# The COUGHVID crowdsourcing dataset: A corpus for the study of large-scale cough analysis algorithms

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#### **ABSTRACT**

Cough audio signal classification has been successfully used to diagnose a variety of respiratory conditions, and there has been significant interest in leveraging Machine Learning (ML) to provide widespread COVID-19 screening. However, there is currently no validated database of cough sounds with which to train such ML models. The COUGHVID dataset provides over 20,000 crowdsourced cough recordings representing a wide range of subject ages, genders, geographic locations, and COVID-19 statuses. First, we filtered the dataset using our open-sourced cough detection algorithm. Second, experienced pulmonologists labeled more than 2,000 recordings to diagnose medical abnormalities present in the coughs, thereby contributing one of the largest expert-labeled cough datasets in existence that can be used for a plethora of cough audio classification tasks. Finally, we ensured that coughs labeled as symptomatic and COVID-19 originate from countries with high infection rates, and that their expert labels are consistent. As a result, the COUGHVID dataset contributes a wealth of cough recordings for training ML models to address the world's most urgent health crises.

# **Background & Summary**

The novel coronavirus disease (COVID-19), declared a pandemic by the World Health Organization on March 11, 2020, has claimed over 950,000 lives worldwide as of September 2020<sup>1</sup>. Epidemiology experts concur that mass testing is essential for isolating infected individuals, contact tracing, and slowing the progression of the virus<sup>2,3</sup>. While advances in testing have made these tools more widespread in recent months, there remains a need for inexpensive, rapid, and scalable COVID-19 screening technology<sup>4</sup>.

One of the most common symptoms of COVID-19 is a dry cough, which is present in approximately 67.7% of cases<sup>5</sup>. Cough sound classification is an emerging field of research that has successfully leveraged signal processing and artificial intelligence (AI) tools to rapidly and unobtrusively diagnose respiratory conditions like pertussis<sup>6</sup>, pneumonia and asthma<sup>7</sup> using nothing more than a smartphone and its built-in microphone. Several research groups have begun developing algorithms for diagnosing COVID-19 from cough sounds<sup>8,9</sup>. One such initiative, AI4COVID<sup>8</sup>, provides a proof-of-concept algorithm but laments the lack of an extensive, labeled dataset that is needed to effectively train Deep Learning (DL) models.

There are several existing COVID-19 cough sound datasets used to train Machine Learning (ML) models. Brown et al.<sup>9</sup> have amassed a crowdsourced database of more than 10,000 cough samples from 7,000 unique users, 235 of which claim to have been diagnosed with COVID-19. However, the authors have not automated the data filtering procedure and consequently needed to endure the time-consuming process of manually verifying each recording. Furthermore, this dataset is not yet publicly available and therefore cannot be used by other teams wishing to train their ML and DL models. The Coswara project<sup>10</sup>, on the other hand, has publicly provided manual annotations of the crowdsourced COVID-19 coughs they have received, but as of September 2020, their dataset contains just slightly over 1,3000 samples. An alternative approach to crowdsourcing is the NoCoCoDa<sup>11</sup>, a database of cough sounds selected from media interviews of COVID-19 patients. However, this database only includes coughs from 10 unique subjects, which is not enough for AI algorithms to successfully generalize to the global population.

In this work, we present the COUGHVID crowdsourcing dataset, which is an extensive, validated, and publicly-available dataset of cough recordings. With more than 20,000 recordings – 1,010 claiming to have COVID-19 – originating from around the world, it is the largest known COVID-19-related cough sound dataset in existence. In addition to publicly providing our cough corpus, we have trained and open-sourced a cough detection ML model to filter non-cough recordings from the database. Furthermore, we have undergone an additional layer of validation whereby 3 expert pulmonologists annotated a fraction of the

dataset to determine which crowdsourced samples realistically originate from COVID-19 patients.

In addition to COVID-19 diagnoses, our expert labels and metadata provide a wealth of insights beyond those of existing public cough datasets. These datasets either do not provide labels or contain a small number of samples. For example, the Google Audio Set<sup>12</sup> contains 871 cough sounds, but it does not specify the diagnoses or pathologies of the coughs. Conversely, the IIIT-CSSD<sup>13</sup> labels coughs as wet vs dry and short-term vs long-term ailments, but it only includes 30 unique subjects. The COUGHVID dataset contributes over 2,000 expert-labeled coughs, all of which provide a diagnosis, severity level, and whether or not audible health anomalies are present, such as dyspnea, wheezing, and nasal congestion. Using these expert labels along with subject metadata, our dataset can be used to train models that detect a variety of subjects' information based on their cough sounds. Overall, our dataset contains samples from a wide array of subject ages, genders, COVID-19 statuses, pre-existing respiratory conditions, and geographic locations, which potentially enable AI algorithms to successfully perform generalization.

Finally, we assert the validity of our data by ensuring that samples labeled as COVID-19 originate from countries where the virus was prevalent at the time of recording, and that the experts exhibit a reasonable degree of agreement on the cough diagnoses. The first step to building robust AI algorithms for the detection of COVID-19 from cough sounds is having a reliable, high-quality dataset, and the COUGHVID dataset effectively meets this pressing global need.

#### **Methods**

#### **Data Collection**

All of the recordings were collected between April 1st, 2020 and September 10th, 2020 through a Web application deployed on a private server located at the facilities of the École Polytechnique Fédérale de Lausanne (EPFL), Switzerland. The application was designed with a simple workflow and following the principle "one recording, one click", according to which if someone simply wants to send a cough recording, they should have to click on no more than one item.

The main Web interface has just one "Record" button that starts audio recording from the microphone for up to 10 seconds. Once the audio recording is completed, a small questionnaire is shown to get some metadata about the age, gender, and current condition of the user, but even if the questionnaire is not filled, the audio is sent to the server. The variables captured in the questionnaire are described in Table 1. Also, the user is asked for permission to provide their geolocation information, which is not mandatory. Finally, since coughing is a potentially dangerous activity in the scope of a global pandemic, we provide easy-to-follow safe coughing instructions, such as coughing into the elbow and holding the phone at arm's length, that can be accessed from the main screen.

#### **Database Cleaning**

A common pitfall of crowdsourced data is that it frequently contains samples unrelated to the desired content of the database. In order to allow users of the COUGHVID database to quickly exclude non-cough sounds from their analyses, we developed a classifier to determine the degree of certainty to which a given recording constitutes a cough sound. These output probabilities of the classifier were subsequently included in the metadata of each record under the cough\_detected entry.

To train the classifier, we first hand-selected a set of 121 cough sounds and 94 non-cough sounds including speaking, laughing, silence, and miscellaneous background noises. These recordings were preprocessed by lowpass filtering ( $f_{cutoff} = 6$  kHz) and downsampling to 12 kHz. Next, 68 audio features commonly used for cough classification were extracted from each recording. 40 of the features are those described by Pramono et al.<sup>6</sup>, and the implementation of our 19 Energy Envelope Peak Detection features is detailed by Chatrzarrin et al.<sup>14</sup>. We also included a signal length feature, as well as the power spectral density (PSD) of the signal in 8 hand-selected frequency bands. These bands were chosen by analyzing the PSDs of cough vs non-cough signals and selecting the frequency ranges with the highest variation between the two classes. Finally, we trained an eXtreme Gradient Boosting (XGB)<sup>15</sup> classifier using 78% of the available data. The hyperparameters of the XGB model were tuned using Tree-structured Parzen Estimators (TPE)<sup>16</sup> with a precision objective using the training data for 10-fold, 20%-test shuffle-split cross-validation.

The ROC curve of the cough classifier is displayed in Figure 1, which users of the COUGHVID database can consult to set a cough detection threshold that suits their specifications. As this figure shows, only 10.4% of recordings with a cough\_detected value less than 0.8 actually contain cough sounds. Therefore, they should be used only for robustness assessment, and not as valid cough examples.

#### **Expert Annotation**

To enhance the quality of the dataset with clinically validated information, we were assisted by three expert pulmonologists. Each of them revised 1000 recordings, selecting one of the predefined options to each of the following 10 items:

- 1. Quality: Good; Ok; Poor; No cough present.
- 2. **Type of cough**: Wet (productive); Dry; Can't tell.

3. Audible dyspnea: Checkbox.

4. Audible wheezing: Checkbox.

5. Audible stridor: Checkbox.

6. Audible choking: Checkbox.

7. Audible nasal congestion: Checkbox.

8. Nothing specific: Checkbox.

- 9. **Impression:** I think this patient has...: An upper respiratory tract infection; A lower respiratory tract infection; Obstructive lung disease (Asthma, COPD, ...); COVID-19; Nothing (healthy cough).
- 10. **Impression: the cough is probably...**: Pseudocough / Healthy cough (from a healthy person); Mild (from a sick person); Severe (from a sick person); Can't tell.

As a labeling support tool, we used an online spreadsheet using Google Sheets<sup>©</sup>. Thus, the experts could play the recordings directly inside the browser and select their answers in a convenient way. Once a recording had been labeled, the background color of the full row turned to green for easier navigation. The time required for each expert for labeling the 1000 recordings was around 10 hours, without significant differences among the three experts.

In addition to the personal spreadsheets, the experts were provided with the following general instructions:

- For binary variables (Columns E-J) the box should be ticked for any reasonable suspicion of the sounds being heard.
- In Column K ("Impression: I think this patient has..."), you should check what you consider the most likely diagnosis, knowing that the records were collected between 01/04/2020 and 18/05/2020.
- Each row is automatically marked as "completed" after providing an answer to column K. However, please try to give an answer to every column.

Also, the following criteria for assessing quality was indicated to the experts:

- Good: Cough present with minimal background noise.
- **Ok**: Cough present with background noise.
- Poor: Cough present with significant background noise.

The selection of the recordings to be labeled was done through stratified random sampling and after pre-filtering using the automatic cough classifier described above, requiring a minimum probability of 0.8 of containing cough sounds. The stratification was based on the self-reported status variable, as follows:

- 25% of the recordings with COVID value.
- 35% of the recordings with symptomatic value.
- 25% of the recordings with healthy value.
- 15% of the recordings with no reported status.

Finally, we ensured that 15% of the recordings were labeled by all three reviewers, so that we could assess the level of agreement among them.

#### **Data Records**

Each cough recording consists of two files with the same name but different extensions. One of the files contains the audio data, as it was directly received at the COUGHVID servers, and it can be in the WEBM<sup>17</sup> or OGG<sup>18</sup> formats, respectively with the .webm and .ogg extensions. In all cases, the audio codec is Opus<sup>19</sup> and the sampling frequency 48 kHz. The second file contains the metadata encoded as plain text in the JSON format<sup>20</sup>, and has the .json extension. The file name is a random string generated according to the UUID V4 protocol<sup>21</sup>.

In the metadata we may distinguish three types of variables, related to: 1) context information (timestamp and the probability that the recording actually contains cough sounds), 2) self-reported information provided by the user, and 3) the labels provided by expert medical annotators about the clinical assessment of the cough recording. The only processing performed on the metadata was the reduction in the precision of the geolocation coordinates to just one decimal digit to ensure privacy protection. A full description of all the metadata variables is provided in Tables 1 and 2.

As an illustrative example, let us consider the recording with UUID 4e47612c-6c09-4580-a9b6-2eb6bf2ab40c. We can see the audio properties using a tool such as ffprobe (included in the ffmpeg software package<sup>22</sup>), while the metadata can be directly displayed as a text file:

#### 4e47612c-6c09-4580-a9b6-2eb6bf2ab40c.webm

```
Input #0, matroska, webm, from '4e47612c-6c09-4580-a9b6-2eb6bf2ab40c.webm':
 Metadata:
    encoder
                    : Chrome
 Duration: N/A, start: 0.000000, bitrate: N/A
    Stream #0:0(eng): Audio: opus, 48000 Hz, mono, fltp (default)
4e47612c-6c09-4580-a9b6-2eb6bf2ab40c.json
    "datetime": "2020-04-10T10:30:31.576207+00:00",
    "cough_detected": "0.9466",
    "age": "50",
    "gender": "male",
    "respiratory_condition": "True",
    "fever_muscle_pain": "False",
    "status": "COVID-19",
    "expert_labels_1": {
        "quality": "ok",
        "cough_type": "dry",
        "dyspnea": "False",
        "wheezing": "False",
        "stridor": "False",
        "choking": "False",
        "congestion": "False",
        "nothing": "True",
        "diagnosis": "COVID-19",
        "severity": "mild"
    }
}
```

For convenience, a file compiling all of the available metadata is also provided. This file is named metadata\_compiled.csv, and is a CSV file with 40 columns and one row per record. The first column corresponds to the UUID of each recording, and may be used as an index, while the rest of the columns correspond to the variables described in Tables 1 and 2. The expert annotation variables have been expanded, and are named quality\_1, cough\_type\_1 ... diagnosis\_3, severity 3.

## **Technical Validation**

#### Demographic representativeness

An important requirement for large datasets is that they must represent a wide range of subject demographics. Demographic statistics were collected across all recordings that provided metadata and that were classified as coughs with a probability above 0.8 by the XGB cough detection model. There were slightly more male subjects than female (65.5% and 33.8%, respectively), and the majority of subjects did not have pre-existing respiratory conditions (81.9%). The percentages of healthy, COVID-19 symptomatic, and COVID-19 positive subjects were 77%, 15.5%, and 7.5%, respectively. The average age of the recordings was 34.4 years with a standard deviation of 12.8 years. This shows that a wide variety of ages, genders, and health statuses are captured within our dataset.

#### Geographic representativeness

In order to assess the plausibility that samples labeled as COVID-19 truly originated from people who tested positive for the disease, we analyzed the geographic locations of the samples for which this data was provided. We then evaluated the COVID-19 statistics of the countries at the time each recording was sent to determine if these countries had high infection rates at the time of recording. Of the 10,743 samples that the XGB model classified as cough sounds, 6,485 of them provided GPS information, 676 of which reported COVID-19 symptoms and 372 claim to have been diagnosed with COVID-19.

Studies have shown that coughing persists in a significant proportion of COVID-19 cases 14-21 days after receiving a positive PCR test<sup>23</sup>. Therefore, we combined the World Health Organization's statistics on daily new COVID-19 cases<sup>1</sup> with the United Nations 2019 population database<sup>24</sup> to determine the rate of new infections in the country from which each recording originated in the 14 days prior to it being uploaded to our web server. This analysis revealed that 94.4% of our recordings labeled as COVID-19 came from countries with more than 20 newly-confirmed COVID-19 cases per 1 million people. Similarly, 91.3% of recordings labeled as symptomatic originated from these countries.

Figure 2 shows a map of the world with countries color coded according to the cumulative COVID-19 positive tests in April and May 2020 per 1 million population. We also show the COVID-19 and symptomatic recordings providing GPS information that were collected within this time period. This figure shows that most recordings were sent from countries with moderate-to-high COVID-19 infection rates at the time.

#### Inter-Rater Reliability

In order to determine the extent to which the three expert pulmonologists agreed on their cough sound labeling, Fleiss' Kappa scores<sup>25</sup>,  $K_{Fleiss}$ , were computed for each question among the 150 common recordings. The results are displayed in Table 3. This analysis revealed moderate agreement on audible nasal congestion, fair agreement on the type of cough, as well as slight agreement on the cough severity, nothing specific, audible wheezing, and audible dyspnea.

There was a poor agreement among experts on the cough diagnosis ( $K_{Fleiss} = 0.0031$ ), which is reflective of the fact that COVID-19 symptomology includes symptoms of both upper respiratory tract infections (e.g., rhinorrhea, sore throat, etc.) and lower respiratory tract infections (e.g., pneumonia, ground-glass opacities, etc.)<sup>26</sup>. There was a slight agreement between Experts 1 and 2 on the diagnosis ( $K_{Fleiss} = 0.0774$ ), whereas Expert 3 did not label any of the common recordings as COVID-19. Out of the 86 coughs that at least one rater labeled as COVID-19, 22 had a majority consensus. When the majority agreed that a cough was COVID-19, Expert 3 diagnosed it as an upper respiratory infection 59.1% of the time, a lower respiratory tract infection 27.3% of the time, and nothing 13.6% of the time. A confusion matrix between Experts 1 and 3 is displayed in Figure 3, which shows a higher degree of agreement between Experts 1 and 2 than either with Expert 3.

# Trends in Expert COVID-19 Cough Labeling

All of the coughs labeled as COVID-19 among the three experts were subsequently pooled together and analyzed for trends in the attributes of the cough recordings. In the case of overlaps, the diagnoses of Expert 1 were taken into account, producing 632 total COVID-19-labeled cough records. The vast majority of coughs do not exhibit audible dyspnea (93.0%), wheezing (90.5%), stridor (98.7%), choking (99.1%), or nasal congestion (99.2%). Additionally, 87.3% of COVID-19-labeled coughs are annotated as dry, which is consistent with literature stating that a dry cough is a common COVID-19 symptom<sup>5,26</sup>. Finally, 86.2% of these coughs are labeled as mild. These commonalities among COVID-19 labeled coughs reflect the consistency of the database.

# **Private Set and Testing Protocol**

In order to ensure the reproducibility of the experimental results that use the COUGHVID crowdsourcing dataset, a private test set has been kept out from publishing. Recordings in this private set have been randomly selected from those having at least labels from one expert.

The evaluation of models on the private test set will be open to the entire scientific community, but to ensure a fair use, the performance measurements will be obtained by an independent evaluator. Any researcher that demonstrates promising results on the public dataset using cross-validation may apply for an independent evaluation on the private test set according to the protocol described in the data repository. This protocol shall be regularly updated in line with the available technology to ensure that it is as convenient as possible for all parties.

Since one of the aims of this project is to go beyond the study of COVID-19, every variable except datetime and cough\_detected may be considered the target of a prediction model. This opens the possibility to study several different problems within the same dataset, from just cough identification and sound quality assessment to the detection of different conditions, or even the estimation of age or gender. Conversely, a prediction model may require as input not just the sound recording, but also other metadata variables to provide the necessary context, such as the age or gender of the subject. The restrictions on the sets of variables that can be used as input or as a result of the algorithms will be kept to a minimum.

# Code availability

The aforementioned XGB classifier used to remove non-cough recordings and feature extraction source code are available on our public c4science repository.

## References

- **1.** Coronavirus (COVID-19) Cases and Deaths Humanitarian Data Exchange. https://data.humdata.org/dataset/coronavirus-covid-19-cases-and-deaths.
- 2. Rosenthal, P. J. The importance of diagnostic testing during a viral pandemic: Early lessons from novel coronavirus disease (CoVID-19). *Am. J. Trop. Medicine Hyg.* **102**, 915–916, 10.4269/AJTMH.20-0216 (2020).
- **3.** Marcel, S. *et al.* COVID-19 epidemic in Switzerland: on the importance of testing, contact tracing and isolation. *Swiss Med. Wkly.* 10.4414/smw.2020.20225 (2020).
- **4.** MacKay, M. J. *et al.* The COVID-19 XPRIZE and the need for scalable, fast, and widespread testing, 10.1038/s41587-020-0655-4 (2020).
- **5.** Report of the WHO-China Joint Mission on Coronavirus Disease 2019 (COVID-19). https://www.who.int/publications/i/item/report-of-the-who-china-joint-mission-on-coronavirus-disease-2019-(covid-19).
- **6.** Pramono, R. X. A., Imtiaz, S. A. & Rodriguez-Villegas, E. A cough-based algorithm for automatic diagnosis of pertussis. *PLoS ONE* **11**, 10.1371/journal.pone.0162128 (2016).
- 7. Amrulloh, Y., Abeyratne, U., Swarnkar, V. & Triasih, R. Cough Sound Analysis for Pneumonia and Asthma Classification in Pediatric Population. In *Proceedings International Conference on Intelligent Systems, Modelling and Simulation, ISMS*, vol. 2015-October, 127–131, 10.1109/ISMS.2015.41 (IEEE Computer Society, 2015).
- **8.** Imran, A. *et al.* AI4COVID-19: AI Enabled Preliminary Diagnosis for COVID-19 from Cough Samples via an App. Tech. Rep. (2020). 2004.01275v5.
- **9.** Brown, C. *et al.* Exploring Automatic Diagnosis of COVID-19 from Crowdsourced Respiratory Sound Data. *arXiv Prepr.* 2006.05919 2006.05919v2.
- 10. iiscleap/Coswara-Data: Data repository of Project Coswara. https://github.com/iiscleap/Coswara-Data.
- **11.** Cohen-McFarlane, M., Goubran, R. & Knoefel, F. Novel Coronavirus (2019) Cough Database: NoCoCoDa. *IEEE Access* 1–1, 10.1109/access.2020.3018028 (2020).
- **12.** Gemmeke, J. F. *et al.* AUDIO SET: AN ONTOLOGY AND HUMAN-LABELED DATASET FOR AUDIO EVENTS. Tech. Rep.
- 13. Singh, V. P., Rohith, J. M., Mittal, Y. & Mittal, V. K. IIIT-S CSSD: A Cough Speech Sounds Database. In 2016 22nd National Conference on Communication, NCC 2016, 10.1109/NCC.2016.7561190 (Institute of Electrical and Electronics Engineers Inc., 2016).
- 14. Chatrzarrin, H., Arcelus, A., Goubran, R. & Knoefel, F. Feature extraction for the differentiation of dry and wet cough sounds. In MeMeA 2011 2011 IEEE International Symposium on Medical Measurements and Applications, Proceedings, 10.1109/MeMeA.2011.5966670 (2011).
- 15. Xgboost documentation xgboost 1.3.0-snapshot documentation. https://xgboost.readthedocs.io/en/latest.

- **16.** Bergstra, J. S., Bardenet, R., Bengio, Y. & Kégl, B. Algorithms for hyper-parameter optimization. In Shawe-Taylor, J., Zemel, R. S., Bartlett, P. L., Pereira, F. & Weinberger, K. Q. (eds.) *Advances in Neural Information Processing Systems* 24, 2546–2554 (Curran Associates, Inc., 2011).
- 17. Bankoski, J. Intro to WebM. In *Proceedings of the 21st international workshop on Network and operating systems support for digital audio and video NOSSDAV '11*, 1, 10.1145/1989240.1989242 (ACM Press, New York, New York, USA, 2011).
- 18. Pfeiffer, S. The Ogg Encapsulation Format Version 0. RFC 3533, 10.17487/RFC3533 (2003).
- 19. Valin, J.-M., Vos, K. & Terriberry, T. Definition of the Opus Audio Codec. RFC 6716, 10.17487/RFC6716 (2012).
- 20. Bray, T. The JavaScript Object Notation (JSON) Data Interchange Format. RFC 7159, 10.17487/RFC7159 (2014).
- 21. Leach, P. J., Salz, R. & Mealling, M. H. A Universally Unique IDentifier (UUID) URN Namespace. RFC 4122, 10.17487/RFC4122 (2005).
- 22. FFmpeg developers. FFmpeg Documentation (accessed July 16, 2020). http://ffmpeg.org/documentation.html.
- **23.** Tenforde, M. W. *et al.* Symptom Duration and Risk Factors for Delayed Return to Usual Health Among Outpatients with COVID-19 in a Multistate Health Care Systems Network United States, March–June 2020. *MMWR. Morb. Mortal. Wkly. Rep.* **69**, 993–998, 10.15585/mmwr.mm6930e1 (2020).
- **24.** World Population Prospects Population Division United Nations. https://population.un.org/wpp/Download/Standard/CSV.
- **25.** Fleiss, J. L. Measuring nominal scale agreement among many raters. *Psychol. Bull.* **76**, 378–382, 10.1037/h0031619 (1971).
- **26.** Rothan, H. A. & Byrareddy, S. N. The epidemiology and pathogenesis of coronavirus disease (COVID-19) outbreak, 10.1016/j.jaut.2020.102433 (2020).

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#### **Author contributions statement**

L.O. and T.T. devised the idea and research. L.O. developed the cough signal processing code, created the cough detection model, and performed data analysis on the user metadata and expert labels. T.T. deployed and managed the data collection website, coordinated expert labeling, and compiled all of the metadata. All authors contributed to the writing and editing of the manuscript.

# **Competing interests**

The authors declare no competing interests

# Figures & Tables

Name	Mandatory	Range of possible values	Description
datetime	Yes	UTC date and time in ISO 8601 format	Timestamp of the received recording.
cough_detected	Yes	Floating point in the interval [0,1]	Probability that the recording contains cough sounds, according to the automatic detection algorithm described in the Methods section.
latitude	No	Floating point value	Self-reported latitude geolocation coordinate with reduced precision.
longitude	No	Floating point value	Self-reported longitude geolocation coordinate with reduced precision.
age	No	Integer value	Self-reported age value.
gender	No	{female, male, other}	Self-reported gender.
respiratory_condition	No	{True, False}	The patient has other respiratory conditions (self-reported).
fever_muscle_pain	No	{True, False}	The patient has fever or muscle pain (self-reported).
status	No	{COVID, symptomatic, healthy}	The patient self-reports that has been diagnosed with COVID-19 (COVID), that has symptoms but no diagnosis (symptomatic), or that is healthy (healthy).
expert_labels_{1,2,3}	No	JSON dictionary with the manual labels from expert 1, 2 or 3	The expert annotation variables are described in Table 2.

**Table 1.** Metadata variables, as they appear in the JSON files.

Name	Range of possible values	Description
quality	{good, ok, poor, no_cough}	Quality of the recorded cough sound.
cough_type	{wet, dry, unknown}	Type of cough.
dyspnea	{True, False}	Audible dyspnea.
wheezing	{True, False}	Audible wheezing.
stridor	{True, False}	Audible stridor.
choking	{True, False}	Audible choking.
congestion	{True, False}	Audible nasal congestion.
nothing	{True, False}	Nothing specific is audible.
diagnosis	<pre>{upper_infection, lower_infection, obstructive_disease, COVID-19, healthy_cough}</pre>	Impression of the expert about the condition of the patient. It can be an upper or lower respiratory tract infection, an obstructive disease (Asthma, COPD, etc), COVID-19, or a healthy cough.
severity	{pseudocough, mild, severe, unknown}	Impression of the expert about the severity of the cough. It can be a pseudocough from a healthy patient, a mild or severe cough from a sick patient, or unknown if the expert can't tell.

**Table 2.** Variables provided by the expert annotators.

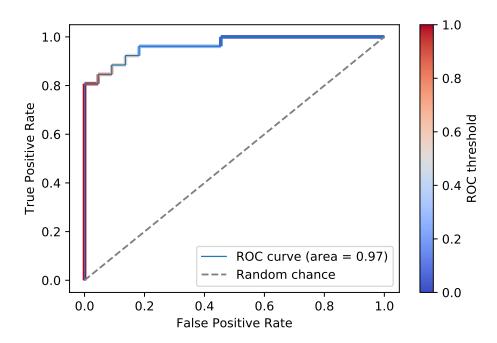
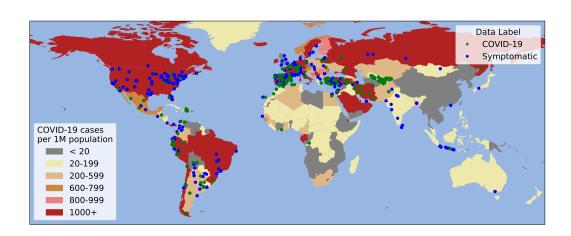


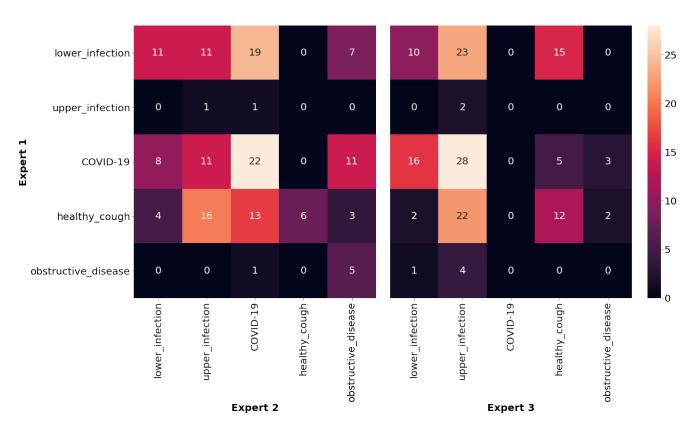
Figure 1. Receiver operating characteristic curve of the cough classifier

 Table 3. Inter-Expert Label Consistency

Item	$K_{Fleiss}$	Agreement
quality	-0.12	Poor
cough_type	0.23	Fair
dyspnea	0.04	Slight
wheezing	0.04	Slight
stridor	-0.01	Poor
choking	-0.01	Poor
congestion	0.49	Moderate
nothing	0.10	Slight
diagnosis	0.00	Poor
severity	0.12	Slight



**Figure 2.** Cumulative COVID-19 cases in April and May 2020 per 1 million population, along with the GPS coordinates of the received recordings



**Figure 3.** Confusion matrix of common cough recording diagnoses between pulmonology experts.