DCASENET: A JOINT PRE-TRAINED DEEP NEURAL NETWORK FOR DETECTING AND CLASSIFYING ACOUSTIC SCENES AND EVENTS

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ABSTRACT

Single task deep neural networks that perform a target task among diverse cross-related tasks in the acoustic scene and event literature are being developed. Few studies exist that investigate to combine such tasks, however, the work is at its preliminary stage. In this study, we propose an integrated deep neural network that can perform three tasks: acoustic scene classification, audio tagging, and sound event detection. Through vast experiments using three datasets, we show that the proposed system, DCASENet, itself can be directly used for any tasks with competitive results, or it can be further fine-tuned for the target task.

Index Terms— Task correlation, deep neural networks, acoustic scene classification, audio tagging, sound event detection

1. INTRODUCTION

With recent advances in deep learning, the performance of acoustic signal processing systems in various tasks are improving [1–6]. The detection and classification of acoustic scenes and events (DCASE) community is providing annual challenges and workshops with public datasets [7–9]. Using the DCASE challenge datasets, various tasks including acoustic scene classification (ASC), audio tagging (TAG), sound event detection (SED), bird audio detection, sound localization are widely studied.

Some of these tasks are being independently studied, although their characteristics and required information largely inter-dependent. Tasks are being separately studied using different deep neural networks (DNNs). In cognitive science, researches (e.g., [10]) show that humans first detect audio events and leverage this information to classify acoustic scenes. For instance, perceiving car horns and traffic sounds can be helpful for knowing that he/she is standing in a street. Motivated by this human perception mechanism, studies such as Jung et al. [11,12] and Imoto et al. [13,14] propose DNNs that perform two inter-related tasks simultaneously. However, studies aiming to integrate related tasks are currently in its preliminary stage, requiring further investigation.

In this study, we explore various DNN architectures (Fig. 1) to integrate two segment-level tasks and a frame-level task using a single DNN that jointly learns and conducts three tasks; ASC, TAG, and SED (three tasks are introduced in details in Section 2). First, we mimic the human perception and propose an architecture that first performs two event detection tasks, TAG and SED, and then conduct the ASC task. We also propose an architecture that performs ASC first and then conducts TAG and SED. This architecture is designed utilizing the complexity of tasks in the perspective of deep learning; a multi-class classification ASC task would require relatively low level of abstractness rather than the SED task which requires frame-level multi-label binary classification. Through comparison experiments we find that the architecture designed considering tasks complexity performs better and propose another architecture by expanding it, using a few separate layers for each task.

The goal of this study is to build a single DNN that integrates three related tasks, ASC, TAG, and SED which can be fine-tuned to perform any of the three tasks. Specifically, we hope that the proposed model, DCASENet, to serve as a pre-trained model alike the Imagenet pre-trained model [15] in acoustic signal processing tasks. The main contributions of this paper are threefold:

1. Propose integrated DNN architectures that jointly performs ASC, TAG, and SED tasks.
2. Compare human perception and deep learning perspective based on task complexity as motivation for design choice.
3. Demonstrate that fine-tuning the joint DNN for separate task improves performance.

The rest of this paper is organized as follows. In Section 2 we introduce three tasks, ASC, TAG, and SED along with some initial studies trying to incorporate them. In Section 3, We explain three proposed DNN designs for the joint DNN. Section 4 addresses experiments and result analysis and the paper is concluded with future works.

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This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Science, ICT & Future Planning(2020R1A2C1007081).
https://dcase.community
2. RELATED TASKS AND WORKS

The ASC is a multi-class classification task, which identifies a given segment into one of the scenes. Scenes (i.e., classes) are predefined and are analyzed to have big intra variance because of its abstract definition (e.g., metro, shopping mall, and park). To deal with such a characteristic, many researches in ASC explore reducing the impact of different recording devices and shared acoustic properties among different scenes [16–19].

The TAG and the SED tasks both are a multi-label binary classification task, which perform event detection (i.e., judge the existence of various sounds). TAG task conducts segment-level detection; it outputs a vector in which each dimension is a real number between 0 and 1 indicating the existence of a sound event throughout an input segment. SED task conducts frame-level detection; it outputs a matrix in which the rows refer to the result of event detection in a single frame and each row show the existence of sound events in a single frame. In other words, the SED task performs TAG task with each sound events onset and offset information.

There exists a few studies which investigated to combine inter-related tasks [11–14]. Imoto et al. assume that the ASC and the SED tasks are inter-related and propose to conduct two tasks simultaneously using a multi-task learning framework. Jung et al. aims to mimic the human perception mechanism of leveraging event detection for the ASC by applying attention to the ASC system using a pre-trained TAG system. However, these studies further require analysis and architecture designs which accounts for the task relationship.

3. INTEGRATED FRAMEWORKS

In this section, we propose and investigate three architectures to jointly perform the three tasks, illustrated in Fig. 1: ASC, TAG, and SED. We refer to these architectures as DcaseNet because it jointly detects and classifies acoustic scenes and events. The design choice of the first DcaseNet architecture (Fig. 1(a)) is motivated from human perception mechanism, which uses event detection for the ASC, expanding [11]. Thus, this architecture first performs the frame-level event detection (i.e., SED) task using a convolution recurrent neural network (CRNN). Then, segment-level event detection (i.e., TAG), and segment-level scene classification (i.e., ASC) is conducted in parallel. Note that among two event detection tasks, TAG and SED, the SED task places in the lower layers based on the assumption that detecting short events would benefit whether an event exists throughout the audio segment.

The second DcaseNet architecture (Fig. 1(b)), on the other hand, considers the complexity of tasks in a DNN perspective. Event detection tasks require relatively lower level of abstraction compared to scene classification. Among two event detection tasks, segment-level task requires relatively higher level of abstraction. Thus, the second architecture performs ASC after a few CNN blocks, and then performs event detection tasks after the gated recurrent unit (GRU) layer. Through comparison experiments, we empirically find that the second architecture performs better.

The third DcaseNet architecture (Fig. 1(c)) modifies the second architecture by adding a layer before conducting each task, which is also concatenated and feed-forwarded to the next layer. Inspired by He et al. [20], we intend to keep an information path (green layers) at the same time allowing few layers to solely perform individual task. In additional, instead...
of performing TAG and SED tasks in parallel, in this architecture, we place hidden layers for SED and TAG tasks sequentially. For all three DcaseNet architectures, we first perform single or joint training. After training is complete, we fine-tune each model, except single task trained DNNs, for each task to see the final performance on the target task.

Each component of the DcaseNet architecture is motivated from successful systems in each task. The CRNN (first two rectangles in Fig. 1) in all three DcaseNet architecture are identical to that of Cao et al. [21], which has the second place in the DCASE 2019 Challenge Task 3. It adopts eight convolutional layers with batch normalization [22], followed by a bidirectional GRU layer [23]. ‘CNN’ in Fig. 1(a)’s top is from authors’ previous work, submitted to the DCASE 2020 Challenge Task 1-a, which is a residual block [12]. ‘Dense’ block before TAG task output comprises two fully-connected layers followed by dropout [25] and ReLU non-linearity.

4. EXPERIMENTS AND RESULTS

Codes and pre-trained DcaseNet weights are available at
https://github.com/Jungjee/DcaseNet

4.1. Datasets and metrics

We use the DCASE 2020 Task 1-a dataset for the ASC Task, DCASE 2019 Task 2 dataset for the TAG task, and DCASE 2020 Task 3 dataset for the SED task. Overall specifications including total duration, number of segments, number of classes are given in Table 1. Note that for the TAG task, we only use the curated subset, excluding noisy trainset, and split 20% of the dataset to report evaluation performance because the labels for the challenge evaluation set is not public and a separate validation set does not exist like the ASC and the SED task. We modify all audio segments, if not already, to a sampling rate of 24,000 Hz, 16-bit, mono.

The performance of the proposed DcaseNet architectures are reported using four metrics: overall classification accuracy (Acc) for ASC, label-weighted label-ranking precision (lwrrap) for TAG, F-score (F1) for SED, and error rate (ER) for SED. Higher is better for all metrics except ER. Due to the limited space, we omit detail instructions on each metric, which is available at the DCASE community homepage.

4.2. Experimental configurations

We use a 128-dimensional Mel-spectrograms as input feature to the DNN, extracted using 2,048 FFT bins, and a 40 ms window length with a 20 ms shift. To train using multiple datasets concurrently, we configure 500 iterations as one epoch, and train 160 epochs. The batch sizes for ASC, TAG, and SED tasks are 32, 24, and 32. In the training phase, for the ASC and the TAG task, the segment duration is randomly cropped to 5 s and 30 s for the SED task for mini-batch construction as well as data augmentation effect. We use Adam [26] with a learning rate of 0.001 and do not use weight decay. For both joint training and fine-tuning towards each task, no change in hyper-parameters are made.

The CRNN used in common for all three DcaseNet architectures comprise 8 convolution layers followed by batch normalization layers where the last convolution layer has 512 output filters. A bidirectional GRU layer with 512 nodes are used. ‘Dense’ block before TAG task output comprises two fully-connected layers, each with 1,024 nodes. Other detailed configurations can be found in the provided Git repository.

4.3. Result analysis

Table 1 depicts overall experiments conducted in this study. Task combination shows on which task(s) the DNN is trained (e.g., fourth row show that the DNN is trained using ASC and TAG). For each DcaseNet architecture, top three rows demonstrate single task training performances which are used as baselines and the bottom four rows describe joint training performances. ‘Fine-tune’ column shows the result of initializing using the joint trained model and conducting fine-tuning for each task.

First, the effect of Mix-up [27] is investigated using the DcaseNet-v1 architecture. Results demonstrate that it is effective, improving most performances; thus we apply Mix-up for both DcaseNet-v2 and DcaseNet-v3 architecture. Joint training DcaseNet-v1 architecture only improved performance in the case of TAG task. Even after fine-tuning, we analyze that the joint trained model does not generalize well across three tasks because without Mix-up, the ASC task performance does not improve whereas with Mix-up, the SED tasks performance does not improve. In other words, a single DNN that outperforms all three baselines does not exist.

The DcaseNet-v2 architecture performs better than DcaseNet-v1. It also shows improvement in joint training of TAG task. After fine-tuning, this architecture demonstrates better performance than the corresponding baseline consistently, except the model that jointly trained ASC and SED task. Compar-

Table 1. Specifications of the three datasets for joint training DcaseNet systems. ‘ASC’: DCASE 2020 Task 1-a, ‘TAG’: DCASE 2019 Task 2, ‘SED’: DCASE 2020 Task 3.

| Task | ASC | TAG | SED |
|------|-----|-----|-----|
| Train duration (hours) | 43.0 | 10.5 | 10.0 |
| # Train segments | 13,965 | 3,976 | 600 |
| Segment duration (seconds) | 10 | 0.3–30 | 60 |
| # Evaluation segments | 2,970 | 994 | 100 |
| # Classes | 10 | 80 | 14 |
| Architecture | #Param | Task combination | Single/Joint training (rand init) | Fine-tune (joint train init) |
|--------------|--------|------------------|----------------------------------|-------------------------------|
|              |        | ASC TAG SED      | ASC Acc lwlrap F1 ER             | ASC TAG SED                   |
|              |        |                  |                                  |                               |
|              |        |                  |                                  |                               |
| DcaseNet-v1  | 8.7M   | ✓ × ×            | 67.68 - - -                      |                               |
|              |        |                  |                                  |                               |
|              |        |                  |                                  |                               |
| (Fig. 1-(a))| 8.7M   | ✓ ✓ ×            | 59.23 53.55 - - -               | 67.18 68.81 - -               |
| (w/o Mix-up)| 8.7M   | ✓ × ✓            | 57.04 - 64.75 0.4939            | 66.84 - 75.86 0.3365          |
|              | 8.7M   | ✓ ✓ ✓            | 56.13 59.25 59.82 0.5367        | 67.08 71.80 75.71 0.3470      |
|              |        |                  |                                  |                               |
|              | 8.9M   | ✓ × ×            | 68.19 - - -                      |                               |
|              |        |                  |                                  |                               |
|              | 8.9M   | × ✓ ×            | - 69.41 - -                      |                               |
|              | 8.9M   | × × ✓            | - - 79.62 0.2926                |                               |
|              |        |                  |                                  |                               |
|              | 9.8M   | ✓ × ×            | 69.54 - - -                      |                               |
|              |        |                  |                                  |                               |
|              | 9.8M   | ✓ × ✓            | - 69.19 - -                      |                               |
|              | 9.8M   | × × ✓            | - - 79.34 0.3085                |                               |
|              |        |                  |                                  |                               |
|              | 9.8M   | ✓ × ×            | 58.92 60.00 - - -               | 69.87 69.68 - -               |
|              |        |                  |                                  |                               |
|              | 9.8M   | ✓ × ✓            | 58.79 - 69.53 0.4416            | 69.07 - 78.98 0.3058          |
|              | 9.8M   | × ✓ ✓            | - 74.54 76.46 0.3571            | - 74.76 81.32 0.2826          |
|              | 9.8M   | ✓ ✓ ✓            | 59.80 62.94 66.67 0.4817        | 69.57 71.38 79.26 0.2968      |
|              |        |                  |                                  |                               |
|              | 13.2M  | ✓ × ×            | 68.33 - - -                      |                               |
|              |        |                  |                                  |                               |
|              | 13.2M  | × ✓ ×            | - 70.62 - -                      |                               |
|              | 13.2M  | × × ✓            | - - 78.61 0.3085                |                               |
|              |        |                  |                                  |                               |
|              | 13.2M  | ✓ × ×            | 61.08 65.03 - - -               | 70.35 71.42 - -               |
|              |        |                  |                                  |                               |
|              | 13.2M  | ✓ × ✓            | - 75.62 0.3512                 | 69.44 - 79.61 0.2948          |
|              | 13.2M  | × ✓ ✓            | - 76.23 77.93 0.3232            | - 75.99 79.28 0.2958          |
|              | 13.2M  | ✓ ✓ ✓            | 56.80 70.40 75.19 0.3586        | 69.37 74.59 78.80 0.3185      |

**Table 2.** Experimental results on the proposed three integrated architectures. For each architecture, top three rows describe single training (baseline), and the next four rows describe performances for joint training. Fine-tune report the result of using the joint trained model as pre-training and tuning the model for each task. Performances are reported using four metrics for three tasks; ASC: classification accuracy (ACC), TAG: label-weighted label-ranking average precision (lwlrap), SED: F1 score and error rate (F1 and ER). Lower is better for ER and higher is better for the rest three metrics. **Bold** denotes performances that are improved than the baseline and **Italic** refers to the baseline performances for each architecture (-: not applicable).

In this paper, we propose integrated DNN architectures that jointly perform ASC, TAG, and SED tasks. Comparison of mimicking human perception and task complexity in deep learning perspective for the design of integrated DNNs is provided, where performing SED task first demonstrates better result. Having few layers before the output of each intermedia...
ate task is also effective. Jointly trained models can be further fine-tuned for each task.

However, as this is the first study that integrates three inter-related tasks that classify and detect acoustic scenes and events, there are still more explorations to be made. In the future,

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