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AI4COVID-19: AI Enabled Preliminary Diagnosis for COVID-19 from Cough Samples via an App

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ABSTRACT Inability to test at scale has become Achille's heel in humanity's ongoing war against COVID-19 pandemic. An agile, scalable and cost-effective testing, deployable at a global scale, can act as a game changer in this war. To address this challenge, building on the promising results of our prior work on cough-based diagnosis of a motley of respiratory diseases, we develop an Artificial Intelligence (AI)-based test for COVID-19 preliminary diagnosis. The test is deployable at scale through a mobile app named AI4COVID-19. The AI4COVID-19 app requires 2-second cough recordings of the subject. By analyzing the cough samples through an AI engine running in the cloud, the app returns a preliminary diagnosis within a minute. Unfortunately, cough is common symptom of over two dozen non-COVID-19 related medical conditions. This makes the COVID-19 diagnosis from cough alone an extremely challenging problem. We solve this problem by developing a novel multi-pronged mediator centered risk-averse AI architecture that minimizes misdiagnosis. At the time of writing, our AI engine can distinguish between COVID-19 patient coughs and several types of non-COVID-19 coughs with over 90% accuracy. AI4COVID-19's performance is likely to improve as more and better data becomes available. This paper presents a proof of concept to encourage controlled clinical trials and serves as a call for labeled cough data. AI4COVID-19 is not designed to compete with clinical testing. Instead, it offers a complementing tele-testing tool deployable anytime, anywhere, by anyone, so clinical-testing and treatment can be channeled to those who need it the most, thereby saving more lives.

INDEX TERMS Artificial Intelligence, COVID-19, preliminary medical diagnosis, pre-screening, public healthcare.

I. INTRODUCTION

By April 1, 2020 coronavirus disease 2019 (COVID-19) has 823,626 confirmed cases, caused 40,598 deaths while disrupting life in 206 countries and territories around the world [1]. The losses are compounding everyday. Given no vaccination or cure exists as of now, minimizing the spread by timely testing the population and isolating the infected people is the only effective defense mankind has at its disposal against the unprecedentedly contagious COVID-19. However, ability to deploy this defense strategy at this stage of pandemic hinges on a nation's ability to timely test significant fractions of its population including those who are not contacting medical system yet. Agile, scalable, and proactive testing capability has emerged as the key differentiator in some nations' ability to cope and reverse the curve of the pandemic, and the lack of the same is resulting in historic losses for others.

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A. WHY CLINIC VISIT BASED COVID-19 TESTING MECHANISMS ALONE MAY NOT SUFFICE TO CONTROL THE PANDEMIC AT THIS STAGE?

"Trace, Test and Treat" strategy succeeded in flattening the pandemic curve (e.g., in South Korea, China, and Singapore) at early stages of the spread. However, now in many parts

of the world the pandemic has already spread to an extent that this strategy is not proving effective anymore [2]. Recent studies show that, it is virus shedding often through coughing by undiagnosed population that is contributing to much rapid and covert spread [3]. Data shows that 81% of COVID-19 carriers do not develop symptoms too severe to seek medical help and yet act as active spreaders [4]. Others develop symptoms severe enough to prompt medical intervention only after several days of being infected. These findings call for a new strategy centered on *"Pre-screen/test proactively at population scale, self-isolate those tested positive for self-healing without further spreading and channel medical care towards the most vulnerable"*.

As per World Health Organization (WHO) guidance, Nucleic Acid Amplification Tests (NAAT) such as real-time Reverse Transcription Polymerase Chain Reaction (rRT-PCR) should be used for routine confirmation of COVID-19 cases by detecting unique sequences of virus ribonucleic acid (RNA). This test method while being the current gold standard is not sufficing to control the pandemic for reasons that include but are not limited to:

1) The geographical and temporal availability of such tests is limited.
2) The clinical tests are too expensive and scarce to cover the massive time-sensitive demand. Cost is not only an issue in poor countries but even in rich countries like the USA where 26 million Americans remain uninsured.
3) This kind of test requires an in-person visit to a hospital, clinic, lab or mobile lab. This inevitably requires breach of isolation of the suspected patients. Such visit exposes more members of the public to COVID-19 while the patient is en route to the test facility. This is not a trivial problem given the recent studies that show how highly stable and hence contagious COVID-19 appears to be. For example, [5] shows that the aerosol stability of COVID-19 is up to three hours in aerosols and up to seven days on different surfaces.
4) Hospitals are already becoming over-crowded. Even if the test is eventually done, while waiting for the medical staff to take nasopharyngeal or oropharyngeal swab, the patient is likely to expose many in the waiting rooms to the virus.
5) Turnaround time for current tests is several days, recently stretching to 10 days in some countries as labs are becoming overwhelmed [6], [7]. By the time a patient is diagnosed with current methods, the virus has already been passed to many.
6) Even with social distancing in place, the presence of untested carriers in the population exposes the first responders to the infection because of the nature of their job. For example, by the time of writing, hundreds of New York Police Department members have been tested positive and 3 have lost their lives [8].
7) In person testing methods put the medical staff, particularly those with limited protection, at serious risk of infection. This fact is becoming clear from the alarming number of doctors and nurses being tested positive. For example, recent reports show that thousands of healthcare workers around the globe have been infected by COVID-19 [9]. This trend is seriously concerning because medics are the first line of defense in this war against pandemic. Their safety will ultimately ensure a nation's ability to safely navigate through this pandemic. Inability to protect our medics can lead to further shortage of medical care, and increased distress on the already stressed medical staff. This in turn will deteriorate the system's ability to provide care to those most in need.

To make tests more readily accessible, on Mar. 28th the United States Food and Drug Administration (FDA) has approved a faster test that can yield results in 15 minutes [10]. The test works similar to Polymerase Chain Reaction (PCR) by identifying a portion of the COVID-19 RNA in the nasopharyngeal or oropharyngeal swab. While a leap forward, this test still requires an office visit and thus breach of social distancing and self-isolation, i.e., though much faster, the newly approved test still does not solve many of the aforementioned problems. Furthermore, emerging reports of shortages of critical equipment used to collect patient specimens, like masks and swabs, could blunt its impact on controlling the pandemic [11], [12].

In last few weeks, two alternative approaches leveraging AI-based analysis of the either X-ray [13] or CT Scan [14] images have been proposed in literature. Thanks to recent advances in AI-based image processing, these diagnosis approaches offer very high accuracy, in some cases even better than the rRT-PCR based test. However, both of these approaches while bypassing the need for a radiologist to perform the diagnosis, still require a visit to a well-equipped clinical facility. As a result, these approaches also inherit the issues of office visit based tests highlighted above.

It is mainly due to the difficulty of testing large swaths of populations timely, safely and cost effectively and exactly track the actual spread that even the richest nations on earth are finding it difficult to contain the pandemic.

B. PROPOSED COUGH BASED COVID-19 SCREENING APPROACH

The idea of using cough for possible preliminary diagnosis of COVID-19 and its feasibility is motivated by the following key findings:

1) Our prior studies have shown that cough from distinct respiratory syndromes have distinct latent features [15]. These distinct features can be extracted by appropriate signal processing and mathematical transformations of the cough sounds. The features can then be used to train a sophisticated AI engine for performing the preliminary diagnosis solely based on cough. Our in-depth analysis of the pathomorphological alternations caused by COVID-19 in the respiratory system (reported in Section II), shows that the alternations are distinct from those caused by other common non-

COVID-19 respiratory diseases. This finding is corroborated by the meta-analysis of several independent recent studies (reported in Section II) that shows that COVID-19 infects the respiratory system in a unique way. Therefore, it is logical to hypothesize that cough caused by COVID-19 is also likely to have distinct latent features. These distinct latent features can be exploited to train a domain aware AI engine to differentiate COVID-19 caused cough from non-COVID-19 cough. Our experiments (Figure 1, Section III-C) show that this is indeed possible.

2) Cough is manifested as a symptom in majority (e.g., 67.7% as per [16]), but not all COVID-19 carriers. However, studies show that coughing is the main mechanism of social spreading of COVID-19 [3]. Droplets containing virus emitted through cough and landing on the surfaces where the virus has been shown to survive for long periods of time, have been reported to be the most prolific mechanism of spreading the COVID-19 [17]. Hence, if a COVID-19 patient is not showing cough as a symptom, that patient is most likely not spreading as actively as a coughing COVID-19 patient. In other words, cough-based testing, even if far from being as authentic as clinical testing, can actually directly help in reducing R_0 and thus flattening the curve of the pandemic [4].

3) Due to the ease of measure, currently temperature scan is the predominant screening method for COVID-19, e.g., used at the airports. However, between cough and fever, the number of non-COVID-19 medical conditions that can cause fever is much larger than the non-COVID-19 conditions that can cause cough. Our analysis shows that cough contains COVID-19 specific features even if it is non-spontaneous, i.e., when the COVID-19 patient is asked to cough. This means cough can be used as a pre-screening method by asking the suspect patient to simulate cough, even if the patient is not showing it as a spontaneous symptom.

C. CONTRIBUTIONS AND PAPER CONTENTS

The contributions and contents of this paper are outlined below:

1) We analyze the pathomorphological changes caused by the COVID-19 in the respiratory system from the studies examining X-rays and CT scans of live COVID-19 patients. Our analysis also includes the autopsy report studies of deceased patients. The purpose of this analysis is to apply first principle-based approach. The goal is to see if the pathomorphological alterations caused by COVID-19 in the respiratory system (i.e., the part of body that produces cough sound) are different from those caused by other common bacterial or viral infections. This is to determine: is it even theoretically possible for the COVID-19 cough to have any unique latent features. The in-depth study of pertinent pathomorphological alterations suggests that it is possible.

2) Building on the insights from first principle-based approach and our prior work that shows cough alone can be used for successful AI based diagnosis of several respiratory diseases [15], we hypothesize that "Cough sound can be used at least for preliminary diagnosis of the COVID-19 by performing differential analysis of its unique features relative to other non-COVID-19 coughs".

3) Continuing the medical literature review, we further identify and shortlist the non-COVID-19 respiratory syndromes that are relatively common and are known to cause similar sounding cough as that of COVID-19 patients. The shortlist includes pertussis, bronchitis, influenza, asthma, pneumonia, bronchiolitis, and croup.

4) Given that even the shortlist is too long to gather reliable data for this time sensitive project, we reduce the size of our data gathering campaign to a manageable one by leveraging the findings from literature which shows that cough caused by the last five medical conditions in the shortlist above does have features unique to each condition. Therefore, in the interest of time, we go on to focus on the differential analysis of COVID-19 cough, and coughs associated with pertussis and bronchitis as these two conditions are not examined earlier.

5) We gather cough data of COVID-19, pertussis, and bronchitis patients. Cough samples from COVID-19 patients include both spontaneous cough (symptomatic) and non-spontaneous (i.e., when the patient is asked to cough). This is to make the test applicable to those who may not be showing cough as a symptom yet but are already infected. We also gather cough samples from otherwise healthy individuals with no known medical condition, hereafter referred to as normal cough. The normal cough is included in the analysis to see if it can be differentiated from the simulated cough produced by the COVID-19 patients. Using these data, we test the hypothesis using a variety of data analysis and pre-processing tools. Multiple alternative analysis approaches show that COVID-19 associated cough does have unique features, at least when compared to pertussis, bronchitis, and the normal cough.

6) Building on the insights from domain knowledge and data, we develop an AI engine for preliminary diagnosis of COVID-19 from cough sounds. This engine runs on a cloud server with a front-end programmed as a simple user-friendly mobile app called AI4COVID-19. The app listens to cough when prompted, and then sends it to the AI engine wirelessly. The AI engine first runs a test to see if the recorded sound is a cough or not a cough. In case the sound is not a cough, it commands the app to indicate so. The cough detection part of the AI engine is designed to detect cough even in the presence of background noise. This is to make the app a useful screening tool even at public places such as airports and crowded shopping malls. If a cough is detected, it is passed on to the diagnosis part of the AI engine. After the AI engine completes the analysis, the app renders the result with three possible outcomes:

- COVID-19 likely.
- COVID-19 not likely.
- Test inconclusive.

7) To make the results as reliable as possible with the

limited data available at the moment, we propose and implement a novel architecture for the AI engine. It consists of three parallel classification solutions designed independently by three teams. The classifiers outcomes are cross-validated by an automated mediator. Each classifier has a veto power, i.e., if all three classifiers do not agree, the app returns 'Test inconclusive'. This novel architecture thus minimizes chances of misdiagnosis, compared to stand alone classifiers with binary diagnosis.

II. HYPOTHESIS FORMULATION AND DEVISING A MANAGEABLE VALIDATION STRATEGY GUIDED BY RELEVANT CLINICAL FINDINGS

Our hypothesis in question is: *"Cough sound of the COVID-19 patients contains unique enough latent features to be used as a diagnosis medium"*. In this section, we describe our first principle-based approach that established the theoretical possibility of our hypothesis to be true. Then we describe the deep domain knowledge-based approach we take to reduce the amount of data required to test this hypothesis, thereby making this project feasible in a constrained time.

A. IS COVID-19 COUGH UNIQUE ENOUGH TO YIELD AI BASED DIAGNOSIS?

Unfortunately, cough is a very common symptom of over a dozen medical conditions caused by either bacterial or viral respiratory infections not related to COVID-19. Several non-respiratory conditions can also cause cough. Table 1 summarizes the non-COVID-19 medical conditions all of which are known to cause cough. Theoretically, a cough based COVID-19 diagnosis, therefore, must take into account the cough sound data associated with all of the conditions listed in the Table 1.

Table 1: Non-COVID-19 Medical Conditions that can Cause Cough

RESPIRATORY	NON-RESPIRATORY
Upper respiratory tract infection (mostly viral infections)	Gastro-esophageal reflux
Lower respiratory tract infection (pneumonia, bronchitis, bronchiolitis)	Drugs (angiotensin converting enzyme inhibitors; beta blockers)
Upper airway cough syndrome	Laryngopharyngeal reflux
Pertussis, parapertussis	Somatic cough syndrome and tic cough
Tuberculosis	Vocal cord dysfunction
Asthma and allergies	Obstructive sleep apnea
Early interstitial fibrosis, cystic fibrosis	Somatic cough syndrome and tic cough
Chronic obstructive pulmonary disease (emphysema, chronic bronchitis)	Smoking
Postnasal drip	Foreign body
Croup	Mediastinal tumor
Laryngitis	Air pollutants
Tracheitis	Tracheo-esophageal fistula
Lung abscess	Left-ventricular failure
Lung tumor	Congestive heart failure
Pleural diseases	Psychogenic cough
Interstitial lung disease	Idiopathic cough

Human ear is definitely not capable to differentiate cough from all the conditions listed in Table 1. If there are no unique latent features in the cough sound of COVID-19 patients, there is a risk for a cough-based AI diagnosis tool to confuse cough caused by any of the diseases identified in Table 1 with the cough caused by COVID-19. A brute force-based approach to evaluate this risk would require gathering cough data from a large number of patients for each of the conditions listed in Table 1. This deluge of data can be then used to train a powerful AI engine such as very deep neural network to see if it can differentiate COVID-19 cough from that caused by all of other medical conditions listed in Table 1. This approach is not practical at the moment given gathering such all-encompassing data will take too much time, rendering this approach of no help for the current pandemic.

To ensure that our developed solution works in practice with useful accuracy while being trainable with timely available data, we take another approach that we call domain-aware AI-design. Domain-aware here refers to the fact that the proposed AI engine does not solely rely on blind big data churning, e.g., through a deep neural network. Instead it relies on the deep domain knowledge of medical researchers trained in respiratory and infectious diseases to assess and narrow down the hypothesis testing space, and minimize the amount of data needed to test our hypothesis.

To this end, the medical researcher in our team began by analyzing in-depth the pathomorphological changes caused by COVID-19 in respiratory system by examining the data reported in numerous recent X-rays [13], [18]–[20] and CT-scans based studies [14], [21], [22] of COVID-19 patients. The goal here is to see if the pathomorphological alterations caused by COVID-19 are distinct from that of other common medical conditions, particularly the ones identified in Table 1, that are well known to cause cough. If this turns out to be the case, then in cough caused by COVID-19 we should have latent features distinct from the cough caused by the other medical conditions. An appropriately designed AI should then be able to pick these cough feature idiosyncratic to COVID-19 infection and yield a reliable diagnosis, given enough labeled data. If no such differences exist at pathomorphological level, the idea of cough based COVID-19 diagnosis should be dropped. Because in that case, any AI based diagnosis yielded from cough is more likely to be frivolous correlation and not a meaningful causal relationship. Such-AI based diagnosis will be an artifact of the training data rather than unique latent features of COVID-19 caused cough. Such domain oblivious solution irrespective of its performance in lab, will not be useful in practice.

B. DISTINCT PATHOMORPHOLOGICAL ALTERNATIONS IN RESPIRATORY SYSTEM CAUSED BY COVID-19

Recent studies show that in COVID-19 infected people, there are distinct early pulmonary pathological signs even before the onset of the symptoms of COVID-19 such as dry cough, fever and some difficulty in breathing [23]. Early histological changes include evident alveolar damage with alveolar edema and proteinaceous exudates in alveolar spaces, with granules; inflammatory clusters with fibrinoid material and multinucleated giant cells; vascular congestion. Reactive alveolar epithelial hyperplasia and fibroblastic proliferation (fibroblast plugs) was indicative of early organization [23].

CT scan based studies shows that on the early stage of COVID-19 disease, it mainly manifests as inflammatory infiltration restricted to the subpleural or peribronchovascular regions of one lung or both lungs, exhibiting patchy or segmental pure ground-glass opacities (GGOs) with vascular dilation. There is an increasing range of pure GGOs and involvement of multiple lobes of lung, consolidation of lesions and crazy-paving patterns during the progressive stage. There are diffuse exudative lesions and lung "white-out" during advanced stage [24].

In some patients, COVID-19 leads to onset of pneumonia and pneumonia is marked by a peculiar cough. However, pneumonia can also be caused by many other factors including non-COVID-19 viral or bacterial infections. Therefore, the question arises: is there a difference between COVID-19 caused pneumonia and other types of pneumonia that can be expected to translate into a difference in associated cough's latent features? Researches show that compared to non-COVID-19 related pneumonia, COVID-19 related pneumonia on chest CT scan was more likely to have a peripheral distribution (80% vs. 57%), ground-glass opacity (91% vs. 68%), vascular thickening (59% vs. 22%), reverse halo sign (11% vs. 9%) and less likely to have a central+peripheral distribution (14% vs. 35%), air bronchogram (14% vs. 23%), pleural thickening (15% vs. 33%), pleural effusion (4% vs. 39%) and lymphadenopathy (2.7% vs. 10.2%) [25].

These findings suggest that cough sound signatures with COVID-19 caused pneumonia are likely to have some idiosyncrasies stemming from the distinct underlying pathomorphological alterations.

Furthermore, AI based analyses of X-ray [13] and CT scan [14] of the respiratory system have also shown to exploit the differences in pathomorphological alternations caused by COVID-19 to perform differential diagnosis among bacterial infection, non-COVID-19 viral infection and COVID-19 viral infection, with remarkable accuracy. This further implies that COVID-19 affects the respiratory system in a fairly distinct way compared to other respiratory infections. Therefore, it is logical to hypothesize that the sound waves of cough produced by COVID-19 infected respiratory system is also likely to have unique latent features and the risk of these features overlapping with those associated with other respiratory infections is low. This hypothesis is supported not only by our own prior studies for diagnosing several common respiratory diseases using cough [15], but also in a recent clinically validated and widely publicized study [26]. In [26], a large team of researchers showed that cough alone can be used to diagnose asthma, pneumonia, bronchiolitis, croup, and lower respiratory tract infections with over 80% sensitivity and specificity. Another very recent study shows that cough can be used to successfully diagnose influenza [27].

However, to the best of authors' knowledge, no study so far has leveraged cough for diagnosis of COVID-19 while presenting a mobile app base solution for anytime, anywhere virtual testing and pre-screening for COVID-19.

III. DATA DESCRIPTION AND PRACTICAL VIABILITY OF THE SOLUTION WITH AVAILABLE DATA

As mentioned earlier, ideally cough data associated with all diseases listed in Table 1 is desirable for such a project. However, gathering such mammoth data is not possible in this time constrained project, as COVID-19 pandemic needs rapid response. To achieve meaningful results in the constrained time, we leverage domain knowledge, instead of just seeking big data. From Table 1, using the insights from Section II, we shortlist cough causing infections that are most likely to confuse our AI engine due to having similar pathomorphological changes in the respiratory system as of COVID-19 and, hence, similar cough signatures. The shortlist includes pertussis, bronchitis, asthma, pneumonia, bronchiolitis, croup, and influenza. We further note that prior studies have shown that cough associated with all of these seven medical conditions, except pertussis and bronchitis [26], [27], have unique latent features. We use findings from these earlier studies to reduce the scope of our data gathering campaign and differential analysis to only the respiratory diseases, the cough for which has not been analyzed before for having unique features, i.e., pertussis and bronchitis.

A. DATA USED FOR TRAINING COUGH DETECTOR

In order to make AI4COVID-19 app employable in a public place or where various background noises may exist (e.g., airport), we design and include a cough detector in our AI-Engine. This cough detector acts as a filter before the diagnosis engine and is capable to distinguish sound from 50 other common environmental noise. To train and test this detector, we use ESC-50 dataset [28]. The ESC-50 dataset is a publicly available dataset that provides a huge collection of speech and environmental sounds. This collection of sounds is categorized into 50 classes, one of these being cough sounds. We have used 993 cough sounds and 993 non-cough environmental sounds for training of our cough detection system.

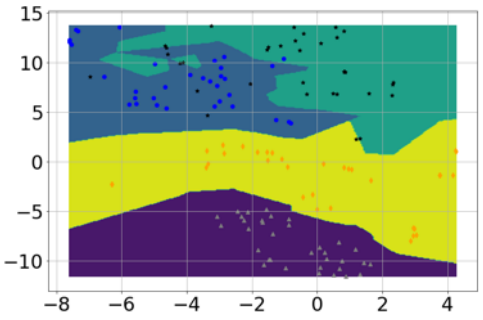

Figure 1: Visualization of features for the four classes via t-SNE (gray triangles correspond to normal, blue circles correspond to bronchitis, black stars correspond to pertussis, and orange diamonds represent COVID-19 cough.

B. DATA USED FOR TRAINING COVID-19 DIAGNOSIS ENGINE

To train our cough diagnosis system, we collected cough sounds from COVID-19 patients as well as pertussis and bronchitis. We also collected normal coughs, i.e., cough sounds from healthy people. At the time of writing, we had access to 102 bronchitis, 131 pertussis, 48 COVID-19, and 76 normal cough sounds to train and test our diagnosis system. Obviously these are very small numbers of samples and more data is needed to make the solution more reliable. New COVID-19 cough samples are arriving daily and we are using these unseen samples to test the trained algorithm. Even with small training data, very promising accuracy has been observed on unseen test samples, as reported in Section V.

C. DATA PRE-PROCESSING AND VISUALIZATION TO EVALUATE PRACTICAL FEASIBILITY OF AI4COVID-19

In Section II, we assessed and established the theoretical viability of our hypothesis using deep domain knowledge. However, in machine learning based solutions, theoretical viability does not guarantee practical viability as the end outcome depends on the quantity and quality of the data, in addition to the sophistication of machine learning algorithm used. Therefore, here we use the available cough data from the four classes to first evaluate the practical feasibility of a cough based COVID-19 diagnosis solution.

We convert the cough data for all four classes into Mel scale for further processing. The Mel scale is a pitch categorization where listeners judge changes in pitch to be equal in distance from one another along this scale. It is meant to make changes in frequency, such as with a spectrogram, more closely reflect audible changes. There are several methods for converting the frequency scale to Mel. Here, we convert frequency f into Mel scale m as:

$$m = 2595 \times \log_{10}\left(1 + \frac{f}{700}\right) \tag{1}$$

We perform Cepstral analysis on the Mel spectrum of audio cough samples to compute their Cepstral coefficients, commonly known as Mel Frequency Cepstral Coefficients (MFCC). The extracted MFCC features for every sample result in an $M \times N$ matrix, where each column represents one signal frame and each row represents extracted MFCC features for a specific frame. The number of frames N can vary from sample to sample. There are several possible ways to use these extracted features for classification. In our approach, we extract two $M \times 1$ MFCC based feature vectors for each input cough sample and concatenate them into a single final $2M \times 1$ feature vector for that sample. For the first feature vector, we take the mean of MFCC features corresponding to all the frames. For the second feature vector, we take the top few Principle Component Analysis (PCA) projections of the MFCC features across all the frames and combine them into a single $M \times 1$ vector by taking their magnitude. Finally, we concatenate both feature vectors into a single $2M \times 1$ feature vector. This approach is further illustrated in Figure 5 in Section IV-C.

Figure 1 illustrates the 2-D visualization of these features for the four classes through t-distributed Stochastic Neighbor Embedding (t-SNE) with classification decision boundaries/contours. It can be seen from the figure that different cough types possess features distinct from each other, and the features for COVID-19 are different from other cough types, such as bronchitis and pertussis. Hence, this observation validates the practical viability of AI4COVID-19 based diagnosis encouraging us to proceed towards AI-engine design for maximum accuracy and efficient implementation.

IV. THE AI4COVID-19 AI-ENGINE

In this section we explain the system architecture and the details of a two stage solution that we developed for: 1) detection of cough sound from mixed cough, non-cough, and noisy sounds; and 2) diagnosis of COVID-19 from the cough sound.

A. SYSTEM ARCHITECTURE

The overall system architecture is illustrated in Figure 2. The smartphone app records sound/cough when prompted with the press and release button. The recorded sounds are transmitted to the server when the diagnosis button is pressed. At the server, the sounds are first fed into the cough detector. In case, the sound is not detected to be cough, the server commands the app to prompt so. In case, the sound is detected to be a cough, the sound is forwarded to the three parallel, independent classifier systems: Deep Learning-based Multi Class classifier (DL-MC), Classical Machine Learning-based Multi Class classifier (CML-MC), Deep Learning-based Binary Class classifier (DL-BC). The results of the all three classifiers are then passed on to a mediator. The app reports a diagnosis only if all three independent classifiers return identical classification results. If the classifiers do not agree, the app returns 'test inconclusive'. This tri-pronged mediator centered novel architecture is designed to effectively minimize the probability of misdiagnosis. With this architecture, results show that AI4COVID-19 engine predicting 'COVID-19 likely' when

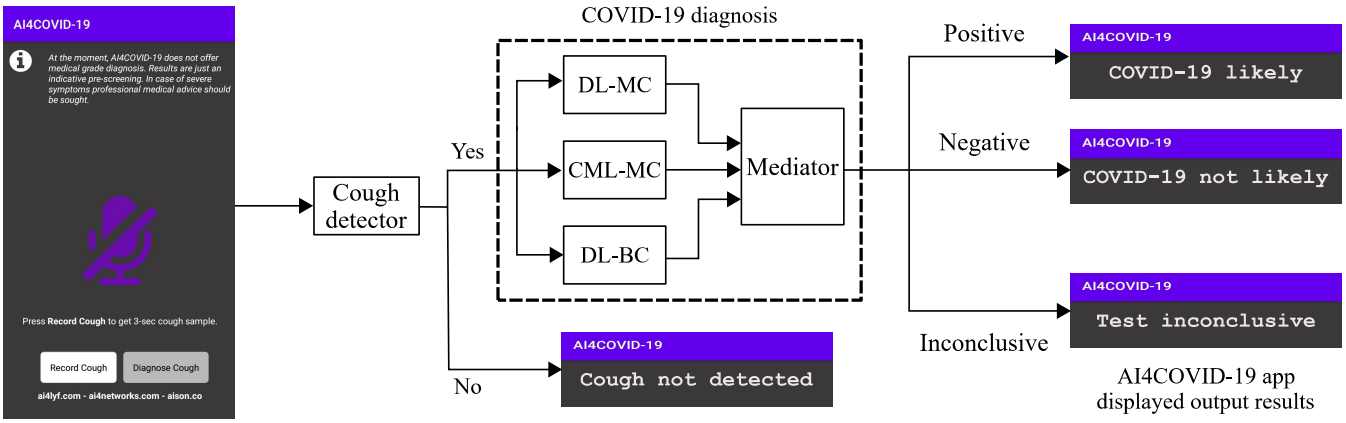

Figure 2: Proposed system architecture of AI4COVID-19, showing snapshot of Smartphone App at user front-end and back-end cloud AI-engine blocks consisting of Cough Detector block (further elaborated in Figure 3) and COVID-19 diagnosis block containing Deep Learning-based Multi-Class classifier (DL-MC), Classical Machine Learning-based Multi-Class classifier (CML-MC), and Deep Learning-based Binary-Class classifier (DL-BC), further elaborated in Figure 4 and Figure 5.

the subject is not suffering from COVID-19 or vice-versa is extremely low, almost zero on the testing data available at the time of writing. This idea is inspired from the "second opinion" practice in health care. The added caution here is that three independent opinions (diagnosis) are solicited, each with veto power. How this novel architecture manages to reduce the overall misdiagnosis rate of the AI4COVID-19 despite the relatively higher misdiagnoses rate of individual classifiers is further explained in Section V-C through (9) and (10).

The details of detection and diagnosis classifiers are presented below.

B. COUGH DETECTION

The recorded cough sample is forwarded to our network server where the cough detector engine first computes its Mel-spectrogram (as explained in Section III-C), converts it into grayscale to unify the intensity scaling and reduce the image dimensions, and feed it into the Convolutional Neural Network (CNN) to decide whether the recorded sound is of cough or not.

An overview of our used CNN structure is shown in Figure 3. As the input Mel spectrogram image is of high dimensions, it's first passed through a 2×2 max-pooling layer to reduce the overall model complexity before proceeding. This relatively smaller image is then passed to two convolutional layers consisting of 32 filters and 5×5 kernel size with a max-pooling layer in between to learn the complex features, which are then passed to a 2×2 max-pooling to represent the learned features in lower dimensions. The image is flattened to 1 dimension and then passed to two fully connected layers with 128 neurons each. 0.5 dropout is used in both of these to avoid overfitting.

The final layer is the softmax classification layer with 2 neurons to distinguish between cough and not cough for the given input. The number of convolutional and fully connected layers are kept low to minimize potential overfitting issues. Since ReLU is the current standard for CNNs, it is used for the activation functions of this model, while Adam [29] is used as the optimizer due to its relatively better efficiency and flexibility. A binary cross entropy loss function completes the detection model.

C. COVID-19 DIAGNOSIS

In the case of cough detection, the cough sound is forwarded to our tri-pronged mediator-centered AI engine to diagnose between COVID-19 and non-COVID-19 coughs. In order to produce results with maximum reliability, with the limited data available at the moment, the three classifiers used in the system use different approaches and are designed independently by three teams and cross-validated. The three classification approaches are described below.

1) Deep Learning-based Multi Class classifier (DL-MC)

The first solution leverages a CNN based four class classifiers using Mel spectrograms (described above) as input. The four classes here are cough caused by: 1) COVID-19, 2) pertussis, 3) bronchitis, or 4) normal person with no known infection. The same type of machine learning categorization procedure used for binary-class cough detection is applied to the labeled cough data originating from several different illnesses. However, due to the differences between two coughs of differing illnesses typically being subtler than a cough and non-cough event, a more complex set of layering is required for this version of the CNN. This classifier architecture is illustrated in Figure 4. The diagnosis CNN begins with a 2×2 max-pooling layer which is followed by two blocks of layers, each block comprising two convolutional layers followed by a 2×2 max pooling layer and a 0.15 dropout. All the convolutional layers have 16 filters and a 3×2 kernel size. The complex learned features from these 4 convolutional layers are flattened and then passed to a fully connected layer of 256 neurons followed by a 0.15 dropout layer to prevent overfitting. Finally, the output layer with 4 neurons and softmax activation function is used to classify the input between 4 possible diseases.

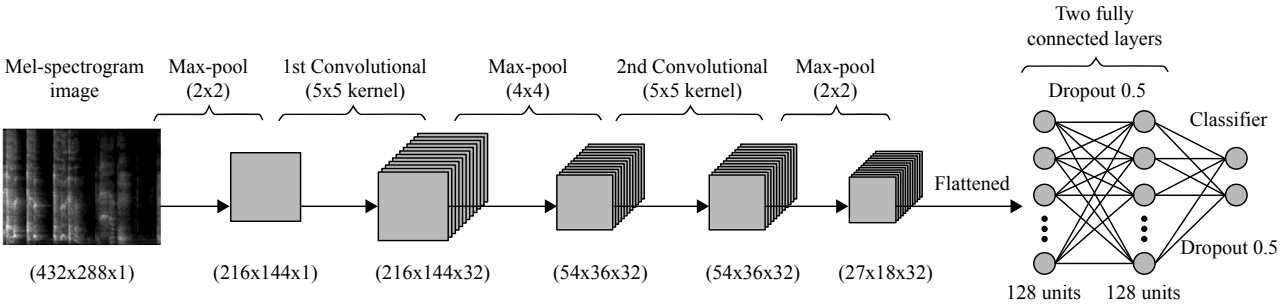

Figure 3: Cough detection classifier.

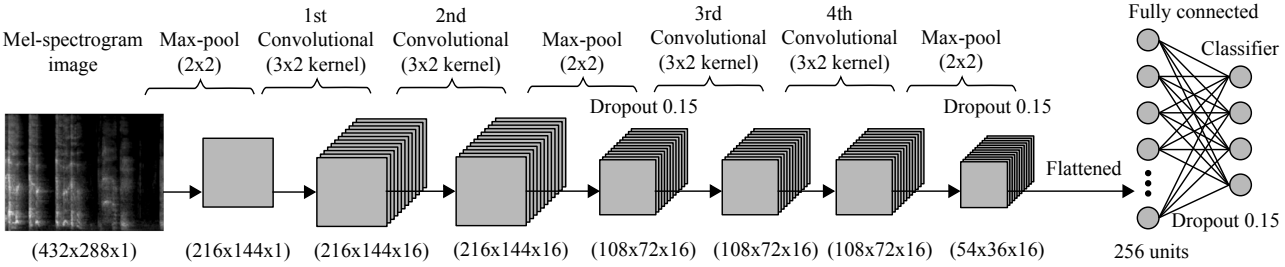

Figure 4: Deep Learning-based Multi-Class classifier (DL-MC).

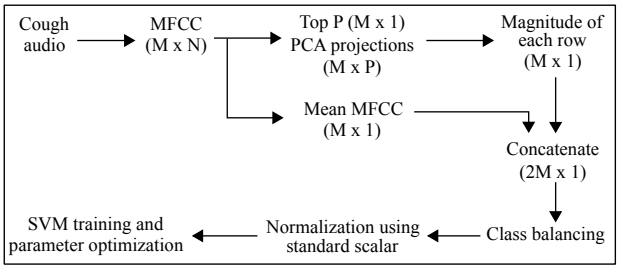

Figure 5: Classical Machine Learning-based Multi-Class classifier (CML-MC).

2) Classical Machine Learning-based Multi Class classifier (CML-MC)

A second parallel diagnosis test uses classic machine learning instead of deep learning. It begins with a different preprocessing of cough sounds. Instead of using spectrogram like the first classifier, it uses MFCC and PCA based feature extraction as explained in Section III-C. These smart features are then fed into a multi-class support vector machine for classification.

Class balance is achieved by sampling from each class randomly such that the number of samples equals to the number of minority class samples, i.e., class with the lowest number of samples. Using the concatenated feature matrix (of mean MFCC and top few PCAs) as input, we perform SVM with k-fold validation for 100,000 iterations. This approach is illustrated in Figure 5.

3) Deep Learning-based Binary Class classifier (DL-BC)

The third parallel diagnosis test also uses deep learning based CNN on the Mel spectrogram image of the input cough samples, similar to the first branch of the AI engine, but performs only binary classification of the same input, i.e., is the cough associated COVID-19 or not. The CNN structure used for this technique is the same as the one used for cough detector, elaborated in Figure 3.

V. RESULTS AND DISCUSSION

In order to evaluate the model we use the performance metrics of *accuracy*, *specificity*, *sensitivity/recall*, *precision*, *F1-score* on validation set and also cross-validate the models. These metrics are calculated as follows:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$specificity = \frac{TN}{TN + FP} \tag{3}$$

$$sensitivity/recall = \frac{TP}{TP + FN} \tag{4}$$

$$precision = \frac{TP}{TP + FP} \tag{5}$$

$$F1 - score = 2 * \left(\frac{precision \times recall}{precision + recall} \right) \tag{6}$$

Here, TP, TN, FP, and FN refer to True Positives, True Negatives, False Positives, and False Negatives, respectively.

These performance metrics are based on mean confusion matrices from 2-fold cross validation.

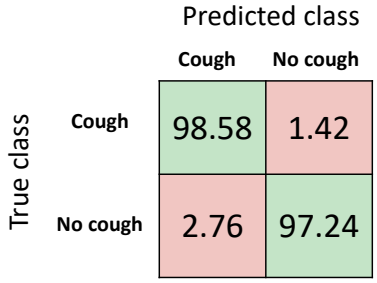

Figure 6: Normalized confusion matrix for cough detection (in percentage).

Table 2: Performance Metrics for Cough Detection

F1-Score (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
97.92	98.58	97.24	97.28	97.91

A. COUGH DETECTION

The confusion matrix and performance metrics for detection algorithm are reported in Figure 6 and Table 2, respectively. Results demonstrate that our cough detection algorithm can classify between cough event and no cough event with an overall accuracy of 97.91%.

B. COVID-19 DIAGNOSIS

The performance metrics for the first classifier, DL-MC classifier are reported in Table 3. At the moment, with limited data available, the overall accuracy of deep learning based multi-class classifier is 93.56%. Future work will continue to improve this model as more training data becomes available for CNN.

For the second classifier, i.e., CML-MC classifier, the normalized confidence matrix is shown in Figure 7 and the CDF of overall accuracy with varying k's in k-fold cross validation is shown in Figure 8. Table 4 reports the performance metrics for this approach, utilizing data available at this moment. Results indicate an overall accuracy of 94.06%.

Table 3: Performance Metrics for DL-MC

	F1-Score (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
Overall	-	-	-	-	93.56
COVID-19	93.14	99.67	97.50	87.42	-
Pertussis	94.74	90.00	100.0	100.0	-
Bronchitis	90.32	93.33	93.74	87.50	-
Normal	99.77	100.0	99.95	99.54	-

Table 4: Performance Metrics for CML-MC

	F1-Score (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
Overall	-	-	-	-	94.06
COVID-19	97.99	96.76	99.76	99.27	-
Pertussis	89.12	85.33	97.94	93.26	-
Bronchitis	90.45	94.13	95.33	87.04	-
Normal	98.58	100.0	99.04	97.19	-

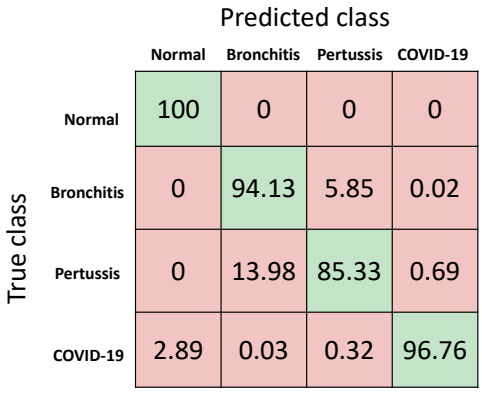

Figure 7: Normalized confusion matrix for cough diagnosis (in percentage).

Table 5: Performance Metrics for DL-BC

F1-Score (%)	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
90.32	93.33	83.33	87.50	88.89

Performance metrics for the third approach, DL-BC are reported in Table 5. Currently, the classification accuracy with this approach is 88.89%. The lower classification accuracy of this classifier can be attributed to class bias, since the number of non-COVID cough samples are much larger than COVID-19 cough samples, when binary classification is chosen. This artifact is likely to diminish once more data becomes available.

While at the moment, the performance of the two deep learning based classifiers (DL-MC and DL-BC) is slightly lower than the manual feature extraction based classic machine learning classifier (CML-MC), as the data becomes abundant, the deep learning based classifiers are likely to yield better performance. This is expected, because with large amount of training data automatic feature extraction capability of the deep neural network is expected to extract even more subtle distinct features hidden in the data than the manual feature extraction used in the second classifier, i.e., CML-MC.

C. OVERALL PERFORMANCE OF AI4COVID-19 AI ENGINE

After looking at the performance of the three different independent classifiers used in our architecture, we now analyze the overall performance of AI4COVID-19 AI engine that utilizes a mediator based novel architecture. Let k_1, k_2, k_3 be the predicted class labels for the three classifiers, DL-MC, CML-MC and DL-BC, respectively and k_f be the predicted diagnosis result of the app. The possible values that k_f can take are 'COVID-19 likely' (C), 'COVID-19 not likely' (C') and 'test inconclusive' (I).

Then, the probability that the app predicts 'COVID-19 likely', when the patient actually has COVID-19, can be calculated as:

Table 6: The Overall Current Performance of AI4COVID-19 AI Engine

Event	Probability
App reports 'COVID-19 likely' when the subject actually has COVID-19	0.893
App reports 'COVID-19 likely' when the subject actually does not have COVID-19	0.0000084
App reports 'COVID-19 not likely' when the subject actually does not have COVID-19	0.809
App reports 'COVID-19 not likely' when the subject actually has COVID-19	0.00000643
App reports 'test inconclusive' when the subject actually has COVID-19	0.107
App reports 'test inconclusive' when the subject actually does not have COVID-19	0.191

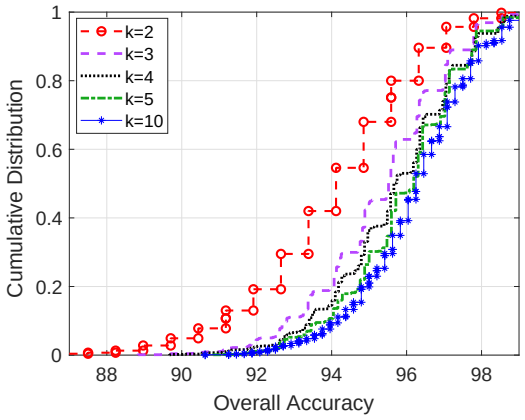

Figure 8: Overall accuracy CDF for varying k-fold experiments in classical ML approach.

$$P(k_f = C|C) = P(k_1 = C|C) \cdot P(k_2 = C|C) \cdot P(k_3 = C|C) = 0.99 \cdot 0.97 \cdot 0.93 = 0.893 \quad (7)$$

The probability that the app predicts 'COVID not likely' when the subject actually does not have COVID-19 can be represented as:

$$P(k_f = C'|C') = P(k_1 = C'|C') \cdot P(k_2 = C'|C') \cdot P(k_3 = C'|C') = 0.975 \cdot 0.997 \cdot 0.833 = 0.809 \quad (8)$$

The app can also predict 'COVID-19 likely' when the subject is not suffering from COVID-19 or vice-versa. In these cases, we can write the probabilities as:

$$P(k_f = C|C') = P(k_1 = C|C') \cdot P(k_2 = C|C') \cdot P(k_3 = C|C') = 0.025 \cdot 0.002 \cdot 0.167 = 0.0000084 \quad (9)$$

$$P(k_f = C'|C) = P(k_1 = C'|C) \cdot P(k_2 = C'|C) \cdot P(k_3 = C'|C) = 0.003 \cdot 0.032 \cdot 0.067 = 0.00000643 \quad (10)$$

Equations (9) and (10) signify the importance of the mediator in our system architecture and show how this novel architecture is able to reduce the overall misdiagnosis rate of AI4COVID-19. From (9), the probability that the app will predict 'COVID-19 likely' when the subject is not suffering from COVID-19 is near zero owing to the near zero false positive rate of CML-MC classifier. Conversely, probability that app will predict 'COVID-19 not likely' when the subject is actually suffering from COVID-19 is almost zero owing to the almost zero false negative rate of DL-MC classifier. Hence, the mediator in AI4COVID-19 architecture complements the weakness of one classifier with the strength of other and vice versa, resulting in reduced misdiagnosis rate as compared to using these classifiers independently, i.e., without the proposed mediator.

In the cases where app reports 'test inconclusive', the person can either have COVID-19 or not, in reality. The respective probabilities for those cases are:

$$P(k_f = I|C) = 1 - [P(k_f = C|C) + P(k_f = C'|C)] \quad 1 - [0.893 + 0.00000643] = 0.107 \quad (11)$$

$$P(k_f = I|C') = 1 - [P(k_f = C|C') + P(k_f = C'|C')] \quad 1 - [0.0000084 + 0.809] = 0.191 \quad (12)$$

Currently, the app would predict an inconclusive test result 29.8% of the time ($P(k_f = I) = P(k_f = I|C) + P(k_f = I|C')$). This percentage can be reduced by switching to a mediation scheme where app result reflects simple or weighted majority of the N number of classifiers. However, to keep the misdiagnosis rate close to zero, this scheme will be explored once more data becomes available. The results are summarized in Table 6.

VI. POTENTIAL UTILITIES OF THE AI4COVID-19

The AI4COVID-19 app based preliminary diagnosis is not meant to replace or compete with the medical grade testing by any means. Instead, the proposed solution offers the following complementing use cases to control the pandemic.

1) Enabling tele-screening for anyone, anywhere, anytime.
2) Addressing the shortage of testing facilities.
3) Opportunity to protect medics from unnecessary exposure, particularly for non-critical patients where the medical advice for whom anyway would be "stay at home" or "self-isolate" to wait for self-healing.
4) Minimizing covert spread that happens to be the biggest problem at this stage of pandemic.
5) Tracing and monitoring the spread. This is particularly easy with AI4COVID-19 as the cough samples can be spatio-temporally tagged anonymously, without having to compromise the patient's privacy.

6) AI4COVID-19 can be used as a low cost screening tool, instead of or in addition to the temperature scanner at the airports, borders or elsewhere as needed. This is possible because our tests show that the app can diagnose COVID-19 even in a non-spontaneous cough of COVID-19 positive people.

7) The app can help in enabling and maintaining informed social distancing and self-isolation.

8) By default the app can provide centralized record of tests with spatial and temporal stamps. Thus, the data gathered from the app can be used for long term planning of medical care and policy making.

VII. KEY LIMITATIONS OF CURRENT VERSION OF AI4COVID-19

At the time of writing, the performance of AI4COVID-19 app is limited by the following factors:

1) The quantity of the training and testing data. Due to time constraints and difficulty of getting cough data, we could gather data only from a small number of patients for each of the four groups. We tried to minimize the impact of this limitation by developing a novel architecture that combines data hungry approaches that are capable to extract more hidden features i.e., deep learning, with the ML approaches that can work with a small amount of data through manual feature extraction. Still, the need for more data cannot be overemphasized.

2) The quality of the training and testing data: We have strived to ensure that the data is correctly labeled. However, any error in the labeling of the data that managed to slip through our scrutiny, is likely to impact reported performance. Such impact can be particularly pronounced when the data is not that big in the first place.

3) Our in-depth medical differential analysis suggested that COVID-19 associated pathomorphological alternations are fairly distinct and hence cough of COVID-19 patients is likely to have at least some distinct latent features. However, this does not guarantee the absence of overlap in COVID-19 cough features and those of diseases not included in the training and testing. The approach we used to combat this issue is the clever mediator based architecture that practically eliminates misdiagnosis by declaring test to be inconclusive if the cough samples are even slightly confusing. Still, we are working to address this limitation in future releases of AI4COVID-19 by incorporating cough associated with other non-COVID-19 medical conditions identified in Table 1.

4) Randomized clinical trial-based validation: In the end, the only way to reliably evaluate the performance of the proposed AI4COVID-19 based testing is a controlled clinical trial. The findings of this paper provide promising enough preliminary results and proof of concept to encourage such trials and systematic large-scale cough data gathering campaigns.

VIII. CONCLUSION

Scarcity, cost and long turnaround time of clinical testing are key factors behind covert rapid spread of the COVID-19 pandemic. Motivated by the urgent need, this paper presents a ubiquitously deployable AI-based preliminary diagnosis tool for COVID-19 using cough sound via a mobile app. The core idea of the tool is inspired by our prior studies which show that cough can be used as a test medium for diagnosis of a variety of respiratory diseases using AI. To see if this idea is extendable to COVID-19, we perform in-depth differential analysis of the pathomorphological alternations caused by COVID-19 relative to other cough causing medical conditions. We note that the way COVID-19 affects the respiratory system is substantially unique and hence cough associated with it is likely to have unique latent features as well. We validate the idea further by the visualization of latent features in cough of COVID-19 patients and two common infections, pertussis and bronchitis as well as non-infectious coughs, all of which sound the same to a human ear. Building on the insights from the medical domain knowledge, we propose and develop a novel tri-pronged mediator centered AI-engine for cough based diagnosis for COVID-19, named AI4COVID-19. The results show that the AI4COVID-19 app is able to perform diagnosis of COVID-19 with negligible misdiagnosis probability, thanks to its novel risk-avert architecture.

Despite its impressive performance, AI4COVID-19 is not meant to compete with clinical testing. Instead, it offers a unique functional tool to timely, cost-effectively and most importantly safely monitor, trace, track and thus control the rampant spread of the global pandemic by virtually enabling testing for everyone. While we are working on improving the AI4COVID-19, this paper is meant to present a proof of concept to encourage clinical trial and community support for more labeled data. Our hope is that AI4COVID-19 app can be leveraged to pre-screen for COVID-19 at a population scale. The AI4COVID-19 enabled tele-screening can alleviate the current crushing burden on the overwhelmed medical systems around the world and thus can help save countless lives.

ACKNOWLEDGMENT

This work is dedicated to those affected by the COVID-19 pandemic and those who are helping to fight this battle in anyway they can.

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