

The Second DiCOVA Challenge:

Dataset And Performance Analysis for Diagnosis of COVID-19 using Acoustics

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Sound based Diagnosis



COVID-19 diagnosis methods:

- RT-PCR testing
- RAT testing
- Point-of-care testing (POCT)
- Advantages of sound based diagnosis of COVID-19



Motivation



DiCOVA Challenge series

- Diagnosis of COVID-19 using acoustics
- COSWARA dataset [1]
- First DiCOVA Challenge [2]: 12 Feb 23rd March, 2021
 - Focused on cough audio recordings
 - Special Session in Interspeech 2021
 - 29 teams from around the world
 - 19 outperformed baseline

1. Neeraj Sharma, Prashant Krishnan, Rohit Kumar, Shreyas Ramoji, Srikanth Raj Chetupalli, R Nirmala, Prasanta Kumar Ghosh, and Sriram Ganapathy, "Coswara – a database of breathing, cough, and voice sounds for COVID-19 diagnosis," in Proc. Interspeech, 2020, pp. 4811–4815

2. Sharma, N. K., Muguli, A., Krishnan, P., Kumar, R., Chetupalli, S. R., & Ganapathy, S. (2022). Towards sound based testing of COVID-19—Summary of the first Diagnostics of COVID-19 using Acoustics (DiCOVA) Challenge. Computer Speech & Language, 73, 101320.



Motivation



भारतीय विज्ञान संस्थान

Second DiCOVA Challenge:





Second DiCOVA Challenge!





http://dicovachallenge.github.io/







- Development set: 965 individuals, 172 are COVID-19 positive
 - released as 5 train-val folds
- Evaluation set: 471 individuals, 71 are COVID-19 positive









Non-COVID subject distribution



- healthy (no symptoms)
- resp. ail. (asthma, chronic lung disease, pneumonia)
- symptoms (cold, cough, fever, loss of taste or smell)





COVID subject distribution



- Asymp (COVID-19 positive without symptoms)
- Symp(COVID-19 positive with symptoms)







Gender and age distribution









- 5 fold cross-validation
- Tuned based on average validation performance
- Evaluation



Divided into five-fold Train-Val (~80-20%) split



Track Details



4 tracks:

- Track 1, 2 and 3 on breathing, cough and speech sounds
- Track 4 fusion of the first 3 modalities





Timeline







Baseline System



- Bi-LSTM based baseline classifier
- log mel-spectrogram features
- Baseline codes are made open source to encourage further work on it.



Baseline System





• Two bi-directional long-short term memory (BiLSTM) layers and a fully connected layer

- Trained on segments of utterances
- Inference based on average probability scores over segments





Baseline Results



- Receiver operating characteristics (ROC) curve
- AUC-ROC



Validation	AUC-ROC Performance (in %)			
	Breathing	Cough	Speech	Fusion
fold-0	74.8	71.8	75.4	77.3
fold-1	73.9	78.2	87.2	82.4
fold-2	74.3	77.2	80.6	81.8
fold-3	80.0	74.0	78.2	80.3
fold-4	83.2	74.9	79.5	86.6
Avg. Validation	77.3	75.2	80.2	81.7
Test	84.5	74.9	84.3	84.7

Table 1. Baseline system performance on the validation folds in the development dataset, and the blind test dataset.





Distribution based on country of origin







































Blind Test AUC versus Sensitivity







Conclusions



- Few teams surpassed the baseline
- Breathing and speech signals showed effectiveness
- Effectiveness of fusion strategy





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