FAIR4Cov: Fused Audio Instance and Representation for COVID-19 Detection

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Abstract

Audio-based classification techniques on body sounds have long been studied to support diagnostic decisions, particularly in pulmonary diseases. In response to the urgency of the COVID-19 pandemic, a growing number of models are developed to identify COVID-19 patients based on acoustic input. Most models focus on cough because dry cough is the best known symptom of COVID-19. However, other body sounds, such as breath and speech, have also been revealed to correlate with COVID-19 as well. In this work, rather than relying on a specific body sound, we propose \textbf{Fused Audio Instance and Representation for COVID-19 Detection (FAIR4Cov)}. It relies on the construction of a joint feature vector obtained from a plurality of body sounds in waveform and spectrogram representation. The core component of FAIR4Cov is a self-attention fusion unit that is trained to establish the relation of multiple body sounds and audio representations and integrate it into a compact feature vector. We set up our experiments on different combinations of body sounds using only the waveform, spectrogram, and a joint representation of waveform and spectrogram. Our findings show that the use of self-attention to combine extracted features from cough, breath, and speech sounds leads to the best performance with an Area Under the Receiver Operating Characteristic Curve (AUC) score of 0.8658, a sensitivity of 0.8057, and a specificity of 0.7958. This AUC is 0.0227 higher

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than the one of the models trained on spectrograms only and 0.0847 higher than
the one of the models trained on waveforms only. The results demonstrate that
the combination of spectrogram and waveform representation helps to enrich
the extracted features and outperforms the models with a single representation.

Keywords: COVID-19, audio classification, multi-instance learning,
self-attention

1. Introduction

Our body produces innumerable sounds every day, but most of the time we
do not pay enough attention to them. Body sounds are known to reveal an
individual state of health. A slight change in the physical state can modify
the responsible organ and consequently produce irregular sound patterns. For
example, snoring is a common sound produced when certain parts of the body,
such as the tongue or pharynx, block airflow as we breathe during sleep. Snoring
alone is generally not considered symptomatic, but if coupled with breathing
pauses, it can be a symptom of obstructive sleep apnea. More generally, body
sounds can be used extensively to support diagnostic decisions. In particular,
auscultation is a medical procedure in which a clinician listens to the internal
sounds of the body using a stethoscope. Organs and systems such as the heart,
lungs, and gastrointestinal system are usually listened to detect abnormal pat-
terns. In respiratory diseases such as pneumonia, auscultation can be performed
to look for crackles or percussion dullness, an indication of fluid in the lungs.
Hence, body sound analysis is part of automated diagnostic applications such
as in respiratory diseases [1, 2, 3, 4], Parkinson’s disease [5], sleep apnea [6]. Al-
though detecting irregular internal sounds might be insufficient for a conclusive
diagnostic decision, it serves as a hallmark that can be combined with other
clinical tests obtained from different diagnostic tools to conclude.

In this article we study an audio-based approach to detect Coronavirus Dis-
ease 2019 (COVID-19), a disease caused by Severe Acute Respiratory Syndrome
CoronaVirus 2 (SARS-CoV-2). The SARS-CoV-2 infects most heavily the res-
piratory tract [7]. Therefore, infected individuals express flu-like symptoms, which can often be mistaken for a cold or flu. Complications are also typically related to pulmonary disorders, such as pneumonia or acute respiratory distress syndrome. The best diagnostic approach is viral testing, often done using nucleic acid tests such as polymerase chain reaction (PCR) to detect viral RNA fragments. Although a gold standard, PCR tests return the result after approximately 4-6 hours, excluding the delivery time, and can take up to 24 or 48 hours. As the ultimate goal of management strategies is to break the infection chain by quickly identifying suspected cases for immediate isolation or quarantine, a test with such a long waiting time as PCR is not optimal. In addition, PCR testing requires qualified staff and well-equipped facility to operate, which are hardly accessible in remote and low-income countries. An alternative test, known as the antigen test, can retrieve results in less than 30 minutes by identifying viral proteins with specific antibodies. Although antigen tests are highly suitable for mass testing, they are less sensitive to detection. Meanwhile, since SARS-CoV-2 infects mainly the respiratory systems, it induces changes in body sounds by either modifying them, e.g., dysphonia, or creating them, e.g., cough or breath sounds. Several studies show that these changes are specific to COVID-19. For example, a study by [8] finds abnormal breathing sounds in all COVID-19 patients. The irregular sounds include cackles, asymmetrical vocal resonance, and indistinguishable murmurs. In a different study of vocal changes in COVID-19 individuals [9], the authors validate the hypothesis that vocal fold oscillations are correlated with COVID-19, inducing not only changes in voice but also the inability to speak normally. Body sounds therefore have the potential to serve as standalone or in parallel with antigen tests to detect COVID-19.

There are several advantages of using body sounds for screening COVID-19. First, because PCR testing capacities are limited, screening with body sound or in conjunction with antigen tests can help prioritize who is eligible for PCR tests. If anyone with flu-like symptoms can order a PCR test, it will soon exceed the testing capacity. Only suspects indicated by body sound
screening could proceed with PCR tests. Body sound screening can rapidly identify suspect cases without asking them to quarantine while waiting for PCR results. Second, similar to antigen tests, body sound screening is fast, affordable, and conveniently conducted without medical professionals. The cost of running body sound screening can even be lower than that of antigen tests because it can be installed as software or a mobile application on any device and uses the device microphone. Users do not need to buy additional support kits and can use their device to record, analyze and monitor their status an unlimited number of times. This is particularly useful in regions or countries where testing capacities are scarce, inaccessible, or expensive. Lastly, compared to antigen tests, it does not lead to (medical) waste because no physical products are manufactured, which alleviates the burden on the environment.

Given these advantages, the potential of body sounds for screening COVID-19 is enormous. However, a fully developed screening system using body sounds is not yet available. Current research on COVID-19 detection considering multiple body sounds often focuses on individual sounds and does not consider their interaction [10, 11]. We hypothesize on the contrary that the effects of COVID-19 may occur in different body sounds or in a different combination of them, for different individuals. One or more body sounds may be affected, while the others remain intact. It is thus sensible not to rely on a single one but rather on a combination of several body sounds. We propose combining the most meaningful body sounds that are indicative of COVID-19 expressed in terms of fusion rules within the detection algorithm. Our hypothesis is stated as follows: The cough, breath and speech sounds contain biomarkers that are indicative of COVID-19 and can be combined using an appropriate fusion rule to maximize the chances of correct detection. To this end, we propose self-attention as a fusion rule to combine features extracted from cough, breath, and speech sounds. Mainly, we use waveforms and spectrograms as input to our model. A waveform represents an audio signal in the time domain, whereas a spectrogram is a representation in the time-frequency domain. Our main contributions in this work are summarized as follows:
• We demonstrate that cough, breath, and speech sounds can be leveraged to detect COVID-19 in a multi-instance audio classification approach based on self-attention fusion. Our experimental results indicate that combining multiple audio instances exceeds the performance of single instance baselines.

• We experimentally show that an audio-based classification approach can benefit from combining waveform and spectrogram representations of input signals. In other words, inputting the time- and frequency-domain dual representations into the network allows for a richer latent feature space, which finally improves the overall classification performance.

• We integrate the above contributions into the FAIR4Cov, a classification approach that combines multiple instances of body sound in waveform and spectrogram representations to classify negative and positive COVID-19 individuals. This approach can be extended to other respiratory diseases beyond COVID-19.

2. Related work

We briefly present the related work in body sound analysis for pulmonary diseases with a primary emphasis on the COVID-19 use case. Before COVID-19, there is a well-established line of research on body sound analysis for pulmonary disorders such as tuberculosis, pneumonia, or Chronic Obstructive Pulmonary Disease (COPD). Due to the urgency of the pandemic, this field of research has expanded and seen growing interest in newly developed techniques and collected datasets.

2.1. Screening pulmonary diseases

Most studies are centered on traditional machine learning techniques by building a classifier using extracted audio features of cough or respiratory sounds. Botha et al. [3] study a combination of log spectral energies and Mel Frequency Cepstral Coefficients (MFCC) in screening tuberculosis using cough sounds of
38 subjects acquired in a specially designed facility. The authors achieve an accuracy of 0.98 and an Area Under the Receiver Operating Characteristic Curve (AUC) of 0.95 for the given task. Pahar et al. [12] investigate a similar task on cough sounds of 51 healthy and tuberculosis individuals in a primary healthcare clinic. The authors propose a linear regression model on extracted features, namely MFCC, log spectral energies, Zero-crossing Rate (ZCR), and kurtosis, which leads to a sensitivity and specificity of 0.93 and 0.95, respectively. Song [1] studies breath sounds to classify pneumonia among 376 children at three children’s hospitals in Bangladesh. The author extracts a total of 18 acoustic features for the K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) classifier. The proposed method achieves 0.9198 accuracy, 0.9206 sensitivity, and 0.9068 specificity. Altan et al. [4] investigate on multichannel lung sounds of 50 subjects from a multi-media respiratory database [13] to classify COPD. The authors develop a Deep Belief Network using features extracted using the Hilbert-Huang transform [14]. The model achieves 0.9367 accuracy, 0.91 sensitivity, and 0.9633 specificity. Xu et al. [15] propose a multi-instance learning framework to process raw cough recordings and detect multiple pulmonary disorders including asthma and COPD. The presented framework achieves an F1-score of more than 0.8 in classifying healthy vs. unhealthy, obstructive vs. non-obstructive, and COPD vs. asthma. A recent and detailed review of disease classification from cough sounds can be found in [16].

2.2. Screening COVID-19

Unlike datasets of other pulmonary diseases, there are large corpora of COVID-19 related audios collected from crowdsourcing. Voluntary participants submit recordings of their body sounds to a mobile app or website and provide metadata such as their COVID-19 status and comorbidity. Such large datasets enable researchers to develop COVID-19 detection algorithms as well as to benchmark their research work. To our knowledge, the largest crowdsourcing datasets are COUGHVID [17], Coswara [18], and Covid-19 Sounds [19]. COUGHVID comprises more than 20000 cough recordings, while Coswara
and Covid-19 Sounds consist of cough, breath, and vocal sounds from more than 2000 and 30000 participants, respectively.

In terms of technical development, a few studies follow the traditional machine learning approaches with extracted audio features [20, 21, 22, 10]. The most common audio features are still MFCC, log Mel spectrogram, ZCR, and kurtosis. Fakhry et al. [20] propose an ensemble network of ResNet50 and MLP on MFCC and Mel spectrograms of cough recordings to classify COVID-19 individuals. The proposed solution claims an AUC of 0.99 on the COUGHVID dataset. In a similar approach, the study by [21] benchmarks 15 audio features in the time and frequency domains for the COVID-19 detection task using cough and breath sounds. Their findings indicate that spectral features slightly outperform cepstral features in the classification task, and the best model is achieved using a SVM and Random Forest classifier, with AUCs of 0.8768 and 0.8778, respectively.

Several studies adopt Deep Learning approaches by training CNN on spectrogram or waveform instead of extracted audio features [23, 24, 25, 11]. Rao et al. [23] present a VGG13 network [26] on spectrogram with combined cross-entropy and focal loss. The approach achieves an AUC of 0.78 on the COUGHVID dataset. Xia et al. [24] provide an analysis of combined cough, breath and speech sounds using a simple VGG-ish model. The study introduces the combination of the features of various body sounds to improve classification performance. The best performance has an AUC of 0.75 and sensitivity and specificity of 0.70.

Other studies also attempt pretraining on an external dataset or the same dataset without labels. The pretrained model is later finetuned on the target dataset with labels [27, 28, 25]. Harvill et al. [27] pretrain all samples in COUGHVID dataset using autoregressive predictive coding with Long Short-Term Memory. The Mel spectrogram is split into several frames, and the model attempts to predict the next frame given the previous frames. The pretrained model is later finetuned on the DiCOVA dataset [29] and achieves an AUC of 0.95. Similarly, Pinkas et al. [25] pretrains a transformer-based architecture to predict the next frame of the spectrogram and transfers the pretrained features.
to a set of RNN expert classifiers. The final prediction is the average of the
scores produced by all expert classifiers. The proposed training scheme reaches
a sensitivity of 0.78 on a private dataset collected by the authors. Xue and Salim
[28] propose use contrastive learning in a self-supervised pretraining phase. The
contrastive pairs are created by randomly masking the inputs. The model is
pretrained on the Coswara dataset without labels and finetuned with Covid-19
Sounds in the downstream task. The proposed technique achieves 0.9 AUC in
the COVID-19 negative vs. positive classification task.

2.3. Relation to our study

In previous research, cough sounds have often been studied more than other
body sounds. This is reasonable because dry cough is a known symptom of
COVID-19. However, different body sounds, either being used together with
cough or individually, are reported to have a performance comparable to or bet-
ter than cough sounds. For example, Suppakitjanusant et al. [11] compare two
separately trained models in cough and speech and show that speech outper-
forms cough in classifying COVID-19 patients. Xia et al. [24] also achieve the
highest performance by concatenating features of cough, breath, and speech.
Unlike research works that usually study each body sound independently [11]
or combined them by significant voting of prediction scores [10], we explore fu-
sion rules that combined them at the feature level. In other words, we train
a network that learns a joint feature vector of all body sounds. Hence, the
joint feature vector is optimized to implicitly reflect the relative importance of
each body sound toward the final prediction. Although our work falls along the
lines of [24], we investigate a more complex fusion rule than simply concate-
nating features. We use self-attention [30], which captures the dependencies
among body sounds into a joint feature vector. Self-attention is used not only
as a layer in the transformer architecture but can also be used to aggregate
features [31]. In addition, instead of using handcrafted audio features, we train
our model using waveform and spectrogram representations, therefore creating
more robust features compared to previous methods. We experiment our ap-
proach on the Coswara dataset and achieve state-of-the-art results. We report an average performance of the models obtained from cross-validation on a split test set (Section 3.3.2). However, we emphasize that there is no unique test set generated for the Coswara dataset and the data size was growing at the time we conducted our experiment.

3. Materials and Methods

We begin this section by first summarizing self-attention [30], which is an attention mechanism used as the fusion rule and as a layer in the backbone network in our approach. We then describe the proposed FAIR4Cov approach with detailed components and how they interact with each other to extract the features of body sound.

3.1. Self-attention

Self-attention [30] is originally developed for language models. A sequence in language models consists of many tokens (e.g., words) that the model needs to memorize to synthesize the global information on top of that sequence. However, memorizing a long sequence is not always possible and the model is likely to forget the tokens that emerge early in the sequence. Self-attention therefore seeks to find a set of highly important tokens in the sequence and divert the focus of the model into these ones. The reason why these tokens are chosen is that they are highly similar in their content. Instead of memorizing the whole sequence, the model just needs to memorize these tokens because they carry the same (important) message repeatedly along the sequence. Let $I$ be an input sequence of $n$ tokens in $d$ dimensions. The fundamental components of a self-attention layer are query ($Q$), key ($K$), and value ($V$), which are the projection of the input sequence $I$ with weights $W_Q$, $W_K$, $W_V$. A $n \times n$ self-attention matrix $W_a$ is then computed by taking the dot product of each query token with $n$ keys. Each row $i$ of $W_a$ denotes the similarity scores of the query token $i$ with the $n$ keys that include itself. The dot product is scaled
by $\sqrt{d}$ to stabilize the gradient. Hence, it is known as scaled dot product. Next, a softmax function is applied across each row of $W_a$ to normalize the scores between 0 and 1. The final output is a product between $W_a$ and $V$. The output has the same $n$ tokens, but each new token is the sum of tokens in $V$ weighted by each row in $W_a$. In other words, every new token $i$ in $V$ is constructed based on the similarity of the query token $i$ with other tokens.

$$Attention(Q, K, V) = W_a V = \text{softmax} \left( \frac{QK^T}{\sqrt{d}} \right) V$$  \hspace{1cm} (1)

Each self-attention layer can comprise many heads in parallel and is called multiheaded self-attention [30]. The intuition behind multihead is that each head pays attention to a different property of the input token. Assume $h$ is the number of heads, the self-attention layer outputs $h$ different sequences where each token in the sequence has the length of $d/h$. The output tokens are then concatenated across the sequences, forming the final output of shape $n \times d$.

3.2. Fused Audio Instance and Representation for COVID-19 Detection (FAIR4Cov)

We present in this section our proposed architecture. Let $D = \{x_{ij}\}$ be a dataset of $n$ subjects, where $i \in \{1,...,n\}$ denotes the subject index and $j \in \{1,...,2c\}$ denotes the index of sound instances in the set of $c$ body sounds. The components $x_{i1}^{(i)},...,x_{ic}^{(i)}$ denote the fixed-length waveform vectors related to the different $c$ audio instances. The components $x_{c+1}^{(i)},...,x_{2c}^{(i)}$ denote the associated spectrogram representation of $c$ audio instances. The spectrogram is constructed by transforming the waveform representation with Discrete Short-Time Fourier Transform [32]. In our experiments, we use the Mel-Spectrogram, which is the logarithmic transformation of the frequency in Hertz to Mel scale given by the equation:

$$m = 1127 \ln \left( 1 + \frac{f}{700} \right)$$  \hspace{1cm} (2)

Our objective is to derive a representative feature vector for $c$ body sounds per subject across waveform and spectrogram inputs. We denote by $X^{(i)} = [x_{i1}^{(i)},...,x_{2c}^{(i)}]$ the aggregated input instance related to the $i$-th subject. The
FAIR4Cov approach takes the input $x^{(i)}$ of the $i$-th subject and returns a joint feature vector $z^{(i)}$ that aggregates the information across multiple body sounds and representations as shown in the following equation.

$$z^{(i)} = \phi \left( \left[ g_w \left( \left\{ x^{(i)}_1, \ldots, x^{(i)}_c \right\} \right), g_s \left( \left\{ x^{(i)}_{c+1}, \ldots, x^{(i)}_2 \right\} \right) \right] \right)$$  \hspace{1cm} (3)

Figure 1: An overview of FAIR4Cov approach. The feature extractors wav2vec and DeiT-S/16 are responsible for extracting waveform and spectrogram features across all body sounds. The fusion unit receives the extracted waveform and spectrogram features and fuses them into a single and compact feature vector using self-attention. The classifier uses this joint feature vector to make the final prediction.

Here, $g_w$ and $g_s$ denote neural networks that extract features from waveform and spectrogram input, and $\phi$ is the attention-based fusion unit. Figure 1 shows an overview of the FAIR4Cov approach and the main components along the pipeline. The feature extractors and the fusion unit are instrumental components in our proposed approach and are further detailed in the next sections.

3.2.1. Feature extractors

Feature extractors are neural networks responsible for learning representative features for each body sound. As the input consists of waveform and spectrogram, two neural networks $g_w$ and $g_s$ are trained in parallel to handle both representations. In each network, the weights are shared across the input channels $1, \ldots, c$ and $c + 1, \ldots, 2c$. We choose $g_w$ to be a pretrained wav2vec [33]
and $g_s$ to be DeiT-S/16, a Vision Transformer (ViT) model [34]. DeiT-S/16 and wav2vec are transformer-based models and achieve state-of-the-art results in language and vision models.

**wav2vec.** The wav2vec network [33] was developed to process audio for the speech-to-text translation task. It comprises both convolutional and self-attention layers and is pretrained on a large audio corpus in an unsupervised fashion. Therefore, we take advantage of the pretrained wav2vec features and designed a finetuning unit to effectively leverage them in our target dataset. As shown in Figure 2, we first resample the audio at 8000 Hz to meet the input requirement of wav2vec. We freeze the whole wav2vec unit and use it to extract the features in every 25 ms of the input sequence. The wav2vec output has a shape of $(t, d)$ where $t$ is the time dimension and $d$ is the feature dimension. For each feature along the time axis, we select the values at the 0.1 and 0.9 quantiles, which can be considered to approximate the min and max pooling of feature vectors. The purpose of this step is to aggregate information over time by choosing only important information. After this step, we flatten the new feature matrix and feed it to a Multilayer Perceptron (MLP) layer to reduce the dimension of the feature embedding to 128.

**DeiT-S/16.** The DeiT-S/16 architecture is a variant of ViT introduced by Touvron et al. [35] as part of the DeiT (Data-efficient image Transformers), which has the exact architecture of the original ViT [34] and differs only in the training strategy. The model is categorized into a small group where the projected embedding dimension through self-attention blocks is 384. It consists of 12 multi-headed self-attention layers, and each layer uses six heads. The resolution of each patch in the attention layer is $16 \times 16$ pixels. We change the last dense layer of DeiT-S/16 to be an identity unit so that we can extract the features from the previous layer. We use the pretrained DeiT-S/16 on ImageNet and finetune on our target dataset in all of our experiments. We projected the output unit with 128 feature vectors to have a fair comparison with wave2vec.
Figure 2: Wav2vec-based model for extracting waveform features. (Step 1) 8 kHz sampled audio is fed into the pretrained wav2vec model to extract features. (Step 2) wav2vec outputs a feature vector per every 25 ms of the audio, resulting in a $t \times d$ matrix where $t$ is the total time indices and $d$ is the dimension of the feature vector. We select in each feature vector the element at the 0.1 and 0.9 quantile. (Step 3) The new feature matrix is flattened into a single vector. (Step 4) A MLP layer receives the feature vector and (Step 5) projects it into a fixed dimension of 128.

3.2.2. Fusion unit

We denote $f_k^{(i)}$ with $k \in [1, c]$ the joint feature vector obtained by concatenating the feature vector of each individual body sound extracted from $g_w$ and $g_s$:

$$f_k^{(i)} = [g_w(x_k^{(i)}), g_s(x_{k+c}^{(i)})]$$  \hspace{1cm} (4)

The fusion unit $\phi$ combines $f_k^{(i)}$ with $k = 1, \ldots, c$ into a single vector $z^{(i)}$ by using a multiheaded self-attention layer (MSA) and a MLP $h$:

$$z^{(i)} = \phi(f_1^{(i)}, \ldots, f_c^{(i)}) = h\left(MSA\left(f_1^{(i)}, \ldots, f_c^{(i)}\right)\right)$$  \hspace{1cm} (5)

The output of MSA for each subject $i$ is a new set of feature vectors $\left\{f'_k^{(i)}\right\}_{k=1}^c$ where each $f'_k^{(i)}$ is a linear combination of original feature vectors $\left\{f_k^{(i)}\right\}_{k=1}^c$ weighted by the similarity score between feature $k$ and all $c$ features. Next, we concatenate all $f'_k^{(i)}$ across $c$ vectors and feed the new concatenated vector into a MLP layer $h$ to project it to the final 128-dimensional feature vector $z^{(i)}$. The classifier takes $z^{(i)}$ and outputs the predicted probability of whether the subject
is infected with COVID-19 or not.

3.3. Experiments

3.3.1. Dataset

Coswara [18] is a crowdsourcing project to build an audio corpus from COVID-19 negative and positive individuals. The dataset is available publicly\(^1\) to enable research on the development of diagnostic tools for respiratory diseases, in this case COVID-19. The audio recordings were collected between April 2020 and September 2021 through crowdsourcing. We accessed the database when it was still in the last collection stage. Data collection occurs through a web interface where users are prompted to provide their metadata and recordings using a device microphone. The metadata covers age, sex, location and in particular COVID-19 status. Users are then instructed to submit nine audio recordings of (heavy and shallow) cough, (deep and shallow) breath, (fast and slow) counting from 1 to 20, and uttering the phonemes /a/, /e/ and /o/. The COVID-19 status must be selected from the categories negative, positive with or without symptoms, recovered and not identified respiratory disease. There is no restriction on the duration of the recordings, so users can decide when they want to start and stop recording.

Data preprocessing. The first step in the preprocessing pipeline is to remove the leading and trailing silence. We observe that long recordings (>20 seconds) mainly contain silence, and the duration at which people cough, breathe or speak lasts only 3-10 seconds. Hence, we automatically trim the silence and take only the clip with detectable amplitude. The next important step is to remove corrupted files. We define corrupted files as those that contain no sound, noise, or a different sound type than the one reported in the label. First, we remove recordings whose duration is less than 1 second because they do not contain any detected sound. Second, similar to the approach of [24], we use a pretrained

\(^{1}\text{https://github.com/iiscleap/Coswara-Data}\)
model called YAMNet\textsuperscript{2} to systematically remove recordings where the detected sound is not the same as the provided label. YAMNet is a pretrained model on YouTube audio to classify 521 events, including cough, speech, and breath. If most of the predicted events in a recording are not cough, speech, or breath, we will remove all recordings associated with this participant. In addition, we decide not to use shallow cough and breath in our experiments because the quality of such recordings is low and can be misdetected as noise. Altogether, 710 participants are discarded from the initially curated dataset through this process and the 1359 remaining participants are considered for our analysis. Out of them, 1136 people (83.6\%) are COVID-19 negative and 223 people are COVID-19 positive. Each participant has exactly 7 recordings, which amounts to 9513 recordings used in our experiments. We provide in Table 1 the statistics of the audio length of all body sound instances after the preprocessing step. In our experiments, the participants are split into six folds for training and testing purposes. The details of the split are presented in Section 3.3.2.

| Body sound         | Min (sec) | Max (sec) | Median (sec) | Mean (sec) |
|--------------------|-----------|-----------|--------------|------------|
| Heavy cough        | 1.58      | 30.04     | 6.06         | 6.27       |
| Deep breath        | 2.65      | 30.04     | 16.30        | 17.08      |
| Normal counting    | 1.62      | 29.95     | 14.34        | 14.58      |
| Fast counting      | 1.86      | 29.95     | 7.94         | 8.00       |
| Phoneme /a/        | 1.19      | 29.95     | 10.03        | 10.53      |
| Phoneme /e/        | 1.28      | 29.95     | 10.96        | 11.73      |
| Phoneme /o/        | 1.37      | 29.95     | 10.41        | 11.19      |

Table 1: The statistics of audio length (in second) after the preprocessing step.

Data transformation and augmentation. For audio processing and transformation, we use Torchaudio\textsuperscript{3}, a library for audio and signal processing with Pytorch.

\textsuperscript{2}https://www.tensorflow.org/hub/tutorials/yamnet
\textsuperscript{3}https://pytorch.org/audio/stable/index.html
The values of loaded audio are automatically normalized between -1 and 1. As users record with different device microphones, the sample rate is not consistent across all recordings. We resample all recordings with two sample rates; 44100 Hz and 8000 Hz. The DeiT-S/16 uses a sample rate of 44100 Hz while the wav2vec model uses a sample rate of 8000 Hz. We decide to use only four seconds of each recording, which is an optimal value to get the best results after we finetune with different values. In terms of spectrogram transformation, we take the Mel-spectrogram with 128 Mel filterbanks operating in 1025 frequency bins, i.e., FFT size of 2048, window size of 2048, and hop size of 1024. We perform data augmentation on-the-fly during training. For each training audio, we randomly select a continuous 4-second interval out of the first 5 seconds of the recording to ensure a slight variation. However, during evaluation, we select the first 4 seconds in the audio. We investigate many audio augmentation techniques such as pitch shift, time stretch, or masking, but not all prove helpful in our tasks. Ultimately, only amplitude scaling, time and frequency masking are retained. In the amplitude scaling, we randomly inject an amplitude gain between 0.9 and 1.3 on the waveform. Amplitude scaling is always performed before spectrogram transformation in case the spectrogram representation is used. For the spectrogram, we apply random time and frequency masking with a length of 10. This augmentation randomly sets consecutive blocks of size 10 in time or frequency bins to a value of 0 to help the network be robust to deformation in the time and frequency direction.

3.3.2. Experimental setup

Baseline and benchmark experiments. Our hypothesis states that the combination of body sounds can improve the detection of COVID-19 from audio recordings. Therefore, we compare the models developed with a single body sound instance, the baseline (BA) with multiple combinations of body sounds, the benchmark (BE). Table 2 shows an overview of the baseline and benchmark

4https://pytorch.org/
experiments. In **baseline experiments**, we train seven models, each using only a single body sound instance and therefore without the fusion unit. The seven instances are heavy cough, deep breath, fast and normal counting, and the utterance of the phonemes /a/, /e/ and /o/. In **benchmark experiments**, we group counting and utterance of the three vowels as a single instance, thereafter speech. We investigate the following combinations: (1) speech, (2) cough and breath, (3) cough and speech, (4) breath and speech, and (5) cough, breath, and speech. In both baseline and benchmark experiments, we consider the input to be represented as either waveform or spectrogram in two separate experiments. The last experiment (BE3) is our FAIR4Cov model, for which we use both waveform and spectrogram input.

| No. | Representation | Architecture | Body sound fusion | No. models |
|-----|----------------|--------------|-------------------|------------|
| BA1 | Waveform       | wav2vec      | None              | 7          |
| BA2 | Spectrogram    | DeiT-S/16    | None              | 7          |
| BE1 | Waveform       | wav2vec      | Attention         | 5          |
| BE2 | Spectrogram    | DeiT-S/16    | Attention         | 5          |
| BE3 | Spectrogram    | DeiT-S/16    | Attention         | 5          |
|     | Waveform       | wav2vec      |                   |            |

Table 2: Baseline and benchmark experiments. The last experiment (BE3) is our proposed FAIR4Cov model that uses both waveform and spectrogram inputs and the body sound fusion unit.

**Inputs.** The input of DeiT-S/16 [35] is a spectrogram of size $128 \times 173$ calculated from a 4-second audio clip sampled at 44100 Hz. The waveform input to wav2vec has a sample rate of 8000 Hz to be compatible with the pretrained wav2vec network. For 4 seconds, this waveform input corresponds to a length of 32000.

**Cross-Validation.** A set of 226 subjects (191 covid-19 negative and 35 positive), thereafter the test fold, is randomly selected from our data to serve as a fixed test set for all experiments. The remaining 1133 subjects are used as training
and validation in a 5-fold cross-validation scheme as follows: the subjects are split into 5 folds of similar size (see Table 3), 4 folds are used for training and the remaining fold for validation in a rotating process so that each subject is used exactly once as the validation fold. It provides five different models; each of them is tested on the fix test fold and the average of the results is reported in this article.

| Subset | Label | Trial 1 | Trial 2 | Trial 3 | Trial 4 | Trial 5 |
|--------|-------|---------|---------|---------|---------|---------|
| Train  | Negative | 761     | 756     | 751     | 760     | 752     |
|        | Positive | 146     | 151     | 155     | 146     | 154     |
| Validation | Negative | 184     | 189     | 194     | 185     | 193     |
|        | Positive | 42      | 37      | 33      | 42      | 34      |

Table 3: Repartition of the subjects for the 5-fold cross-validation scheme

Hyperparameters. Table 4 shows the complete hyperparameter settings in our experiments. Most hyperparameters are identical across architectures, representations, or fusion rules. For example, we train all models for 30 epochs without early stopping, and the best checkpoint is saved based on the best AUC obtained in the validation fold. The loss function that we use is binary cross-entropy (BCE), and we optimize this loss with AdamW (Adam with weight decay) [36]. However, concerning the learning rate, we fix a base learning rate of 0.0001 for all experiments and adjust the learning rate scheduler and weight decay conditional on the architecture or fusion rules. The weight decay factor is set between 0.1 and 0.001.

Evaluation. Our primary metric for model selection is AUC. During training, we save the checkpoint with the highest performance based on AUC. During validation, we use AUC to compute the optimal threshold and take this threshold to compute other metrics such as sensitivity and specificity in the test set. We report the AUC scores in the main paper and provide the sensitivity and specificity in the Appendix.
Table 4: Hyperparameter settings in baseline and benchmark experiments.

| Architecture              | wav2vec          | DeiT-S/16        | FAIR4Cov         |
|---------------------------|------------------|------------------|------------------|
| Body sound fusion         | None  Attention  | None  Attention  | Attention        |
| Optimizer                 | AdamW AdamW      | AdamW AdamW      | AdamW            |
| Base learning rate        | 1e-4 1e-4        | 1e-4 1e-4        | 1e-4             |
| Weight decay              | 1e-3 1e-3        | 1e-1 1e-1        | 1e-3             |
| Optimizer momentum        | (0.9, 0.99)      | (0.9, 0.99)      | (0.9, 0.99)      |
| Batch size                | 32 32            | 32 32            | 32               |
| Training epochs           | 30 30            | 30 30            | 30               |
| Learning rate scheduler   | cosine cosine    | cosine cosine    | cosine           |
| Warmup epochs             | 10 10            | 10 10            | 10               |
| Loss function             | BCE BCE          | BCE BCE          | BCE              |

4. Results and Discussion

4.1. Baseline results

Table 5 shows the performance of the models trained on a single body sound instance. The input to the model is either a waveform (BA1) or a spectrogram (BA2). The results reveal that the models trained on spectrograms perform substantially better than those trained on waveforms. The average AUC scores for DeiT-S/16 (BA2) and wav2vec (BA1) are, respectively, 0.7549 and 0.6126. The performance of different body sounds across architectures and representations does not establish a consistent pattern. For example, using only cough sounds leads to the highest AUC score in DeiT-S/16, but a lower score in wav2vec. There appears to be a countertrend between DeiT-S/16 and wav2vec. For example, the counting sound achieves better results than the fast counting sound in DeiT-S/16 but worse in wav2vec. Similarly, the utterance of /o/ outperforms other vowels in DeiT-S/16 but performs poorly in wav2vec.

4.2. Benchmark results

Table 6 shows the results for the FAIR4Cov model (BE3) compared to the DeiT-S/16 (BE2) and wav2vec (BE1) models in different combinations of body
sounds using self-attention fusion. In general, the FAIR4Cov approach significantly outperforms models trained on a single representation. The average AUC score of FAIR4Cov is 0.8316, which is 0.0227 more than DeiT-S/16 and 0.0847 more than wav2vec. FAIR4Cov achieves the highest AUC scores in all combinations of body sound with the only exception in the cough-breath combination, which will be discussed in the next section. The cough-breath combination results in the lowest AUC score in all alternatives in terms of the body sound combination. The largest combination, cough-breath-speech, gives the best results in FAIR4Cov and wav2vec but is behind the cough-speech combination in DeiT-S/16 by a margin of AUC 0.007. FAIR4Cov achieves the highest AUC score of 0.8658 with the combination of cough, breath, and speech. This score is 0.0343 and 0.0941 higher than the best scores produced by DeiT-S/16 and wav2vec. The results of the FAIR4Cov models find clear support for the use of dual audio representation along with body sound fusion.

4.3. Discussion

4.3.1. Influence of body sound combinations

As can be seen in Table 6, the AUC scores are not comparable among all combinations of body sound. Therefore, it is valid to doubt whether there is a

| Body sound     | wav2vec (BA1) | DeiT-S/16 (BA2) |
|----------------|---------------|-----------------|
| Cough - heavy  | 0.4574 ± 0.0093 | 0.7782 ± 0.0132 |
| Breath - deep | 0.6597 ± 0.0222 | 0.7552 ± 0.0254 |
| Counting - fast | 0.7090 ± 0.0136 | 0.7291 ± 0.0196 |
| Counting - normal | 0.6285 ± 0.0155 | 0.7943 ± 0.0326 |
| Phoneme /a/    | 0.6484 ± 0.0150 | 0.7418 ± 0.0399 |
| Phoneme /e/    | 0.6209 ± 0.0197 | 0.7399 ± 0.0318 |
| Phoneme /o/    | 0.5649 ± 0.0293 | 0.7457 ± 0.0288 |
| Average        | 0.6127 ± 0.0751 | 0.7549 ± 0.0215 |

Table 5: AUC scores of the baseline experiments for spectrogram (DeiT-S/16) and waveform (wav2vec) models. The bold scores denote the highest performance between spectrogram and waveform.
Table 6: AUC of the benchmark experiments for the spectrogram model (DeiT-S/16), the waveform model (wav2vec) and the FAIR4Cov framework. The bold scores denote the highest performance between spectrogram, waveform and FAIR4Cov.

| Model                  | wav2vec (BE1) | DeiT-S/16 (BE2) | FAIR4Cov (BE3) |
|------------------------|---------------|-----------------|----------------|
| Speech                 | .7562 ± .0152 | .8081 ± .0239   | .8434 ± .0290  |
| Cough + Breath         | .6739 ± .0435 | .7685 ± .0183   | .7585 ± .0174  |
| Cough + Speech         | .7644 ± .0088 | .8315 ± .0306   | .8584 ± .0308  |
| Breath + Speech        | .7682 ± .0149 | .8122 ± .0125   | .8319 ± .0187  |
| Cough + Breath + Speech| .7717 ± .0128 | .8241 ± .0266   | .8658 ± .0115  |
| Average                | .7469 ± .0369 | .8089 ± .0218   | .8316 ± .0384  |

preferable combination of body sounds that leads to the best predictive outcome. However, it is not conclusive based on our experimental results or the literature to decide the best combination choice or selection rules. Instead, we argue that no body sound is significantly better than the others and that the performance is correlated rather with the number of body sounds in that combination. To illustrate this point, we look at the performance of our model when (1) only a single body sound instance and (2) a combination of body sounds is used.

When we train models with a single body sound instance as input (Section 4.1), we find that no single body sound instance consistently outperforms the others. A body sound instance may perform better than others under specific architectures or audio representations while worse in another setting. For example, the DeiT-S/16 model (BA2) trained on cough sound is among the best body sounds with an AUC score of 0.7782. However, when the feature extractor is wav2vec (BA1), the AUC score drops to 0.4574. We also observe a similar standard error when replacing the DeiT-S/16 architecture with ResNet50 (Appendix B.2). This indicates that the subtle difference observed among body sounds may be due merely to stochasticity or the setting of the feature extractor, and no body sound is significantly better than the others as input to our model.

Regarding the combinations of body sounds (Section 4.2), we observe that
the combination of cough and breath invariably leads to the lowest AUC scores for all models. At the same time, this combination considers only two body sound instances, heavy cough, and deep breath, while all other combinations consider at least five sound instances. This observation suggests that the performance is likely to correlate with the number of body sound instances. To support this, we conduct additional experiments in a similar setting to benchmark experiments with the following combinations; counting (incl. fast and normal counting) and vowel (incl. utterance of /a/, /e/ and /o/). Figure 3 shows that counting and cough-breath combination, both with two instances, achieve roughly similar performance. The combination of the /a-e-o/ utterances performs better than the 2-instance combinations, i.e., cough-breath and (fast-normal) counting, by a margin of 0.03-0.04 AUC. This supports a correlation between performance and the number of body sounds.

Figure 3: AUC scores of the DeiT-S/16 model and FAIR4Cov framework vs. number of instances in each combination. The x-axis shows the combination with the number of instances in the ascending order of quantity. Additional results can be found in Appendix B.1 and C.1.

In addition to the number of body sounds in each combination, the varying
duration of each instance can influence the results. In this study, we truncate each recording to 4 seconds. However, a body sound such as cough could last less than 4 seconds and the rest of the audio be just breath. A finer analysis taking this aspect into account should be considered in a follow-up study.

4.3.2. Influence of dual representations

We analyze the effect of the dual representation of the spectrogram and waveform in the absence of body sound fusion by conducting an ablation study similar to the FAIR4Cov framework but with the input of a single body sound. As there are no rules for body sound fusion, the features extracted from two representations are concatenated, flattened, and then projected onto a 128-dimensional vector by a MLP layer. Similar to the baseline experiment, we present the AUC scores of seven models trained on 7 body sound instances in Table 7. Overall, the average AUC scores are on par with those of the DeiT-S/16 model (BA2) in Table 5. Breath and counting sounds achieve the highest AUC score, whereas the utterance of vowel /e/ and /o/ leads to the lowest performance. The benefit of joint features from dual representation is not observed because the change in the individual AUC scores of each body sound does not follow any pattern. Compared to the DeiT-S/16 results in Table 5, except for cough, the difference in performance is subtle. The result suggests that the waveform representation contributes little to the final classifier. The performance is indeed strongly influenced by the powerful DeiT-S/16 in the spectrogram representation, which eclipses the features obtained from the waveform. Therefore, we conclude that using dual representation in the absence of body sound fusion did not improve any performance. However, when the dual representation is used for body sound fusion, the extra information from multiple body sounds is picked up by the fusion unit and enriches the joint extracted feature. We will discuss the role of dual representation when used with body sound fusion in the next section.
Dual representation without fusion rules

| Architecture       | DeiT-S/16 & wav2vec |
|--------------------|---------------------|
| Cough - heavy      | .7426 ± .0268       |
| Breath - deep      | .7661 ± .0113       |
| Counting - fast    | .7698 ± .0204       |
| Counting - normal  | .7581 ± .0938       |
| Phoneme /a/        | .7577 ± .0213       |
| Phoneme /e/        | .7299 ± .0174       |
| Phoneme /o/        | .7394 ± .0168       |
| Average            | .7519 ± .0137       |

Table 7: Baseline performance (in AUC) of FAIR4Cov on a single body sound.

4.3.3. Influence of attention-based fusion

The fusion rule for body sound relies on self-attention. One of the interesting properties of self-attention is scaling, which is discussed in the work of Dosovitskiy et al. [34]. The authors note that the performance of the transformer-based model could be scaled up in response to an increase in resolution of patches or number of blocks. This contrasts with convolutional networks, in which accuracy can reach saturation at a certain level of complexity. This scaling property explains why adding more body sounds leads to a steady increase in AUC scores. Adding more body sounds means adding more tokens and establishing stronger dependencies among them. When only two or three instances of body sound are adopted, the effect of body sound fusion is less significant. Figure 3 shows the AUC scores of the FAIR4Cov and DeiT-S/16 models on the different combinations of body sounds sorted in ascending order of instances. Combinations with less than or equal to three instances, i.e., cough-breath, fast and normal counting, /a-e-o/ vowel utterance achieve AUC scores in the range of 0.75-0.79, which is on par or slightly better than the performance of models on a single instance (Table 7). This happens because the number of instances
is insufficient to establish long-range dependencies. As more body sounds are added, these dependencies are captured, and the performance of models with fusion units started to improve substantially. Likewise, the joint feature vector embeds more information when a dual representation is adopted. When the number of instances in the combination is small, i.e., less than three, the gain due to the dual representation is not noticeable. However, starting from five instances, the gap between FAIR4Cov and DeiT-S/16 becomes wider in favor of FAIR4Cov. We attribute this gain to the resonance of extra information given by the dual representation and the number of body sounds, which efficiently captured the self-attention fusion rule.

5. Conclusion

In this article, we study Deep Learning approaches to detect COVID-19 using body sounds. To this end, we propose FAIR4Cov, a multi-instance audio classification approach with attention-based fusion on waveform and spectrogram representation. We prove the effectiveness of our approach by conducting extensive experiments on the Coswara dataset. The results demonstrate that the fusion of body sounds using self-attention helps extract richer features that are useful for the classification of COVID-19 negative and positive patients. In addition, we perform an in-depth analysis on the influence of the fusion rule on the performance. We found that the scaling property of self-attention shows great efficiency when more instances of body sounds and representations are adopted. The best setting with a combination of cough, breath, and speech sounds in waveform and spectrogram representation results in an AUC score of 0.8658, a sensitivity of 0.8057, and a specificity of 0.7958 on our test set. The sensitivity of our model exceeds 0.75, the required threshold of the COVID-19 screening test [37]. The FAIR4Cov approach can be scaled to an unlimited number of body sounds and applied to other respiratory diseases.
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Appendix A. Self-attention fusion with only waveform inputs

| Feature Extractor | wav2vec (BE1) |
|-------------------|---------------|
|                   | AUC | Sensitivity | Specificity |
| **Body sound**    |     |             |             |
| Speech            | .7562 ± .0152 | .3557 ± .0409 | .7592 ± .0586 |
| Cough + Breath    | .6739 ± .0435 | .2694 ± .0363 | .7200 ± .0524 |
| Cough + Speech    | .7644 ± .0088 | .3922 ± .0771 | .7906 ± .0937 |
| Breath + Speech   | .7682 ± .0149 | .3747 ± .0675 | .6743 ± .0966 |
| Cough + Breath + Speech | .7717 ± .0128 | .3358 ± .0347 | .7236 ± .0669 |

Table A.1: AUC, sensitivity, and specificity of wav2vec models on different combination of body sounds using self-attention fusion
## Appendix B. Self-attention fusion with only spectrogram inputs

| Feature Extractor | DeiT-S/16 (BE2) |
|-------------------|-----------------|
|                   | AUC | Sensitivity | Specificity |
| Speech            | .8081 ± .0239 | .7486 ± .0775 | .7717 ± .0711 |
| Cough + Breath    | .7685 ± .0183 | .6400 ± .0642 | .8293 ± .0718 |
| Cough + Speech    | .8315 ± .0306 | .7371 ± .0836 | .7927 ± .0892 |
| Breath + Speech   | .8122 ± .0125 | .6571 ± .0313 | .8796 ± .0298 |
| Cough + Breath + Speech | .8241 ± .0266 | .6914 ± .0796 | .8408 ± .0838 |
| Counting (fast + normal) (*) | .7467 ± .0124 | .6629 ± .0946 | .7790 ± .0774 |
| Phoneme (/a/-/e/-/o/) (*) | .7806 ± .0208 | .7886 ± .0100 | .6827 ± .0753 |

Table B.1: AUC, sensitivity, and specificity of DeiT-S/16 models on different combination of body sounds using self-attention fusion.

(*) Ablation experiments on additional body sound combination for discussion in Section 4.3.3

| Feature Extractor | ResNet50 |
|-------------------|----------|
|                   | AUC | Sensitivity | Specificity |
| Speech            | .7531 ± .0362 | .7314 ± .0983 | .6817 ± .0818 |
| Cough + Breath    | .7585 ± .0259 | .6400 ± .0859 | .8188 ± .0832 |
| Cough + Speech    | .7817 ± .0282 | .8000 ± .1352 | .6628 ± .0992 |
| Breath + Speech   | .7862 ± .0238 | .7314 ± .0878 | .7466 ± .1058 |
| Cough + Breath + Speech | .8026 ± .0229 | .6914 ± .1120 | .7959 ± .1175 |

Table B.2: AUC, sensitivity, and specificity of ResNet50 models on different combination of body sounds using self-attention fusion.
### Appendix C. FAIR4Cov

| Feature Extractors | DeiT-S/16 & wav2vec (BE3) |
|--------------------|---------------------------|
|                    | AUC    | Sensitivity | Specificity |
| Speech             | .8434 ± .0290 | .7429 ± .0767 | .8356 ± .0266 |
| Cough + Breath     | .7585 ± .0174 | .6629 ± .0874 | .8168 ± .0754 |
| Cough + Speech     | .8584 ± .0308 | .8171 ± .1063 | .7738 ± .0977 |
| Breath + Speech    | .8319 ± .0187 | .7771 ± .0554 | .7895 ± .0644 |
| Cough + Breath + Speech | .8658 ± .0115 | .8057 ± .0554 | .7958 ± .0678 |
| Counting (fast + normal) (*) | .7702 ± .0313 | .7086 ± .0836 | .7717 ± .0470 |
| Phoneme (/a/-/e/-/o/) (*) | .7906 ± .0095 | .7886 ± .0530 | .6848 ± .0499 |

Table C.1: AUC, sensitivity, and specificity of FAIR4Cov models (DeiT-S/16 & wav2vec) on different combination of body sounds.

(*) Ablation experiments on additional body sound combination for discussion in Section 4.3.3