Grand Challenge on Respiratory Sound Classification for SPRSound Dataset

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***Abstract*—It is important to continuously monitor our respiratory system to prevent us from suffering respiratory-releated diseases. This demands for an automatic respiratory sounds software to speed up diagnosis and to reduce the workload of physicians. In the IEEE BioCAS 2022 conference, we have organized the first grand challenge on respiratory sound classification using the paediatric respiratory sound (SPRSound). This event has invited 45 teams with more than 100 open source entries and the top 5 teams are invited to present their works in the IEEE BioCAS 2022.**

***Index Terms*—Open-source, respiratory sound classification, grand challenge, feature extractions, data augmentation, and machine-learning models, deep-learning models**

I. Organization of the Grand Challenge

Respiratory-related diseases are one of the top global causes of death, which has seriously threatened our life and brought enormous socioeconomic burdens [1]. Early diagnosis can prevent our respiratory system from getting worse [2]. In recent years, there are numerous automatic respiratory research have been proposed to speed up diagnosis and to reduce the workload of physicians [3]–[19]. However, there is a need to further improve the performance of classification models.

The IEEE BioCAS conference has organized the first grand challenge on respiratory sound classification using the open-source SJTU paediatric respiratory sound dataset (SPRSound) [20]. This event has invited 45 teams with more than 100 participants from all over the world to explore different types of feature extraction and classification algorithms, pushing the limits of the current state-of-the-art results. The registration phase starts from 1st April to 17th May 2022. The timeline of the grand challenge on respiratory sound classification is summarized in Fig. 1.

We have provided the following guidelines to ensure fairness and transparency among our participants. (i) To prevent any non-essential downloading and sharing of the dataset before the contest is over, the submission portal and repository websites are only opened to them. (ii) Prior to the release of the second dataset, teams that did not submit their initial paper to IEEE BioCAS will not be able to access the repository. (iii) The scoreboard updates based on their best entry of each team and each team is only allowed to submit one entry per a day. In this way, the team cannot analyze the relationship between their classification models and their corresponding results.

We have organized a special session to allow the teams to submit their paper. To ensure a high quality of the paper submission, we have adopted the same reviewing process as regular submissions. Since the models and content of the paper might be subject to changes after the initial paper submission deadline, the second round of review for the selected paper will ensure a higher quality of the submission. Finally, the top 5 teams are invited to present their work in the IEEE BioCAS 2022 and compete for the top 3 prizes.

II. Summary of Participants

The IEEE BioCAS Grand Challenge has drawn a total of 45 teams with more than 100 participants from 33 universities/companies. The demographic distribution of the teams is presented in Fig. 2. There are more than 100 solutions

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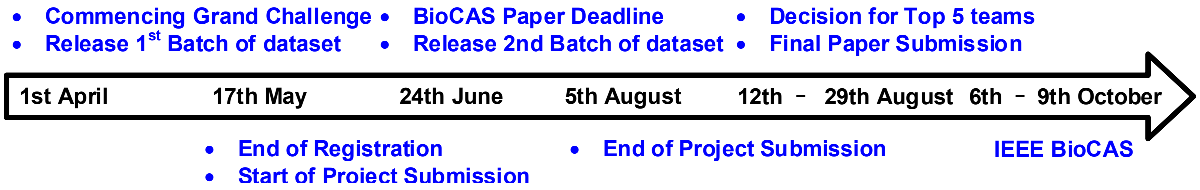

Figure 1. Timeline of Grand Challenge on Respiratory Sound Classification.

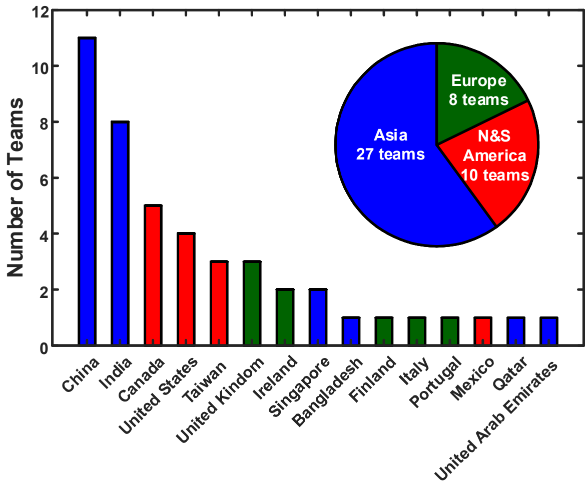

Figure 2. Country and region distribution of the teams.

submitted to this contest. After two rounds of peer reviews, the top 5 teams were selected based on the quality of their paper submissions and their solutions. The acceptance rate is approximately 11.11%.

III. SPRSound: Open-Source SJTU Paediatric Respiratory Sound Database

The SPRSound database [20] is the first open-access pediatric respiratory sound database, jointly developed by Shanghai Jiao Tong University and its affiliated hospital, Shanghai Children's Medical Center (SCMC). A total of 2,683 records and 9,089 RS events from 292 participants with a total duration of 8.2 hours consist in the database. Records were annotated at the event level and record level by 11 experienced physicians with our customized website-based annotation tool (SoundAnn). Unlike prior lung sound datasets, the SPRSound database have introduced a *Poor Quality* label at the record level to encourage the researchers to identify the records of poor signal quality. Thus, the remaining records with high signal quality were annotated as *Normal*, *CAS*, *DAS*, or *CAS & DAS* labels. Each respiratory sound record can be further segmented into multiple respiratory events and annotated as *Normal*, *Rhonchi*, *Wheeze*, *Stridor*, *Coarse Crackle*, *Fine Crackle*, or *Wheeze & Crackle*. Note that the *Rhonchi*, *Wheeze*, and *Stridor* respiratory sound events are classified under continuous adventitious sounds (*CAS*). The *Coarse Crackle*, *Fine Crackle* respiratory sound events are classified under discontinuous adventitious sounds (*DAS*).

Table I
The detailed statistics of the training and testing sets [20]

Level	Type	Training	Testing-1 (intra-patient)	Testing-2 (inter-patient)	Total
Record	Normal	1,303	241	241	1,785
	CAS	126	42	65	233
	DAS	248	75	24	347
	CAS & DAS	95	19	17	131
	Poor Quality	177	2	8	187
	Total	1,949	379	355	2,683
Event	Normal	5,159	688	1040	6,887
	Rhonchi	39	14	0	53
	Wheeze	452	108	305	865
	Stridor	15	2	0	17
	Coarse Crackle	49	14	3	66
	Fine Crackle	912	175	80	1,167
	Wheeze & Crackle	30	3	1	34
	Total	6,656	1,004	1,429	9,089

To facilitate a comprehensive assessment, two subsets (testing-1 and testing-2) consist in the testing set for both intra-patient and inter-patient evaluation. Specifically, the training set contains 1,949 records and 6,656 respiratory sound events from 251 participants. For the intra-patient testing (testing-1), we have used another set of data based on the same group of participants, which consists of 379 records and 1,004 respiratory sound events. The inter-patient testing (testing-2) dataset is collected from another 41 participants, which contains 355 records and 1,429 respiratory sound events. Table I reports the details of the dataset.

IV. Grand Challenge

The grand challenge focus on the respiratory sound classification at both event level and record level.

A. Classification Tasks

Task 1 (Respiratory Sound Classification at Event Level). Task 1-1 is a binary class classification challenge, focusing on classifying the respiratory events as either *Normal* or *Adventitious*. Task 1-2 is a multiclass classification challenge, focusing on classifying the respiratory events as*Normal*, *Rhonchi*, *Wheeze*, *Stridor*, *Coarse Crackle*, *Fine Crackle*, or *Wheeze & Crackle*.

Task 2 (Respiratory Sound Classification at Record Level). Task 2-1 is a ternary class classification challenge, focusing on classifying the respiratory records as *Normal*, *Adventitious*, or

Poor Quality. Task 2-2 is a multiclass classification challenge, focusing on classifying the respiratory records as *Normal*, *CAS*, *DAS*, *CAD & DAS*, or *Poor Quality*.

B. Evaluation Criteria

Each task is evaluated based on the following metrics including *Sensitivity* (*SE*), *Specificity* (*SP*), *Average Score* (*AE*), *Harmonic Score* (*HS*).

$$SE = \frac{\#\ of\ correctly\ predicted\ adventitious\ sounds}{\#\ of\ total\ adventitious\ sounds}, \tag{1}$$

$$SP = \frac{\#\ of\ correctly\ predicted\ normal\ sounds}{\#\ of\ total\ normal\ sounds}, \tag{2}$$

$$AS = \frac{SE + SP}{2}, \tag{3}$$

$$HS = \frac{2 * SE * SP}{SE + SP}. \tag{4}$$

The *Score* for each task is the arithmetic mean of *AS* and *HS*.

$$Score = \frac{AS + HS}{2}. \tag{5}$$

Eventually, there is a need for the automated respiratory algorithm to be executed in real-time. Thus, a bonus score based on runtime is awarded to the top-6 solutions. *Bonus* is calculated based on the logarithm scale of runtime difference as compared to the worst-case solution.

$$Bonus = log_a(t) - log_a(t_0), \tag{6}$$

where t and t_0 are runtimes of the solution and worst-case solution, respectively. a is the base of logarithm, which is set as 10. *Bonus* will be normalized to the best result to limit the maximum bonus score.

Overall, the *total score* for each entry is the weighted sum of the each task's score and the runtime bonus.

$$\begin{aligned} Total\ Score = & 0.2 * Score_{1-1} + 0.3 * Score_{1-2} + \\ & 0.2 * Score_{2-1} + 0.3 * Score_{2-2} + \\ & 0.1 * Bonus. \end{aligned} \tag{7}$$

Table II
THE STATISTICAL RESULTS OF TOP-10 TEAMS FOR EACH TASK.

Task	Rank	Team	SE	SP	AS	HS	Score
Task 1-1	1	ECE UofT	0.8894	0.8958	**0.8926**	**0.8926**	**0.8926**
	2	NIIT	**0.9319**	0.8472	0.8896	0.8876	0.8886
	3	IESOC A	0.8170	0.8825	0.8498	0.8485	0.8491
	4	SVNIT	0.7887	**0.8981**	0.8434	0.8398	0.8416
	5	WELMO-Team	0.8043	0.8762	0.8402	0.8387	0.8394
	6	Naseem Babu	0.8355	0.8356	0.8356	0.8356	0.8356
	7	UCD	0.7730	0.8935	0.8333	0.8289	0.8311
	8	The Superego	0.8411	0.7986	0.8199	0.8193	0.8196
	9	SleepdB	0.7404	0.8657	0.8031	0.7982	0.8006
	10	INTJ	0.7972	0.7633	0.7802	0.7799	0.7801
Task 1-2	1	NIIT	**0.7943**	0.8472	**0.8208**	**0.8199**	**0.8203**
	2	ECE UofT	0.6766	**0.9387**	0.8076	0.7864	0.7970
	3	UCD	0.6014	0.9363	0.7689	0.7324	0.7506
	4	SVNIT	0.6454	0.8715	0.7585	0.7416	0.7500
	5	IESOC A	0.7660	0.7292	0.7476	0.7471	0.7473
	6	The Superego	0.6610	0.8339	0.7475	0.7375	0.7425
	7	Naseem Babu	0.6071	0.8860	0.7465	0.7205	0.7335
	8	WELMO-Team	0.5631	0.8385	0.7008	0.6738	0.6873
	9	INTJ	0.4993	0.8490	0.6741	0.6288	0.6515
	10	SleepdB	0.4894	0.8657	0.6776	0.6253	0.6514
Task 2-1	1	NIIT	0.6901	**0.7469**	**0.7185**	**0.7174**	**0.7179**
	2	ECE UofT	0.7727	0.6618	0.7173	0.7130	0.7151
	3	The Superego	**0.7769**	0.6515	0.7142	0.7087	0.7114
	4	IESOC A	0.7273	0.6763	0.7018	0.7009	0.7013
	5	INTJ	0.7273	0.6452	0.6863	0.6838	0.6850
	6	Naseem Babu	0.6157	0.7282	0.6720	0.6672	0.6696
	7	WELMO-Team	0.5950	0.7344	0.6647	0.6574	0.6611
	8	UCD	0.6116	0.6494	0.6305	0.6299	0.6302
	9	SVNIT	0.6612	0.5602	0.6107	0.6065	0.6086
	10	UofT	0.4835	0.5726	0.5280	0.5243	0.5262
Task 2-2	1	WELMO-Team	**0.5207**	0.5901	0.5554	**0.5532**	**0.5543**
	2	NIIT	0.3802	0.7453	0.5628	0.5035	0.5331
	3	The Superego	0.3843	0.7329	**0.5586**	0.5042	0.5314
	4	IESOC A	0.3926	0.7101	0.5514	0.5056	0.5285
	5	Naseem Babu	0.3719	0.7184	0.5452	0.4901	0.5176
	6	INTJ	0.4587	0.5135	0.4861	0.4845	0.4853
	7	UCD	0.2810	0.7412	0.5111	0.4075	0.4593
	8	ECE UofT	0.2314	**0.8571**	0.5443	0.3644	0.4543
	9	SVNIT	0.2645	0.7391	0.5018	0.3895	0.4457
	10	UofT	0.2438	0.5569	0.4004	0.3391	0.3698

V. SUMMARY OF THE TOP-5 WINNING TEAMS.

Beside selecting the appropriate machine-learning/deep-learning classification model, there is a need to explore the compatible signal pre-processing techniques, feature extraction techniques, feature selection techniques, data augmentation techniques, and weighted loss functions to achieve its best performance. We have summarized the key techniques used in each of the winning team. Table II reports the statistical results of top-10 team for each task. Table III summarizes the performance comparison (including runtime) of the top-6 team results.

(1) Team NIIT [21] from Nanjing Institute of Intelligent Technology (Jun Li et al.) won 1st place in this contest. In their work, they have proposed *Fixing Audio Length*, *abs(STFT)*, and *Spectrogram Clipping* techniques to transform the audios into spectrograms with a size of 40×188. ResNet-based architectures are employed as the deep feature backbone of their classification model. A fully connected (FC) layer followed by the backbone is applied for classification. Furthermore, weighted random sampler and focal loss are applied to address the class imbalance problem. Eventually, they have achieved a *total score* of 0.7919 with *bonus* of 0.6459 and *score* of 0.8886, 0.8203, 0.7179, and 0.5331 for each task.

(2) Team The Superego [22] from Shanghai Jiao Tong University (Lin Zhang et al.) won 2nd place in this contest. They have proposed a feature polymerized based two-level ensemble model (FP-TLEM) for respiratory sound classification. Each event/record is divided into N frames and the short time analysis is applied to transform each frame into a feature vector. By combining the statistical mean and variance of the features, high-level features with length of 136 are obtained. To address the class imbalance problem, synthetic minority oversampling technique (SMOTE) [23] is applied to analyse and synthesize the minority samples. AutoML classifier with multiple machine learning model is employed to achieve more accurate classification results. Finally, they have achieved a *total score* of 0.7884 with *bonus* of 1.0000 and *score* of 0.8196, 0.7425, 0.7114, and 0.5314 for each task.

(3) Team IESOC A [24] from National Yang-Ming Chiao

Table III
Perform comparison of top-6 teams.

Rank	Team	Score_{1-1}	Score_{1-2}	Score_{2-1}	Score_{2-2}	Runtime (s)	Bonus	Total Score
1	NIIT	0.8886	**0.8203**	**0.7179**	0.5331	634	0.6459	**0.7919**
2	The Superego	0.8196	0.7425	0.7114	0.5314	**216**	**1.0000**	0.7884
3	IESOC A	0.8491	0.7473	0.7013	0.5285	443	0.7638	0.7692
4	ECE UofT	**0.8926**	0.7970	0.7151	0.4543	1456	0.3725	0.7342
5	Naseem Babu	0.8356	0.7335	0.6696	0.5176	793	0.5723	0.7336
6	WELMO-Team	0.8394	0.6873	0.6611	**0.5543**	4519	0.0000	0.6726

Tung University (Weibang Ma et al.) won 3rd place in this contest. They have employed a bandpass filter with a frequency range of [200 Hz, 1300 Hz] to eliminate noises. The *timing offset* technique is proposed for data augmentation to expand the sample size of minority classes. After transforming the audios into spectrogram images, the *clipping* technique is proposed to reduce computation complexity. *CenterCrop* and *Normalization* methods are employed to preprocess the spectrogram images for better classification performance. The DenseNet169 model with a warming up learning rate is applied to train a accurate model. *Pruning* techniques alone with fine-tune process is employed to reduce the computation complexity while remaining a high classification accuracy. Eventually, they have achieved a *total score* of 0.7692 with *bonus* of 0.7638 and *score* of 0.8491, 0.7473, 0.7013, and 0.5285 for each task.

(4) Team ECE UofT [25] from University of Toronto (Zizhao Chen et al.) won 4th place in this contest. They have exploared different feature extraction methods extract spectrograms from audios, including short time fourier transformation (STFT), mel spectrograms, and wav2vec. LightCNN-based model, pretrained ResNet18 model, and audio spectrogram transformer have been studied to perform respiratory sound classification. To deal with the class imbalance problem, they have employed weighed loss function according to the proportion of different types of respiratory sound. Eventually, they have achieved a *total score* of 0.7342 with *bonus* of 0.3725 and *score* of 0.8926, 0.7970, 0.7151, and 0.4543 for each task.

(5) Team Naseem Babu [26] from Indian Institute of Technology Patna (Naseem Babu et al.) won 5th place in this contest. They have employed mel frequency cepstral coefficients (MFCCs) as the feature extraction method. A convolutional neural network with four convolutional layer and a dense layer is adopted as the classification model. Different number of MFCC coefficients, window size, and hop length are explored to train an accurate classification model. Eventually, they have achieved a *total score* of 0.7336 with *bonus* of 0.5723 and *score* of 0.8356, 0.7335, 0.6696, and 0.5176 for each task.

VI. Conclusions

A total of 45 teams with more than 100 participants have been participated in the IEEE BioCAS Grand Challenge to develop automatic algorithms for respiratory sound classification using the open access database, SPRSound. A special session is organized for the grand challenge at the IEEE BioCAS conference. This provides an opportunity for the top-5 teams to present their algorithms and classification results. We hope that the grand challenge will increase researchers' interest in developing more accurate algorithms and push forward this medical field.

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