Can Self-Supervised Learning Solve the Problem of Child Speech Recognition?

Rishabh Jain, Mariam Yiwere, Dan Bigioi, Peter Corcoran

National University of Ireland, Galway
{rishabh.jain, mariam.yiwere, d.bigioi1, peter.corcoran}@nuigalway.ie

Abstract

Despite recent advancements in deep learning technologies, Child Speech Recognition remains a challenging task. Current Automatic Speech Recognition (ASR) models require substantial amounts of annotated data for training, which is scarce. In this work, we explore using the ASR model, wav2vec2, with different pretraining and finetuning configurations for self-supervised learning (SSL) towards improving automatic child speech recognition. The pretrained wav2vec2 models were finetuned using different amounts of child speech training data to discover the optimum amount of data required to finetune the model for the task of child ASR. Our trained model achieves the best word error rate (WER) of ‘8.37’ on the in-domain Myst dataset and WER of ‘10.38’ on the out-of-domain Pfstar dataset. We do not use any Language Models (LM) in our experiments.

Index Terms— Child speech recognition, Self-supervised learning, wav2vec2, Automatic Speech Recognition

1. Introduction

Current deep learning based automatic speech recognition models perform remarkably well on adult speech data. However, they struggle when it comes to recognizing speech from children. Models such as wav2vec2, Deep Speech 2, ContextNet, and others [1]–[5] all achieve impressive results on adult speech datasets such as LibriSpeech (~1000h), TIMIT (5.4h), LJSpeech (~24h), MediaSpeech (~10h), and more. This is due in no small part to the vast amounts of annotated adult speech data available for training such models and the ease with which it can be obtained. However, when it comes to child speech recognition, state-of-the-art (SOTA) ASR models trained on adult data perform quite poorly on child voice datasets. This is due to the inherent differences between adult and children’s voices. A child’s voice is quite different from an adult voice [6], [7] in terms of pitch, linguistic and acoustic features, ability to understand and pronounce words, high fundamental frequency, and shorter vocal track length. In addition, it is a challenging task to collect and annotate child speech data in comparison to adult speech data which can be acquired from various sources such as movies, news broadcasts, audiobooks, the internet, etc. Even if child speech can be collected from such sources, providing accurate annotations remains challenging. When compared to adult voice datasets, child voice datasets are quite limited [8].

In the past few years, there have been many different approaches to improving the performance of automatic child speech recognition systems [9]. Most of these approaches consist of various data augmentation techniques for increasing the amount of usable training data. Text-to-Speech based data augmentations as introduced by [10], [11], where ASR models are finetuned using synthetic data, have not shown significant increases in the accuracy of child ASR. Generative Adversarial Networks (GAN) based augmentation [12]–[14] has also been explored to increase the amount of labeled data with acoustic attributes like those of child speech. Some of the other popular augmentation approaches include Vocal Track Length Perturbation [15], Fundamental frequency feature normalization [16], out-of-domain data augmentation using stochastic feature mapping (SFM) [17], and data processing-based augmentations [18] such as Speed Perturbation, Pitch Perturbation, Tempo Perturbation, Volume Perturbation, Reverberation Perturbation, and Spectral Perturbation. Spectrogram Augmentation also seems promising for improving the performance of ASR systems [19], [20]. Each of these methods shows improvements in child ASR accuracy, however, they still require corresponding labeled annotations to speech data.

A recent review of child ASRs [21] determined that most of these SOTA methods are supervised learning approaches. In other words, these are approaches that rely on labeled child speech data during training for the task of ASR. As there is a distinct lack of labeled child speech data compared to an adult, approaches that utilize unsupervised [22] and self-supervised learning [23] were explored for this paper. Therefore, the goal of this work is to present a method to incorporate unlabeled child speech data into the training procedure of a typical ASR model while also making use of abundant, labeled, and unlabeled adult speech data to...
improve the overall accuracy of ASR models on child speech.

Self-supervised learning (SSL) has emerged as a paradigm to learn general data representations from substantial amounts of unlabeled examples allowing one to then fine-tune models on small amounts of labeled data. The use of SSL for child ASR was first seen at Interspeech2021[24] where a model using SSL [25] received first place in the SLT 2021 Children Speech Recognition challenge. A similar approach can be seen in [26] where the author uses a bidirectional unsupervised model pretraining with child speech ASR. After reviewing various approaches to SSL, wav2vec2 [23] was chosen for this paper. Wav2vec2 shows that using self-supervised learning for the task of ASR provides improvements over SOTA supervised learning approaches. This paper explores various pretraining and finetuning configurations with different combinations of adult and child speech data to learn the optimum data requirements for improving the performance of ASR models on child speech data using these learnable speech representations.

The rest of this paper is organized as follows: Section 2 describes the model architecture. Section 3 introduces the datasets used for this paper. Section 4 includes the experiments and results, while conclusions are presented in Section 5.

2. MODEL DESCRIPTION

The wav2vec2 model [23] is used to extract speech representations from raw audio files in a self-supervised learning scenario and use these representations for ASR specific tasks. Wav2vec2 is used in this paper as it can achieve state-of-the-art results when trained on a large amount of unlabeled speech data and finetuned on labeled data as small as 10 minutes. This is ideal for our task, as it is much easier to obtain significant amounts of unlabeled child speech data than gathering accurately labeled data.

As it is a two-step training method, the first step includes a pretraining step in which the model is trained with a large amount of unlabeled data. Wav2vec2 uses a multilayer convolutional neural network to encode the speech audio. After encoding, masking is applied to the resulting latent speech representation which is fed into a transformer network to build a contextualized representation of the speech audio. Gumbel softmax is used to calculate the contrastive loss on which the model is trained. Speech representations are learned from this training.

The second step includes finetuning on labeled data using Connectionist Temporal Classification (CTC) loss [27] for downstream ASR tasks. As the model learns SSL speech representation in pretraining, it can be trained using many unlabeled speech data and can be finetuned with a small amount of labeled data. This way, the problem of scarcity of child speech is solved as we can train the ‘pretraining’ model with a combination of unlabeled speech data and it can also be used to learn representation from adult speech datasets making use of the abundant adult speech data.

![Figure 1: Pretraining and Finetuning steps in Wav2vec2 (from [25])](image)

2.1. Pretraining

The pretraining model of wav2vec2 consists of a feature encoder, context network, and quantization module. A feature encoder encodes the raw audio files with temporal convolution followed by batch normalization which is further normalized to zero mean and unit variance. Context network takes in the output of the feature encoder to calculate relative position embeddings. The quantization module is then used to calculate the contextualized representation by using Gumbel softmax and choosing the quantized representation from multiple codebooks and concatenating them. Experiments configurations are provided as the BASE and LARGE models. The configurations differ in transformer block size but use the same size for the encoder. The feature encoder contains seven blocks with each block having stride (5,2,2,2,2,2) and kernel widths (10,3,3,3,3,2,2) and output temporal convolution of 512 channels. The context network of the BASE model contains 12 transformer blocks, each block with a 512-dim model, 8 attention heads, and a 2048-dim feed-forward innerlayer while the LARGE model contains 24 transformer blocks with model dimension 1,024, inner dimension 4,096, and 16 attention heads.

We use 4 NVIDIA Tesla V100 GPUs to train the pretraining model (wherever required). The model was optimized using ADAM. During the first 8% updates, the learning rate warms up to a peak of $5 \times 10^{-4}$ for the BASE and $3 \times 10^{-4}$ for LARGE, and then it linearly decays. The BASE model is used for most experiments, however, the pretrained LARGE model is also used to provide a comparison in Section 3.
2.2. Finetuning

For finetuning, 29 tokens were used (from the LibriSpeech Dataset) as provided by the authors. Models are optimized by minimizing a CTC loss. A modified version of SpecAugment[19] is applied as masking to timestamps and channels to reduce the overfitting and improve the recognition robustness. We fine-tune on 1 V100 GPU. For the first 1000 updates, only the final output classifier was trained, after which the Transformer block was also trained. The feature encoder was frozen during finetuning training. The learning rate was set to $3 \times 10^{-5}$.

We do not use any external Language Model for this paper. The experiments were only performed to explore the potential of SSL for child ASR. Further improvements in results can be obtained using an external Language Model.

3. DATASET USAGE AND DESCRIPTION

The datasets are divided according to their usage. The child speech data used in this paper include MyST Child Corpus [28] and PF-STAR [29]. Adult Speech datasets include LibriLight[30], SPGI Speech[31], and LibriSpeech [32]. Please see Table 1 for details on the datasets.

Table 1: Dataset Description for Pretraining, Finetuning and Inference usage

| Usage       | Dataset               | Duration     | Type   |
|-------------|-----------------------|--------------|--------|
| Pretraining | Myst_complete         | 393 hrs      | Child  |
|             | Librispeech           | 960 hrs      | Adult  |
|             | SPGI speech           | 5000 hrs     | Adult  |
|             | Libri-light           | 60k hrs      | Adult  |
| Finetuning  | Myst_10m              | 10 mins      | Child  |
|             | Myst_1h               | 1 hr         | Child  |
|             | Myst_10h              | 10 hrs       | Child  |
|             | Myst_55h              | 55 hrs       | Child  |
|             | LS_10m                | 10 mins      | Adult  |
|             | LS_100h               | 100 hrs      | Adult  |
|             | LS_960h               | 960 hrs      | Adult  |
| Inference   | Myst_10h              | 10 hrs       | Child  |
|             | PS_STAR_10h           | 10 hrs       | Child  |

3.1. MyST Cleanup for Finetuning Experiments

The MyST dataset contains over 393 hours of speech data, with only 197 hours of transcribed speech data. For the finetuning setup with child speech, we first extract the speech samples from transcribed MyST that are 10-20 seconds long, which amounts to 65 hours of total data. Within the MyST dataset, typically samples below 10 seconds in length contained non-meaningful, noisy speech, and data above 20 seconds would lead to the GPU running out of memory. The data was then split into 55 hours of training data and 10 hours for the test.

In our experiments, this 55 hours of data with transcriptions is used for all the finetuning experiments with child data. From the 55 hours of training data, several smaller data sets are created with 10 minutes, 1 hour, and 10 hours of MyST data for further finetuning experiments. Additionally, we include the PFSTAR corpus as part of the test set to evaluate the performance of the ASR model on an unseen dataset as the PFSTAR corpus contains British English child speech while MyST contains American English child speech. The test data was used to calculate the WER for each of the trained models. The details of each of these datasets according to their usage can be seen in Table 1.

3.2. Data Cleaning and Processing

All speech data was converted into a 16-bit mono channel with a 16Khz sampling rate. All the transcriptions were cleaned and normalized to remove abbreviations, punctuations, whitespaces, etc. and all the characters were changed to uppercase. All the non-linguistic annotation symbols such as “<unk>, <sil, hmm, <breath>, <noise>, <indiscernible>, [ze], [cham], [***ision], etc.” were removed and only alphanumeric characters were retained in the transcript. This was done for all the labeled data used in this paper.

4. EXPERIMENTS AND RESULTS

4.1. Codebase and Hyperparameters

We use the wav2vec2 implementation as provided by the fairseq1. Most of the hyperparameters were kept the same for both BASE and LARGE configuration as provided by the authors. We prepare our own scripts for cleaning and data processing using FFmpeg and python-based tools such as pydub and scipy.

4.2. Experiments

For our experimental setup, three sets of experiments were prepared, namely, set-A, set-B, and set-C. For set A, the pretrained checkpoints provided by the wav2vec2 repository were used. Two configurations were used in set-A training, namely BASE and LARGE. The BASE configuration includes 960 hours of LibriSpeech pretraining data and the LARGE configuration includes 60k hours of LibriSpeech and Librilight data, which is 60 times as much pretraining data as in the BASE configuration. For finetuning, each of the BASE and LARGE configurations were finetuned with 10 minutes, 100 hours, and 960 hours of adult speech.

---

1https://github.com/pytorch/fairseq/tree/main/examples/wav2vec
The trained model trained on LibriSpeech is speech (more in Section 4.3). The models finetuned with 100 sectors significantly as compared to other learning rates (WER) achieved.

| SETUP | MODEL ID | PRETRAINING MODEL CONFIGURATION | PRETRAINING DATASET | FINE-TUNING DATASET | WER MYST_Test | WER PFSTAR_Test |
|-------|----------|---------------------------------|---------------------|-------------------|---------------|---------------|
| SET - A | 1 | BASE | LibriSpeech | LS_10m | 31.48 | 34.49 |
| | 2 | | | LS_100h | 17.82 | 19.04 |
| | 3 | | | LS_960h | 15.41 | 14.40 |
| | 4 | LARGE | LibriSpeech, Libri-light | LS_10m | 26.47 | 27.97 |
| | 5 | | | LS_100h | 13.15 | 11.94 |
| | 6 | | | LS_960h | 12.50 | **10.38** |
| SET - B | 7 | | MyST_10m | 28.84 | 43.03 |
| | 8 | BASE | LibriSpeech | MyST_1h | 18.75 | 34.82 |
| | 9 | | | MyST_10h | 13.46 | 29.93 |
| | 10 | | | MyST_55h | **8.37** | 23.19 |
| SET - C | 11 | BASE | SPGI Speech, MyST_Complete | MyST_10m | 91.72 | 92.74 |
| | 12 | | | MyST_1h | 28.81 | 48.60 |
| | 13 | | | MyST_10h | 18.21 | 43.01 |
| | 14 | | | MyST_55h | 12.68 | 51.16 |

Therefore, this set contains only adult speech datasets in both the pretraining and finetuning steps. Details of each model and their pretraining/finetuning datasets are presented in Table 2.

For set B, the pretrained model trained on LibriSpeech is used and finetuned over different amounts of the MyST dataset. We use the BASE configuration pretrained with 960 hours of adult speech and finetune it on 10 minutes, 1 hour, 10 hours, and 55 hours of child speech data. Therefore, set B contains adult speech data in pretraining and child speech data in finetuning steps.

And finally, for set C, the SPGI Speech and MyST datasets having 5k hours of adult speech and 393 hours of child speech data respectively were used for pretraining the model which is then finetuned over different amounts of the MyST dataset (similar to set B). Therefore, set C contains both adult and child speech data in pretraining and only child speech in finetuning.

These experiments were chosen to see the effect of different pretrained and finetuning configurations and different amounts of adult and child speech datasets on the trained model. We did not train any independent pretrained model with child speech data alone as more amount of child speech data would be required to learn any meaningful speech representation from child speech (more in Section 4.3). The inference tests were performed over unseen MyST and PFSTAR child speech datasets each having 10 hours of speech. Table 2 shows the word error rates (WER) achieved.

### 4.3. Results and Discussion

For set A, training, Model 6, pretrained on 60k hours of adult speech and finetuned on 960 hours of adult speech, gave the best results with a WER of 12.50 on MyST_test and 10.38 on PF-STAR_test. This is most comparable to the WER of Model 3 which was pretrained on 960 hours of adult speech with WER of 15.41 and 14.40 on the MyST_test and PFSTAR_test. In comparing models {1,2,3} and models {4,5,6} having a different BASE and LARGE configurations respectively, there is not a huge difference in WER considering the difference in the amount of training data.

For set A finetuning with 10 minutes, 100 hours, and 960 hours of data, it can be observed that there is not a large difference in WER between the models finetuned with 100 hours and 960 hours of data. Therefore, 100 hours of finetuning data can be considered an optimum amount of adult speech data to be used with child speech validation. We can also see that between MYST_test and PF-STAR_test in set A experiments, there is a very small difference in WER, implying that finetuning on adult speech has a similar effect on WER for different child speech datasets.

| SETUP | MODEL ID | PRETRAINING MODEL CONFIGURATION | PRETRAINING DATASET | FINE-TUNING DATASET | WER MYST_Test | WER PFSTAR_Test |
|-------|----------|---------------------------------|---------------------|-------------------|---------------|---------------|
| SET - A | 1 | BASE | LibriSpeech | LS_10m | 31.48 | 34.49 |
| | 2 | | | LS_100h | 17.82 | 19.04 |
| | 3 | | | LS_960h | 15.41 | 14.40 |
| | 4 | LARGE | LibriSpeech, Libri-light | LS_10m | 26.47 | 27.97 |
| | 5 | | | LS_100h | 13.15 | 11.94 |
| | 6 | | | LS_960h | 12.50 | **10.38** |
| SET - B | 7 | | MyST_10m | 28.84 | 43.03 |
| | 8 | BASE | LibriSpeech | MyST_1h | 18.75 | 34.82 |
| | 9 | | | MyST_10h | 13.46 | 29.93 |
| | 10 | | | MyST_55h | **8.37** | 23.19 |
| SET - C | 11 | BASE | SPGI Speech, MyST_Complete | MyST_10m | 91.72 | 92.74 |
| | 12 | | | MyST_1h | 28.81 | 48.60 |
| | 13 | | | MyST_10h | 18.21 | 43.01 |
| | 14 | | | MyST_55h | 12.68 | 51.16 |
set. This can also be attributed to the noisy nature of the MyST dataset.

Set-C contained MyST child speech data in the pretraining step, however, the results were much worse compared to set B. This can be attributed to the MyST corpus containing a lot of noise and non-linguistic child speech, and it will be difficult to learn meaningful representations from such 'noisy' data. Model 11 finetuned with 10m of MyST data gave the worst overall WER of 91.72 on MyST_test and 92.74 on PFSTAR_test, however, in comparison, model 7 finetuned with same data gives WER of 28.84 and 43.03 on MyST_test and PFSTAR_test. Similarly, models {8,9,10} outperform models {12,13,14} having been finetuned with the same type and amount of finetuning data. They have an average WER difference of 6.3 for the MyST_test and 18.27 for the PFSTAR_test. The only difference between these sets of models is their pretraining datasets. This observation could imply that a model pretrained with only adult speech data can learn better features than the model pretrained with both adult and child speech data; however, more investigation is required to determine why and how the pretraining of child speech data affects these models.

5. CONCLUSION

In this work, we used the wav2vec2 self-supervised training approach with different pretraining and finetuning datasets for child speech recognition. A combination of adult and child speech datasets was used in pretraining and finetuning to find the optimum data requirements for improving child speech recognition. Experiments were designed to see the performance on the in-domain MyST dataset and out-of-domain PFSTAR dataset, each containing 10 hours of speech. A model trained with adult speech data in pretraining can learn the best features as compared to a model including both adult and child speech in pretraining. It is also observed that a model using adult speech in both the pretraining, and finetuning gives similar WER for both MyST and PFSTAR test sets. 100 hours of adult speech data finetuning shows the best optimum results with child speech inference. A model finetuned with MyST data shows improvement in WER on the seen MyST test set but shows a fall in WER for the unseen PFSTAR test set. Using just 55 hours of MyST finetuning outperformed all the previous WER on the MyST test set. The best WER of 8.37 was achieved on the MyST test set and 10.38 on the PFSTAR test set.

Our work shows how unlabeled child speech data can be used for training an ASR model, while also making use of abundant, labeled, and unlabeled adult speech data, to improve the overall accuracy of ASR models on child speech. Using self-supervised features learned from adult speech can be the key to improving child speech recognition.

For future work, we plan to utilize this model to transcribe more of the MyST data to generate more usable child speech data. We also plan to perform more experiments with other combinations of child and adult speech datasets using this self-supervised learning approach. PF-STAR finetuning will also be explored in future experiments.

6. ACKNOWLEDGEMENT

The authors would like to acknowledge experts from Xperi-Ireland: Gabriel Costache, George Sterpu, and the rest of the team members for providing their expertise and feedback throughout.

7. REFERENCES

[1] Amodei, Dario, Sundaram Ananthanarayanan, Rishita Anubhai, Jingliang Bai, Eric Battenberg, Carl Case, Jared Casper et al. "Deep speech 2: End-to-end speech recognition in English and Mandarin." In International conference on machine learning, pp. 173-182. PMLR, 2016.

[2] Kriman, Samuel, Stanislav Beliaev, Boris Ginsburg, Jocelyn Huang, Oleksii Kuchaiev, Vitaly Lavrukhin, Ryan Leary, Jason Li, and Yang Zhang. "Quartznet: Deep automatic speech recognition with 1d time-channel separable convolutions." In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 6124-6128. IEEE, 2020.

[3] Nassif, Ali Bou, Ismail Shahin, Imtitan Attili, Mohammad Azzez, and Khaleed Shaalan. "Speech recognition using deep neural networks: A systematic review." IEEE access 7 (2019): 19143-19165.

[4] Han, Wei, Zhengdong Zhang, Yu Zhang, Jiahui Yu, Chung-Cheng Chiu, James Qin, Anmol Gulati, Ruoming Pang, and Yonghui Wu. "Contextnet: Improving convolutional neural networks for automatic speech recognition with global context." arXiv preprint arXiv:2005.03191 (2020).

[5] Gulati, Anmol, James Qin, Chung-Cheng Chiu, Niki Parmar, Yu Zhang, Jiahui Yu, Wei Han et al. "Conformer: Convolution-augmented transformer for speech recognition." arXiv preprint arXiv:2005.08100 (2020).

[6] Lee, Sungbok, Alexandros Potamianos, and Shrikanth Narayanan. "Acoustics of children’s speech: Developmental changes of temporal and spectral parameters." The Journal of the Acoustical Society of America 105, no. 3 (1999): 1455-1468.

[7] Lee, Sungbok, Alexandros Potamianos, and Shrikanth Narayanan. "Analysis of children's speech: Duration, pitch and formants." In Fifth European Conference on Speech Communication and Technology. 1997.

[8] Claus, Felix, Hamurabi Gamboa Rosales, Rico Petrick, Horst-Udo Hain, and Rüdiger Hoffmann. "A survey about databases of children's speech." In INTERSPEECH, pp. 2410-2414. 2013.
[9] Shahnawazuddin, S., Nagaraj Adiga, Hemant Kumar Kathania, and B. Tarun Sai. "Creating speaker independent ASR system through prosody modification based data augmentation." Pattern Recognition Letters 131 (2020): 213-218.

[10] Wang, Wei, Zhikai Zhou, Yizhou Lu, Hongji Wang, Chenpeng Du, and Yanmin Qian. "Towards data selection on tts data for children’s speech recognition." In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 6888-6892. IEEE, 2021.

[11] Kadyan, Virender, Hemant Kathania, Prajval Govil, and Mikko Kurimo. "Synthesis speech based data augmentation for low resource children ASR." In International Conference on Speech and Computer, pp. 317-326. Springer, Cham, 2021.

[12] Shahnawazuddin, S., Nagaraj Adiga, Kunal Kumar, Aayushi Poddar, and Waqar Ahmad. "Voice Conversion Based Data Augmentation to Improve Children's Speech Recognition in Limited Data Scenario." In Interspeech, pp. 4382-4386. 2020.

[13] Singh, Dipeash K., Preet P. Amin, Hardik B. Sailor, and Hemant A. Patil. "Data Augmentation Using CycleGAN for End-to-End Children ASR." In 2021 29th European Signal Processing Conference (EUSIPCO), pp. 511-515. IEEE, 2021.

[14] Jia, Ning, Chunjun Zheng, and Wei Sun. "Speech synthesis of children’s reading based on cycleGAN model." In Journal of Physics: Conference Series, vol. 1607, no. 1, p. 012046. IOP Publishing, 2020.

[15] Serizel, Romain, and Diego Giuliani. "Vocal tract length normalisation approaches to DNN-based children's and adults' speech recognition." In 2014 IEEE Spoken Language Technology Workshop (SLT), pp. 135-140. IEEE, 2014.

[16] Yeung, Gary, Ruchao Fan, and Abeer Alwan. "Fundamental frequency feature normalization and data augmentation for child speech recognition." In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 6993-6997. IEEE, 2021.

[17] Fainberg, Joachim, Peter Bell, Mike Lincoln, and Steve Renals. "Improving Children's Speech Recognition Through Out-of-Domain Data Augmentation." In Interspeech, pp. 1598-1602. 2016.

[18] Chen, Guoguo, Xingyu Na, Yongqing Wang, Zhiyong Yan, Junbo Zhang, Sifan Ma, and Yujun Wang. "Data Augmentation For Children's Speech Recognition--The "Ethiopian" System For The SLT 2021 Children Speech Recognition Challenge." arXiv preprint arXiv:2011.04547 (2020).

[19] Park, Daniel S., William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D. Cubuk, and Quoc V. Le. "Specaugment: A simple data augmentation method for automatic speech recognition." arXiv preprint arXiv:1904.08779 (2019).

[20] Singh, Vishwanath Pratap, Hardik Sailor, Supratik Bhattacharya, and Abhishek Pandey. "Spectral Modification Based Data Augmentation For Improving End-to-End ASR For Children's Speech." arXiv preprint arXiv:2203.06600 (2022).

[21] Shivakumar, Prashanth Gurunath, and Shrikant Narayanan. "End-to-end neural systems for automatic children speech recognition: An empirical study." Computer Speech & Language 72 (2022): 101289.

[22] Baevski, Alexei, Wei-Ning Hsu, Alexis Conneau, and Michael Auli. "Unsupervised speech recognition." Advances in Neural Information Processing Systems 34 (2021): 27826-27839.

[23] Baevski, Alexei, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli. "wav2vec 2.0: A framework for self-supervised learning of speech representations." Advances in Neural Information Processing Systems 33 (2020): 12449-12460.

[24] Yu, Fan, Zhuoyuan Yao, Xiong Wang, Keyu An, Lei Xie, Zhijian Ou, Bo Liu, Xiulin Li, and Guanqiong Miao. "The SLT 2021 children speech recognition challenge: Open datasets, rules and baselines." In 2021 IEEE Spoken Language Technology Workshop (SLT), pp. 1117-1123. IEEE, 2021.

[25] Xu, Gaopeng, Song Yang, Lu Ma, Chengfei Li, and Zhongqin Wu. "The TAL System for the INTERSPEECH2021 Shared Task on Automatic Speech Recognition for Non-Native Childrens Speech." In Interspeech, pp. 1294-1298. 2021.

[26] Fan, Ruchao, Amber Afshan, and Abeer Alwan. "Bi-apc: Bidirectional autoregressive predictive coding for unsupervised pre-training and its application to children’s asr." In ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 7023-7027. IEEE, 2021.

[27] Graves, Alex, Santiago Fernández, Faustino Gomez, and Jürgen Schmidhuber. "Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks." In Proceedings of the 23rd international conference on Machine learning, pp. 369-376. 2006.

[28] Ward, Wayne, Ron Cole, and Sameer Pradhan. "My science tutor and the myst corpus." (2019).

[29] Russell, Martin. "The p-f-star british english childrens speech corpus." The Speech Ark Limited (2006).

[30] Kahn, Jacob, Morgane Rivière, Weiyi Zheng, Evgeny Kharitonov, Qiantong Xu, Pierre-Emmanuel Mazaré, Julien Karadayi et al. "Libri-light: A benchmark for asr with limited or no supervision." In ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 7669-7673. IEEE, 2020.

[31] O'Neill, Patrick K., Vitaly Lavrukhin, Somshubra Majumdar, Vahid Noroozi, Yuekai Zhang, Oleksii Kuchaiev, Jagadeesh Balam et al. "Spapispeech: 5,000 hours of transcribed financial
audio for fully formatted end-to-end speech recognition." arXiv preprint arXiv:2104.02014 (2021).

[32] Panayotov, Vassil, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur. "Librispeech: an asr corpus based on public domain audio books." In 2015 IEEE international conference on acoustics, speech and signal processing (ICASSP), pp. 5206-5210. IEEE, 2015.