Improving Deep-learning-based Semi-supervised Audio Tagging with Mixup

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Abstract—Recently, semi-supervised learning (SSL) methods, in the framework of deep learning (DL), have been shown to provide state-of-the-art results on image datasets by exploiting unlabeled data. Most of the time tested on object recognition tasks in images, these algorithms are rarely compared when applied to audio tasks. In this article, we adapted four recent SSL methods to the task of audio tagging. The first two methods, namely Deep Co-Training (DCT) and Mean Teacher (MT), involve two collaborative neural networks. The two other algorithms, called MixMatch (MM) and FixMatch (FM), are single-model methods that rely primarily on data augmentation strategies. Using the Wide ResNet 28-2 architecture in all our experiments, 10% of labeled data and the remaining 90% as unlabeled, we first compare the four methods’ accuracy on three standard benchmark audio event datasets: Environmental Sound Classification (ESC-10), UrbanSound8K (UBS8K), and Google Speech Commands (GSC). MM and FM outperformed MT and DCT significantly, MM being the best method in most experiments. On UBS8K and GSC, in particular, MM achieved 18.02% and 3.25% error rates (ER), outperforming models trained with 100% of the available labeled data, which reached 23.29% and 4.94% ER, respectively. Second, we explored the benefits of using the mixup augmentation in the four algorithms. In almost all cases, mixup brought significant gains. For instance, on GSC, FM reached 4.44% and 3.31% ER without and with mixup.

Index Terms—Audio tagging, semi-supervised deep learning.

I. INTRODUCTION

SEMI-SUPERVISED learning (SSL) aims to reduce the dependency of deep learning systems on labeled data by integrating non-labeled data during the learning phase. It is essential since the conception of a large labeled dataset is expensive, dependent on the task to be learned, and time-consuming. On the contrary, the acquisition of non-labeled data is cheaper and quicker regardless of the learning task. Using unlabeled data while maintaining high performance can be done in three different ways: Consistency regularization [1], [2], which encourages a model to produce consistent predictions whereas the input is perturbed; Entropy minimization [3]–[5], which encourages the model to output high confidence predictions on unlabeled files, and Standard regularization by using weight decay [6], [7], mixup [8] or adversarial examples [9]. The most direct approach for SSL is pseudo-labeling [5], but since then, many new and better approaches came out such as Mean Teacher [10], Deep Co-Training [11], MixMatch [12] and FixMatch [13].

In this work, we adapted these four SSL methods to the task of audio tagging. One difficulty lies in choosing which audio data augmentation techniques to use, that work for different types of sound events and spoken words. We compare the methods’ accuracy on three audio datasets with different scopes and size: Environmental Sound Classification 10 (ESC-10) Dataset [14], with audio event categories such as human noise not related to speech, natural ambient noise, UrbanSound8k (UBS8K) [15], more specific to urban noises, and Google Speech Commands (GSC) Dataset v2 [16] containing spoken words exclusively.

In the MixMatch algorithm, a successful data augmentation technique called mixup [8] is used. It consists of mixing pairs of samples, both the data samples and the labels with a random coefficient. We propose to add mixup to the three other SSL approaches, namely MT, DCT and FM, which do not already use it. The results reported in this article will highlight the positive impact of mixup in almost all our experiments.

This paper’s contributions are two-fold: i) the application and comparison of recent SSL methods for audio tagging on three different datasets, ii) the modification of these methods with the integration of mixup resulted in systematic accuracy gains. We shall see that in most cases, MixMatch outperformed the other methods, closely followed by FixMatch+mixup.

The structure of the paper is as follows. Section II describes the augmentations we used and the mixup mechanism at the core of the present work. Section III describes the four SSL methods, Section IV presents the experimental settings, and finally, Section V presents and discusses the results.

II. AUDIO DATA AUGMENTATION

Augmentations are at the heart of semi-supervised learning mechanisms to take advantage of the non-labeled examples they are provided with. In this section, we begin by describing the mixup mechanism, which we explore in this work, and the different audio data augmentations used in some of the SSL approaches.

A. mixup

Mixup [8] is a successful data augmentation/regularization technique, that proposes to mix pairs of samples (images, audio clips, etc.). If $x_1$ and $x_2$ are two different input samples (spectrograms in our case) and $y_1, y_2$ their respective one-hot encoded labels, then the mixed sample and target are obtained by a simple convex combination:

$$x^{mix} = \lambda x_1 + (1-\lambda)x_2$$
$$y^{mix} = \lambda y_1 + (1-\lambda)y_2$$

where $\lambda$ is a random coefficient in $(0, 1)$.
where $\lambda$ is a scalar sampled from a symmetric Beta distribution at each mini-batch generation:

$$\lambda \sim \text{Beta}(\alpha, \alpha)$$

where $\alpha$ is a real-valued hyper-parameter to tune (always smaller than 1.0 in our case).

In the original MM algorithm, an “asymmetric” version of mixup is used, in which the maximum value between $\lambda$ and $1 - \lambda$ is retrieved:

$$\lambda = \max(\lambda, 1 - \lambda)$$

(1)

This allows the resulting mixed batch to be closer to one of the two original batches (the one with the $\lambda$ coefficient). This is useful when the method mixes labeled and unlabeled samples.

B. Audio signal augmentation methods

For supervised learning, MM and FM, we use three different augmentations: Occlusion, StretchPadCrop, and CutOutSpec. During training, one of these augmentations is randomly applied to each sample.

- **Occlusion**: applied to the raw audio signal, Occlusion consists of setting a segment of the file to zero. The size of the segment is randomly chosen to a user-defined maximum size. The position of the segment is also chosen randomly.
- **StretchPadCrop**: also applied to the raw audio signal, StretchPadCrop consists of up-sampling or down-sampling the signal. The rate with which the signal is modified is chosen randomly within a predefined interval. The resulting augmented file is either shorter or longer. It is then necessary to apply zero padding or cropping to keep the shape of the samples constant.
- **CutOutSpec**: applied to the log-mel-spectrogram, CutOutSpec sets the values within a random rectangle area with the -80 dB value, which corresponds to the silence energy level in our spectrograms. The length and width of the removed sections are randomly chosen from predefined intervals and depend on the spectrogram size.

To select and tune these augmentations, we trained on GSC several Wide ResNet28-2 models [17], which architecture will be described in details in Section IV-B. During training, a different augmentation was applied to the input data with a 100% chance. We ran a grid search to tune the parameter values for each augmentation. In addition to the three augmentations described above, we also tried to apply uniform noise on the log-Mel spectrograms, invert the Mel-band axis or the time axis, and apply a frequency and time dropout. Table 1 details the different augmentations we tested.

FM makes use of so-called “weak” and “strong” augmentations. The difference between the two lies in the strength and frequency with which an augmentation is applied. The specific parameters of each augmentation are defined in Table 1.

Figure 1 shows examples of a weak and a strong StretchPadCrop augmentation, as well as two spectrograms mixed using mixup as done in our experiments.

| Name             | Parameters | Weak range     | Strong range   |
|------------------|------------|----------------|----------------|
| Occlusion        | max_size  | [0.25, 0.25]   | [0.75, 0.75]   |
| StretchPadCrop   | rate       | [0.50, 1.50]   | [0.25, 1.75]   |
| CutOutSpec       | scale      | [0.10, 0.50]   | [0.50, 1.00]   |

Fig. 1. Example of different augmentations on an audio file from UrbanSound8k, from top to bottom: original, weak augmentation, strong augmentation, and mixup augmentation. The weak and strong augmentations correspond to StretchPadCrop with a factor randomly taken from the interval [0.5, 1.5] and [0.25, 1.75], respectively.

III. SEMI-SUPERVISED DEEP LEARNING ALGORITHMS

This section provides a detailed description of each of the methods we decided to experiment with. We chose them for their performance and novelty. Two of these approaches, Mean Teacher (MT) [10] and Deep Co-Training (DCT) [11] use the principle of consistency regularization between the output of two models. The other methods, MixMatch (MM) and FixMatch (FM), use only one model and combine the three SSL mechanisms described in the introduction.
Fig. 2. MT workflow. Both models receive as input labeled $x_s$ and unlabeled $x_u$. A supervised loss $L_s$ is computed between the ground truth and the student model predictions, whereas a consistency cost $L_{cc}$ is computed between the student and teacher model predictions.

We considered a fifth method, ReMixMatch, that has been proposed by the same authors to enhance MM, but before introducing FM. ReMixMatch uses an additional self-supervised loss term, related to predicting a rotation angle applied to an input image. For audio, we replaced the rotations with horizontal and vertical flips on the spectrograms, but we did not obtain better results compared to MixMatch, so that we do not report results with this method.

We provide a figure to illustrate each of the four methods. In Section III-E, we explain how we add mixup to each method, except MM that already uses mixup in its original version. We included the mixup operation in a green-colored box in the method workflow figures, to show where mixup is optionally integrated. We will refer to the modified methods as “method+mixup”, for instance, FM+mixup.

### A. Mean-Teacher (MT)

We can find audio applications of MT [10] in the Detection and Classification of Acoustic Scenes and Events (DCASE) task 4 challenges, namely the weakly supervised Sound Event Detection task.

MT uses two neural networks: a “student” $f$ and a “teacher” $g$, which share the same architecture. The weights $\omega$ of the student model are updated using the standard gradient descent algorithm, whereas the weights $W$ of the teacher model are the Exponential Moving Average (EMA) of the student weights. The teacher weights are computed at every mini-batch iteration $t$, as the convex combination of its weights at $t-1$ and the student weights, with a smoothing constant $\alpha_{ema}$:

$$ W_t = \alpha_{ema} \cdot W_{t-1} + (1 - \alpha_{ema}) \cdot \omega_t $$

There are two loss functions applied either on the labeled or unlabeled data subsets. On the labeled data $x_s$, the usual cross-entropy (CE) is used between the student model’s predictions and the ground-truth $y_s$.

$$ L_{sup} = CE(f(x_s), y_s) $$

The consistency cost is computed from the student prediction $f(x_u)$ and the teacher prediction $g(x'_u)$, where $x_u$ is a sample from the unlabeled subset, and $x'_u$ the same sample but slightly perturbed with Gaussian noise and a 15 dB signal-to-noise ratio. In our case, this cost is a Mean Square Error (MSE) loss.

$$ L_{cc} = MSE(f(x_u), g(x'_u)) $$

The final loss function is the sum of the supervised loss function and the consistency cost weighted by a factor $\lambda_{cc}$ which controls its influence.

$$ L_{total} = L_{sup} + \lambda_{cc} \cdot L_{cc} $$

### B. Deep Co-Training (DCT)

DCT has been recently proposed by Qiao and colleagues [11]. It is based on Co-Training (CT), the well-known generic framework for SSL proposed by Blum and colleagues in 1998 [18]. The main idea of Co-Training is based on the assumption that two independent views on a training dataset are available to train two models separately. Ideally, the two views are conditionally independent given the class. The two models are then used to make predictions on the non-labeled data subset. The most confident predictions are selected and added to the labeled subset. This process is iterative, like pseudo-labeling.

DCT is an adaptation of CT in the context of deep learning. Instead of relying on views of the data that are different, DCT makes use of adversarial examples to ensure the independence in the “view” presented to the models. The second difference is that the whole non-labeled dataset is used during training.
Each batch is composed of a supervised and an unsupervised part. Thus, the non-labeled data are directly used, and the iterative aspect of the algorithm is removed.

Let $S$ and $U$ be the subsets of labeled and unlabeled data, respectively, and let $f$ and $g$ be the two neural networks that are expected to collaborate.

The DCT loss function is comprised of three terms, as shown in Eq. 6. These terms correspond to loss functions estimated either on $S$, $U$, or both. Note that during training, a mini-batch is comprised of labeled and unlabeled samples in a fixed proportion. Furthermore, in a given mini-batch, the labeled examples given to each of the two models are sampled differently.

\[
L = L_{sup} + \lambda_{cot} L_{cot} + \lambda_{diff} L_{diff} \quad (6)
\]

The first term, $L_{sup}$, given in Eq. 7 corresponds to the standard supervised classification loss function for the two models $f$ and $g$, estimated on examples $x_1$ and $x_2$ sampled from $S$. In our case, we use categorical Cross-Entropy (CE), the standard loss function used in classification tasks with mutually exclusive classes.

\[
L_{sup} = CE(f(x_1), y_1) + CE(g(x_2), y_2) \quad (7)
\]

In SSL and Co-Training, the two classifiers are expected to provide consistent and similar predictions on both the labeled and unlabeled data. To encourage this behavior, the Jensen-Shannon (JS) divergence between the two sets of predictions is minimized on examples $x_u$ sampled from the unlabeled subset $U$ only. Indeed, there is no need to minimize this divergence also on $S$ since $L_{sup}$ already encourages the two models to have similar predictions on $S$. Eq. 8 gives the JS analytical expression, with $H$ denoting entropy.

\[
L_{cot} = H\left(\frac{1}{2}(f(x_u) + g(x_u))\right) - \frac{1}{2}\left(H(f(x_u)) + H(g(x_u))\right) \quad (8)
\]

For DCT to work, the two models need to be complementary: on a subset different from $S \cup U$, examples misclassified by one model should be correctly classified by the other model [19]. This can be achieved in deep learning by generating adversarial examples with one model and training the other model to be resistant to these adversarial samples. To do so, the $L_{diff}$ term (Eq. 2) is the sum of the Cross-Entropy losses between the predictions $f(x_1)$ and $g(x')$, where $x_1$ is sampled from $S \cup U$ and $x'$ is the adversarial example generated with model $f$ and $x_1$ taken as input. The second term is the symmetric term for model $g$.

\[
L_{diff} = CE(f(x_1), g(x')) + CE(g(x_2), f(x')) \quad (9)
\]

For the adversarial examples generation, we use the Fast Gradient Signed Method (FGSM, [20]), as in Qiao’s work.

For more in-depth details on the technical aspects of DCT, the reader may refer to [11]. We implemented DCT as precisely as described in Qiao’s article, using PyTorch, and made sure to accurately reproduce their results on CIFAR-10: about 90% accuracy when using only 10% of the training data as labeled data (5000 images).

### C. MixMatch

MixMatch [12] (MM) is an SSL approach that uses entropy minimization and standard regularization, namely pseudo-labeling [5], mixup, and weak data augmentation, to leverage the unlabeled data and provide better generalization capabilities. Unlike MT and DCT, this approach uses only one model. The different steps are shown in Fig. 4 and detailed in the following paragraphs.

During the learning phase, each minibatch is composed of labeled $x_s$ and non-labeled $x_u$ samples in equivalent proportions. The first step consists of applying an augmentation to the labeled part of the mini-batch and $k$ augmentations to the non-labeled part. In the second step, pseudo-labels $y_u$ are generated for the non-labeled files using the model’s prediction averaged on these $k$ variants as shown in Eq. 10, where $x_{u,i}$ denotes the $i$-th variant of an unlabeled augmented file.

\[
y_u = \frac{1}{k} \sum_{i=1}^{k} f(x_{u,i}) \quad (10)
\]

For encouraging the model to produce confident predictions, a post-processing step is necessary to decrease the output’s entropy. To do so, the highest probability is increased and the other ones decreased. This process is called “sharpening” by the method authors, and it is defined as:

\[
\text{sharpen}(p, T)_i := p_i^{1/T} / \sum_{j=1}^{|p|} p_j^{1/T} \quad (11)
\]
The sharpen function is applied on the pseudo-labels $p = \hat{y}_u$. The parameter $T$, called Temperature, controls the strength of the sharpen function. When $T$ tends towards zero, the entropy of the distribution produced is lowered.

Finally, the labeled and unlabeled augmented samples are concatenated and shuffled into a $W$ set then used as a pool of training samples used by the asymmetric mixup function. Asymmetric mixup is applied separately on the labeled and unlabeled parts of the mini-batch, as formulated here:

$$x'^{\text{mix}}_s = \text{mixup}(x_s | W_{1...|x_s|})$$

$$x'^{\text{mix}}_u = \text{mixup}(x_u | W_{|x_u|...|W|})$$

The $W$ set and the corresponding labels are shuffled in the same order. Each labeled sample is then perturbed by a second labeled or unlabeled sample. Mixing the two is done so that the original labeled sample remains the main component of the resulting sample. The operation has been detailed in Section II-A. The same procedure is applied onto the unlabeled files using the remaining samples from $W$.

The original MixMatch loss function is composed of the standard cross-entropy (CE) for the supervised loss $L_s$, and a squared l2 norm for the unsupervised loss $L_u$. We replace the l2 norm with a cross-entropy in all our experiments, as proposed in the ReMixMatch paper. Indeed, it seems that CE performs better than the l2 norm in our experiments.

$$L_s = \frac{1}{B_s} \sum_{(x^s, y^s)} \text{CE}(f(x'^{\text{mix}}_s), y^{\text{mix}}_s)$$

$$L_u = \frac{1}{B_u} \sum_{(x'^{\text{mix}}_u, \hat{y}^{\text{mix}}_u)} \text{CE}(f(x'^{\text{mix}}_u), \hat{y}^{\text{mix}}_u)$$

The final loss is the sum of the two components, with a hyper-parameter $\lambda_u$ :

$$L = L_s + \lambda_u \cdot L_u$$

### D. FixMatch

FixMatch [13] (FM) is another SSL method which proposes a simplification of MM and ReMixMatch. The method also uses one model, removes mixup and replaces the sharpen function by binary pseudo-labels. FM uses both weak augmentations (weak) and strong augmentations (strong). The strong augmentations can mislead the model predictions by disrupting too much the training data. Figure 5 shows the main pipeline of FixMatch. As in the other method illustrations, we added a mixup box in blue, to indicate where we add it to the algorithm in our modified FM algorithm, thus called FM+mixup.

The supervised loss component is the standard cross-entropy applied to the weakly augmented data :

$$L_s = \text{CE} \left( f(\text{weak}(x_s)), y_s \right)$$

Then, we guess the labels of the weakly augmented unlabeled data and apply a binarization (argmax) of these predictions to have a "one-hot" encoded label. This label is used as target for training the model with strongly augmented unlabeled data. It allows the model to generalize with weak and strong augmentations and it also uses the guessed label to improve the model accuracy with unlabeled data:

$$\hat{y}_u = f(\text{weak}(x_u))$$

To avoid training on incorrect guessed labels, FM uses a threshold $\tau$ that ensures that the unsupervised cost function can only be applied to predictions made with high confidence, i.e., above this threshold. This can be easily implemented in the form of a mask:

$$\text{mask} = \mathbb{1}(\max(\hat{y}_u) > \tau)$$

$$L_u = \text{mask} \cdot \text{CE} \left( f(\text{strong}(x_u)), \argmax(\hat{y}_u) \right)$$

As in MixMatch, we sum the loss components to compute the final loss:

$$L = L_s + \lambda_u \cdot L_u$$

### E. Adding mixup to MT, DCT and FM

As we described here-above, MM already uses mixup in its workflow. In order to measure the impact of mixup in MM, we will report results when we remove mixup from MM. On the contrary, the three other SSL methods explored in our work (MT, DCT, FM) do not use mixup in their original version. How should we add mixup to those then? We explored several ways to do so, and retained the best one for each of the three methods. Note that we illustrate where the mixup operation has been added in the figures describing the different methods in the previous section.
Since the labeled and unlabeled data flow is very similar in MM and FM, we added mixup to FM at the same place as in MM: both labeled and unlabeled samples are mixed up. Similarly, it is also the asymmetric mixup variant that we in MM and FM since mixup is applied to labeled and unlabeled samples together, as in the original MM method. Using mixup on labeled and unlabeled examples separately seems to hurt performance with these two methods.

In MT, mixup is applied on labeled and unlabeled samples separately and only for the teacher model. The perturbation with Gaussian noise applied to the unlabeled samples is removed, since no gain was observed when mixup is used instead.

For DCT, mixup is applied on the unlabeled samples only, common to both models in each minibatch during training. Applying mixup on the labeled samples, which are sampled differently for the two models at each training step, lead yo worse results. It is then, not necessary to use the asymmetrical variant for MT and DCT.

Finally, in all cases, we apply mixup on the log-Mel spectrograms, which are the input features given to our deep neural networks (feature extraction is detailed in the experiment section).

IV. EXPERIMENTS

In this section, we describe our experimental setup. We give a brief description of the datasets and metrics, describe the Wide ResNet architecture we used, together with the training strategy details.

A. Datasets and evaluation metrics

Environmental Sound Classification 10 (ESC-10) [14] is a selection of 400 five-second-long recordings of audio events separated into ten balanced categories. The dataset is provided with five uniformly sized cross-validation folds that will be used to perform the evaluation. The files are sampled at 44 kHz and are converted into 431 x 64 log-Mel spectrograms.

UrbanSound8k (UBS8K) [15] is a dataset composed of 8742 files between 1 and 4 seconds long, separated into ten balanced categories. The dataset is provided with ten cross-validation folds of uniform size that will be used to perform the evaluation. The files are zero-padded to 4 seconds, resampled to 22 kHz, and converted to 431 x 64 log-Mel spectrograms.

Google Speech Commands Dataset v2 (GSC) [16] is an audio dataset of spoken words designed to evaluate keyword spotting systems. The dataset is split into 8551 training files, 10102 validation files, and 4890 testing files. The latter is used for the evaluation of our systems. We ran the task of classifying the 35 word categories of this dataset. The files are zero-padded to 1 second if needed and sampled at 16 kHz before being converted into 32 x 64 log-Mel spectrogram.

In all cases, the 64 Mel-coefficients were extracted using a window size of 2048 samples and a hop length of 512 samples. For ESC-10 and UBS8K, we used the official cross-validation folds. We report the average classification Error Rate (ER) along with standard deviations.

| Layer | Architecture |
|-------|--------------|
| input | Log Mel spectrogram |
| conv1 | BasicBlock(32) |
|       | Max pool |
| block1 | BasicBlock(32) × 4 |
| block2 | BasicBlock(64) × 4 |
| block3 | BasicBlock(128) × 4 |
|       | Avg pool |
|       | ReLU |
|       | Linear |

TABLE II
ARCHITECTURE OF WIDE RESNET28-2. DOWNSAMPING IS PERFORMED BY THE FIRST LAYERS IN BLOCK2 AND BLOCK3.

B. Models

We used the Wide ResNet 28-2 [17] architecture in all our experiments. This model is very efficient, achieving SOTA performance on the three datasets when trained in a 100% supervised setting. Moreover, its small size, comprised of about 1.4 Million parameters, allows to experiment quickly. Its structure consists of an initial convolutional layer (conv1) followed by three groups of residual blocks (block1, block2, and block3). Finally, an average pooling and a linear layer act as a classifier. The residual blocks, composed of two BasicBlock, are repeated three times and their structure is defined in Eq. 21. The number of channels of the convolution layers is referred as l, BN stands for Batch Normalization and ReLU [21] for the Rectified Linear Unit activation function. We used the official implementation available in PyTorch [22].

$$\text{BasicBlock}(l) = (\text{conv } 3 \times 3 \circ l, \text{BN}, \text{ReLU})$$ (21)

C. Training configurations

Each model was trained using the ADAM [23] optimizer. Table III shows the hyper-parameter values used for each method, such as the learning rate lr, the mini-batches’ size bs,
the warm up length \( wl \) if used, and the number of epochs \( e \). These parameters are identical regardless of the dataset used, unless otherwise specified.

For supervised training, MM and FM, the learning rate remains constant throughout training. For MT and DCT, the learning rate is weighted by a descending cosine rule:

\[
\text{lr} = 0.5 \left( 1 + \cos \left( \left( \frac{t}{e} \right) \frac{\pi}{2} \right) \right)
\]  

(22)

All the SSL approaches, but FixMatch, introduce one or more subsidiary terms to the loss. To alleviate their impact at the beginning of the training, these terms are weighted by a lambda \( \lambda \), which ramps up to its maximum value within a warm up length \( wl \). The ramp-up strategy is defined in Eq. 23 for MT and DCT, and is linear in MM during the first 16k learning iterations.

\[
\lambda = \lambda_{\text{max}} \times \left( 1 - e^{-5 \times (1-(t/wl))^2} \right)
\]  

(23)

In MT, the maximum value of \( \lambda_{cc} \) is 1 and \( \alpha_{\text{ema}} \) is set to 0.999. In DCT, the maximum values of \( \lambda_{\text{bott}} \) and \( \lambda_{\text{diff}} \) are 1 and 0.5, respectively. In MM, the maximum value of \( \lambda_u \) is 1.

In MM, we use two augmentations \( (k = 2) \), the sharpening temperature \( T \) is set to 0.5. In FM, we use a threshold \( \tau = 0.8 \) on ESC-10 and GSC datasets, and \( \tau = 0.95 \) for UBS8K.

For MM and FM, on ESC-10, the batch size is 60 because ESC-10 is a small dataset of 400 files only. During training, only four folders are used, that is, 320 files. In a 10% configuration and due to the whole division’s restrictions, this represents only 30 supervised files in total. Each mini-batch must contain as many labeled as unlabeled files, hence the batch size of 60. Moreover, because of this small number of files, the training phase only lasts for 2700 iterations, and therefore, warm-up ends prematurely.

For our proposed variants, which include mixup, we kept the same configurations and parameter values.

V. RESULTS

We first report the results obtained in a supervised setting, with and without the same data augmentation methods used in the SSL algorithms, including mixup. We compare the error rates obtained by the four SSL methods and then show that adding mixup is almost in all cases beneficial.

A. Supervised learning

This section presents the results obtained with supervised learning in different settings while using either 10% or 100% of the labeled data available. MM and FM use augmentations as their core mechanism. Therefore, it seems essential for fair comparisons to use the same augmentations in the supervised settings too. Indeed, FM uses weak and strong augmentations, while MM uses a combination of weak augmentations and mixup.

We trained models without any augmentation (Supervised), using mixup alone (mixup), weak augmentations alone (Weak), a combination of weak augmentations and mixup (Weak+mixup), strong augmentations alone (Strong), and to finish, a combination of strong augmentations with mixup (Strong+mixup). Table IV presents the results on ESC-10, UBS8K, and GSC.

**TABLE IV**

| Labeled fraction | ESC-10          |          | UBS8K          |          | GSC          |          |
|------------------|-----------------|----------|-----------------|----------|--------------|----------|
|                  | 10%             | 100%     | 10%             | 100%     | 10%          | 100%     |
| Supervised       | 32.00 ± 6.17    | 8.00 ± 5.06 | 33.80 ± 4.82    | 23.29 ± 5.80 | 10.01        | 4.94     |
| +mixup           | 36.00 ± 5.22    | 8.33 ± 4.56 | 31.41 ± 5.56    | 22.04 ± 5.99 | 8.83         | 3.86     |
| +Weak            | 22.67 ± 3.46    | 4.67 ± 3.43 | 27.08 ± 4.58    | 20.09 ± 5.50 | 7.62         | 3.90     |
| +Weak+mixup      | 24.67 ± 4.92    | 4.67 ± 1.39 | 23.75 ± 4.73    | 17.96 ± 3.64 | 6.58         | 3.00     |
| +Strong          | 23.00 ± 5.19    | 5.00 ± 2.64 | 25.58 ± 4.15    | 20.69 ± 4.92 | 7.60         | 3.27     |
| +Strong+mixup    | 24.00 ± 8.71    | 5.00 ± 4.25 | 24.73 ± 4.42    | 18.52 ± 4.38 | 6.86         | 2.98     |

In this section, we report in Table V the results of the SSL methods with and without the mixup augmentation. For MM, mixup is already used in the original method, thus, we compare MM to MM without mixup (MM-mixup). For the three other methods, we denote, for instance FM+mixup the FM algorithm augmented with mixup.
In all the three datasets, the four SSL methods brought ER decreases compared to the 10% supervised learning setup, when no augmentation is performed. Only MM and FM performed better than the best supervised training result, that used the weak augmentations.

Furthermore, MM and FM significantly outperformed MT and DCT in all cases, showing that using single-model SSL methods is more efficient than two-model-based methods, at least on these three datasets.

For ESC-10, in the 10% setting, the lowest ER was achieved by FM with a 13.33% ER, compared to a 22.67% ER for a weakly augmented supervised training. It represents a 9.34 points improvement, 41.20% relative. The difference with a fully supervised training using weak augmentations reaching a 4.67% ER is still notable with a 8.66 points difference.

On UBS8K, the best ER was achieved using MM with an 18.02% ER. The difference with the best supervised training Weak+mixup, reaching a 23.75% ER, represents a difference of 5.73 points, a 24.13% relative improvement. The performance of MM is also very close to the best fully supervised training Weak+mixup, which reached an ER of 17.96%. The difference is then only 0.06 points. Similarly to ESC-10, if MT and DCT outperformed the supervised training, they did not score better than a supervised training using Weak+mixup augmentation.

The GSC dataset results confirm the previous observations in UBS8K. The MM method is again the best method with an ER of 3.25%, representing a relative gain of 6.76 (67.53%) or 3.33 points (50.61%) compared to supervised training without and with Weak+mixup augmentations, respectively.

C. Impact of mixup

Given that the best SSL method so far was MM, and that mixup is used in MM and not in the three other methods, we decided to try to add mixup to MT, DCT and FM, in different ways for each method as explained in Section III-E.

In Table V, we reported the results when adding mixup to MT, DCT and FM, (MT+mixup, DCT+mixup, FM+mixup). We also give the ER when removing mixup from MM, in the row named MM-mixup.

As a first comment, MM-mixup is always worse than MM. For instance, on USB8K, ER increased from 18.02% to 20.42%.

With the other SSL methods, adding mixup brought performance improvements on all the datasets tested. The only counter-example observed is FM on ESC-10, which went from an ER of 13.33% to an ER of 14.67%.

Similarly, FM on UBS8K went from 21.44% ER without mixup to 18.24% with mixup. On GSC, MM once again presented the most significant improvement with 4.49% and 3.25% ERs without and with mixup.

It is also important to note that using mixup allowed to get ER values very close to the ones obtained with a fully (100% setting) supervised training using augmentations, on UBS8K and GSC. This is observable with MM and FM+mixup, which, compared to a Weak+mixup 100% supervised, have only 0.06 and 0.31 points difference on UBS8K, and 0.25 and 0.31 points difference on GSC.

When we look at our supervised training performance, we can observe that an improvement in performance does not systematically follow the use of weak or strong augmentation. However, when combined with mixup, ER is frequently improved. This can be partly explained by the fact that audio augmentations are often difficult to choose and that their impact is often dependent on the dataset and the task at hand [24]. With this in mind, mixup seems to be beneficial regardless of the dataset used.

VI. Conclusion

In this article, we reported monophonic audio tagging experiments in a semi-supervised setting on three standard datasets of different sizes and content, the very small-sized ESC-10 with generic audio events, urban noises with Urban-Sound8K, and speech with Google Speech Commands, using only 10% of the labeled data samples and the remaining 90% as unlabeled samples. We adapted and compared four SSL existing algorithms for this task, two methods that use two neural networks in parallel: Mean Teacher and Deep Co-Training, and the two single-model methods MixMatch and FixMatch, that rely in particular on data augmentation.

All the four methods brought significant gains compared to a supervised training setting using 10% of labeled data. They performed better than supervised learning without augmentation, and MixMatch and FixMatch were even better than supervised learning with augmentation. On ESC-10, FixMatch reached the best Error Rate of 13.33%. The relative gains were
58.34% and 41.20%, when compared to a supervised training using 10% of labeled data, without and with augmentation, respectively. On UrbanSound8K, MixMatch outperformed all the other methods, reaching a 18.02% Error Rate. Compared to a 10% supervised training without and with augmentation, the respective relative improvements were 46.69% and 24.13%. On Google Speech Commands, it is also MixMatch that reached the best Error Rate of 3.25%. The relative improvement was 67.53% and 49.70% when compared to a 10% supervised training without and with augmentation, respectively.

Mixup is an efficient regularization technique that is at the heart of the MixMatch mechanism. Its significant impact on this method has encouraged us to add it on the three other SSL approaches. Adding mixup systematically brought performance gains, which allowed us to get closer to supervised learning performance when using 100% of the labeled data available, and when using with data augmentation. Using FixMatch with mixup, the difference was 0.31 points (1.70%) only for UrbanSound8K and Google Speech Commands (10.33%).

In conclusion, if we were to recommend a method out of the ones tested in our work, we would recommend MixMatch, and FixMatch-mixup also, with very similar performances.

In future work, we plan to adapt these SSL methods to multi-label audio tagging, for instance on Audioset [25] or FSD50K [26]. In particular, we would have to adapt the sharpen method in MixMatch, and the thresholding operations in FixMatch. In DCT, the adversarial example generation would also need some changes. Finally, other SSL methods exist and could be added to our list, such as Unsupervised Data Augmentation (UDA) [27], and the very recent method called Meta Pseudo Labels [28].

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