The EIHW-GLAM Deep Attentive Multi-model Fusion System for Cough-based COVID-19 Recognition in the DiCOVA 2021 Challenge

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Abstract

Aiming to automatically detect COVID-19 from cough sounds, we propose a deep attentive multi-model fusion system evaluated on the Track-1 dataset of the DiCOVA 2021 challenge. Three kinds of representations are extracted, including hand-crafted features, image-from-audio-based deep representations, and audio-based deep representations. Afterwards, the best models on the three types of features are fused at both the feature level and the decision level. The experimental results demonstrate that the proposed attention-based fusion at the feature level achieves the best performance (AUC: 77.96 %) on the test set, resulting in an 8.05 % improvement over the official baseline.

Index Terms: COVID-19, cough, deep representations, multimodel fusion, attention

1. System Description

To describe our system, the methodology will be briefly introduced in Section 1.1. The pre-processing procedure of the audio signals will be then explained in 1.2. Afterwards, the methods of single-model feature extraction and classification will be described in Section 1.3, and the fusion methods of multiple models will be given in Section 1.4. Finally, the experimental results will be shown and analysed in Section 1.5.

1.1. Methodology Overview

Our proposed system consists of three major types of representations as the input: i) hand-crafted features, ii) high-level image-from-audio-based representations extracted by pre-trained models from natural image datasets, and iii) high-level audio-based representations extracted by pre-trained models from audio datasets. The extracted features are then classified via training a feed-forward deep neural network (DNN) on the hand-crafted features or fine-tuning the transferred models on the high-level representations. The outputs of all classifiers are the probabilities of audio samples being COVID-19 positive. Finally, the multiple classifiers are assembled using a feature-decision-level fusion.

1.2. Pre-processing

In our experiments, the officially provided audio waves with a sampling rate of 44.1 kHz in the Track-1 of the DiCOVA challenge 2021 are resampled into 16 kHz. To train a deep learning model, all of the audio signals are cut into smaller segments with a time length of 57,600 frames. Notably, the log Mel spectrograms (cf. Figure 1) with a time length of 224 frames are generated using a window size of 512 and an overlap of 256. For each audio sample, the probabilities of all its segments are averaged as the final prediction. Further, to make the input size consistent with the hyperparameters in the pre-trained model, all of the audio signals are cut into smaller segments with a time length of 256 frames. Notably, the log Mel functionals are then extracted by pre-trained models from natural image datasets, and the audio-based representations are averaged as the final prediction. Further, to make the input size consistent with the hyperparameters in the pre-trained models, all of the audio signals are cut into smaller segments with a time length of 256 frames.
and 1, respectively.

1.3.2. Transfer-learning-based Representations

To tackle small-scale datasets using deep learning topologies, transfer learning \[7\] has shown potential of extracting highly abstract representations with pre-trained models learnt from large-scale datasets. Both image-based and audio-based pre-trained models are utilised to extract features from the Track-1 dataset of the DiCOVA 2021 challenge.

Image-based models. A large number of deep learning models have proven to be effective in processing large-scale natural image datasets, such as ImageNet \[8\]. In this work, we choose VGG11 \[9\] and ResNet34 \[10\] to extract high-level representations from log Mel spectrograms. Particularly, the final two linear layers of VGG11 are replaced with three new linear layers, which output the number of neurons 1, 024, 256, and 1. As only one linear layer is used in ResNet34 as the final layer, it is replaced with three new linear layers as those in VGG11, and updated along with the final convolutional block.

Audio-based models. While transferring pre-trained image-based models to audio classification tasks, the data difference between images and audio waves might be a potential bottleneck of improving the performance \[11\]. Therefore, deep learning models trained on large-scale audio databases (e.g., AudioSet \[12\]) are applied to extract representations from the log Mel spectrograms. We initialise our models with the parameters of the pre-trained CNN14_16k and ResNet38 \[2\], which have shown state-of-the-art performances on AudioSet. The first linear layer in both models is replaced with a trainable linear layer which outputs the number of neurons 1, 024, and followed by two trainable linear layers with the number of output neurons 256, and 1.

1.4. Multi-model Fusion

With the trained models on the hand-crafted features and the transfer-learning-based representations, a set of fusion approaches are employed to improve the performance. Especially, an attention mechanism \[13,14\] is proposed in our study to fuse the multiple models. Next, the feature-level and decision-level fusion methods will be introduced in Section 1.4.1 and Section 1.4.2.

1.4.1. Feature-level Fusion

We apply feature-level fusion methods at the output of the second linear layer in each best model of the three methods in Section 1.3 (i.e., a DNN model on hand-crafted features, an image-based model, and an audio-based model), including max fusion, average fusion, and attention-based fusion.

Max fusion selects the maximum values from the learnt three representations, and outputs a vector with a length of 256. The feature vector is finally processed by a linear layer, which outputs a probability value for each audio segment.

Average fusion calculates the average vector of the three representations, and outputs a 256 dimensional vector, which is then fed into a linear layer.

Attention-based fusion aims to calculate the contribution of each unit in the three representations. An additional one-dimensional convolutional layer with a kernel size of 1 and an output channel number of 256, followed by a sigmoid function, is applied to the representations. Afterwards, the normalised output of the convolutional layer is multiplied with the representations. The summed results of the multiplication are finally fed into a linear layer to calculate the probability.

1.4.2. Decision-level Fusion

Apart from the feature-level fusion, decision-level fusion works on the output activation of the final linear layer. Similarly, the max, average, and attention-based decision-level fusion methods will be introduced as follows.

Max fusion at the decision level selects the maximum probability. Average fusion computes the average probability of the obtained three probabilities for each audio segment. Attention-based fusion processes the output of the second linear layer with two one-dimensional convolutional layers, with a kernel size of 1 and an output channel number of 1. Next, one of the convolutional layers is followed by a sigmoid function and normalisation. Furthermore, the normalised output is multiplied with the output of the other convolutional layer, and the multiplication result is summed up to give the final probability.

1.5. Experimental Results

1.5.1. Database

Our proposed approaches are evaluated on the dataset of Track-1 (cough sounds) of the DiCOVA 2021 challenge \[1\]. The dataset is composed of 1, 040 audio files (965 non-COVID) recorded from COVID-19 positive and negative individuals. The majority of the individuals are COVID-negative male individuals with their age in 15 – 30 years \[1\]. All cough sound recordings are sampled to 44.1 kHz and compressed as FLAC format. The dataset is split into five folds for cross-validation, where each fold has a training and a validation set. Additionally, the blind test set is composed of 233 audio samples. The evaluation metrics of the results consist of the sensitivity, the specificity, and the Area Under the Curve (AUC) \[1\].

1.5.2. Experimental Setup

During training, the parameters are updated with 30 epochs and iterated with a batch size of 16. The ‘Adam’ optimiser with a learning rate of 0.001 is experientially applied during the training process. As for the loss function, BCEWithLogitsLoss is used with the weight set as ratio of the number of COVID-positive samples to the number of COVID-negative ones in the training data. Moreover, after every 10 epochs, the learning rate decays by 0.1 to stabilise the training procedure. To recognise COVID-19 on the test set, the whole dataset with 1, 040 samples contributes to training models.

1.5.3. Results and Discussion

The results evaluated on the validation and test sets are given in Table 1. Compared to the official baseline (average validation AUC: 68.81 %, test AUC: 69.91 %), the results of the three single-model methods are comparable or slightly lower on the validation and test sets. However, the multi-model fusion approaches achieve improvements over the single-model methods, and mostly outperform the baseline system. Especially, the proposed feature-level attention and decision-level attention fusion approaches perform better than both the max and average fusion methods. Finally, the feature-level attention achieves an AUC of 77.96 % on the test set, resulting in an improvement of the baseline.

In future efforts, more data pre-processing and augmentation techniques, such as signal enhancement and Generative Adver-
Table 1: Performances of our proposed approaches evaluated on the Track-1 database of DiCOVA challenge 2021 for COVID-19 detection. The performances on the validation sets are the average results over the five folds, followed by the standard deviations (std).

| [\%] | Validation | Test |
|------|------------|------|
|      | Sensitivity (std) | Specificity (std) | AUC (std) | Sensitivity | Specificity | AUC |
| Log Mel | 80.00 (0.00) | 33.16 (8.49) | 60.67 (6.15) | 80.49 | 27.60 | 67.41 |
| MFCC | 80.00 (0.00) | 30.88 (7.63) | 61.16 (3.65) | 80.49 | 23.44 | 55.63 |
| COMPARE | 80.00 (0.00) | 33.58 (8.08) | 65.50 (1.96) | 80.49 | 40.10 | 66.90 |

Transfer Learning from ImageNet

| VGG11 | 80.00 (0.00) | 32.23 (2.73) | 63.09 (2.55) | 80.49 | 42.71 | 65.69 |
| ResNet34 | 80.00 (0.00) | 20.41 (3.83) | 51.69 (3.80) | 80.49 | 38.02 | 58.75 |

Transfer Learning from AudioSet

| CNN14 _16k | 80.00 (0.00) | 42.28 (5.49) | 67.82 (3.29) | 80.49 | 44.27 | 67.77 |
| ResNet38 | 80.00 (0.00) | 39.27 (14.81) | 68.36 (4.54) | 80.49 | 45.31 | 65.66 |

Multi-model Fusion

| Feature-Max | 100.00 (0.00) | 00.00 (0.00) | 63.73 (3.94) | 80.49 | 28.12 | 65.56 |
| Feature-Avg | 80.00 (0.00) | 35.54 (8.59) | 68.51 (2.09) | 80.49 | 61.46 | 73.72 |
| Feature-Attention | 80.00 (0.00) | 44.56 (6.29) | 70.56 (3.01) | 80.49 | 59.38 | 77.96 |
| Decision-Max | 80.00 (0.00) | 31.40 (8.20) | 66.66 (2.25) | 80.49 | 38.02 | 66.44 |
| Decision-Avg | 80.00 (0.00) | 35.03 (9.67) | 68.57 (2.98) | 80.49 | 55.73 | 73.25 |
| Decision-Attention | 80.00 (0.00) | 39.17 (9.41) | 68.21 (3.92) | 80.49 | 59.38 | 77.36 |

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