 cough patients and other coughs such as bronchitis, pertussis and non- infectious cough. From the perception of medical domain knowledge, we developed an application based on Artificial Intelligence centered tri- pronged mediator for cough-based analysis. The outcomes show this application can detect the COVID- 19 people from the public. The accuracy of the application is reliable because we collected huge cough related data samples from various open source websites and applied our proposed methodology in it. Our proposed methodology is trustworthy and shows reliable accuracy. This application also reduced the possibility of misdiagnosis because we developed this structure as the risk-avert architecture. This application can't compete with clinical testing. But it is a distinct functional application for tracing, monitoring, tracking and cost-effective tool and also helps to reduce the rapid spread of this pandemic virus by the virtual environment. In future, we are going to do this proposed methodology in real time and compared our results with other experimental data.

REFERENCES

[1] "CORD-19 | Semantic Scholar." https://www.semanticscholar. org/cord19(accessed Aug. 06, 2020).

[2] K. Sulaiman, T. Muhammad, M. AP, K. A.- medRxiv, and undefined 2020, "Trace, Quarantine, Test, Isolate and Treat: A Kerala Model of Covid-19 Response," *medrxiv.org*, Accessed: Aug. 01, 2020. [Online]. Available: https://www.medrxiv.org/content/10.1101/2020.06.15.20132308v1.abstract.

[3] "Test trace and treat COVID - Google Scholar." https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Test+trace+and+treat+COVID&btnG= (accessed Aug. 01, 2020).

[4] J. Cao, "A case report of an undiagnosed COVID-19 infection," 2020, Accessed: Aug. 01, 2020. [Online]. Available: https://www.researchsquare.com/article/rs-26291/latest.pdf.

[5] "active spreaders COVID - Google Scholar." https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=active+spreaders+COVID&btnG= (accessed Aug. 01, 2020).

[6] C. Bales *et al.*, "Can Machine Learning Be Used to Recognize and Diagnose Coughs?" Accessed: Aug. 01, 2020. [Online]. Available: https://arxiv.org/abs/2004.01495.

[7] M. S. Niederman, L. Richeldi, S. H. Chotirmall, and C. Bai, "Rising to the challenge of CovID-19: Advice for pulmonary and critical care and an agenda for research," *American Journal of Respiratory and Critical Care Medicine*, vol. 201, no. 9. American Thoracic Society, pp. 1019–1022, May 01, 2020, doi: 10.1164/RCCM.202003-0741ED.

[8] L. Li *et al.*, "Artificial intelligence distinguishes COVID-19 from community acquired pneumonia on chest CT," *ncbi.nlm.nih.gov*, Accessed: Aug. 01, 2020. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/pmc7233473/.

[9] A. Alimadadi, S. Aryal, I. Manandhar, P. B. Munroe, B. Joe, and X. Cheng, "Artificial intelligence and machine learning to fight covid-19," *Physiological Genomics*, vol. 52, no. 4. American Physiological Society, pp. 200–202, Apr. 01, 2020, doi: 10.1152/physiolgenomics.00029.2020.

[10]   K. Gostic, A. Gomez, R. Mummah, A. K.- Elife, and undefined 2020, "Estimated effectiveness of symptom and risk screening to prevent the spread of COVID-19," *elifesciences.org*, Accessed: Aug. 01, 2020. [Online]. Available: https://elifesciences.org/articles/55570.

[11]   R. Pal, A. A. Sekh, S. Kar, and D. K. Prasad, "Neural network based country wise risk prediction of COVID-19," Mar. 2020, Accessed: Aug. 01, 2020. [Online]. Available: http://arxiv.org/abs/2004.00959.

[12]   "AI-BASED   COUGH   DIAGNOSIS   FOR   COVID-19   -   Google   Scholar." https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=AI-BASED+COUGH+DIAGNOSIS+FOR+COVID-19+&btnG= (accessed Aug. 02, 2020).

[13]   A. Kelsall *et al.*, "How to quantify coughing: correlations with quality of life in chronic cough," *Eur Respir. Soc*, doi: 10.1183/09031936.00101307.

[14]   J. Vandermeulen, C. Bahr, D. Johnston, … B. E.-… and E. in, and undefined 2016, "Early recognition of bovine respiratory disease in calves using automated continuous monitoring of cough sounds," *Elsevier*, Accessed: Aug. 02, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169916305105.

[15]   S. Diwan, S. Ravichandran, … R. G.-T. of the, and undefined 2020, "Understanding Transmission Dynamics of COVID-19-Type Infections by Direct Numerical Simulations of Cough/Sneeze Flows," *Springer*, Accessed: Aug. 01, 2020. [Online]. Available: https://link.springer.com/content/pdf/10.1007/s41403-020-00106-w.pdf.

[16]   N. Sharma *et al.*, "Coswara-A Database of Breathing, Cough, and Voice Sounds for COVID-19 Diagnosis." Accessed: Aug. 02, 2020. [Online]. Available: https://github.com/.

[17]   T. Togun, B. Kampmann, N. G. Stoker, and M. Lipman, "Anticipating the impact of the COVID-19 pandemic on TB patients and TB control programmes," *Annals of Clinical Microbiology and Antimicrobials*, vol. 19, no. 1. BioMed Central Ltd., May 23, 2020, doi: 10.1186/s12941-020-00363-1.

[18]   X. Li, X. Zeng, B. Liu, and Y. Yu, "COVID-19 Infection Presenting with CT Halo Sign," *Radiol. Cardiothorac. Imaging*, vol. 2, no. 1, p. e200026, Jan. 2020, doi: 10.1148/ryct.2020200026.

[19]   C. Brown *et al.*, "Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data," *arxiv.org*, doi: 10.1145/nnnnnnn.nnnnnnn.

[20]   M. Lv *et al.*, "Coronavirus disease (COVID-19): A scoping review," *Eurosurveillance*, vol. 25, no. 15. European Centre for Disease Prevention and Control (ECDC), Apr. 16, 2020, doi: 10.2807/1560-7917.ES.2020.25.15.2000125.

[21]   D. Meidan *et al.*, "Alternating quarantine for sustainable mitigation of COVID-19," 2020. Accessed: Aug. 01, 2020. [Online]. Available: https://arxiv.org/abs/2004.01453.

[22]   "FDA   COVID   Quarantine   -   Google   Scholar." https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=FDA+COVID+Quarentine&btnG= (accessed Aug. 02, 2020).

[23]   Y. Zhang *et al.*, "Rapid Molecular Detection of SARS-CoV-2 (COVID-19) Virus RNA Using Colorimetric LAMP," *medrxiv.org*, doi: 10.1101/2020.02.26.20028373.

[24]   S. Woloshin, N. Patel, and A. S. Kesselheim, "False Negative Tests for SARS-CoV-2 Infection — Challenges and Implications," *N. Engl. J. Med.*, Jun. 2020, doi: 10.1056/nejmp2015897.

[25]   J. Hopkins and T. N. York, "Covid-19: FDA approves use of convalescent plasma to treat critically ill patients," *mariopolese.it*, 2020, doi: 10.1136/bmj.m1256.

[26]   X. Yang, U. San Diego, U. San Diego Jinyu Zhao, U. San Diego Yichen Zhang, U. San Diego Shanghang Zhang, and P. Xie, "COVID-CT-Dataset: A CT Image Dataset about COVID-19." Accessed: Aug. 02, 2020. [Online]. Available: https://www.medrxiv.org/.

[27]   S. Ying *et al.*, "Deep learning Enables Accurate Diagnosis of Novel Coronavirus (COVID-19) with CT images."

[28]   T. Liang *et al.*, "Evolution of CT findings in patients with mild COVID-19 pneumonia," *Springer*, doi: 10.1007/s00330-020-06823-8.

[29]   Y. Li and L. Xia, "Coronavirus disease 2019 (COVID-19): Role of chest CT in diagnosis and management," *Am. J. Roentgenol.*, vol. 214, no. 6, pp. 1280–1286, Jun. 2020, doi: 10.2214/AJR.20.22954.

[30]   X. Yang, X. He, J. Zhao, Y. Zhang, S. Zhang, and P. Xie, "COVID-CT-Dataset: A CT Scan Dataset about COVID-19," Mar. 2020, Accessed: Aug. 02, 2020. [Online]. Available: http://arxiv.org/abs/2003.13865.

[31]   F. Grillet, J. Behr, P. Calame, S. Aubry, and E. Delabrousse, "Acute Pulmonary Embolism Associated with COVID-19 Pneumonia Detected by Pulmonary CT Angiography," *Radiology*, p. 201544, Apr. 2020, doi: 10.1148/radiol.2020201544.

[32]   L. Wang and A. Wong, "COVID-Net: A Tailored Deep Convolutional Neural Network Design for Detection of COVID-19 Cases from Chest X-Ray Images," Mar. 2020, Accessed: Aug. 02, 2020. [Online]. Available: http://arxiv.org/abs/2003.09871.

[33]   A. Narin, C. Kaya, and Z. Pamuk, "Automatic Detection of Coronavirus Disease (COVID-19) Using X-ray Images and Deep Convolutional Neural Networks," Mar. 2020, Accessed: Aug. 02, 2020. [Online]. Available: http://arxiv.org/abs/2003.10849.

[34]   A. Abbas, M. M. Abdelsamea, and M. M. Gaber, "Classification of COVID-19 in chest X-ray images using DeTraC deep convolutional neural network," Mar. 2020, Accessed: Aug. 02, 2020. [Online]. Available: http://arxiv.org/abs/2003.13815.

[35]   J. Zhang *et al.*, "Viral Pneumonia Screening on Chest X-ray Images Using Confidence-Aware Anomaly Detection," 2020. Accessed: Aug. 02, 2020. [Online]. Available: https://arxiv.org/abs/2003.12338.

[36]   A. Khan, J. Shah, M. B.-C. M. and P. in, and undefined 2020, "Coronet: A deep neural network for detection and diagnosis of COVID-19   from   chest   x-ray   images,"   *Elsevier*,   Accessed: Aug.   02,   2020.   [Online].   Available: https://www.sciencedirect.com/science/article/pii/S0169260720314140.

[37]   E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, "COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-Ray Images," Mar. 2020, Accessed: Aug. 02, 2020. [Online]. Available: http://arxiv.org/abs/2003.11055.

[38]   Y. Fang *et al.*, "Sensitivity of Chest CT for COVID-19: Comparison to RT-PCR," *Radiology*, p. 200432, Aug. 2020, doi: 10.1148/radiol.2020200432.

[39]   P. van Kasteren, … B. van der V.-J. of C., and undefined 2020, "Comparison of commercial RT-PCR diagnostic kits for COVID-19," *Elsevier*, Accessed: Aug. 02, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1386653220301542.

[40]   A. I. Qureshi *et al.*, "Management of acute ischemic stroke in patients with COVID-19 infection: Report of an international panel," *Int. J. Stroke*, vol. 15, no. 5, pp. 540–554, Jul. 2020, doi: 10.1177/1747493020923234.

[41]   Preventing the spread of coronavirus disease 2019 in homes and residential communities. Centers for Disease Control and Prevention

website. https://www.cdc.gov/coronavirus/2019-ncov/hcp/guidance-prevent-spread.html. Updated March 6, 2020. Accessed March 27, 2020.

[42]   Flowchart to identify and assess 2019 novel coronavirus. Centers for Disease Control and Prevention website. https://www.cdc.gov/coronavirus/2019-ncov/hcp/clinical criteria.html?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fhcp%2Fidentify-assess-flowchart.html. Updated February 27, 2020. Accessed March 27, 2020..

[43]   Y. Wang, M. Hu, Q. Li, X.-P. Zhang, G. Zhai, and N. Yao, "ABNORMAL RESPIRATORY PATTERNS CLASSIFIER MAY CONTRIBUTE TO LARGE-SCALE SCREENING OF PEOPLE INFECTED WITH COVID-19 IN AN ACCURATE AND UNOBTRUSIVE MANNER," *arxiv.org*, doi: 10.6084/m9.figshare.11493666.v1.

[44]   T. Greenhalgh, X. H. Chan, Q. Durand-Moreau, and S. Straube, "What is the efficacy of standard face masks compared to respirator masks in preventing COVID-type respiratory illnesses in primary care staff?," 2020. Accessed: Aug. 01, 2020. [Online]. Available: www.cebm.net/oxford-covid-19/.

[45]   M. Faezipour and A. Abuzneid, "Smartphone-Based Self-Testing of COVID-19 Using Breathing Sounds," *liebertpub.com*, Jun. 2020, doi: 10.1089/tmj.2020.0114.

[46]   S. Cui, S. Chen, X. Li, S. Liu, and F. Wang, "Prevalence of venous thromboembolism in patients with severe novel coronavirus pneumonia," *J. Thromb. Haemost.*, vol. 18, no. 6, pp. 1421–1424, Jun. 2020, doi: 10.1111/jth.14830.

[47]   Y. Zhang *et al.*, "COVID-DA: Deep Domain Adaptation from Typical Pneumonia to COVID-19." Accessed: Aug. 02, 2020. [Online]. Available: https://arxiv.org/abs/2005.01577.

[48]   L. Zhang, D. C. Wang, Q. Huang, and X. Wang, "Significance of clinical phenomes of patients with COVID-19 infection: A learning from 3795 patients in 80 reports," *Clin. Transl. Med.*, vol. 10, no. 1, pp. 28–35, Jan. 2020, doi: 10.1002/ctm2.17.

[49]   S. P. Adhikari *et al.*, "Epidemiology, causes, clinical manifestation and diagnosis, prevention and control of coronavirus disease (COVID-19) during the early outbreak period: A scoping review," *Infectious Diseases of Poverty*, vol. 9, no. 1. BioMed Central Ltd., Mar. 17, 2020, doi: 10.1186/s40249-020-00646-x.

[50]   B. Udugama *et al.*, "Diagnosing COVID-19: The Disease and Tools for Detection," *ACS Publ.*, vol. 14, no. 4, pp. 3822–3835, Apr. 2020, doi: 10.1021/acsnano.0c02624.

[51]   "Piczak, Karol J. "ESC: Dataset for Environmental Sound Classification." http://dx.doi.org/10.1145/2733373.2806390. (2015)

[52]   E. Frigieri, P. Campos, A. Paiva, P. B.-A. Acoustics, and undefined 2016, "A mel-frequency cepstral coefficient-based approach for surface roughness diagnosis in hard turning using acoustic signals and gaussian mixture models," *Elsevier*, Accessed: Aug. 02, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0003682X16301840.

[53]   "Mel Frequency Cepstral Coefficients COVID - Google Scholar." https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Mel+Frequency+Cepstral+Coefficients+COVID&btnG= (accessed Aug. 02, 2020).

[54]   G. Deshpande and B. Schuller, "An Overview on Audio, Signal, Speech, & Language Processing for COVID-19," May 2020, Accessed: Aug. 02, 2020. [Online]. Available: http://arxiv.org/abs/2005.08579.

[55]   "Principal Component Analysis (PCA) COVID - Google Scholar." https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=Principle+Component+Analysis+%28PCA%29+COVID&btnG= (accessed Aug. 02, 2020).

[56]   A. Chandiok and D. K. Chaturvedi, "CIT: Integrated cognitive computing and cognitive agent technologies based cognitive architecture for human-like functionality in artificial systems," *Biol. Inspired Cogn. Archit.*, vol. 26, no. January, pp. 55–79, 2018, doi: 10.1016/j.bica.2018.07.020.

[57]   E. El-Din Hemdan, M. A. Shouman, and M. E. Karar, "COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-Ray Images." Accessed: Aug. 02, 2020. [Online]. Available: https://arxiv.org/abs/2003.11055.

[58]   A. Imran, I. Posokhova, H. Qureshi, … U. M.-I. in M., and undefined 2020, "AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an app," *Elsevier*, Accessed: Aug. 02, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2352914820303026.