

IATos: AI-powered pre-screening tool for COVID-19 from cough audio samples

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Abstract

OBJECTIVE Our objective is to evaluate the possibility of using cough audio recordings (spontaneous or simulated) to detect sound patterns in people who are diagnosed with COVID-19. The research question that led our work was: what is the sensitivity and specificity of a machine learning based COVID-19 cough classifier, using RT-PCR tests as gold standard?

DESIGN Diagnostic test validation study.

SETTING The audio samples that were collected for this study belong to individuals who were swabbed in the City of Buenos Aires in 20 public and 1 private facilities where RT-PCR studies were carried out on patients suspected of COVID, and 14 out-of-hospital isolation units for patients with confirmed COVID mild cases. The audios were collected through the Buenos Aires city government WhatsApp chatbot that was specifically designed to address citizen inquiries related to the coronavirus pandemic (COVID-19).

PARTICIPANTS The data collected corresponds to 2821 individuals who were swabbed in the City of Buenos Aires, between August 11 and December 2, 2020. Individuals were divided into 1409 that tested positive for COVID-19 and 1412 that tested negative. From this sample group, 52.6% of the individuals were female and 47.4% were male. 2.5% were between the age of 0 and 20 , 61.1% between the age of 21 and 40 , 30.3% between the age of 41 and 60 and 6.1% were over 61 years of age.

MAIN OUTCOME MEASURES The audio files corresponding to each individual were categorized as "positive" and "negative" based on their PCR swab test results.

RESULTS Using the dataset of 2821 individuals our results showed that the neural network classifier was able to discriminate between the COVID-19 positive and the healthy coughs with an accuracy of 88%. This accuracy obtained during the training process was later tested and confirmed with a second dataset corresponding to 492 individuals.

CONCLUSION Based on the reported results, we consider that the cough audio analysis could be used as a COVID-19 digital pre-entry screening tool to be used prior to conventional testing tools such as RT-PCR tests. This could help reduce wait times, ease stress, and lower exposure risk of healthcare personnel and other citizens.

FUNDING STATEMENT The project was carried out with the resources of the Secretariat of Innovation and Digital Transformation and the Ministry of Health of Buenos Aires City Government and with volunteers from other government areas for the field duties.

AUTHOR DECLARATIONS

All relevant ethical guidelines have been followed; any necessary IRB and or ethics committee approvals have been obtained and details of the IRB oversight body are included in the manuscript. **Yes**

All necessary patient - participant consent has been obtained and the appropriate institutional forms have been archived. **Yes**

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report.

1 Introduction

As from April 26, 2021, the SARS-CoV-2 Coronavirus has spread to 213 countries around the world, has over 147 million confirmed cases and has caused over 3.1 million deaths (1) (22).

The SARS-CoV-2 Coronavirus causes a respiratory infection called COVID-19. The COVID-19 virus spreads primarily through droplets of saliva or discharge from the nose when an infected person coughs or sneezes (36).

Given that access to vaccines is limited and treatments are still in development, minimizing the spread through timely testing and isolating infected people is the best effective defense humanity has at its disposal against COVID-19[REF]. However, the ability to deploy this defense strategy depends on each country's capability to test significant fractions of their populations, including those that are not yet in contact with the medical system. Agile, scalable and proactive testing have become the key differentiator for some nations in coping with and reversing the curve of the pandemic[REF].

1.1 Diagnostic strategies

The main types of tests used for COVID-19 are:

- Rapid serology antibody tests (ICT, LFA)
- Enzyme Linked Immunosorbent Assays (ELISA)
- Real-time polymerase chain reaction (RT-PCR) through swab tests

Rapid serology tests and ELISAs detect the presence of IgG / IgM antibodies produced by the immune system in response to a SARS-CoV-2 infection, while RT-PCR tests are molecular tests that detect the presence of viral RNA of SARS-CoV-2.

The Triage remains as the fastest method for pre-screening a person, and this

method is the one that can be scaled faster and at a low cost using exponential technologies. Triage is the process of sorting people based on their need for medical treatment as compared to their chance of benefiting from such care. Triage is usually performed in emergency rooms, disasters and wars, when limited medical resources must be allocated to maximize the number of survivors. During infectious disease outbreaks, triage is particularly important to separate patients likely to be infected with the pathogen of concern.

The main route of transmission of COVID-19 is through respiratory droplets generated when an infected person coughs or sneezes. Any person who is in close contact with someone who has respiratory symptoms (e.g., sneezing, coughing, etc.) is at risk of being exposed to potentially infective respiratory droplets (37).

Recently, the US FDA (18) has written about the importance of expanding rapid COVID-19 serological antibody testing. Current laboratory diagnostic tests for COVID-19 are based on labor-intensive molecular techniques (RT-PCR swab tests) and have generally been reserved for patients whose disease severity, age and/or comorbidities place them in high risk of serious illness, specially in countries with limited testing resources.

Recent work has also described that SARS-CoV-2 viral shedding often occurs in early pre-symptomatic stages, which could affect the dynamics and diagnostic accuracy of SARS-CoV-2 RT-PCR swab tests, especially if patients do not undergo molecular diagnostic tests until several days after the onset of symptoms. On the other hand, COVID-19 rapid serology antibody tests detect IgM/IgG antibodies, which are generated 1-3 weeks after the onset of symptoms.

Together, the SARS-CoV-2 RT-PCR swab test, combined with a rapid COVID-19 serological antibody test provides a more complete picture of COVID-19 disease progression, in a given individual and across populations.

1.2 Importance of early diagnosis

Many authors have highlighted that the key to safely returning back to normal life (35), especially while we wait for the COVID-19 vaccination process to be completed, does not lie in a single "perfect" COVID-19 test - but through multiple rapid and affordable tests, non-clinic pre-screening tools, from a variety of supply chains and technologies.

RT-PCR tests have been the gold standard for COVID-19 diagnosis. Nevertheless, their high cost and relatively long processing times make them a less appealing option when deploying population wide testing strategies. On the other hand, antibody and antigen detection tests have proved to be an excellent complement to RT-PCR tests. Their lower costs, shorter processing times and higher availability

allows for a more wide spread testing strategy and also shorter testing-isolation times.

1.3 Difficulties with early diagnosis

Currently, existing RT-PCR tests take considerably long to deliver results, are expensive to run frequently, or are often considered uncomfortable, which discourages people from going to get tested.

There are already some rapid tests for COVID-19 on the market. The Sofia SARS antigen test performed by the Quidel Corporation is approximately 99% accurate, takes about 15 minutes to deliver results, and is already in use. A pharmacy in Arkansas, USA, reported that they had dispensed more than 800 in about two weeks. The test costs USD 95, which is a considerable price for most people's budget, especially if they have to take the test periodically.

OpenCovidScreen (17), a coalition of scientists and biotech leaders working to drive innovation in COVID-19 testing and, in turn, accelerate return to work and school, says that a good COVID-19 testing solution needs four items: frequency (at least weekly), more test points, an affordable price (around USD 10-20), and an easy method of collection (e.g. saliva, quick test, cough). Currently, there are tests available on the market that address one or two of these considerations, but there is nothing that brings all four together.

1.4 Audio signals for pre-screening and disease monitoring

Audio signals generated by the human body (e.g. sighs, breathing, heart, digestion) have often been used by physicians and clinical researchers in the diagnosis and monitoring of diseases. However, until recently, such signals were generally collected by manual auscultation during scheduled visits to a medical facility. Medical research has begun to use digital technology to collect body sounds (e.g. digital stethoscopes) and perform automated data analysis (1), (e.g. for wheezing detection in asthma (2) (3)).

Researchers have also been testing the use of the human voice to aid in the early diagnosis of a variety of diseases. For example, in Parkinson's disease the patient's speech is analyzed for variations in smoothness to determine if there exists a lack of coordination in the vocal muscles (4) (5). Also vocal tone, rhythm, and volume have also been explored to diagnose illnesses such as post-traumatic stress disorder (7), traumatic brain injury, and some psychiatric conditions (8).

The use of human-generated audio as a biomarker for various diseases offers enormous potential for early diagnosis, as well as for affordable solutions that could be widely applied if integrated into devices such as cell phones. This is even more powerful if such solutions could monitor people throughout their daily lives

in a discreet way.

Clinical work has focused on the use of voice analysis for specific diseases: for example, in Parkinson's disease, microphone and laryngoscope equipment have been used to detect the softness of speech resulting from lack of coordination on the vocal muscles (6) (12). Voice characteristics have also been used to diagnose bipolar disorder; and to correlate pitch, rhythm, and volume with signs of invisible conditions such as post-traumatic stress disorder (7), traumatic brain injury, and depression. Voice frequency has been linked to coronary artery disease (as a result of hardening of the arteries that can affect voice production) (6). Companies such as Israel-based Beyond Verbal and Mayo Clinic have indicated in press releases that they are testing these approaches.

More recently, the microphone in basic devices such as smartphones and wearables has been used for sound analysis. In (12), the microphone is used to understand the context of the user and this information is added to generate a view of the surrounding environment of the recorded sound.. In (13) the authors analyze the sounds emitted while the user is sleeping, to identify episodes of sleep apnea. Similar work has also used sound to detect asthma and wheezing (2) (3).

1.5 IATos: proposal and background

Machine learning methods have been designed to recognize and diagnose respiratory diseases from sounds (1) and more specifically cough: (14) uses convolutional neural networks (CNN) to detect cough within ambient audio and diagnose three potential diseases (bronchitis, bronchiolitis and whooping cough) based on its unique audio characteristics.

With the advent of COVID-19, researchers have begun to explore whether cough sounds could be diagnostic (15). A COVID-19-related cough detection study is presented in (15) using a cohort of 48 patients tested with COVID-19 versus other pathological coughs, in which a set of models is trained. In (11) the voice recordings of COVID-19 patients are analyzed to automatically classify the health status of the patients in four aspects, namely, the severity of the disease, the quality of sleep, fatigue and anxiety. Quatieri et al. (26) showed that changes in vocal patterns could be a potential biomarker for COVID-19.

The research project that is explained in this paper aims to explore the use of human cough sounds as pre-diagnostic markers for COVID-19. Within the framework of this research study, we worked on the data acquisition of audio samples from people who quarantined in out-of-hospital isolation units for COVID-19 mild cases and close contacts or who were admitted to hospitals.

This research project differs from other similar initiatives in two main aspects. In the first place, the acquisition of audio samples was done through WhatsApp,

and not through web pages. This allowed for a more streamlined data collection from the study participants and simplified the signing of informed consents. On the other hand, only people who underwent a PCR swab test participated in the study. This helped us classify the audio samples of each individual according to the result of their RT-PCR results, considered as the current "gold standard" for COVID-19 diagnosis.

The expected outcome is to be able to analyze the patient's cough as an additional marker that can be incorporated into the medical Triage strategy. We seek to improve the pre-screening process that is carried out today prior to undergoing diagnosis testing methods such as PCR or rapid antigen tests. Having a digital Triage, which can be performed from anywhere using WhatsApp, allows us to exponentially scale the detection strategy for symptomatic and asymptomatic cases.

2 Methodology

Based on the objective of studying cough as a way to pre screen individuals for COVID-19, the research question that guided our work was: what is the sensitivity and specificity of a machine learning based COVID-19 cough classifier, compared to the standard diagnosis test for COVID-19?

In order to answer this question and prior to the development of the neural network, we consider the following steps as our methodology of work. The steps of this process are:

- Generate a data acquisition process
- Generate a dataset
 - Define the selection process for study participants
 - Contact people who agree to participate in the study
 - Start the audio acquisition flow
- Establish a preprocessing strategy for the collected audios

2.1 Data description

Observational or experimental studies require a priori sample size calculation in order to achieve the necessary statistical power to reject the null hypothesis (25). In the field of pattern recognition though, there is no standardized priori determination method to evaluate the generated models performance based on sample size of the datasets used for training.

Review of previous literature from past research uses an empirical approach through learning curves and the use of surrogate models to provide an answer to the problem of sample size (26). However, these ex-post-facto solutions do not take into account the nature of the classificatory problem to be solved, the complexity of the model used, the use of feature augmentation techniques, or the

use of pre-trained models with the transfer learning method.

As an approach to determining the necessary sample size, we revised the literature that refers to the use of pattern recognition models applied to the audio signal produced by coughing. We reviewed pre-existing literature and studied the differences of different samples sizes and their related metrics (see Table 1).

Table 1. *Bibliographic search of works that refer to the use of pattern recognition models applied to the audio signal produced by the act of coughing.*

Author (Year)	Samples	COVID +	Others ^a	Control	S/E	AUC
Imran (2020)	1838	70	226	247	.96/.95	NR
Brown (2020)	491	141	52	298	NR	0.875
Bales (2020)	268	-	268	-	.89/.948	NR

^a Another non-COVID-19 positive respiratory disease.

In light of the studied literature we established that a sample size of 5000 cough audio sounds could enable the correct performance of the generated model.

The data acquisition process was approved by the Ethics Committee of the Elizalde Hospital (Comité de Etica - Hospital Elizalde). In August 2020 we started the process of collecting cough audios through the Buenos Aires City Government chatbot with the aim of creating an Open Voice dataset for COVID-19 cough discrimination.

We only used samples with two conditions:

- The person providing the cough had undergone a PCR test.
- The audio files were recorded within 3 days of that PCR test.

At the end of the data acquisition process, we had collected 6,000 audio files, from 2,821 individuals. This collection of audio files was split into two groups:

- Training and validation: 2,412 audio files from individuals that tested negative for COVID-19, and 2,477 audio files for individuals that tested positive. These audio files belong to 2,329 individuals.
- Test: 995 audio files that belong to 492 individuals.

Each person included in the study had to generate a variety of representative audios of the act of coughing. We collected on average 3 coughs per subject accompanied by general subject information: age, sex, date of the swab/cough, location, outcome of medical diagnosis, and finally information regarding timing of onset of

COVID-19 signs and symptoms (fever, tiredness, sore throat, difficulty breathing, persistent pain or pressure in the chest, diarrhoea and coughing).

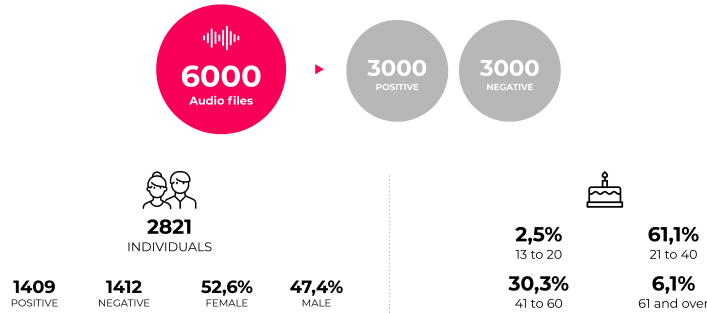


Fig. 1. Dataset general information.

Data was anonymized before being collected on our secure server and samples were saved without compression in WAV format. Samples that had no coughs, too much noise or were silent were removed. No segmentation was performed on the cough recordings used to train and test the neural network.

2.2 Data acquisition

Individuals who participated in the study were asked to send one audio per day, for 3 consecutive days following the PCR test. The primary goal was to obtain multiple samples per person. Secondly, we seek to study the evolution of audio patterns to detect if there are changes that show evidence of the evolution of the virus.

When someone went to a testing center, health system personnel invited them to participate in this study. If the person agreed, they were guided to start a conversational flow on the Buenos Aires city government WhatsApp chatbot specifically designed to address citizen inquiries related to the coronavirus pandemic (COVID-19). From the beginning of the study until September 30, 2020 people signed a printed informed consent to participate in this study. From September 30, 2020 the informed consent was digitized into the WhatsApp chatbot conversation.

The audio files that were collected for this study belong to individuals who were swabbed in the City of Buenos Aires in public and private facilities, out-of-hospital isolation units for patients with confirmed COVID mild cases and testing points of the strategic testing program "DetectAR". The health personnel who performed the swab briefly explained the study to the individuals and invited them to participate.

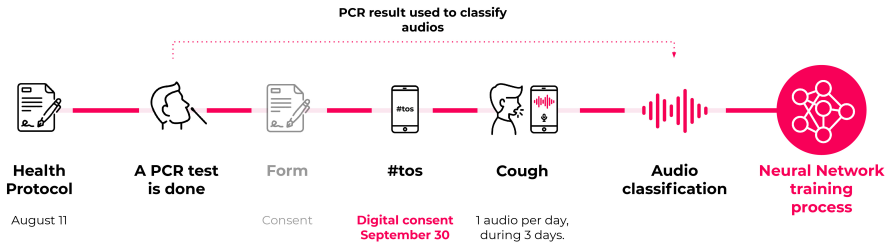


Fig. 2. Data acquisition timeline.

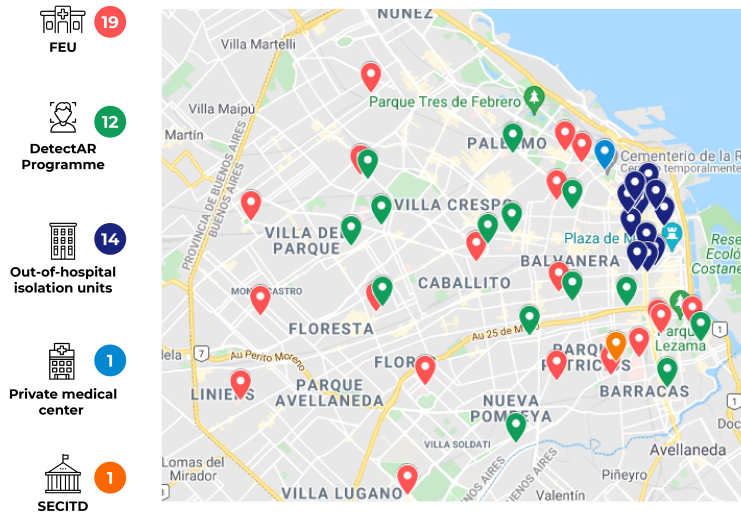


Fig. 3. Data acquisition sites with the Buenos Aires health system.

Data collection sites: 19 Febrile Emergency Units (FEU), 12 testing points of the strategic testing program "DetectAR", 14 out-of-hospital isolation units for COVID-19 mild cases and close contacts and 1 private medical center as well as government personnel.

2.3 Data preprocessing

To ensure the neural network's good performance, it is necessary to analyze the audio files through a preprocessing pipeline. This preprocessing consists of sampling, denoising and cough discrimination from noise and silence audio chunks.

Although these could be extended to more stages, our current proposal (Fig. X) consists of:

- Detect the presence of a cough in an audio, and cut an audio segment of 1 second maximum duration.
- Normalize the audios in amplitude so that they all have a similar amplitude domain.
- Denoise audio files that have a low signal-to-noise ratio (SNR).



Fig. 4. Pre-processing pipeline

As the first stage of preprocessing the audios, they are converted from the .ogg format to the .wav format, and all the audios are sampled equally at 16 kHz.

Subsequently, the audio files are cut into 1 second chunks. Then, using YAMNet and a network trained from the collected audio files, audio chunks that contain coughs are separated from those that are noise or silence. Finally, the resulting fragments are filtered to remove any noise that the signals may have.

The audios are then preprocessed in order to extract their main characteristics. This was achieved through a spectral analysis and selection of features of the signal. Finally the audio samples were normalized in amplitude.

From the information extracted, images were generated and introduced into a deep learning model, in order to be able to classify new cough audio signals.

For data processing, we mainly used a transformation that has broad consensus in the scientific community. In the first place, from the audio signal, the Mel (27) spectrogram was obtained, extracting the most relevant characteristics of the sound using human auditory perception as a criterion. The transformation consists of splitting the signal into short frames, applying the discrete Fourier transform (DFT) to generate the spectrogram, then applying the Mel Filterbank -to calculate the energy in each Mel filter- and finally calculating the logarithm of the energy for each filterbank (28).

We used regularization techniques in our data since, given the complexity of the model to be applied, this will allow a better generalization of them. Specifically, to feed the model we used data augmentation, that is, we performed small random transformations to create new images, for example scaling and/or rotating the data. This technique allowed us to generalize the information and also obtain an improvement in the performance over audio signal data.

3 Neural network model

A deep learning-based COVID-19-associated cough detector was created. That is, a three-class classifier based on Convolutional Neural Networks that uses Mel's spectrograms as input information. Due to the subtle differences that exist between images of coughs corresponding to healthy patients, with various respiratory diseases, or with COVID-19, a neural network with more layers was required. Therefore, we used a CNN architecture.

Regarding the architecture, CNNs have a set of convolutional layers, to which pooling layers are then added and the dimensions of the matrix are adjusted. This is repeated successively and in the end, a fully connected layer is added to perform the prediction through a softmax.

For this project, three widely accepted scientific metrics will be used: Specificity, Recall/Sensitivity and Accuracy. In the training process of the model, a constant monitoring of the precision metric was carried out in order to generate the least amount of false positives. Due to the way COVID-19 spreads, it will always be a priority to maintain a high criterion of reliability and certainty before recommending a patient to seek assistance at a health facility. In parallel, the AUC measurement was monitored, which represents the area under the ROC curve that allows visualizing the sensitivity versus specificity.

We started by using a classification threshold of 0.5. Our proposed architecture, drawn in Fig. XX, takes a recording with one or more coughs, performs pre-processing steps and inputs it into a CNN based model to output a pre-screening result. As pre-processing, each input audio file is split into 1 second audio chunks, padded as needed, processed with the MFCC package[REF] and subsequently passed through the neural network classifier. The output of these steps becomes the input to a CNN.

In order to train the classifier model, the set of spectrograms obtained were divided into train (80%), validation (10%) and internal test (10%). Finally, with the model obtained, inferences were made to a second set of audio files that belong to a test set of 492 individuals. In this way we were able to evaluate the performance of the model on new data that it had never analyzed before.

4 Results

As we explained in the previous section, in order to evaluate the model we use the performance metrics of accuracy, specificity and sensitivity/recall on the test set. The accuracy here refers to the overall accuracy of the model. These performance metrics are based on mean confusion matrices from cross-validation. Tuning of the various hyper-parameters (number of hidden layers, learning rate, activation functions, dropout rate) of deep neural network-based models has also been performed,

Layer (type)	Output Shape	Param #
resizing_1 (Resizing)	(None, 32, 32, 1)	0
normalization_1 (Normalizati	(None, 32, 32, 1)	3
conv2d_2 (Conv2D)	(None, 30, 30, 32)	320
conv2d_3 (Conv2D)	(None, 28, 28, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 14, 14, 64)	0
dropout_2 (Dropout)	(None, 14, 14, 64)	0
flatten_1 (Flatten)	(None, 12544)	0
dense_2 (Dense)	(None, 512)	6423040
dropout_3 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 3)	1539
=====		
Total params: 6,443,398		
Trainable params: 6,443,395		
Non-trainable params: 3		

Fig. 5. CNN Architecture.

based on the cross-validation accuracy. Furthermore, the decay of model loss versus the number of epochs has been investigated to rule out the possibility of overfitting.

4.1 Cough discrimination accuracy

When we receive an audio file, the first step is to discriminate whether it has a cough or not. For this step we combine the use of YAMNet and a neural network that we specially trained to distinguish coughs. The analyzed audio file is cut into 1-second chunks and these fragments are evaluated by this detection stage, to discard the fragments that do not have presence of cough. We achieved an accuracy of 97% determining which fragments have a cough and which have noise. This allows us to move on to the next stage, which is to evaluate the remaining fragments, to determine if the audio corresponds to that of an individual who is potentially COVID-19 positive or not.

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4.2 COVID-19 detection

At the moment, with limited data available, the overall accuracy of the deep transfer learning based classifier is 88.00%. The mean normalized confusion matrix resulting from this approach is shown in Fig. XX. Future work will continue to improve this model as more training data becomes available. Fig. XX shows the mean loss versus epochs of the neural network classifier, for both training and validation data sets. Both the curves start to saturate after around 50 epochs, indicating a reasonable learning time, without overfitting.

5 Discussion and future work

We have shown that COVID-19 can be discriminated with 88% accuracy using only a forced-cough audio recording. We find most remarkable that our model performs better with coughs from positive patients than those from negative ones.

This first stage of developing the model focused on training it on a large dataset to learn good features for discriminating COVID-19 forced-coughs. The results when evaluating the testing set (made with coughs from individuals diagnosed with an official PCR test) serve as an indicator that the model would have similar accuracy when deployed. To verify this we are currently running pilots in multiple testing points in the Buenos Aires City public health system. We will also gather more quality data that can further train, fine-tune, and validate the model.

Since there might be cultural and age differences in coughs, future work could also focus on tailoring the model to different age groups and regions of the world using the metadata captured, and possibly including other sounds or input modalities such as vision or natural language symptom descriptions.

Another issue that may be researched is whether cough segmentation can improve the results. For the screening outputs to have diagnostic validity, there must be a process to verify recordings correspond to coughs. While testing our dataset only three recordings corresponded to speech instead of coughs and we had to sort these manually since there is still no way to do so automatically.

5.1 Potential use cases of IATos

Motivated by an urgent need, we developed a research protocol that was intended to evaluate the usefulness of an AI-based preliminary diagnostic tool for COVID-19, ubiquitously scalable through WhatsApp audio files containing a recording of an individual's forced cough.

The central idea of such a tool is inspired by previous studies (10) (16) showing that cough can be used as a pre-screening tool for the diagnosis of a variety of respiratory diseases using AI techniques. The main objective is that the cough

analysis is a complement and never a replacement for other diagnostic methods.

This non-invasive, free, real-time pre-screening tool may prove to have a great potential to complement current efforts to contain the disease in low-infected areas as well as to mitigate the impact in highly-infected areas, where unknowing asymptomatics may spread the virus.

Possible use cases could include:

- Population daily screening tool: As workers go back to work, students go back to school, and commuters use public transport, to name a few, methods are required to screen infected COVID-19 carriers, especially asymptomatics. The only screening method currently available is using thermometers, however this study (36) showed only 45% of mild-moderate COVID-19 cases have fever (this represents 9% of COVID-19 positives when asymptomatics are included). Meanwhile our AI tool has shown to discriminate a forced cough of COVID-19 positives with 88% accuracy and could act as a complement to the medical triage questions.
- Pre-selection of candidates for test pooling: The test pooling strategy is expected to be employed in many countries, especially in low-incidence areas to rapidly identify a subgroup of individuals likely to be infected, however, “preliminary results show there is no dilution and no decrease on test sensitivity when mini pools of five samples each are used” (37). Group testing with our tool as shown in Fig. X, could pre-screen school classrooms, factories or even countries on a daily basis signalling probable infected candidate groups for smaller test pooling batches.

This technology could be assembled with low levels of effort and risk within the virtual triage that is carried out as a follow-up protocol for close contacts of positive patients.

In the future, subject to the learning curve and validation of the model, additional use cases could include (10):

- Complementing temperature scanners at airports, borders or other key places where the virus circulates.
- Allowing remote pre-monitoring for anyone, anywhere, at any time, regardless of the existing infrastructure/testing facilities.
- Providing a centralized record of tests with location and time stamps. The data collected from the app could serve as input for long-term health care planning and health policy formulation.

Despite the good performance that is preliminarily observed in these tools, they are not intended as a replacement for clinical tests but as a complement. The goal is to investigate the potential for a single functional tool to monitor, track and control the rampant spread of the global pandemic in a timely, cost-effective and most importantly safe manner, by allowing a pre-test for anyone with access to a smartphone and an internet connection.

6 Conclusion

We presented an AI pre-screening tool that uses a neural network classifier that is able to discriminate COVID-19 positives with 88% accuracy from a forced-cough recording, at essentially no cost and with an exponential scaling capacity.

The proposed solution could be seen as a group outbreak detection tool for pre-screening whole-populations on a daily basis, taking the pre-screening to each house.. At the same time, this tool will allow us to send more people, potentially asymptomatic, to be tested. In this way we may be able to detect many positive asymptomatic cases that would normally go undetected.

As part of our ongoing pilots, data pipelines with FEUs and detection points have been set up to continue to improve the neural network. We plan on leveraging this data to further train and validate our models with the aim of improving pandemic management practices.

As part of our efforts to make data public and contribute to open innovation, we are opening our research methods and our dataset to collaborate and inspire others to develop similar tools to fight the COVID-19 pandemic, and hopefully be better prepared for the next pandemic.

7 Ethical aspects

The study will be guided by the rules of good clinical practice, the Declaration of Helsinki and the regulations of the Government of the City of Buenos Aires in force. Authorization was requested from the Research Ethics Committee, the DGDIYDP (Dirección General de Docencia, Investigación y Desarrollo Profesional) and the SSPLSAN (Subsecretaría de Planificación Sanitaria. Ministerio de Salud). Informed consent of those responsible, subjects and / or consent of minors will be requested as appropriate. Due to the context of the study and the specific SOPs of the Ethics Committee of the Elizalde Hospital (CEI-HGNPE, Hospital General de Niños Pedro de Elizalde), the documentation of the process will be protected in images of the forms duly signed by the subjects or their managers, who will keep the originals. The audio data of the patients and their COVID-19 test results will be stored without direct or indirect identifiers. Because it is an observational study and is framed in the context of the COVID-19 pandemic, the CEI-HGNPE requested its expeditious evaluation and approval.

Data Availability All the data referred to in the manuscript are available in <https://data.buenosaires.gob.ar/>.

Declaration of competing interest The authors declare that they have no known competing financial interests or personal relationships that could have

appeared to influence the work reported in this paper.

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References

- (1) Renard Xaviero Adhi Pramono, Stuart Bowyer, and Esther Rodríguez-Villegas. 2017. Automatic adventitious respiratory sound analysis: A systematic review. *PloS One* 12, 5 (May 2017). <https://doi.org/10.1371/journal.pone.017792643>pages.
- (2) Shih-Hong Li, Bor-Shing Lin, Chen-Han Tsai, Cheng-Ta Yang, and Bor-Shyh Lin. 2017. Design of wearable breathing sound monitoring system for real-time wheeze detection. *Sensors* 17, 1 (Jan. 2017), 1–15.
- (3) Dinko Oletic and Vedran Bilas. 2016. Energy-efficient respiratory sounds sensing for personal mobile asthma monitoring. *IEEE Sensors Journal* 16, 23 (Dec. 2016), 8295–8303.
- (4) L Brabenec, J Mekyska, Z Galaz, and Irena Rektorova. 2017. Speech disorders in Parkinson’s disease: Early diagnostics and effects of medication and brain stimulation. *Journal of Neural Transmission* 124, 3 (2017), 303–334.
- (5) Betül Erdogdu Sakar, Gorkem Serbes, and C. Okan Sakar. 2017. Analyzing the effectiveness of vocal features in early tediagnosis of Parkinson’s disease. *PloS One* 12, 8 (Aug. 2017), 1–18. <https://doi.org/10.1371/journal.pone.0182428>.
- (6) Elad Maor, Jaskanwal D Sara, Diana M Orbelo, Lilach O Lerman, Yoram Levanon, and Amir Lerman. 2018. Voice signal characteristics are independently associated with coronary artery disease. *Mayo Clinic Proceedings* 93, 7 (2018), 840–847.
- (7) Debrup Banerjee, Kazi Islam, Keyi Xue, Gang Mei, Lemin Xiao, Guangfan Zhang, Roger Xu, Cai Lei, Shuiwang Ji, and Jiang Li. 2019. A deep transfer learning approach for improved post-traumatic stress disorder diagnosis. *Knowledge and Information Systems* 60, 3 (2019).
- (8) Maria Faurholt-Jepsen, Jonas Busk, Mads Frost, Maj Vinberg, Ellen M Christensen, Ole Winther, Jakob Eyvind Bardram, and Lars V Kessing. 2016. Voice analysis as an objective state marker in bipolar disorder. *Translational Psychiatry* 6, 7 (2016), e856. 8 pages.
- (9) Yinghui Huang, Sijun Meng, Yi Zhang, et al. 2020. The respiratory sound features of COVID-19 patients fill gaps between clinical data and screening methods. *medRxiv* (2020). <https://doi.org/10.1101/2020.04.07.2005106012>pages.
- (10) Ali Imran, Iryna Posokhova, Haneya N. Qureshi, Usama Masood, Sajid Riaz, Kamran Ali, Charles N. John, Muhammad Nabeel, and Iftikhar Hussain. 2020. AI4COVID-19: AI enabled preliminary diagnosis for COVID-19 from cough samples via an App. [arXiv:2004.01275](https://arxiv.org/abs/2004.01275) [eess.AS] 11 pages.
- (11) Jing Han, Kun Qian, Meishu Song, Zijiang Yang, Zhao Ren, Shuo Liu, Juan Liu, Huaiyuan Zheng, Wei Ji, Tomoya Koike, Xiao Li, Zixing Zhang, Yoshiharu Yamamoto, and Björn Schuller. 2020. An early study on intelligent analysis of speech under COVID-19: Severity, sleep Quality, fatigue, and anxiety. [arXiv:2005.00096](https://arxiv.org/abs/2005.00096) [eess.AS] 5 pages.
- (12) Yohan Chon, Nicholas D. Lane, Fan Li, Hojung Cha, and Feng Zhao. 2012. Automatically characterizing places with opportunistic crowdsensing using smartphones. In *Proceedings of the ACM Conference on Ubiquitous Computing (UbiComp)*. Pittsburgh, Pennsylvania.

- (13) Rajalakshmi Nandakumar, Shyamnath Gollakota, and Nathaniel Watson. 2015. Contactless sleep apnea detection on smartphones. In Proceedings of the 13th Annual International Conference on Mobile Systems, Applications, and Services (MobiSys). Florence, Italy.
- (14) Charles Bales, Muhammad Nabeel, Charles N. John, Usama Masood, Haneya N. Qureshi, Hasan Farooq, Iryna Posokhova, and Ali Imran. 2020. Can machine learning be used to recognize and diagnose coughs? [arXiv:2004.01495](https://arxiv.org/abs/2004.01495) [eess.AS] 10 pages.
- (15) Gauri Deshpande and Bjorn Schuller. 2020. An overview on audio, signal, speech, and language processing for COVID-19. arXiv preprint [arXiv:2005.08579](https://arxiv.org/abs/2005.08579) (2020). 5 pages.
- (16) Chloë Brown, Jagmohan Chauhan, Andreas Grammenos, Jing Han, Apinan Hasthanasombat, Dimitris Spathis, Tong Xia, Pietro Cicuta, and Cecilia Mascolo. "Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data." arXiv preprint: [arXiv:2006.05919](https://arxiv.org/abs/2006.05919) (2020).
- (17) Gobierno de la Ciudad de Buenos Aires (2020, Agosto 8). Coronavirus. <https://www.buenosaires.gob.ar/coronavirus>.
- (18) Stephanie Caccamo (2020, Abril 18). Coronavirus (COVID-19) Update: Serological Test Validation and Education Efforts. [fda.gov/coronavirus-covid-19-update-serological-test-validation-and-education-efforts](https://www.fda.gov/coronavirus-covid-19-update-serological-test-validation-and-education-efforts).
- (19) Dr. Rajiv J. Shah (2020, Julio 16). Covid-19 National Testing and Tracing Action Plan. <https://www.rockefellerfoundation.org/national-covid-19-testing-and-tracing-action-plan/>.
- (20) Kristin Toussaint (2020, Julio 31). The solution to our COVID-19 testing dilemma: Lots of different kinds of rapid tests. [fastcompany.com/the-solution-to-our-covid-testing-dilemma](https://www.fastcompany.com/the-solution-to-our-covid-testing-dilemma).
- (21) Johnny Wood (2020, Abril 29). COVID-19 is causing people with other serious illnesses to avoid hospital. [weforum.org/covid-19-hospitals-empty-cardiac-emergencies-pandemic/](https://www.weforum.org/covid-19-hospitals-empty-cardiac-emergencies-pandemic/).
- (22) Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) (2020, Agosto 10). COVID-19 Dashboard. <https://coronavirus.jhu.edu/map.html>.
- (23) Weitz, J.S., Beckett, S.J., Coenen, A.R. et al. Modeling shield immunity to reduce COVID-19 epidemic spread. *Nat Med* 26, 849–854 (2020). <https://doi.org/10.1038/s41591-020-0895-3>.
- (24) Klasse, P.J. and Moore, J.P. Antibodies to SARS-CoV-2 and their potential for therapeutic passive immunization. *eLife* 2020; DOI: [10.7554/eLife.57877](https://doi.org/10.7554/eLife.57877).
- (25) Russell V Lenth (2001) Some Practical Guidelines for Effective Sample Size Determination, *The American Statistician*, 55:3, 187-193, DOI: [10.1198/000313001317098149](https://doi.org/10.1198/000313001317098149).
- (26) Figueroa, R.L., Zeng-Treitler, Q., Kandula, S. et al. Predicting sample size required for classification performance. *BMC Med Inform Decis Mak* 12, 8 (2012). <https://doi.org/10.1186/1472-6947-12-8>.
- (27) Davis and Mermelstein (1980). "Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences," in *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 28, no. 4, pp. 357-366, August 1980, doi: [10.1109/TASSP.1980.1163420](https://doi.org/10.1109/TASSP.1980.1163420).
- (28) McFee et al. (2015). "librosa: Audio and Music Signal Analysis in Python". Center for Data Science, New York University.
- (29) Fukushima, K. (1980). Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position.
- (30) Goodfellow et al. (2016). *Deep Learning*. MIT Press, 228.
- (31) Jaitly, N. and Hinton, G. E. (2013). "Vocal tract length perturbation (VTLP) improves speech recognition". In *ICML'2013*. 241.
- (32) Chollet, F. (2018) *Deep Learning with Python*. Manning Publications Co. 86

- (33) K. He, X. Zhang, S. Ren, and J. Sun. (2015) “Deep residual learning for image recognition”. [arXiv:1512.03385](https://arxiv.org/abs/1512.03385).
- (34) Glorot X. and Bengio Y. (2010). “Understanding the difficulty of training deep feed-forward neural networks”.
- (35) <https://www.nejm.org/doi/pdf/10.1056/NEJMp2025631?articleTools=true>
- (36) <https://www.who.int/health-topics/coronavirus>
- (37) <https://www.who.int/publications/i/item/WHO-2019-nCoV-IPC-2020.4>