

Sound Tagging in Infant-centric Home Soundscapes

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Abstract—Certain environmental noises have been associated with negative developmental outcomes for infants and young children. Though classifying or tagging sound events in a domestic environment is an active research area, previous studies focused on data collected from a non-stationary microphone placed in the environment or from the perspective of adults. Further, many of these works ignore infants or young children in the environment or have data collected from only a single family where noise from the fixed sound source can be moderate at the infant's position or vice versa. Thus, despite the recent success of large pre-trained models for noise event detection, the performance of these models on infant-centric noise soundscapes in the home is yet to be explored. To bridge this gap, we have collected and labeled noises in home soundscapes from 22 families in an unobtrusive manner, where the data are collected through an infant-worn recording device. In this paper, we explore the performance of a large pre-trained model (Audio Spectrogram Transformer [AST]) on our noise-conditioned infant-centric environmental data as well as publicly available home environmental datasets. Utilizing different training strategies such as resampling, utilizing public datasets, mixing public and infant-centric training sets, and data augmentation using noise and masking, we evaluate the performance of a large pre-trained model on sparse and imbalanced infant-centric data. Our results show that fine-tuning the large pre-trained model by combining our collected dataset with public datasets increases the F1-score from 0.11 (public datasets) and 0.76 (collected datasets) to 0.84 (combined datasets) and Cohen's Kappa from 0.013 (public datasets) and 0.77 (collected datasets) to 0.83 (combined datasets) compared to only training with public or collected datasets, respectively.

Index Terms—Infant-centric soundscape, audio spectrogram transformer, domestic sound event detection, pretrained model.

I. INTRODUCTION

A host of studies indicate that certain environmental noises may have negative health and psychological outcomes, including but not limited to elevated blood pressure, elevated endocrine response, sleep disturbance, poor cardiovascular functioning, mental health disturbance, and decreased cognitive functioning for both young children [1] and adults [2]. Additionally, both human and animal studies underscore the deleterious physiological and biological effects of environmental noise in utero and early infancy [1], and indicators of household or environmental noise have been associated with decreases in attention [3], and speech perception/language learning [4] during the first years of life. Mechanisms through which noise may adversely affect child outcomes are likely to be direct via dysregulated stress physiology [5] or indirect

via adults' annoyance or irritability [2] due to environmental noise. Further, certain types of environmental noise (i.e., intermittent or unpredictable nonlinguistic noise) pose greater developmental risks compared with other noise types, including more predictable noise (e.g., white noise) [3], [4]. Thus, in this work, we aim to detect the presence of different types of household noise (white noise, adult speech, TV, percussive noise, music, child voice, and background noise) that have the potential to provide novel insights into the effects of noise on infants' physiological and behavioral health.

Prior work most closely resembling the current study has used the Language ENvironment Analysis (LENA) system [6], which includes an audio recorder worn by the child in the home environment and proprietary software that automates the detection of classes of interest, including child vocalizations, adult speech, electronics, and overlapping speech/noise. Beyond a LENA technical report [6], a limited number of studies have assessed the performance of the LENA algorithm and indicate somewhat low performance when correcting for chance agreement (Cohen's kappa=0.28) and wide variability in F1 scores for the four key classes: child = 0.37, adult = 0.85, electronics = 0.49, and overlap = 0.05 [7]. Using daylong LENA recordings collected among 22 infants, Khante et al. [8] applied novel algorithms to detect levels of household auditory chaos (4 classes: 1=no chaos to 4=high chaos) and achieved the best performance using a Convolutional Neural Network (CNN) on 40 hours of balanced annotations (Macro F1 = 0.701). Although novel, the classification of household chaos is agnostic regarding specific noise types and thus may lose important information relevant to child functioning. Taken together, this prior work underscores the challenges of tagging sounds in infant-centric home recordings and also indicates the need for the current work, which will classify a wider range of household sounds – chosen for their developmental significance – than has been previously attempted.

Acoustic context monitoring from an infant's perspective introduces unique challenges – (1) the position of the microphone is mobile as the infant wearing it constantly changes their position and location; (2) the intensity of the audio stochastically changes due to the infant's changing proximity to the sound sources and the presence of additional obstacles, e.g., when the parent carries the baby; (3) unlike existing works on home environmental noise classification, a baby-worn microphone data is polluted by additional noises such

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as the baby’s own vocalizations, and (4) the lack of existing labeled datasets recorded in home environments without the presence of on-site annotator make developing such an automated sound tagging system complicated.

In this study, we use an infant wearable multi-modal device called LittleBeats™ (LB) that has been utilized in prior research [9] on automated speaker diarization (SD) and vocalization classification (VC) for infants and parents in the home environment. The LB device is housed in the chest pocket of a specially design infant shirt and continuously collects audio from the infant’s perspective in the home environment. In this work, we develop an automatic sound detection pipeline to classify noise collected in an infant-centric soundscape (i.e., sounds recorded from devices worn by the infant and thus from the infant’s perspective). We collected and labeled 3.91 hours of audio data using LB devices from 22 families with children under 14 months of age.

To address the above-mentioned challenges and to provide robust sound tagging in infant-centric noise soundscapes in the home, we first explore the potential of audio representation from a pre-trained model, Audio spectrogram transformer (AST) [10], trained on a large public dataset, AudioSet [11]. Next, given our limited LB training data for training a whole model, we demonstrate that using a pre-trained model and data from a public dataset to fine-tune for the downstream sound classification task can be beneficial. Finally, we evaluate our algorithm on our LB home data and public datasets. To the best of our knowledge, this is the first study to develop an environmental sound classification pipeline on data collected from all relevant noise sources from an infant’s perspective.

II. BACKGROUND AND RELATED WORK FOR SOUND EVENT DETECTION

Various acoustic features have been used for sound event detection, including Mel scaled spectrogram [10], Mel-Frequency Cepstral Coefficients (MFCC) [12], and log-power spectrogram [13] and even raw waveform [14], [15]. Convolutional neural networks alone [14], at multiple time scales [15], and with gamma tone filterbanks [15] have been used to extract significant features from raw acoustic data. Some studies [10], [13] have used weight initialization from popular pre-trained vision models, e.g., DeiT [16] to improve performance. Recently Audio spectrogram transformer [10] and WHISPER-AT [17] used a transformer-based model with initial weights from ImageNet [18] and WHISPER [19] respectively. These models are trained with large datasets AudioSet [11] and WHISPER [19], which are 4971 hours and 680,000 hours long, respectively. Due to the exposure to such large datasets, these models are more robust on unseen data that are not used to train these models. However, their performance in a real-world environment scenario or collected by an infant-worn microphone, such as a home, has yet to be explored.

III. DATA

We assess the performance of a large pre-trained model on household noises using public datasets and collected data at

TABLE I: Data distribution (in minutes) of different classes.

	Public data				LB home audio
	CHiME-home	ESC-24	GTZAN	LibriTTS	
Child voice	79.8	-	-	-	53.4
Adult speech	45.0	-	-	53.4	53.4
TV	78.6	-	-	-	21.0
Percussive noise	50.4	31.8	-	-	34.2
White noise	1.8	-	-	-	53.4
Music	-	-	53.4	-	19.2
Household appliance	3.0	31.8	-	-	51.0

home using infant-worn LB devices (see [20] for more details about the device setup and home use). To characterize the infant-centric soundscape, we divide the audio segments into seven categories – child voice, adult speech, the sound of television, percussive noise, white noise or silence, music, and background noise (household appliance). Table I shows the distribution of data from the public datasets and collected using LB device.

A. Public dataset

We used noise data from two public datasets – CHiME-home [21] and ESC-50 [12]. CHiME-home had a total of 1946 4-second long audio segments from one family. Each audio segment had one or more classes: silence, child voice, male voice, female voice, appliance noise, percussive noise, TV, other, and unknown. We discarded the other and unknown classes and merged male and female voices into adult speech. ESC-50 had 40 5-second audio clips from 50 environmental sound classes (collected from user-uploaded audio [22]), and 24 of them were domestic sounds, where segments fall into percussive noise and household appliance sounds. We evaluated model performance on ESC-50 and only 24 classes of ESC-50 (ESC-24) that can occur in a home environment. We also re-recorded noise data from two public datasets – CHiME-home [21], ESC-50 [12] – using the LB device in an anechoic chamber to assess whether performance varies as a function of recording set up.

To address the lack of adult speech and music in these datasets while fine-tuning our pretrained model, we used speech and music data from a small LibriSpeech corpus (libriTTS) [23] and GTZAN [24] to balance the training/fine-tuning dataset. We collected 800 adult speech and 800 music samples for fine-tuning; each sample was 4 seconds long. Note that we did not re-record GTZAN and libriTTS audio, as these were used only for pre-training and not for evaluation.

B. Collected Infant-Centric Audio (LB Home Audio)

Twenty-two families with infants between 0-14 months were recruited for this study through study brochures posted in local community organizations (e.g., libraries) and online forums serving families with young children. The Institutional Review Board (IRB) approved all study procedures at the University of Illinois, Urbana-Champaign. To protect participants’ privacy and confidentiality of the data and to increase participants’ trust, consent forms specified that identifiable information, including audio, would only be accessible to the research team. Our consent forms stated that human coders will only hear small samples of the data (the labeled data) and that

the majority of the recordings will be analyzed automatically without human intervention.

To collect the data, we placed the device on the infant's chest pocket and collected daylong data (8-10 hours) from each device. We separated each daylong recording into 10-minute segments to manually annotate the collected home recordings. As continuous manual annotation of the audio recordings is time- and labor-intensive, human coders only annotated a few 10-minute segments for each family, selected based on the highest active vocalization rates computed by a statistical voice activity detector (VAD) [25]. Human coders manually labeled child, female adult, male adult, music, percussive or sharp noise, white noise, and TV sounds using Praat [26] (an annotation software), with cross-coder validation at a precision of 0.2s. Ten percent of selected 10-min segments were double coded, and inter-coder reliability (Cohen's kappa score) was between 0.80 and 0.89 for child and adult speakers. All other segments were single-coded. In total, we obtained 3.91 hours of data from 22 families.

However, we found only two background noise samples from these families. Thus, we collected background noise data using LB devices from different household appliances, e.g., seven vacuum cleaners, two washing machines, and one dishwasher in three homes. These data were collected from a static position instead of an infant's perspective.

C. Data Pre-Processing

We resampled all collected data to 16kHz using librosa [27] as most pre-trained models are developed for 16KHz audio. To prepare labeled data for fine-tuning, we extracted each labeled segment in intervals of 4 seconds. For segments shorter than 4 seconds, we appended the neighbored left and right audio contexts evenly to make up to 4 seconds. For our task, we used a total of 800 segments of white noise, 318 segments of TV, 800 samples of child voice, 800 samples of adult speech, 290 samples of music, 768 samples of background noise, and 509 samples of percussive noise. We randomly split the dataset for fine-tuning (80%) and testing (20%), where we include non-overlapping intervals from each of our 22 families in both fine-tuning and test sets. Thus, our results are multi-family internal validation results rather than external validation results.

D. Data augmentation

We use two data augmentation techniques – spectrogram augmentation [28] that incorporates frequency masking and time masking, and (2) random noise addition [28]. The maximum frequency and time mask lengths used in this study are 24 and 96, respectively. We further experimented with Specmixup [28], where two data samples are mixed by applying time-frequency masks. Although spectrogram augmentation and random noise addition improve the model performance, we found that AST performs better without using any mixup as AST is already trained to recognize a large set of classes.

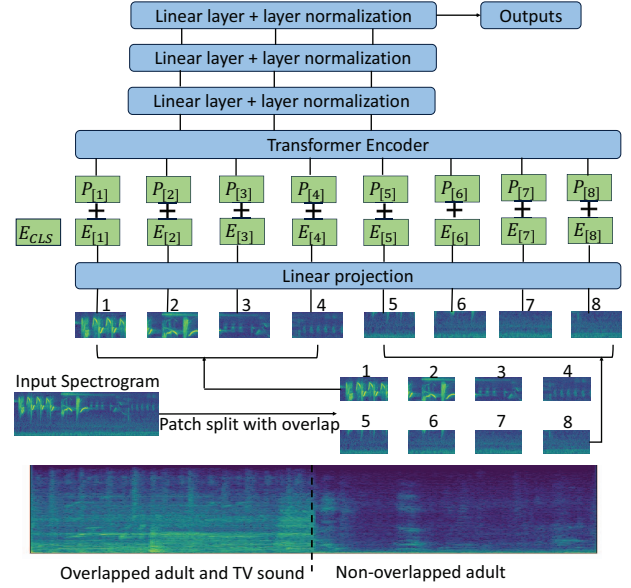


Fig. 1: Model architecture for fine-tuning and example of an overlapped and non-overlapped audio segments.

IV. EXPERIMENTAL SETUP

Audio Spectrogram Transformer (AST) [10] is a pre-trained sound classifier model that uses a transformer encoder architecture [29]. The transformer encoding has an embedding dimension of 768, 12 layers, and 12 heads. The input raw audio is converted to a 128-dimensional log Mel filterbank using a 25ms Hamming window with 10ms slide. The spectrogram is divided into a sequence of 16×16 patches with an overlap of 6 in both time and frequency. We flatten each patch to a 1D patch embedding of size 768 with a linear projection layer. A trainable positional embedding of size 768 captures the spatial structure of the 2D spectrogram. AST uses cross-modality transfer learning by using the pre-trained vision transformer (ViT) trained on ImageNet [18], assuming that the image and audio spectrogram have a similar format, which also helps to reduce computational complexity. As spectrograms are single-channel images, AST averages the 3-channel weight of ViT to make it comparable to the spectrograms. It uses cut and bi-linear interpolation to match the input positional dimension.

Figure 1 illustrates the overall model architecture for fine-tuning the AST model. After the transformer layer, we add two fully connected (FC) layers of dimensions 3072 and 768 with layer normalization for normalized data distributions and faster training. A linear layer with sigmoid activation maps the audio spectrogram representation to labels for classification. We normalize the input using the training dataset to make the dataset mean and standard deviation 0 and 0.5. We fine-tune for 25 epochs on both the public and collected infant-centric datasets using two NVIDIA RTX 3090Ti and a single NVIDIA GTX 1080 Ti GPUs, respectively. We used a multistep learning rate (LR) scheduler with 10^{-5} starting rate and 0.85 decay and saved the best model for inferring the test data. We use accuracy, unweighted precision, recall, F1-scores, and Cohen's

TABLE II: Comparative Analysis of the Performance between AST and Whisper-AT.

	ESC-50 (Accuracy)	AudioSet (Mean Average Precision)	Number of Parameters
Whisper-AT [17]	0.91	0.42	665M
AST [10]	0.96	0.48	87M
AST (fine-tuned)	0.95	0.46	87M

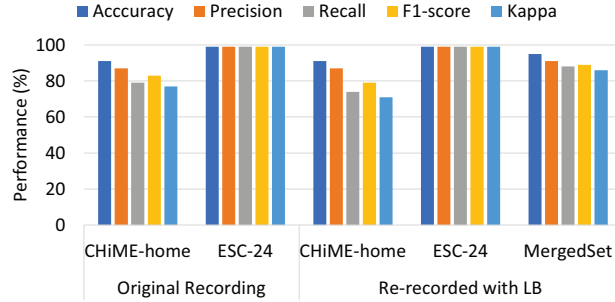


Fig. 2: Evaluation of AST on public dataset

Kappa [30] as evaluation metrics.

V. RESULTS & DISCUSSION

First, we evaluate the fine-tuned AST on public data and compare against baseline algorithms. Next, we demonstrate the performance of fine-tuned AST on the infant-centric audio data collected from 22 families and evaluate our proposed training schemes using the public and collected datasets.

A. Evaluation on Public Dataset

We compare the performance of AST with one of the most recent pre-trained environmental acoustic event classification models, Whisper-AT. Whisper-AT is based on Whisper [19], which is trained on large noise-conditioned speech audio to learn the noise signature inherently during training for ASR tasks. However, in Table II, we observe that AST outperforms Whisper-AT on popular sound classification datasets – ESC-50 and AudioSet. Although Whisper-large [19] is fine-tuned end-to-end to generate Whisper-AT and has 665 million parameters, it fails to outperform a fine-tuned AST with 87 million parameters when the whole model has been fine-tuned as Whisper is mainly trained on ASR tasks.

Next, we evaluate the performance of AST on two different datasets – CHiME-home and ESC-24 (original and re-recorded with LB device) as described in Section III. Figure 2 shows that AST performs well with 83% and 99% of F1-score for CHiME-home and ESC-24, respectively. To study the device-specific effect of LB on the classification, we evaluate AST on the acoustic recording of these two datasets when recorded with LB. In Figure 2, we observe that performance slightly degrades with a 4.8% F1-score drop for CHiME-home. This shows that using a low-cost and lightweight recording device compared to a professional microphone has negligible impact on the classification performance. We further observe that in both recording scenarios (original publicly available data and recorded LB data), the performance is higher for ESC-24 than CHiME-home due to unbalanced training data in CHiME-home. Additionally, we get identical values for all

TABLE III: Evaluation of AST on LB audio using three different training schemes.

	Accuracy	Precision	Recall	F1-score	Kappa
Public data	0.12	0.29	0.19	0.11	0.013
Resampled data	0.79	0.81	0.77	0.76	0.72
Mixed data	0.86	0.84	0.84	0.84	0.83

TABLE IV: Comparison of different fine-tuning strategies of AST on Mixed data.

Fine-Tuning Layers	Accuracy	Precision	Recall	F1-score	Kappa
Last two layers	0.83	0.82	0.82	0.81	0.80
Whole model	0.86	0.84	0.84	0.84	0.83

evaluation metrics on the original ESC-24 and LB recorded ESC-24 due to a perfectly balanced dataset. Thus, we merge four public datasets to generate a balanced acoustic domestic environment dataset that reflects the soundscape around an infant at home. To understand the effect of environmental parameters, we combine data re-recorded with LB (ESC-24 and CHiME-home) and originally collected (GTZAN and libriTTS) to create the dataset. We call this combined dataset **MergedSet**. This dataset combines all data from CHiME-home (child voice, adult speech, TV sound, percussive noise, white noise) with adult speech data from LibriSpeech-small, music data from GTZan, and percussive noise from ESC-24. We further add synthesized white noise with random Gaussian noise for mean 0 and standard deviation 1.

Figure 2 shows that AST performs better on MergedSet than CHiME-home. MergedSet has a 12.7% improvement in the F1-score and a 21.1% improvement in the Cohen’s Kappa score than LB recorded CHiME-home. It also outperforms the original CHiME-home data with a 7.2% and 11.7% improvement in the F1-score and Cohen’s Kappa score, respectively.

B. Evaluation on Infant LB Data in the Home

Data collected using the LB at home are highly unbalanced and have very few samples of certain classes (e.g., 318 samples of TV and 290 samples of music) due to the uncontrolled and unscripted nature of the data collection process. As the samples are highly sparse and unbalanced for fine-tuning, we use three different training schemes to fine-tune the AST model – (1) training on public data and evaluation on LB audio data (named **Public Data**), (2) balancing training data with resampling using LB training audio (named **Resampled Data**), and (3) training using both public and LB data while evaluating only on collected LittleBeats data (named **Mixed Data**).

Table III shows the performance of AST on LB home audio using the three different training datasets. The Public Data scheme, which infers on the model trained with public data only, fails to predict the sound classes of the LB home audio. When we fine-tune with LB home data only in the Resampled Data scheme, AST shows noteworthy performance in all metrics. We caution, however, that too much resampling when a small amount of data is available can lead to overfitting and poor performance in some classes. Finally, with the Mixed Data scheme where AST is fine-tuned with both LB home audio and public datasets to create a balanced dataset we

observe an improvement of performance by 10.5% in the F1-score.

Finally, we assess how much of the AST model is required to be fine-tuned to perform well for real-world infant-centric sound classification at home. In Table IV, we compare the performance between fine-tuning only the last two layers and the whole model. As AST is already trained on a large dataset, fine-tuning a few layers gives us good performance. However, fine-tuning the whole model is beneficial to get noise features and identify variability from a moving microphone.

C. Discussion

The performance of the AST on the original public datasets and LB device re-recorded audio of public datasets is comparable (4.8% degradation of F1-score on re-recorded audio), as AST is already trained on Audioset [11] to learn human and non-human speech well. AST also performs better on our MergedSet than LB recorded CHiME-home with a 12.7% improvement in F1-score due to the balanced nature of the MergedSet. However, training using the balanced public dataset is not sufficient on real-world data obtained from infant-worn devices that bring unique challenges, including (a) the child's own vocalization and (b) the child's movement toward and away from other noise sources. Thus, training using Resampled Data improves the performance appreciably. Finally, the Mixed-data scheme not only improves the model's performance but also reduces the necessity of resampling data, which can result in overfitting due to too much oversampling.

VI. CONCLUSION & FUTURE WORK

In this study, we have collected, labeled, and analyzed environmental data from an infant-centric soundscape. We show that fine-tuning a large pre-trained model provides satisfactory performance when we combine publicly available data with a limited amount of infant-centric data collected in the home instead of using only public or collected audio. In the future, we aim to collect data from more families and improve the model's performance. Valid assessments of noise soundscapes in the home and from the infant's perspective may provide significant opportunities for early detection and intervention of infant behavioral or physiological disturbance due to noisy and unpredictable environments.

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