Predicting Respiratory Anomalies and Diseases Using Deep Learning Models

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Abstract—In this paper, robust deep learning frameworks are introduced, aims to detect respiratory diseases from respiratory sound inputs. The entire processes firstly begins with a front-end feature extraction that transforms recordings into spectrograms. Next, a back-end deep learning model classifies the spectrogram features into categories of respiratory disease or anomaly. Experiments are conducted over the ICBHI benchmark dataset of respiratory sounds. According to obtained experimental results, we make three main contributions toward lung-sound analysis: Firstly, we provide an extensive analysis on common factors (type of spectrogram, time resolution, cycle length, or data augmentation, etc.) that affect final prediction accuracy in a deep learning based system. Secondly, we propose novel deep learning based frameworks by using the most influencing factors indicated. As a result, the proposed deep learning frameworks outperforms state of the art methods. Finally, we successfully to apply the Teacher-Student scheme to solve the trade-off between model performance and model size that helps to increase ability of building real-time applications.

Clinical relevance—Respiratory disease, wheezes, crackles, anomaly detection, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), mixup data augmentation, Mixture of Expert (MoE), Gammatone spectrogram.

I. INTRODUCTION

According to an analysis conducted by the World Health Organization [1], it is fact that respiratory illness, which comprises of lung cancer, tuberculosis, asthma, chronic obstructive pulmonary disease (COPD), and lower respiratory tract infection (LRTI), account for a high percentage of mortality worldwide. Indeed, annual record indicates around 10, 65 and 334 million people currently suffering from tuberculosis (TB), chronic obstructive pulmonary disease (COPD), and asthma, respectively. Noticeably, there are about 1.4, 1.6, and 3 million people die by TB, lung cancers, and COPD each year. To deal with respiratory diseases, early detection is the key factor to increase effectiveness of treatment as well as limit spread. In an respiratory examination, lung auscultation is an important part to diagnose respiratory diseases. By listening to the sounds produced during lung auscultation, experts can recognize adventitious sounds (e.g., Crackles and wheezes) in the respiratory cycle that usually occurs in people suffering pulmonary disorders. If automated methods can be developed to detect these anomaly sounds, it may be useful in enhancing the early detection of respiratory disease in future. Although automated analysis of respiratory sounds were early conducted [2], [3], [4], the research field attracted little attention. However, it has drawn much attention in recent years due to applying robust machine learning and deep learning techniques.

As regards machine learning approach, proposed systems used for respiratory sound analysis tend to rely upon frame-based representations. Most researches [5], [6] approached Frequency Cepstral Coefficients (MFCC), the most popular feature used in Automatic Speech Recognition (ASC) research field, to derive feature vectors. Using both spectral and temporal features, Melbye et al. [7] extracted five-dimensional feature vectors from draw audio signal, comprising of four features from the time domain (variance, range, and sum of simple moving average, sum of simple moving average) and one feature from the frequency domain (spectrum mean). Meanwhile, Hanna et al. [8] firstly extracted spectral information from barkbands, energybands, melbands, mfcc, etc., the rhythm features from beats loudness, bpm, etc), the harmonic and inharmonicity features, and the tonal features (chords strength, tuning frequency, etc). Next, they computed statistical values such as standard deviation, variance, minimum and maximum, median, mean, means of first and second derivatives and variances of first and second derivatives from the features to maximize the chance of correct feature representation. To further explore audio features, Mendes et al. [9] proposed to use 35 different types of features, mainly come from the research of Music Information Retrieval. Inspire that only some certain features mainly affect the final result, Datta et al. [10] firstly extracted various features such as power spectral density (PSD), FFT and Wavelet spectrogram, Frequency Cepstral Coefficients (MFCC), and Linear Frequency Cepstral Coefficients (LFCC). Next, they applied a Maximal Information Coefficient (MIC) [11] to score these features, thus selected the the most influencing features before feeding into a classifier. Similarly, Kok et al. [6] applied the Wilcoxon Sum of Rank test to indicate which feature among MFCC, Discrete Wavelet Transform (DWT) and Time Domain Features (the power, mean, variance, skewness and kurtosis of audio signal) mainly affect the final accuracy. Approach image processing techniques, Sengupta et al. [12] applied Local Binary Pattern (LBP) analysis on mel-frequency spectral coefficient (MFSC) spectrogram to capture texture information of the spectrogram. Next, LBP spectrogram is converted into Histogram presentation before feeding into a back-end classification. Ordinarily, frame-based features, likely vectors, are classified by traditional machine learning models such as Logistic Regression [9], K-Nearest Neighbor (KNN) [7], [12], Hidden Markov Model [5], [13], Support Vector Machine [7], [10], [12], [14] or decision trees [6],

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Regarding deep learning techniques achieved strong and robust detection performance for general sounds [15], [16], feature extraction involves generating two-dimensional spectrograms that is able to capture both temporal and spectral information and present much wider time context than single frame analysis. While there are a variety of spectrogram transformations, Mel-based methods such as log-Mel [17], [18], [19] and MFCC [20], [17], [21], [22], [23], [24] are the most popular approach. Some papers approached different spectrograms such as a combination of two spectrograms (STFT and Wavelet) proposed by Minami et al. [25], optimized S-Transformation in [26]. Current deep learning classifiers exploring spectrogram representation of respiratory sounds mainly base on Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), or hybrid architectures. As regard CNN-based network, published papers presented diverse architectures such as Lenet6 [21], [20], VGG5 [18], two parallel VGG16 [25], and Resnet50 [26]. Inspire that adventitious respiratory sounds such as Crackles and Wheeze present certain temporal sequence and RNN-based networks able to capture these structures, Perna and Tagarelli [22] conducted a comprehensive analysis of using Long Short-term Memory (LSTM) network, which is used for both tasks of classifying anomaly respiratory sounds and respiratory diseases. By using both LSTM and Gated Recurrent Unit (GRU) cells, learning components in a RNN-based network, Kochetov et al. [24] proposed a novel architecture, namely Noise Masking Recurrent Neural Network, which aims to distinguish both noise and anomaly respiratory sounds. As regards hybrid architectures proposed in [19], [25], CNN is firstly used to map spectrogram input to a time sequence. Next, LSTM [19] or GRU [25] cells are used to learn structure of the sequence before sending to fully-connected layers for final classification.

Compare with machine learning approach, state-of-the-art comparison presented in [22], [26] indicates that deep learning classifiers are more robust and effective to achieve good scores. However, deep learning based models show much more complicated architecture, thus require a large memory when large models are integrated into wearable devices or certain embedded systems for real-time applications. In other words, the state-of-the-art systems present a trade-off between model performance and model size. Additionally, although recent deep learning techniques help to achieve good performance in terms of classification of respiratory sounds, it is hard to compare systems due to the use of different datasets, mainly collected by authors, and often not publicly available.

In this paper, we propose robust deep learning frameworks evaluated on ICBHI dataset [27], aim to

- Compare our results to the state-of-the-art systems due to using the published ICBHI dataset. Furthermore, as ICBHI is one of the biggest datasets of respiratory sounds currently, it is beneficial to make proposed deep learning models general.
- Provide a comprehensive analysis of various factors, such as type of spectrogram, overlap/non-overlap patches and patch size, data augmentation, etc., thus propose two best deep learning models, each targets individual task of either anomaly respiratory sound classification or respiratory disease detection.
- Solve the trade-off between model performance and model size by applying Student-Teacher scheme. In particular, we consider the best deep learning model as Teacher. We extract middle layers’ information from Teacher model and consider the values as soft labels. Next, we use the soft labels to train another model, called Student, with smaller size. Eventually, we obtain the small-size model (Student network trained with soft labels), showing similar performance to Teacher model.

II. ICBHI dataset AND OUR TASKS PROPOSED

A. ICBHI dataset

The 2017 Internal Conference on Biomedical Health Informatics (ICBHI) [27] provided a large dataset of respiratory sounds. Particularly, it comprises of 920 audio recordings over 5.5 hours. The audio recordings have various lengths from 10 to 90 s, recorded with a wide range of sampling frequencies from 4 kHz to 44.1 kHz. ICBHI dataset was collected from a total of 128 patients, thus identified their situation in terms of being healthy or exhibiting one of the following respiratory diseases or conditions (COPD, Bronchiectasis, Asthma, Upper and Lower respiratory tract infection, Pneumonia, Bronchiolitis) and labelled diseases’ name on each audio recording. Inside each audio recording, different types of respiratory cycle, called Crackles, Wheeze, Crackles & Wheeze, and Normal, are presented. These cycles were labelled by experts, thus provide onset and offset time. Noticeably, these cycles have various recording lengths (from 0.2 s up to 16.2 s), with the number of cycles being unbalanced (1864, 886, 506 and 3642 cycles respectively for Crackles, Wheeze, Crackles & Wheeze, and Normal).

B. Main tasks from ICBHI dataset

Given this metadata, the ICBHI challenge is separated into two main tasks. Task 1, referred to as respiratory anomaly classification, is separated into two sub-tasks. The first sub-task aims to classify four different cycles (Crackles, Wheeze, Crackles & Wheeze, and Normal). The second sub-task is for classifying four types of cycles into two groups of Normal and Anomaly cycles (the latter consisting of Crackles, Wheeze, Both Crackles & Wheeze). We named these tasks as Task 1-1 and Task 1-2.

Task 2, referred to as respiratory disease prediction, also comprises two sub-tasks. The first sub-task aims to classify audio recordings into groups of disease conditions: Healthy, Chronic Disease (i.e. COPD, Bronchiectasis and Asthma) and Non-Chronic Disease (i.e. Upper and Lower respiratory tract infection, Pneumonia, and Bronchiolitis). The second sub-task is for two groups of healthy or unhealthy (i.e. the chronic and non-chronic disease groups combined). We named these tasks as Task 2-1 and Task 2-2. While Task
CQT mixup 64 x 32/.../192

1-1 and 1-2 are evaluated over respiratory cycles, Task 2-1 and 2-2 are evaluated over entire audio recordings.

C. Evaluation metric and our setting

In this paper, we attempt all of the ICBHI challenge tasks recently mentioned. To evaluate our systems over each task, we separate the ICBHI dataset (6898 respiratory cycles for Task 1-1, Task 1-2 and 920 entire recordings for Task 2-1 and Task 2-2) into five-folds for cross validation. We firstly introduce a baseline system, thus conduct experiments on the baseline to indicate the most influencing factors over just the first fold. From the analysis of such factors, we propose the best system configurations and evaluate over all folds. Noting that we eventually propose two deep learning framework, each for individual task of either anomaly cycle detection (Task 1-1 and 1-2) or respiratory disease detection (Task 2-1 and 2-2). To evaluate proposed system and compare to the state of the art, we follow the ICBHI criteria and settings, and report results in terms of sensitivity, specificity and ICBHI score as defined in [27], [22] below,

\[
\text{Sensitivity} = \frac{C_{\text{crackles}} + C_{\text{wheezes}} + C_{\text{both}}}{N_{\text{crackles}} + N_{\text{wheezes}} + N_{\text{both}}} \tag{1}
\]

for classifying four classes of cycles in Task 1-1,

\[
\text{Sensitivity} = \frac{C_{\text{crackle-or-wheeze}}}{N_{\text{crackle-or-wheeze}}} \tag{2}
\]

for two groups of normal or adventitious cycle in Task 1-2, and

\[
\text{Specificity} = \frac{C_{\text{normal}}}{N_{\text{normal}}} \tag{3}
\]

where \(C_{\text{...}}\) and \(N_{\text{...}}\) are the number of correct inference and the total cases. Similarly, respiratory-disease classification in Task 2-1 and 2-2 provides criteria as below equations.

\[
\text{Sensitivity} = \frac{C_{\text{chronic}} + C_{\text{non-chronic}}}{N_{\text{chronic}} + N_{\text{non-chronic}}} \tag{4}
\]

for three groups of diseases in Task 2-1,

\[
\text{Sensitivity} = \frac{C_{\text{chronic-or-nonchronic}}}{N_{\text{chronic-or-nonchronic}}} \tag{5}
\]

for two groups of healthy or unhealthy in Task 2-2, and

\[
\text{Specificity} = \frac{C_{\text{healthy}}}{N_{\text{healthy}}} \tag{6}
\]

where \(C_{\text{...}}\) and \(N_{\text{...}}\) are the number of correct inference and the total cases. The ICBHI score is computed by averaging of Sensitivity and Specificity.
Next, each cycle or recording audio is then transformed into a log-Mel spectrogram with window size=1024 samples, hop size=256, FFT length=2048 and filter number=64. The resulting spectrogram is then non-overlap split into smaller patches of $64 \times 64$. As data augmentation is one of factors evaluated, we do not apply this technique on the baseline system. As regards deep learning model used for the baseline system, we propose a C-DNN network architecture, likely VGG-7, as shown in Table I. The C-DNN contains 7 sub-blocks, comprising 6 Conv. Blocks and 1 Dense Block, which perform batch normalization (Bn), convolution (Conv[kernel size]), rectified linear units (Relu), average pooling (Ap[kernel size]), global average pooling (Gap), drop out (Dr [percentage drop]), Fully-connected (Fl) and final Softmax layer for classification. C is the number of categories classified that depends on specific tasks. In particular, we use two C-DNN models, each set textiC to 3 and 4 for Task 1-1, 1-2 and Task 2-1, 2-2, respectively. Note that as each model is used for each Task, obtained parameters of each model are different after training.

### Table II

| Architecture | layers | Output |
|--------------|--------|--------|
| Conv. Block 01 | Bn - Cy [3x3] - Relu - Bn - Ap [2x2] - Dr (10%) | $64\times64$ |
| Conv. Block 02 | Bn - Cy [3x3] - Relu - Bn - Ap [2x2] - Dr (10%) | $32\times32\times64$ |
| Conv. Block 03 | Bn - Cy [3x3] - Relu - Bn - Dr (20%) | $16\times16\times128$ |
| Conv. Block 04 | Bn - Cy [3x3] - Relu - Bn - Dr (20%) | $8\times8\times256$ |
| Conv. Block 05 | Bn - Cy [3x3] - Relu - Bn - Dr (25%) | $8\times8\times512$ |
| Conv. Block 06 | Bn - Cy [3x3] - Relu - Bn - Gap - Dr (25%) | $512$ |

### C. Experimental setting of the baseline system

We use TensorFlow framework to build C-DNN models with hyperparameters set to Adam optimiser [28], 100 epochs, batch size of 100, and cross-entropy loss as below,

$$loss_{\text{Entropy}}(\theta) = \frac{1}{N} \sum_{i=1}^{N} y_i \cdot \log \{\hat{y}_i(\theta)\} + \frac{\lambda}{2} ||\theta||^2_2$$  \hspace{1cm} (7)

where $\theta$ is all trainable parameters, $N$ is batch size, and constant $\lambda$ set initially to 0.0001. $y_i$ and $\hat{y}_i$ denote expected and predicted results.

As an entire spectrogram or cycle is separated into patches and applied patch-by-patch to the C-DNN model which then returns the posterior probability computed over each patch. The posterior probability of an entire spectrogram can then be computed by taking the average of all patches’ posterior probabilities. Let us consider $P_i^n = (p_1^n, p_2^n, ..., p_C^n)$, with $C$ being the category number and the $n^{th}$ out of $N$ patches fed into learning model, as the probability of a test sound instance, then the mean classification probability is denoted as $\bar{p} = (\bar{p}_1, \bar{p}_2, ..., \bar{p}_C)$ where,

$$\bar{p}_c = \frac{1}{N} \sum_{n=1}^{N} P_i^n$$  \hspace{1cm} for  \hspace{1cm} 1 \leq n \leq N \hspace{1cm} (8)

and the predicted label $\hat{y}$ from the C-DNN is determined using,

$$\hat{y} = \text{argmax}(\bar{p}_1, \bar{p}_2, ..., \bar{p}_C)$$  \hspace{1cm} (9)

### IV. Analyse Influencing Factors

By using the baseline system recently proposed, we conduct experiments to evaluate effect of factors mentioned, thus propose the best options of these factors in this Section.

#### A. Spectrogram analysis

As our previous work’s results on sound scene DCASE dataset [29], [30], spectrogram is one of the most important factors affect the final classification. Therefore, effect of spectrogram factor on the baseline is firstly evaluated on all tasks. In particular, baseline system’s setting as described in Table I is remained, but type of spectrogram is replaced by log-Mel [31], Gammatone filter (Gamma.) [32], Mel-Frequency Cepstral Coefficient (MFCC) [31], and Constant Q Transform (CQT) [31] in the order. The obtained results
Gamma. performance are equal in general and much better than CQT over all Tasks. If we consider log-Mel scores as standard, Figure 3 indicates how performance difference between log-Mel and Gamma, or MFCC. It can be seen that Gamma outperforms other spectrograms over Task 1, reports an improvement of 4% and 3.2% compared with log-Mel and MFCC, respectively. However, both Gamma and MFCC shows little poorer performance than log-Mel in Task 2. From obtained results on spectrograms, we decide to use Gamma. for anomaly cycles detection (Task 1-1 and 1-2) and log-Mel for respiratory diseases detection (Task 2-1 and 2-2). Note that using Gamma and log-Mel are applied for next all experiments presented below.

B. Cycle length analysis

Respiratory cycles in the ICBHI dataset have diverse lengths ranging from 0.2 s to 16.2 s with 80% of cycles being less than 5 s. It is, therefore, interesting to understand how respiratory cycle length affects classification accuracy. By using the baseline proposed in Section III-C with Gamma. spectrogram indicated in Section VII-A, we evaluated cycle length from 3 to 8 s, called standard lengths. To deal with short cycles, we duplicate them to obtain new cycles that are equal or longer than standard lengths before transforming into spectrograms. The Table III reports Task 1-1 and 1-2 results for different cycle lengths. The best ICBHI scores are 78.64 and 83.95 for 4- and 2-category sub-tasks respectively with cycle length set to 5 s (same as the baseline ’s setting). Although 7 or 8-s cycle lengths also show competitive results, we choose the shorter length of 5 s for further experiments due to reducing running cost and the best results obtained.

C. Overlap/non-overlap splitting analysis

As spectrogram representation of an entire cycle or audio recording is too long in terms of temporal dimension, they are split into smaller patches of $64 \times 64$ that is suitable for back-end deep learning models. Overlap splitting is considered to be useful to make temporal sequence continuous. This Section, therefore, evaluates if overlap splitting should be applied. As obtained results shown in Figure 4 classifying anomaly cycles in sub task 1-1 and 1-2 achieves the best core of 76.59% and 78.57% respectively with overlap patches. By contrast, non-overlap splitting is more effective for Task 2-1 and 2-2 with entire recordings, reports 78.64% and 83.95%, respectively.

D. Time resolution analysis

The baseline network operates on patches, with the horizontal dimension denoting the time span for each feature. Features are sequential, so the time span also sets the temporal resolution of the features. To explore, we adjust patch widths to 0.6 s, 1.2 s, 1.8 s, 2.4 s, and 3 s by setting the patch dimension to be $64 \times 32$, $64 \times 64$, $64 \times 96$, $64 \times 128$, and $64 \times 160$, respectively, then retrain and evaluate performance of each. Results shown in Figure 5 indicate that while patch size of $64 \times 64$ (1.2 s) is the best choice with 78.64% and 83.95% for Task 1-1 and Task 1-2 respectively, Task 2-1 and 2-2 achieve the best score of 80.63% and 84.58% with patch size of $64 \times 128$ (2.4 s).

E. Data augmentation analysis

Data augmentation is useful to enforce learning ability of deep learning models that was proven in [30], [29]. In this paper, we, therefore, apply a data augmentation method, namely mixup [33], [34], [35], and evaluate if it is useful for respiratory sounds. Let consider $X_1$ and $X_2$ as two image patches randomly selected from the set of original image patches with their labels $y_1$ and $y_2$, respectively, mixup...
Obtained results in Figure 6 indicates that applying mixup denote the ground-truth and the network output, respectively.

\[
X_{mp1} = X_1 \cdot \lambda + X_2 \cdot (1 - \lambda) \quad (10)
\]

\[
X_{mp2} = X_1 \cdot (1 - \lambda) + X_2 \cdot \lambda \quad (11)
\]

\[
y_{mp1} = Y_1 \cdot \lambda + Y_2 \cdot (1 - \lambda) \quad (12)
\]

\[
y_{mp2} = Y_1 \cdot (1 - \lambda) + Y_2 \cdot \lambda \quad (13)
\]

where \( \alpha \) is drawn from both uniform distribution or beta distribution, \( X_{mp1} \) and \( X_{mp2} \) are two new image patches resulted by mixing \( X_1 \) and \( X_2 \) with a random mixing coefficient \( \alpha \). After mixup, old data and generated data from mixup data augmentation are shuffled and feed into C-DNN baseline proposed, double batch size and consider learning time (Noting that as categories classified in Task 1-1 and 1-2 comprise of Cracke, Wheeze, Cracke & Wheeze and Normal, each of two original patches selected for mixup data augmentation is from either Normal or the group of anomaly cycles. However, this selection is randomly in Task 2-1 and 2-2).

By applying mixup data augmentation technique, the new labels \( y_{mp1} \) and \( y_{mp2} \) of the two mixup patches are no longer one-hot labels, Kullback-Leibler (KL) divergence loss [36] rather than the standard cross-entropy loss is used as shown in Equation below,

\[
Loss_{KL}(\theta) = \sum_{n=1}^{N} y_n \log \left( \frac{y_n}{\hat{y}_n} \right) + \frac{\lambda}{2} \| \theta \|^2, \quad (14)
\]

where \( Loss(\theta) \) is KL-loss function, \( \theta \) denotes the trainable network parameters and \( \lambda \) denote the \( \ell_2 \)-norm regularization coefficient, set to 0.0001, \( N \) is the batch number, \( y_c \) and \( \hat{y}_c \) denote the ground-truth and the network output, respectively. Obtained results in Figure [6] indicates that applying mixup data augmentation helps to generate new image patches as Equations below.

\[
\text{Fig. 6. Improve performance by using mixup data augmentation}
\]

\[
\text{CBHI score %}
\]

\[
\text{Task 1-1} \quad \text{Task 1-2} \quad \text{Task 2-1} \quad \text{Task 2-2}
\]

\[
\text{non-mixup} \quad \text{mixup}
\]

\[
\text{50} \quad \text{70} \quad \text{85} \quad \text{90}
\]

By reviewing the C-DNN baseline as shown in Table I the first six Conv. Blocks are used to map image patch input to condensed vector features (output of the global mean pooling layer in Conv. Block 06). Thus, these vectors are classified by a fully-connected layer and a Softmax layer in the final Dense Block. Inspire that the condensed vector features extracted by global mean across channel dimension may not capture enough information, we extract more information by separately using two other pooling layers which are global max pooling and global conv. pooling. While global max pooling is widely used, the global conv. pooling proposed is an added convolutional layer with kernel size set to frequency and temporal dimensions and filter number set to channel dimension. In particular, the output shape of the tensor at the final convolutional layer in C-DNN baseline is \([n \times 8 \times 8 \times 512]\) where \( n \) is batch size and 8, 8, and 512 are frequency, and temporal dimensions respectively.
temporal and channel dimensions, respectively. Thus, we apply a convolutional layer with kernel size of $[8 \times 8]$ and 512 filter on the tensor, thus obtain a 512-dimensional vectors. By using three types of pooling layers (global max pooling, global mean pooling, and conv. pooling), we capture as much information as possible. Each type of pooling layer extracts a 512-dimensional vector as shown in Figure 8. The second improvement is focusing on Dense Block architecture which takes the role of final classification. Particularly, we replace Dense Block by MoE block. A conventional MoE block architecture comprises many experts and incorporates a gate network to decide which expert is applied in which input region as shown in Figure 7. In our context, the 512-dimensional input vector extracted from pooling layers mentioned goes through the experts. Next the experts is gated before passing through a softmax to determine the final score. Each MoE expert comprises a fully-connected layer and a ReLu activation function. Its input dimension is 512 and its output size is the number or categories $C$ classified. The gate network is implemented as a Softmax Gate – an additional fully-connected layer with softmax activation function and a gating dimension equal to the number of experts. Let $e_1, e_2, \ldots, e_K \in \mathbb{R}^C$ be the output vectors of the $K$ experts, and $g_1, g_2, \ldots, g_K$ be the outputs of the gate network where $g_k \in \mathbb{R}$, $\sum_{k=1}^{K} g_k = 1$. The predicted output is then found as,

$$\hat{y} = \text{softmax} \left\{ \sum_{k=1}^{K} e_k g_k \right\}. \quad (15)$$

**B. Experimental setting and accuracy fusion**

As setting mentioned in Table IV for proposed deep learning frameworks, mixup data augmentation is used, thus make label not shape of one-hot coding. Therefore, Kullback-Leibler (KL) divergence loss [36] mentioned in Section IV-E and Equation (13) is used to train deep learning models proposed (C-DNN with MoE). We use TensorFlow framework to build the model and set learning rate=0.0001, epoch num=100, batch size=100, initial trainable parameters by Normal Distribution with mean=0 and standard deviation=0.1.

As using three types of pooling layers, we apply mean-fusion method to fuse posterior probability obtained. Let us consider $P_{m,n}^{m,n} = (p_{1,n}^{m,n}, p_{2,n}^{m,n}, \ldots, p_C^{m,n})$, with $C$ being the category number, the $n^{th}$ out of $N$ patches fed into learning model, and the $m^{th}$ out of 3 types of pooling layers to be the probability of a test sound instance. The mean classification probability is then denoted as $\bar{p} = (\bar{p}_1, \bar{p}_2, \ldots, \bar{p}_C)$ where,

$$\bar{p}_c = \frac{1}{3N} \sum_{m=1}^{3} \sum_{n=1}^{N} P_{c,n}^{m,n} \quad for \quad 1 \leq n \leq N, 1 \leq m \leq 3 \quad (16)$$

and similarly the predicted label is determined as in Equation (9).

**C. Performance compared to the state of the art**

From the experimental analysis results, we propose separate network configurations for ICBHI challenge Tasks 1 and 2, although both share the same deep learning model (C-DNN+MoE).

Table V (top) compares the proposed Task 1 system against the state of the art, demonstrating the highest accuracy of 0.81 and 0.86 for the 4-category and 2-category subtasks, respectively. Task 2 results (Table V, bottom) reveal
TABLE V

| Task     | Method          | train/test | Spec. | Sen. | ICBHI Score |
|----------|-----------------|------------|-------|------|-------------|
| 1-1, 4-class | Boosted Tree [8] | 60/40      | 0.78  | 0.21 | 0.49        |
| 1-1, 4-class | CNN [21]        | 80/20      | 0.77  | 0.45 | 0.61        |
| 1-1, 4-class | CDRNN [24]      | 50/50      | 0.74  | 0.56 | 0.65        |
| 1-1, 4-class | LSTM [22]       | 80/20      | 0.85  | 0.62 | 0.74        |
| 1-1, 4-class | Our system     | five folds | 0.87  | 0.74 | 0.81        |
| 1-2, 2-class | LSTM [22]      | 80/20      | -     | -    | 0.81        |
| 1-2, 2-class | CNN [18]       | 75/25      | -     | -    | 0.82        |
| 1-2, 2-class | Our system     | five folds | 0.86  | 0.85 | 0.86        |
| 2-1, 3-class | CNN [21]       | 80/20      | 0.78  | 0.97 | 0.88        |
| 2-1, 3-class | LSTM [22]      | 80/20      | 0.82  | 0.98 | 0.91        |
| 2-1, 3-class | Our system     | five folds | 0.86  | 0.95 | 0.91        |
| 2-2, 2-class | CNN-RNN [19]  | 60/40      | -     | -    | 0.71        |
| 2-2, 2-class | CNN [21]       | 80/20      | 0.78  | 0.97 | 0.88        |
| 2-2, 2-class | RUSBoost [6]   | 50/50      | 0.93  | 0.86 | 0.90        |
| 2-2, 2-class | LSTM [22]      | 80/20      | 0.82  | 0.99 | 0.91        |
| 2-2, 2-class | Our system     | five folds | 0.86  | 0.98 | 0.92        |

Teacher-Student scheme as described in Figure 9 comprises of two networks, namely Teacher (the upper) and Student (the lower), respectively. Teacher network reuses the C-DNN+MoE architecture introduced in Section V-A with only using global mean pooling. As regards the Student network architecture, it comprises of two Conv. Block 07, 08, and a Dense Block with configuration as denoted in Table VI. Note that Conv. Bocks used in Student network do not apply Batchnorm and Dropout layers. To operate the scheme, training Teacher-Student scheme is separated into two phases. The Teacher is firstly trained, thus extract the output of global mean pooling layer. The extracted features, likely 512-dimensional vectors, are referred as to soft labels that will be used to train Student network. Since we obtain the soft labels from the Teacher network, we train the Student network by combining two loss functions. The first loss function used Euclidean distance aims to minimize difference between soft labels and 512-dimensional vectors extracted from the output of global mean pooling layer on the Student network. Meanwhile, the second Cross-Entropy loss function is used for classification of three groups of respiratory diseases. Eventually, the final loss is described below,

\[
\text{Loss}(\theta) = \text{Loss}_{\text{Entropy}}(\theta) + \gamma \cdot \text{Loss}_{\text{Euclidean}}(\theta) \tag{17}
\]

where \(\text{Loss}_{\text{Entropy}}\) and \(\text{Loss}_{\text{Euclidean}}\) are the Cross-Entropy and Euclidean distance losses respectively. Hyper-parameter \(\gamma\) is experimentally set to 1/2. \(\theta\) is total trainable parameters.

Fig. 9. Teacher-Student scheme architecture

an accuracy of 0.91 and 0.90 for the 3-category and 2-category subtasks respectively. These results indicate that our proposed deep learning frameworks outperform the state-of-the-art methods. However, the comparison may be not 100% exact due to different proportion splitting over dataset.

VI. STUDENT-TEACHER SCHEME TO REDUCE MODEL SIZE FOR RESPIRATORY DISEASES DETECTION

A. Student-Teacher scheme

Inspiration from effectively applying Teacher-Student scheme on sound scenes and sound events [37], [38], we apply this technique on Task 2 to deal with the trade-off between model size and performance. The proposed Teacher-Student scheme as described in Figure 9 comprises of two networks, namely Teacher (the upper) and Student (the lower), respectively. Teacher network reuses the C-DNN+MoE architecture introduced in Section V-A with only using global mean pooling. As regards the Student network architecture, it comprises of two Conv. Block 07, 08, and a Dense Block with configuration as denoted in Table VI. Note that Conv. Bocks used in Student network do not apply Batchnorm and Dropout layers. To operate the scheme, training Teacher-Student scheme is separated into two phases. The Teacher is firstly trained, thus extract the output of global mean pooling layer. The extracted features, likely 512-dimensional vectors, are referred as to soft labels that will be used to train Student network. Since we obtain the soft labels from the Teacher network, we train the Student network by combining two loss functions. The first loss function used Euclidean distance aims to minimize difference between soft labels and 512-dimensional vectors extracted from the output of global mean pooling layer on the Student network. Meanwhile, the second Cross-Entropy loss function is used for classification of three groups of respiratory diseases. Eventually, the final loss is described below,

\[
\text{Loss}(\theta) = \text{Loss}_{\text{Entropy}}(\theta) + \gamma \cdot \text{Loss}_{\text{Euclidean}}(\theta) \tag{17}
\]

where \(\text{Loss}_{\text{Entropy}}\) and \(\text{Loss}_{\text{Euclidean}}\) are the Cross-Entropy and Euclidean distance losses respectively. Hyper-parameter \(\gamma\) is experimentally set to 1/2. \(\theta\) is total trainable parameters.
B. Experimental results

| Task   | Method                          | Spec. | Sen. | ICBHI Score |
|--------|---------------------------------|-------|------|--------------|
| 2-1    | 3-class Teacher                  | 0.86  | 0.93 | 0.91         |
| 2-1    | 3-class Student only             | 0.43  | 0.94 | 0.68         |
| 2-1    | 3-class Student with soft labels | 0.86  | 0.90 | 0.88         |
| 2-2    | 2-class Teacher                  | 0.86  | 0.98 | 0.92         |
| 2-2    | 2-class Student only             | 0.43  | 0.99 | 0.71         |
| 2-2    | 2-class Student with soft labels | 0.86  | 0.96 | 0.91         |

From results obtained as in Table VII, Student network trained with soft labels from Teacher network achieves 0.88 and 0.91 on Task 2-1 and 2-2, respectively. Although Student network cannot reach the scores of Teacher network with 0.91 and 0.92 on Task 2-1 and 2-2 respectively, Student network helps to significantly reduce the size of reference model without reducing performance too much. Look at results on Student network without soft labels from Teacher, the performance significantly reduces to 0.68 and 0.71 for Task 2-1 and 2-2, respectively. As a result, apply Teacher-Student scheme helps to achieve a Student network with lower parameter of 7296, compared with 30912 trainable parameters in Teacher network, which is effectively used for detection processes in low-parameter required systems.

VII. CONCLUSION

This paper has presented an exploration of deep learning models for detecting respiratory disease from auditory recordings. By conducting intensive experiments over the ICBHI dataset, we propose deep learning frameworks for four challenge tasks of respiratory sound classification. The proposed systems are shown to outperform the state of the art on all tasks. Furthermore, effectively applying Teacher-Student scheme helps to significantly reduce model size used for reference process but still achieves high performance. Obtained experimental results validate application of deep learning for early diagnosis of respiratory disease.

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