The Automatic Speaker Verification Spoofing Countermeasures Workshop (ASVspoof 2024)
31 August 2024, Kos, Greece

Exploring WavLM Back-ends for Speech Spoofing and Deepfake Detection

Theophile Stourbe, Victor Miara, Theo Lepage, Reda Dehak

EPITA Research Laboratory (LRE), France
{theophile.stourbe, victor.miara, theo.lepage, reda.dehak}@epita.fr

Abstract

This paper describes our submitted systems to the ASVspoof 5 Challenge Track 1: Speech Deepfake Detection - Open Condition, which consists of a stand-alone speech deepfake (bonafide vs spoof) detection task. Recently, large-scale self-supervised models become a standard in Automatic Speech Recognition (ASR) and other speech processing tasks. Thus, we leverage a pre-trained WavLM as a front-end model and pool its representations with different back-end techniques. The complete framework is fine-tuned using only the trained dataset of the challenge, similar to the close condition. Besides, we adopt data-augmentation by adding noise and reverberation using MUSAN noise and RIR datasets. We also experiment with codec augmentations to increase the performance of our method. Ultimately, we use the Bosaris toolkit for score calibration and system fusion to get better Cllr scores. Our fused system achieves 0.0937 minDCF, 3.42% EER, 0.1927 Cllr, and 0.1375 actDCF.

1. Introduction

With the development of Deep Neural Networks (DNN), speech synthesis and Voice Conversion (VC) are making significant progress in generating natural speech audio. This increases the relevance of spoofing speech detection to protect speaker identities and make biometric systems based on Automatic Speaker Verification (ASV) systems more robust. The challenge of anti-spoofing speech recognition is to detect the artifacts produced by the generation process or the VC of the spoof attacks. Over the past few years, many challenges have been proposed to promote the consideration of spoofing and speech deepfakes detection. ASVspoof is a series of challenges that focus on developing and benchmarking systems to detect and mitigate various spoofing attacks in ASV systems. ASVspoof 5 [1, 2], the fifth edition in this series, comprises two different tracks. The first track, which is the goal of our work, is to develop a countermeasure system to detect deepfake audio. This task comprises two challenges; the first one (the close condition) consists of creating a system using only the training dataset of the challenge. In the other challenge, the open condition, pre-trained models, and other training datasets are allowed, except those used to generate the test data.

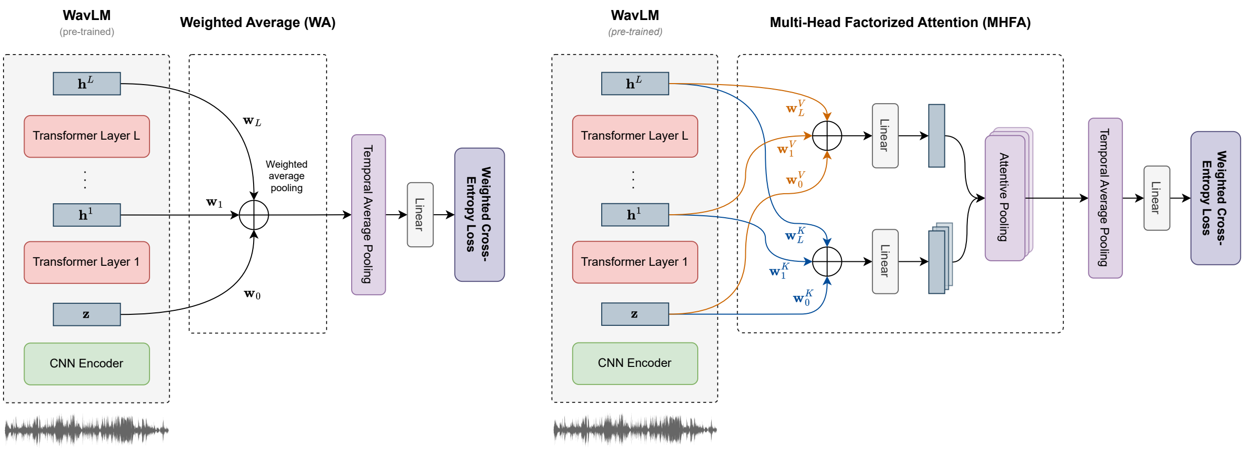
Initially, most anti-spoofing methods were based on DNN processing frame-level handcrafted acoustic features, such as MFCC, LFCC, log-linear filter bank, CQCCs, and CQT spectrogram [3]. Other approaches adopt raw waveforms as the input to train an end-to-end DNN to detect deepfake audio [4].

With the success of large self-supervised models for speech processing, many solutions were proposed using HuBERT [5], wav2vec 2.0 [6] and XLS-R [7] models as a feature extractor for a downstream system. Wang et Yamagishi [8] explore the use of HuBERT and wav2vec2.0 as a feature extractor for audio spoofing detection. Tak *et al.* [9] succeed in using XLS-R as a front-end speech features extractor for an AASIST model and get a significant improvement over previous techniques. These two works show that fine-tuning the front-end module is necessary to get better performances since this model was only trained with bonafide data. We can conclude that using large self-supervised pre-trained models for spoofing detection is very efficient. Thus, we decided to develop a submission for ASVspoof 5 based on the WavLM model [10] which demonstrates impressive results in many areas related to speech processing, emotion recognition [11] and speaker recognition [12, 13].

Our system is based on the WavLM Base model as a front-end feature extractor; pre-trained on $960h$ of Librispeech [14] which is compliant with the ASVspoof 5 open condition track rules[1]. We used the CNN encoder layer and the first 12-th Transformers encoder layers as features for a downstream back-end system. We use two different back-ends to aggregate all representations into one embedding vector: Weighted Average (WA) pooling and Multi-Head Factorized Attentive (MHFA) pooling proposed for speaker recognition in [12]. Several works show that data-augmentation is necessary to learn robust detection systems and to avoid over-fitting and improve generalization [15, 16]. Codec augmentation, background noise augmentation, reverberation as well as RawBoost [17] were tested and used to improve the generalization and robustness of our approach.

The paper is organized as follows: Section 2 presents the dataset used in model training, model scoring, and systems fusion and calibration steps. Section 3 details our approach for data augmentation, and Section 4 describes the front-end and the back-end of the models we devel-

 10.21437/ASVspoof.2024-11



(a) Weighted Average (WA)

(b) Multi-Head Factorized Attention (MHFA)

Figure 1: Diagram of our framework for fine-tuning WavLM with WA (a) and MHFA (b) back-ends.

oped. Section 5 describes the different hyper-parameters used for the training process. The results and performances are presented in Section 6. The conclusions are given in Section 7.

2. Datasets

Table 1: Summary of the contents of the training dataset and development subsets.

Subset	Usage	# utterances Bonafide	Spoof
Training	Model training	18,797	163,560
Development (1)	Scoring	8,245	28,846
Development (2)	Fusion and calibration	23,089	80,770

For system development, ASVspoof released a training dataset containing $182,357$ utterances and a development dataset containing $140,950$ utterances distributed as 16 kHz, 16 bits per sample FLAC files. We used the training dataset to fine-tune the WavLM and the back-end models. The development dataset was split into two parts: the **scoring** set used to compute and compare the models' performances; and the **fusion and calibration** set used for score calibration and model fusion. The contents of each dataset are summarized in Table 1.

3. Data-augmentation

Previous works show the importance of data-augmentation to obtain better performance and improve generalization. During the model training, we tested a combination of 4 different data-augmentation techniques described below.

- Utterances are augmented with background noises randomly selected from the 929 various noises of the MUSAN corpus [18]. The SNR is uniformly sampled between 0 and 15 dB.

- To apply reverberation, we convolve the input audio segment with an impulse response randomly sampled from the Simulated Room Impulse Response Database [19]

- We use torchaudio library to apply low and high-quality mp3 and ogg encoder. m4a could not be tested as it is not implemented in the torchaudio library. We also tested four trans-codecs configuration: high mp3 → high ogg, low mp3 → low ogg, high mp3 → low ogg, high ogg → low mp3.

- We also experiment with RawBoost similar to [20]. This method requires no additional data sources, e.g., noise recordings or impulse responses, and it is data, application, and model-agnostic. This data augmentation algorithm is not used in combination with the other techniques mentioned above.

All our data augmentation was implemented online (parallel) in our training framework so that the model is trained on different data at each epoch. For each sample, we first apply or not randomly selected noise from MUSAN noise, random reverberation from RIR dataset, or both. Second, we apply or not a random codec augmentation. In the case of RawBoost, we tested the different algorithms proposed in [20].

4. Models

4.1. Baseline: ResNet-based spoof detection system

We chose a ResNet-based backbone as a baseline system and submitted this system for the closed condition. We chose this model because we get better performance compared to the RawNet2 [4] and the AASIST [21] methods proposed in the ASVspoof 5 Toolkit.

We rely on the Fast ResNet-34 architecture, described in [22], processing 40-dimensional log-mel spectrogram input features with a Hamming window of 25 ms length and 10 ms frame-shift. The encoder dimension is set to 512 and we add a ReLU activation function followed by a linear layer for the spoofing detection task.

4.2. WavLM-based spoof detection system

WavLM [10] is a Transformer-based model designed for Automatic Speech Recognition (ASR). It is pre-trained in a self-supervised way that also captures non-ASR information. During the pre-training, the model processes raw audio through a multi-layer convolutional feature encoder, transforming a sequence $\{\mathbf{x}_t\}_{t=1}^{T}$ of T time windows to produce $\{\mathbf{z}_t\}_{t=1}^{T}$. These representations are then subject to noise and overlapping before masking and fed into the Transformer encoder, which outputs a series of hidden states $\left\{\mathbf{h}^l\right\}_{l=1}^{L}$, where L denotes the number of Transformer layers. Additionally, the model incorporates gated relative position bias, enhancing its ability to focus on relevant speech features. WavLM is trained on a masked speech denoising and prediction task which implicitly models speaker and speech-related information as the objective is to predict the pseudo-labels of the original speech on masked regions.

4.2.1. Weighted Average (WA) back-end

Several works show that the intermediate representation of the self-supervised model contains essential features that can be used in various speech downstream tasks. Generally, the top layers, which are closer to the objective of the pre-training task, tend to be the most helpful for automatic speech recognition (ASR). In contrast, the speech and speaker features are mainly represented in the low- and mid-level features, which carry most information about speech signals. Thus, using only the last Transformer layer's output might be sub-optimal for speech spoofing detection.

As shown in Figure 1-a, following [10], using the outputs $\mathbf{z}_t$ and $\left\{\mathbf{h}_t^l\right\}_{l=1}^{L}$ of the l-th transformer layer for each frame t, we learn a weighted average of all these outputs to generate a new frame representation O_t such that

$$O_t = w_0\mathbf{z}_t + \sum_{l=1}^{L} w_l\mathbf{h}_t^l, \tag{1}$$

where $\{w_k \mid 0 \leq k \leq L\}$ represent the learnable weights.

Next, the weighted frame-level representation O_t is fed into a temporal average pooling layer followed by a fully connected layer to obtain the final score for spoof detection.

4.2.2. Multi-Head Factorized Attention (MHFA) back-end

Following [12], Multi-Head Factorized Attention (MHFA) back-end (Figure 1-b) consists of aggregating layer-wise outputs from WavLM's transformer layers into an attentive pooling mechanism that clusters frame-level representations into acoustic units discovered by the transformer model. The frame-level representations are then aggregated (pooled) within each cluster and combined to produce the final frame embedding. This mechanism allows frame embeddings to be conditioned on the phonetic content of the input utterances. Refer to [12] for more details.

4.2.3. Reducing overfitting

To mitigate the effect of overfitting from the WavLM font-end, these two aggregation methods rely on two components: (1) L2 regularization between the updated weights and the initial weights from the pre-trained WavLM model, which helps control overfitting caused by the large number of parameters; (2) layer-wise learning rate decay, following [23]. Given the progressive abstraction of information across Transformer layers [10], this technique allows more flexible weight updates in higher layers to adapt ASR capabilities, while ensuring lower layers preserve speech signals-related information.

5. Experimental setup

The front-end of all our models is based on the pre-trained WavLM Base model [1], it is composed of a CNN encoder and 12 Transformer layers. The dimension of each Transformer layer's output is 768. The number of parameters of the WavLM is $\sim 94M$, 1551 for the linear weighted average pooling back-end, and $\sim 1M$ for the 32 heads MHFA back-end.

All our models were trained on the whole training set released by ASVspoof 5 using an NVIDIA A100 80 GB GPU using the cross-entropy loss with a weight of 9 for the bonafide class and 1 for the spoof class to solve the class imbalance issue of the training set. The systems were trained on $4s$ speech utterance's length, randomly selected at each epoch from each training sample. We train for 100 epochs with a default batch size of 120 or 32, and we stop the training if the EER on the scoring dataset does not improve after 50 epochs. We use Adam optimizer with a learning rate of 5×10^{-3} for the back-end and 2×10^{-5} for the encoder, each reduced by 5% every epoch. The test score was computed on the entire speech utterance. Results are reported in terms of Equal Error Rate (EER) and minimum Detection Cost Function (minDCF) following the setup described in [2].

We train different models: first, by fixing the param-

[1] `https://huggingface.co/microsoft/wavlm-base`

Table 2: Spoof detection results of the different models trained during the ASVspoof 5 challenge on our scoring and progress datasets. The best performances are represented in bold text.

	Model		**Training**	**Data-augmentation**			**Scoring Dataset**		**Progress Dataset**	
#	Back-end	Fine-tune WavLM	Batch size	Noise and RIR	Rawboost	Codec	**EER (%)**	**minDCF**	**EER (%)**	**minDCF**
	Baseline (ResNet)		120	✓		✓	15.60	0.3469	16.19	0.3915
1	MHFA		120				6.78	0.1581		
2	MHFA		120	✓			8.78	0.2155		
3	MHFA	✓	120				6.41	0.1628		
4	MHFA	✓	120	✓			3.37	0.0872	1.42	0.0380
5	MHFA	✓	120		✓		28.91	0.7160		
6	MHFA	✓	120	✓		✓	2.18	0.0552	1.22	0.0320
7	MHFA	✓	32	✓		✓	**1.82**	**0.0498**	1.13	0.0279
8	WA	✓	32	✓		✓	1.89	0.0503	**1.01**	**0.0251**
9	**Fusion of model 6, 7 and 8**						**1.10**	**0.0272**	**0.88**	**0.0226**

eters of the encoders and training only the parameters of the MHFA back-end. Similar to previous work [8, 9], we decide next to fine-tune the parameters of the encoder. We use a lower learning rate for the WavLM model to avoid overfitting. To make the training faster, these first experiments were conducted using only the noise and reverberation data augmentation. We also tested the efficiency of the RawBoost data-augmentation. Finally, we added the codec augmentation to the best configuration and retrained the model.

6. Results and discussions

Our strategy consisted of the development of a main system that achieved the best possible individual performance before training a fusion that could improve the performance of the final system.

Table 2 summarizes some preliminary results obtained during the development of our main system. We report the performances on our scoring dataset and the progress dataset when the system was submitted during the progress phase of the challenge. We did not succeed in performing well with the baseline systems proposed in the ASVspoof 5 toolkit. We obtained the best performance for the baseline system based on a ResNet with noise, RIR, and codec augmentations.

The results of the first four systems were expected: (1) the WavLM performed better than the baseline, this has been demonstrated on other speech processing tasks; (2) fine-tuning the WavLM is necessary to reach better performance. Data-augmentation is also fundamental as fine-tuning the WavLM with the noise and RIR augmentations allowed for reaching the best results. Since the WavLM has a large number of parameters, the model is more subject to overfitting in this case compared to the case where the WavLM weights are frozen.

Data augmentation becomes necessary to increase the performance of the WavLM and reduce overfitting; we experiment with different RawBoost algorithms proposed in [17]. We achieve an EER of 28.91%, which is worse than the performance obtained with the noise and RIR data-augmentation.

With systems numbers 6 and 7, the performances obtained by using codec augmentation in addition to the noise and RIR augmentation are better. We obtain a 35% relative improvement of the EER with a batch size of 120 samples and a 47% relative improvement of the EER with a batch size of 32. This result was expected because it has been observed in practice that when using a larger batch, there is a degradation in the quality of the model, as measured by its ability to generalize [24, 25]. Initially, we selected a large batch size to make the experiments run faster using data parallelism.

To reduce the effect of overfitting, we implement a Weighted Average (WA) back-end, which has a limited number of parameters compared to the MHFA back-end. Thus, this model is less subject to overfitting compared to the MHFA. As expected, the result of this system was a little bit worse on our scoring dataset than the MHFA, but it performed better on the progress dataset and obtained an EER of 1.01 and a minDCF of 0.0251, which is our best performance on the progress dataset with an individual system. This result confirms that we would need more training samples or data augmentation algorithms to avoid overfitting when using the MHFA back-end.

In the end, fusion and calibration were performed using linear logistic regression with the Bosaris toolkit [26]. To select the best fusion combination, we implemented a greedy fusion scheme. First, we calibrated all the systems and selected the best, given the lowest minDCF cost. The best three systems were linearly fused to obtain the submission system. This fusion performed the best on the scoring and progress dataset. This result confirms the complementarity between the MHFA and WA back-ends.

On the evaluation dataset, the fused system achieves 0.0937 minDCF, 3.42% EER, 0.1927 Cllr, and 0.1375 actDCF. Unlike our previous results with the progress dataset, this performance is worse than on our scoring dataset. This results from new acoustic conditions where the model could not generalize better.

Table 3: Detailed performance of fusion system on the evaluation dataset according to different acoustic conditions.

	pooled	-	codec-1	codec-10	codec-11	codec-2	codec-3	codec-4	codec-5	codec-6	codec-7	codec-8	codec-9
pooled	0.0937	0.0249	0.0644	0.1764	0.0726	0.0450	0.0728	0.1298	0.0311	0.0511	0.1824	0.1468	0.1096
A17	0.0081	0.0000	0.0006	0.0076	0.0021	0.0004	0.0032	0.0053	0.0000	0.0007	0.0102	0.0256	0.0025
A18	0.0328	0.0027	0.0144	0.0749	0.0118	0.0124	0.0186	0.0392	0.0069	0.0081	0.0693	0.0532	0.0388
A19	0.1622	0.0624	0.1298	0.1633	0.0646	0.0830	0.1007	0.2096	0.0721	0.0987	0.2797	0.1539	0.1001
A20	0.0631	0.0160	0.0386	0.0865	0.0169	0.0322	0.0242	0.0971	0.0229	0.0311	0.1432	0.0553	0.0427
A21	0.0227	0.0013	0.0101	0.0340	0.0118	0.0045	0.0202	0.0261	0.0024	0.0042	0.0389	0.0555	0.0169
A22	0.0506	0.0071	0.0279	0.1120	0.0225	0.0145	0.0518	0.0753	0.0079	0.0152	0.1080	0.0910	0.0489
A23	0.0351	0.0033	0.0158	0.0735	0.0145	0.0107	0.0278	0.0467	0.0059	0.0098	0.0739	0.0552	0.0499
A24	0.0968	0.0083	0.0604	0.2239	0.0711	0.0233	0.0980	0.1012	0.0107	0.0531	0.1388	0.2302	0.1327
A25	0.0216	0.0020	0.0092	0.0364	0.0036	0.0062	0.0144	0.0303	0.0040	0.0034	0.0648	0.0372	0.0160
A26	0.0261	0.0006	0.0102	0.0551	0.0130	0.0020	0.0226	0.0304	0.0002	0.0057	0.0533	0.0592	0.0297
A27	0.0608	0.0074	0.0328	0.1427	0.0188	0.0275	0.0270	0.1155	0.0145	0.0197	0.1938	0.0830	0.0725
A28	0.3332	0.0810	0.2403	0.6971	0.4099	0.1624	0.3527	0.3589	0.0890	0.2091	0.4293	0.7063	0.5634
A29	0.0095	0.0011	0.0031	0.0095	0.0065	0.0012	0.0033	0.0054	0.0012	0.0024	0.0061	0.0308	0.0060
A30	0.0641	0.0110	0.0357	0.1430	0.0203	0.0258	0.0317	0.1233	0.0174	0.0246	0.1923	0.0873	0.0612
A31	0.1172	0.0283	0.0815	0.2383	0.0495	0.0511	0.0745	0.1831	0.0400	0.0598	0.2719	0.1740	0.1303
A32	0.0504	0.0060	0.0271	0.1176	0.0093	0.0217	0.0164	0.1096	0.0113	0.0173	0.1843	0.0550	0.0440

(a) Minimum Detection Cost Function

	pooled	-	codec-1	codec-10	codec-11	codec-2	codec-3	codec-4	codec-5	codec-6	codec-7	codec-8	codec-9
pooled	3.42	0.92	2.49	6.45	3.16	1.66	3.00	4.66	1.13	2.04	6.37	6.02	4.45
A17	0.30	0.00	0.04	0.26	0.09	0.01	0.15	0.20	0.00	0.05	0.37	0.92	0.14
A18	1.17	0.10	0.50	2.67	0.46	0.46	0.71	1.44	0.29	0.39	2.43	1.92	1.41
A19	5.61	2.19	4.69	5.82	2.32	2.93	3.56	7.29	2.49	3.65	9.89	5.70	3.60
A20	2.18	0.55	1.37	3.01	0.59	1.14	0.86	3.36	0.81	1.12	5.11	2.03	1.54
A21	0.82	0.05	0.46	1.21	0.50	0.18	0.78	1.07	0.12	0.14	1.42	1.92	0.68
A22	1.79	0.28	1.09	3.88	0.80	0.54	1.94	2.77	0.29	0.53	3.85	3.18	1.74
A23	1.23	0.13	0.58	2.67	0.55	0.41	1.03	1.69	0.22	0.43	2.58	1.97	1.74
A24	3.44	0.32	2.22	8.43	2.53	0.96	3.64	3.61	0.41	1.94	4.98	8.13	4.75
A25	0.75	0.07	0.38	1.42	0.12	0.22	0.54	1.08	0.13	0.14	2.37	1.39	0.58
A26	0.94	0.02	0.42	1.92	0.51	0.08	0.86	1.12	0.01	0.20	2.01	2.05	1.06
A27	2.19	0.28	1.23	5.40	0.68	1.09	0.99	4.29	0.55	0.69	6.89	2.90	2.64
A28	12.01	3.03	8.61	25.29	15.13	6.30	12.75	12.85	3.33	8.02	15.31	24.79	21.20
A29	0.39	0.07	0.25	0.50	0.42	0.04	0.25	0.33	0.04	0.19	0.37	1.21	0.48
A30	2.28	0.41	1.26	5.04	0.75	1.00	1.12	4.32	0.63	0.87	6.69	3.04	2.19
A31	4.07	1.04	2.93	8.32	1.74	1.86	2.63	6.47	1.39	2.11	9.44	6.02	4.75
A32	1.84	0.22	1.02	4.30	0.34	0.89	0.67	4.07	0.39	0.63	6.64	2.04	1.68

(b) EER

We report in Table 3 the detailed performances of our submitted system according to the different acoustic conditions. The first analysis of these two tables shows that condition A28, which uses audio speech generated using the pre-trained YourTTS model [27], is the most challenging task in our case. A detailed analysis shows that using limited bandwidth codec compression is also difficult because we lose speech information in higher frequencies. Finally, we can notice that some specific combinations are very challenging such as A28-codec10 and A28-codec8.

7. Conclusions

In this article, we have presented our countermeasure systems based on the pre-trained WavLM Base model for the ASVspoof 5 challenge open condition task. These systems significantly outperformed the baseline. We have shown that this model can be a good feature extractor for a back-end detection system. Similar to previous work based on large models such as wav2vec 2.0, this model needs to be fine-tuned using a spoofed dataset. The MHFA back-end obtained good performance on our development dataset, but it was more subject to overfitting than WA, which has fewer parameters. This simple Weighted Average (WA) pooling obtains the best performances on the progress dataset. We would need more training samples and augmentation algorithms to avoid this issue. The fusion of the systems based on MHFA and WA achieved the best performance and confirmed the complementary relationship between the two techniques. As WavLM representations also contain valuable speaker identity information, we could explore combining the two tasks with a back-end for each downstream task.

8. Acknowledgements

This work was performed using HPC resources from GENCI-IDRIS (Grant 2023-AD011014623) and has been partially funded by the French National Research Agency (project APATE - ANR-22-CE39-0016-05).

9. References

[1] ASVspoof consortium, "ASVspoof 5 evaluation plan," `https://www.asvspoof.org/file/ASVspoof5___Evaluation_Plan_Phase2.pdf`, 2024.

[2] X. Wang et al., "ASVspoof 5: Crowdsourced data, deepfakes and adversarial attacks at scale," in *ASVspoof 2024 workshop (submitted)*, 2024.

[3] Zhizheng Wu, Nicholas Evans, Tomi Kinnunen, Junichi Yamagishi, Federico Alegre, and Haizhou Li, "Spoofing and countermeasures for speaker verification: A survey," *Speech Communication*, 2015.

[4] Hemlata Tak, Jose Patino, Massimiliano Todisco, Andreas Nautsch, Nicholas Evans, and Anthony Larcher, "End-to-End anti-spoofing with RawNet2," in *INTERSPEECH*, 2021.

[5] Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhotia, Ruslan Salakhutdinov, and Abdelrahman Mohamed, "HuBERT: Self-Supervised Speech Representation Learning by Masked Prediction of Hidden Units," *IEEE TASLP*, 2021.

[6] Alexei Baevski, Yuhao Zhou, Abdelrahman Mohamed, and Michael Auli, "wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations," in *NeurIPS*, 2020.

[7] Arun Babu, Changhan Wang, Andros Tjandra, Kushal Lakhotia, Qiantong Xu, Naman Goyal, Kritika Singh, Patrick von Platen, Yatharth Saraf, Juan Pino, Alexei Baevski, Alexis Conneau, and Michael Auli, "XLS-R: Self-supervised Cross-lingual Speech Representation Learning at Scale," in *INTERSPEECH*, 2022.

[8] Xin Wang and Junichi Yamagishi, "Investigating Self-Supervised Front Ends for Speech Spoofing Countermeasures," in *Odyssey*, 2022.

[9] Hemlata Tak, Massimiliano Todisco, Xin Wang, Jee weon Jung, Junichi Yamagishi, and Nicholas Evans, "Automatic Speaker Verification Spoofing and Deepfake Detection Using Wav2vec 2.0 and Data Augmentation," in *Odyssey*, 2022.

[10] Sanyuan Chen, Chengyi Wang, Zhengyang Chen, Yu Wu, Shujie Liu, Zhuo Chen, Jinyu Li, Naoyuki Kanda, Takuya Yoshioka, Xiong Xiao, Jian Wu, Long Zhou, Shuo Ren, Yanmin Qian, Yao Qian, Jian Wu, Michael Zeng, Xiangzhan Yu, and Furu Wei, "WavLM: Large-Scale Self-Supervised Pre-Training for Full Stack Speech Processing," *IEEE JSTSP*, 2022.

[11] Daria Diatlova, Anton Udalov, Vitalii Shutov, and Egor Spirin, "Adapting WavLM for Speech Emotion Recognition," in *Odyssey*, 2024.

[12] Junyi Peng, Oldřich Plchot, Themos Stafylakis, Ladislav Mošner, Lukáš Burget, and Jan Černocký, "An Attention-Based Backend Allowing Efficient Fine-Tuning of Transformer Models for Speaker Verification," in *IEEE SLT*, 2022.

[13] Victor Miara, Theo Lepage, and Reda Dehak, "Towards Supervised Performance on Speaker Verification with Self-Supervised Learning by Leveraging Large-Scale ASR Models," in *INTERSPEECH*, 2024.

[14] Vassil Panayotov, Guoguo Chen, Daniel Povey, and Sanjeev Khudanpur, "Librispeech: an ASR corpus based on public domain audio books," in *ICASSP*, 2015.

[15] Ariel Cohen, Inbal Rimon, Eran Aflalo, and Haim H. Permuter, "A study on data augmentation in voice anti-spoofing," *Speech Communication*, 2022.

[16] Wanying Ge, Xin Wang, Junichi Yamagishi, Massimiliano Todisco, and Nicholas Evans, "Spoofing Attack Augmentation: Can Differently-Trained Attack Models Improve Generalisation?," in *ICASSP*, 2024.

[17] Hemlata Tak, Madhu Kamble, Jose Patino, Massimiliano Todisco, and Nicholas Evans, "Rawboost: A Raw Data Boosting and Augmentation Method Applied to Automatic Speaker Verification Anti-Spoofing," in *ICASSP*, 2022.

[18] Snyder David, Chen Guoguo, and Povey Daniel, "MUSAN: A Music, Speech, and Noise Corpus," *arXiv preprint arXiv:1510.08484*, 2015.

[19] Tom Ko, Vijayaditya Peddinti, Daniel Povey, Michael L. Seltzer, and Sanjeev Khudanpur, "A study on data augmentation of reverberant speech for robust speech recognition," in *ICASSP*, 2017.

[20] Hemlata Tak, Madhu Kamble, Jose Patino, Massimiliano Todisco, and Nicholas Evans, "Rawboost: A Raw Data Boosting and Augmentation Method Applied to Automatic Speaker Verification Anti-Spoofing," in *ICASSP*, 2022.

[21] Jee-Weon Jung, Hee-Soo Heo, Hemlata Tak, Hye-Jin Shim, Joon Son Chung, Bong-Jin Lee, Ha-Jin Yu, and Nicholas Evans, "AASIST: Audio Anti-Spoofing Using Integrated Spectro-Temporal Graph Attention Networks," in *ICASSP*, 2022.

[22] Joon Son Chung, Jaesung Huh, Seongkyu Mun, Minjae Lee, Hee-Soo Heo, Soyeon Choe, Chiheon Ham, Sunghwan Jung, Bong-Jin Lee, and Icksang Han, "In Defence of Metric Learning for Speaker Recognition," in *INTERSPEECH*, 2020.

[23] Sun Chi, Qiu Xipeng, Xu Yige, and Huang Xuanjing, "How to Fine-Tune BERT for Text Classification?," in *CCL*, 2019.

[24] Yann A. LeCun, Léon Bottou, Genevieve B. Orr, and Klaus-Robert Müller, *Efficient BackProp*, pp. 9–48, Springer Berlin Heidelberg, Berlin, Heidelberg, 2012.

[25] Nitish Shirish Keskar, Dheevatsa Mudigere, Jorge Nocedal, Mikhail Smelyanskiy, and Ping Tak Peter Tang, "On large-batch training for deep learning: Generalization gap and sharp minima," in *5th International Conference on Learning Representations, ICLR 2017*, 2017.

[26] Niko Brümmer and Edward de Villiers, "The BOSARIS toolkit: theory, algorithms and code for surviving the new DCF," in *NIST SRE11 Speaker Recognition Workshop*, 2011.

[27] Edresson Casanova, Julian Weber, Christopher D Shulby, Arnaldo Candido Junior, Eren Gölge, and Moacir A Ponti, "YourTTS: Towards zero-shot multi-speaker TTS and zero-shot voice conversion for everyone," in *ICML*, 2022.