

SONAR: A Synthetic AI-Audio Detection Framework and Benchmark

Xiang Li
Fordham University
xl5@fordham.edu

Pin-Yu Chen
IBM Research
pin-yu.chen@ibm.com

Wenqi Wei
Fordham University
wenqiwei@fordham.edu

Abstract

Recent advances in Text-to-Speech (TTS) and Voice-Conversion (VC) using generative Artificial Intelligence (AI) technology have made it possible to generate high-quality and realistic human-like audio. This introduces significant challenges to distinguishing AI-synthesized speech from the authentic human voice and could raise potential issues of misuse for malicious purposes such as impersonation and fraud, spreading misinformation, deepfakes, and scams. However, existing detection techniques for AI-synthesized audio have not kept pace and often exhibit poor generalization across diverse datasets. In this paper, we introduce SONAR, a Synthetic AI-Audio Detection Framework and Benchmark, aiming to provide a comprehensive evaluation for distinguishing cutting-edge AI-synthesized auditory content. SONAR includes a novel evaluation dataset sourced from 9 diverse audio synthesis platforms, including leading TTS providers and state-of-the-art TTS models. It is the first framework to uniformly benchmark AI-audio detection across both traditional and foundation model-based deepfake detection systems. Through extensive experiments, we reveal the generalization limitations of existing detection methods and demonstrate that foundation models exhibit stronger generalization capabilities, which can be attributed to their model size and the scale and quality of pretraining data. Additionally, we explore the effectiveness and efficiency of few-shot fine-tuning in improving generalization, highlighting its potential for tailored applications, such as personalized detection systems for specific entities or individuals. *Code and dataset are available at <https://github.com/JesseGator/SONAR>*

1 Introduction

Recent advances in Text-to-Speech (TTS) and Voice-Conversion (VC) using Artificial Intelligence (AI) technology have made it possible to generate high-quality and realistic human-like audio efficiently [1, 2, 3, 4]. This introduces significant challenges in distinguishing AI-synthesized speech from the authentic human voice and could raise potential misuse for malicious purposes such as impersonation and fraud, spreading misinformation, and scams. For example, a deep fake AI voice of the US President Joe Biden was recently utilized in robocalls to advise them against voting¹, demonstrating how deepfakes can significantly manipulate public opinions and influence presidential elections. In response to such risks, the US Federal Communications Commission (FCC) now deems robot calls for election as illegal, which underscores the urgent need for enhanced detection of AI-synthesized audio.

While TTS models are advancing rapidly, AI-synthesized audio detection techniques are not keeping pace. First, previous studies [5, 6] have highlighted the lack of generalization and robustness in these detection methods. Second, existing detection models [7, 6, 8, 9, 10] often take advantage of different

¹<https://www.cnn.com/2024/01/22/politics/fake-joe-biden-robocall/index.html>

audio features and evaluation datasets, complicating the comparison of their detection effectiveness. Third, a comprehensive evaluation to determine the effectiveness of these detection methods against the latest TTS models has not been conducted. This gap in research leaves a significant challenge in developing reliable detection techniques that can effectively counter the growing sophistication of AI-generated audio.

To address the aforementioned research gap and explore the strengths and limitations of existing AI-synthesized audio detection methods, especially those with increasingly advanced TTS models, we present a synthetic AI-Audio Detection Framework and Benchmark, coined as SONAR. This framework aims to provide a comprehensive evaluation for distinguishing state-of-the-art AI-synthesized auditory content. Our study benchmarks the state-of-the-art fake audio detection models using a newly collected fake audio dataset that includes a variety of synthetic speech audios sourced from diverse cutting-edge TTS providers and TTS models. We further investigate the potential of enhancing the generalization capabilities of these detection models from different perspectives. The main contributions of our work can be summarized as follows.

- We introduce a novel evaluation dataset specifically designed for audio deepfake detection. This dataset is sourced from 9 diverse audio synthesis platforms, including those from leading TTS service providers and state-of-the-art TTS models. To the best of our knowledge, this dataset is by far the largest collection of fake audio generated by the latest TTS models.
- SONAR is the first comprehensive framework to benchmark AI-audio detection uniformly across advanced TTS models. It covers 5 state-of-the-art traditional and 6 foundation-model-based audio deepfake detection models.
- Leveraging SONAR, we conduct extensive experiments to analyze the generalizability limitations of current detection methods. Our findings reveal that foundation models demonstrate stronger generalization capabilities than traditional models. We further explore factors that may contribute to this improved generalization, such as model size and the scale and quality of pre-training data.
- We further explore the potential of few-shot fine-tuning to enhance the generalization of detection models. Our empirical results demonstrate the effectiveness and efficiency of this approach, highlighting its potential for tailored applications, such as personalized detection systems for specific entities or individuals.

2 Related work

Text-to-Speech synthesis. Human voice synthesis is a significant challenge in the field of AI. State-of-the-art TTS synthesis approaches such as VALLE [4], AudioBox [1], VoiceBox [11], NaturalSpeech3 [4], and YourTTS [3] have demonstrated the possibility of generating high-quality, human-realistic audio with generative models trained on large datasets. Current TTS models can be classified into two primary categories: cascaded and end-to-end methods. Cascaded TTS models [12, 13, 14] typically employ a pipeline involving an acoustic model and a vocoder utilizing mel spectrograms as intermediary representations. To address the limitations associated with vocoders, end-to-end TTS models [15, 16] have been developed to jointly optimize both the acoustic model and vocoder. In practical applications, it is preferable to customize TTS systems to generate speech in any voice with limited accessible data. Consequently, there is increasing interest in zero-shot multi-speaker TTS techniques [17, 3, 2].

AI-synthesized audio detection. Recent advancements in AI technology have significantly enhanced the ability to generate high-quality and realistic audio, calling for an urgent need for more robust and reliable detection methods. Several datasets have been developed to support research in this area. The ASVspoof challenges [18, 19, 20] are among the most notable, offering comprehensive datasets that cover a variety of attack vectors, including replay attacks, voice conversion, and directly synthesized audio. These resources aim to facilitate thorough evaluations of countermeasures against various spoofing techniques. In addition, newer datasets such as WaveFake [21] and LibriSeVoc [22] provide fake audio samples generated with state-of-the-art vocoders, offering diverse distributions to enhance the development of deepfake audio detection systems. By comparison, the In-the-Wild dataset [6] targets real-world applications by collecting deepfake audios from publicly accessible sources, capturing the complexity and diversity of manipulations encountered in everyday environments. Similarly, the SingFake dataset [6] focuses on the detection of synthetic singing voices, presenting

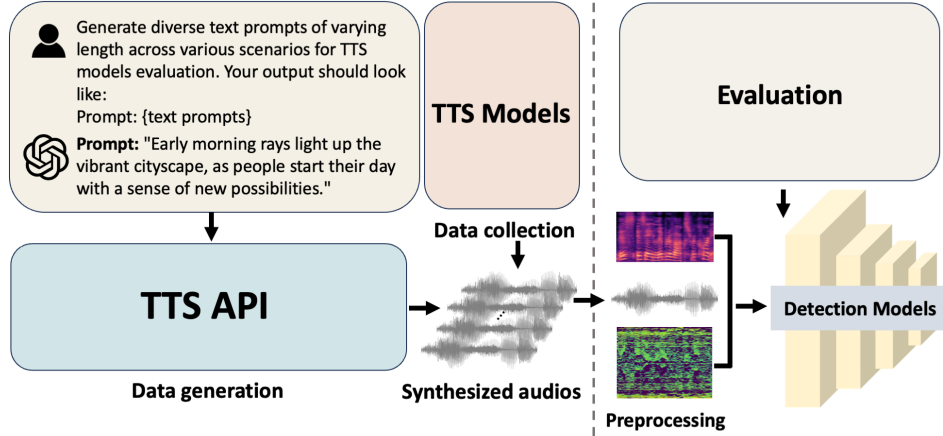


Figure 1: Overview of SONAR. **Left:** Audio deepfake data generation and collection. **Right:** Benchmark evaluation.

unique challenges due to the musical content and variation in vocal expressions. These datasets are crucial for developing and testing next-generation AI-synthesized audio detection systems, pushing the boundaries of what is achievable in identifying and mitigating the threats posed by advanced audio synthesis technologies.

Building upon these datasets, a significant body of research has focused on distinguishing AI-generated audio from genuine audio by designing advanced model architectures [8, 10, 7, 9] tailored for extracting different levels of representations of speech data for audio deepfake detection. Additionally, recent works [23, 24, 25] have leveraged speech foundation models for audio deepfake detection tasks. For instance, [23] and [24] fine-tune Wav2Vec2 [26] models on the ASVspoof dataset, while [25] uses Whisper as a front-end to extract audio features and trains various detection models based on these features, achieving state-of-the-art detection performance on the corresponding test datasets. However, none of these models have been evaluated on audio generated by the latest text-to-speech (TTS) models, leaving a gap in understanding their effectiveness against the most recent advancements in synthetic audio generation.

3 Evaluation dataset generalization and collection

Leveraging a set of diverse and high-quality speech data synthesis APIs and models, we create an evaluation dataset for synthetic AI-audio detection. Our approach incorporates two strategies: data generation and data collection. Our dataset includes AI-generated speech and audio from nine distinct sources. We perform speech data generation using one cutting-edge TTS service provider, OpenAI, and two open-sourced APIs, xTTS [27] and AudioGen [28]. For speech data collection, we leverage six state-of-the-art TTS models including Seed-TTS [29], VALL-E [4], PromptTTS2 [30], NaturalSpeech3 [31], VoiceBox [11], FlashSpeech [2]. Table 1 presents the details of our dataset generated by different audio generation models. We next detail our methods of generating and collecting these datasets.

Data generation. Our dataset generation involves OpenAI, xTTS, and AudioGen. Specifically, OpenAI currently provides voice choices from 6 different speakers. Using ChatGPT, we generate 100 different text prompts of varying lengths for each speaker, resulting in a total of 600 synthetic speech audios. xTTS supports synthetic speech generation given text prompts and reference speech. We select 6 speakers from the LibriTTS dataset [32] as the reference speech and also generate 600 text prompts with ChatGPT for each speaker, resulting in 600 synthetic speech audios. AudioGen can generate the corresponding environmental sound given a textual description of the acoustic scene. With AudioGen, we use ChatGPT to generate 100 text descriptions of the environment and background and obtain 100 AI-synthesized environmental sounds. Figure 1 (left) illustrates the data generation and collection process.

Data collection. To evaluate the effectiveness of various detection systems against the state-of-the-art TTS models, we also collect fake speech audio from Seed-TTS, VALL-E, PromptTTS2,

Table 1: Overview of our dataset with fake audios generated by various models. AudioGen lacks speaker and language information as it focuses on environmental sounds. The trainset sizes for OpenAI and Seed-TTS are unavailable due to the use of proprietary data. * denotes the samples that are directly collected from their demo page or provided test set due to the unavailability of their model checkpoints.

Model	Samples	Avg duration (s)	Avg. pitch (Hz)	Std. pitch (Hz)	Languages	Trainset size(H)	Year
PromptTTS2*	25	9.86	126.49	46.27	English	44K	2023
NaturalSpeech3*	32	5.25	143.86	53.94	English	60K	2024
VALL-E*	95	4.86	133.41	56.54	English	60K	2023
VoiceBox*	104	10.28	114.09	37.89	English, German, French, Portuguese, Polish, Spanish	60K	2023
FlashSpeech*	118	7.57	129.30	54.77	English	44.5K	2024
AudioGen	100	5.00	199.45	72.94	-	7K	2022
xTTS	600	5.67	164.67	95.20	English	2.7K	2023
Seed-TTS*	600	4.91	117.28	36.85	English, Mandarin	-	2024
OpenAI	600	4.11	126.89	54.89	English	-	2024

NaturalSpeech3, VoiceBox, and FlashSpeech. Seed-TTS provides a test dataset² consisting of fake audio samples generated by it. Due to the unavailability of pre-trained weights of the other 5 models, we extract the synthesized speech data directly from their demo pages. Specifically, speech audios from VALL-E include variations in emotions and acoustic environment. PromptTTS2 presents fake audio samples with various attributes such as gender, speed, pitch, volume, and timbre. NaturalSpeech3 also includes fake audio samples generated with various attributes such as speeds and emotions and contains fake speech audio samples obtained with voice conversion. VoiceBox provides fake audio samples that feature cross-lingual and expressive audio styles. FlashSpeech includes a set of high-quality fake audios obtained both from speech generation and voice conversion.

To summarize, leveraging the details outlined above, we generate and collect a comprehensive evaluation dataset, encompassing a total of 2274 AI-synthesized audio samples produced by various TTS models. To the best of our knowledge, our dataset is by far the largest collection of fake audio generated by the latest TTS models. Note our motivation for collecting this dataset is for evaluation purposes. Additionally, we only include fake audio samples in this dataset since genuine audio samples can be easily collected from various sources (e.g., internet, self-recording, publicly available datasets, etc.). However, for convenience of evaluation, we also provide an equal number of real speech audio data sampled from the LibriTTS [32] clean-test set.

We believe the collected dataset can serve as a valuable asset for evaluating existing audio deepfake detection models.

4 Benchmarking AI-Audio Detection Models

In this section, we first detail the model, dataset, and evaluation metrics setup for benchmarking. Then, we present the results of evaluating detection models on existing audio deepfake datasets to assess their generalizability across datasets. We next benchmark their detection performance on our proposed dataset and provide analysis for potential model generalization improvement.

4.1 Benchmarking setup

Model architectures. SONAR incorporates 11 models, including 5 state-of-the-art traditional audio deepfake detection models featuring various levels of input feature abstraction and 6 foundation models. Specifically, for the former, SONAR includes (1) AASIST [7], which processes raw waveform directly and utilizes graph neural networks and incorporates spectro-temporal attention mechanisms. (2) RawGAT-ST [9], which employs spectral and temporal sub-graphs along with a graph pooling strategy. (3) RawNet2 [8], which is a hybrid model combining CNN and GRU. (4) Spectrogram(Spec.)+ResNet [6], which transforms the audio to linear spectrogram using a 512-point Fast Fourier Transform (FFT) with a hop size of 10 ms. The spectrogram is then inputted into ResNet18 [33]. (5) LFCC-LCNN [10], which converts audio into Linear-Frequency Cepstral Coefficients (LFCC) for input into a CNN model. Specifically, 60-dimensional LFCCs are extracted from each utterance frame, with frame length set to 20ms and hop size 10ms. It extracts speech embedding directly from raw audio. These models collectively cover a broad spectrum of feature types and architectures, facilitating a detailed examination of their performance in deepfake audio

²<https://github.com/BytedanceSpeech/seed-tts-eval>

detection applications. For *foundation models*, SONAR includes (1) Wave2Vec2 [26], which is pre-trained on 53k hours of unlabeled speech data. (2) Wave2Vec2BERT [34], which is pre-trained on 4.5M hours of unlabeled speech data covering more than 143 languages. (3) HuBERT [35], which is pretrained on 60k hours of speech data. (4) CLAP [36], who is trained on a variety of audio-text pairs. (5) Whisper-small [37], and (6) Whisper-large [37]. Both Whispers are pre-trained on 680K hours of speech data covering 96 languages.

Public datasets for training and testing. We consider three benchmark datasets for deepfake audio detection model training and testing as they are commonly used in the literature [38, 39]. **Wavefake** [21] collects deepfake audios from six vocoder architectures, including MelGAN [40], FullBand-MelGAN, MultiBand-MelGAN [41], HiFi-GAN [42], Parallel WaveGAN [43], and WaveGlow [44]. It consists of approximately 196 hours of generated audio files derived from the LJSPEECH [45] dataset. Similar to wavefake, **LibriSeVoc** [22] collects deepfake audios from six state-of-the-art neural vocoders including WaveNet[46], WaveRNN [47], Mel-GAN [41], Parallel WaveGAN [43], WaveGrad [48] and DiffWave [49] to generate speech samples derived from the widely used LibriTTS speech corpus [32], which is often utilized in text-to-speech research. Specifically, it consists of a total of 208.74 hours of synthesized samples. **In-the-wild** [5] comprises genuine and deepfake audio recordings of 58 politicians and other public figures gathered from publicly accessible sources, including social networks and video streaming platforms.

For LibriSeVoc, we follow the official train-validation-test splits, which are approximately 60%, 20%, and 20%, respectively. For Wavefake, we partition the data generated by each vocoder into training, validation, and testing subsets at ratios of 70%, 10%, and 20%, respectively. To address the class imbalance and mitigate potential evaluation bias, we further downsample LibriSeVoc and WaveFake test datasets, and In-the-Wild datasets, resulting in a balanced dataset with a real-to-fake ratio of 1:1.

Evaluation metrics. To provide a comprehensive evaluation of the detection performance of audio deepfake models, we adopt (1) *Equal Error Rate* (EER), which is defined as the point on the ROC curve, where the false positive rate (FPR) and false negative rate (FNR) are equal and is commonly used to assess the performance of binary classifications tasks, with lower values indicating better detection performance. (2) *Accuracy* evaluates the overall correctness of the detection model’s predictions and is defined as the ratio of correctly predicted data to the total data. To ensure consistency with the EER and provide more intuitive results, we set the threshold for accuracy at the EER point, meaning the accuracy reflects the model’s performance when the FPR equals the FNR. (3) *AUROC* (Area Under the Receiver Operating Characteristic) provides a measure of the model’s ability to distinguish between classes across different decision thresholds, providing a more comprehensive view of its discriminative power across varying conditions. An AUROC score of 1.0 indicates perfect classification, while a score of 0.5 indicates performance no better than random guessing.

Note that the test datasets are class-balanced, and the accuracy score is calculated using the EER threshold. Thus, we omit F1, precision, and recall scores from our evaluation results in the paper, though SONAR provides these metrics as well.

4.2 Results and analysis

4.2.1 How well can detection models generalize across datasets?

We first train all models on Wavefake training dataset and then evaluate the models on its own test set, LibriSeVoc test set, and In-the-wild dataset. Table 2 presents the evaluation results. Particularly, we make the following interesting observations.

Speech foundation models exhibit stronger generalizability. As shown in Table 2, when evaluated on the test set of Wavefake, all models demonstrate near-perfect performance across the three metrics. This can be attributed to the similarity between the test set and the training data. However, when tested on the LibriSeVoc and In-the-wild datasets, models such as LFCC-LCNN, Spec.+ResNet, RawNet2, RawGATST, and AASIST struggle to generalize effectively. This performance gap indicates significant overfitting to the training data, despite these models being specifically designed for audio deepfake detection tasks. In contrast, speech foundation models consistently display stronger generalizability. Notably, Wave2Vec2BERT achieves the highest generalizability, which may be attributed to its large-scale and diverse pretraining data. Pretrained on 4.5 million hours of unlabeled audio in more than 143 languages, Wave2Vec2BERT benefits from both scale and diversity. This suggests that a well-designed self-supervised model trained on diverse speech data can extract

Table 2: Generalization across existing audio deepfake datasets. All models are trained/finetuned on the Wavefake training set. Green and orange indicate the best and second-best performance, respectively.

Model	Wavefake			LibriSeVoc			In-the-wild		
	Accuracy	AUROC	EER(%)	Accuracy	AUROC	EER(%)	Accuracy	AUROC	EER(%)
LFCC-LCNN	0.9984	0.9999	0.153	0.7429	0.8239	25.71	0.5	0.4786	99.2
Spec.+ResNet	0.9924	0.9924	0.076	0.7577	0.8495	24.233	0.4685	0.4723	53.148
RawNet2	0.9416	0.9592	5.839	0.5119	0.5332	48.807	0.5321	0.5393	46.792
RawGATST	0.9988	0.9999	0.115	0.8307	0.9203	16.925	0.6418	0.7015	35.816
AASIST	0.9992	0.9999	0.076	0.886	0.9534	11.397	0.7272	0.7975	27.277
CLAP	0.9996	0.9999	0.038	0.8296	0.9019	24.763	0.3013	0.2252	69.871
Whisper-small	0.9935	0.9997	0.649	0.9345	0.9837	6.551	0.821	0.9025	17.899
Whisper-large	0.9962	0.9992	0.381	0.9572	0.9901	4.279	0.8848	0.9552	11.518
Wave2Vec2	0.9874	0.9987	1.259	0.9705	0.9953	2.953	0.8733	0.9323	12.669
HuBERT	0.9931	0.9996	0.687	0.986	0.9991	1.401	0.9164	0.9653	8.362
Wave2Vec2BERT	0.9996	0.9999	0.038	0.9902	0.9991	0.984	0.9232	0.979	7.676

general and discriminative features, making it more applicable across different datasets for audio deepfake detection. It is important to note that CLAP, unlike other speech foundation models, does not generalize well across datasets. This is likely due to its primary focus on environmental audio data during pretraining, resulting in the extraction of irrelevant features for speech audio. This observation underscores that not all foundation models are equally suited for audio deepfake detection tasks.

Generalizability may increase with model size. In Table 2, it can be observed that Whisper-large always outperforms Whisper-small across all three datasets. In particular, on the LibriSeVoc test set, Whisper-large achieves accuracy, AUROC, and EER of 0.9572, 0.9901, 4.279%, respectively, which improves by 2.27%, 0.64%, and 2.272%, than that of Whisper-small. This trend is more evident in the In-the-wild dataset, which is closer to real-world scenarios since this dataset consists of speech data sourced from the internet. Specifically, Whisper-large achieves accuracy, AUROC, and EER of 0.8848, 0.9552, and 11.518%, respectively, which improves by 6.381%, 5.27%, and 6.381%, than that of Whisper-small. Further investigation will be made in Section 4.2.3

4.2.2 Results on SONAR dataset

We further evaluate all detection models on the proposed dataset. Table 3a, Table 3b, and Table 3c present the accuracy, AUROC, and EER of different detection models on our proposed SONAR dataset as described in Sec 3.

Speech foundation models can better generalize on the SONAR dataset, but still not good enough. As presented in Table 3a, speech foundation models again exhibit better generalizability on the fake audio samples generated by the latest TTS models. For instance, AASIST achieves 0.6975 average accuracy across audios generated by cutting-edge TTS models, which is the best performance among the traditional detection models. In contrast, speech foundation models Whisper-large, Wave2Vec2, HuBERT, and Wave2Vec2BERT achieve an average accuracy of 0.7322, 0.788, 0.8789, and 0.8989, respectively, which is higher than AASIST by 3.47%, 9.05%, 18.14%, and 20.14%, respectively. More specifically, even though Wave2Vec2BERT and HuBERT are only fine-tuned on Wavefake dataset, for PromptTTS2, VALL-E, VoiceBox, FalshSpeech, AudioGen, and xTTS, Wave2Vec2BERT can reach accuracies of 1.0, 0.9062, 0.9474, 0.9712, 0.9237, 0.97, and 0.9867, respectively, and HuBERT can achieve 1.0, 0.9158, 0.9712, 0.9407, 1.0 0.8767, and 0.89, respectively, demonstrating their potential capability of extract more distinguishable features compared to other models. It is also worth noting that Wave2Vec2BERT achieves an accuracy of 0.9062 on NaturalSpeech3, while all other models can only reach that ≤ 0.75 .

It is still challenging for detection models to correctly classify synthesized audio samples, especially those generated by the most advanced TTS service providers. While Wave2Vec2BERT achieves an overall average accuracy of 0.8989, it only reaches 0.6017 on Seed-TTS and 0.7833 on OpenAI. A similar pattern is also evident with HuBERT, Wave2Vec2, Whisper-large, and Whisper-small, which achieve just 0.5658, 0.4342, 0.29, and 0.1883 accuracy on OpenAI, respectively. This performance disparity is likely due to OpenAI and Seed-TTS having more advanced model architectures and being trained on proprietary, self-collected data, leading to higher-quality and more realistic speech generation. We will explore potential strategies to enhance their detection performance in Section 4.2.4. Overall, these results not only indicate that no single model consistently

Table 3: Evaluation on SONAR dataset. Green and orange indicate the best and second-best performance, respectively.

(a) Accuracy (\uparrow).

Model	PromptTTS2	NaturalSpeech3	VALL-E	VoiceBox	FlashSpeech	AudioGen	xTTS	Seed-TTS	OpenAI	Average
LFCC-LCNN	0.5200	0.7500	0.6211	0.8462	0.7034	0.4600	0.7433	0.3058	0.5000	0.6055
Spec.+ResNet	0.5600	0.5000	0.5684	0.5481	0.6356	0.6800	0.8450	0.4167	0.6783	0.6036
RawNet2	0.6800	0.3125	0.4211	0.5385	0.4915	0.2600	0.6533	0.3733	0.3500	0.4534
RawGATST	0.8000	0.5312	0.6842	0.8173	0.5424	0.2400	0.6567	0.5833	0.4900	0.5939
AASIST	0.8400	0.5312	0.7789	0.8750	0.6610	0.6900	0.7300	0.6567	0.5150	0.6975
CLAP	0.5600	0.4688	0.6421	0.5288	0.6017	0.2500	0.4800	0.4000	0.3233	0.4727
Whisper-small	0.8800	0.5625	0.7158	0.7404	0.5678	0.8000	0.8050	0.5983	0.1883	0.6509
Whisper-large	1.0000	0.6562	0.7895	0.7885	0.7288	0.8400	0.9033	0.5933	0.2900	0.7322
Wave2Vec2	0.9600	0.6875	0.8210	0.9327	0.8136	0.9900	0.7333	0.8683	0.5175	0.8138
HuBERT	1.0000	0.7500	0.9158	0.9712	0.9407	1.0000	0.8767	0.8900	0.5658	0.8789
Wave2Vec2BERT	1.0000	0.9062	0.9474	0.9712	0.9237	0.9700	0.9867	0.6017	0.7833	0.8989

(b) AUROC (\uparrow).

Model	PromptTTS2	NaturalSpeech3	VALL-E	VoiceBox	FlashSpeech	AudioGen	xTTS	Seed-TTS	OpenAI	Average
LFCC-LCNN	0.5696	0.7666	0.6967	0.9106	0.7945	0.4559	0.8163	0.2452	0.0967	0.5947
Spec.+ResNet	0.6064	0.4941	0.6217	0.5858	0.6891	0.7293	0.9205	0.4003	0.7450	0.6436
RawNet2	0.6944	0.2422	0.3695	0.6210	0.5203	0.3030	0.7210	0.3120	0.2940	0.4530
RawGATST	0.8704	0.5439	0.7490	0.8989	0.5742	0.2050	0.7317	0.6065	0.4795	0.6288
AASIST	0.9248	0.6172	0.8479	0.9433	0.7485	0.7466	0.8265	0.6893	0.5259	0.7633
CLAP	0.5712	0.4434	0.7223	0.5155	0.6533	0.1777	0.5114	0.3544	0.2407	0.4655
Whisper-small	0.9776	0.5762	0.8050	0.8400	0.6446	0.8284	0.8915	0.6326	0.108	0.7004
Whisper-large	1.0000	0.6992	0.9063	0.8552	0.7933	0.8926	0.9690	0.6558	0.2327	0.7782
Wave2Vec2	0.9952	0.7515	0.8751	0.9674	0.8438	0.9987	0.7931	0.9205	0.4881	0.8482
HuBERT	1.0000	0.8174	0.9719	0.9953	0.9871	1.0000	0.9496	0.9531	0.5585	0.9148
Wave2Vec2BERT	1.0000	0.9658	0.9860	0.9906	0.9666	0.9826	0.9980	0.6165	0.8607	0.9290

(c) EER(%) (\downarrow).

Model	PromptTTS2	NaturalSpeech3	VALL-E	VoiceBox	FlashSpeech	AudioGen	xTTS	Seed-TTS	OpenAI	Average
LFCC-LCNN	48.000	25.000	37.895	15.385	29.661	54.000	25.667	69.5	99.333	44.938
Spec.+ResNet	44.000	50.000	43.158	45.192	36.441	32.000	15.500	58.333	32.167	39.643
RawNet2	32.000	68.750	57.895	46.154	50.848	74.000	34.667	62.667	65.000	54.665
RawGATST	20.000	46.875	31.580	18.269	45.763	76.000	34.330	41.667	51.000	40.609
AASIST	16.000	46.875	22.105	12.500	33.898	31.000	27.000	34.333	48.500	30.246
CLAP	44.000	53.125	35.789	47.115	39.831	75.000	52.000	60.000	67.667	52.725
Whisper-small	12.000	43.750	28.421	25.962	43.220	20.000	19.500	40.167	81.167	34.910
Whisper-large	0.000	34.375	21.053	21.154	27.119	16.000	9.667	40.667	71.000	26.782
Wave2Vec2	4.000	31.250	17.895	6.731	18.644	1.000	26.667	13.167	48.333	18.632
HuBERT	0.000	25.000	8.421	2.885	5.932	0.000	12.333	11.000	43.500	12.119
Wave2Vec2BERT	0.000	9.375	5.263	2.885	7.627	3.000	1.333	39.833	21.667	10.109

outperforms across all datasets but also underscore the ongoing difficulty in detecting synthesized audio from cutting-edge TTS systems, especially those developed by the most advanced TTS service providers. This highlights a huge gap between the rapid evolution of TTS technologies and the effectiveness of current audio deepfake detection methods, emphasizing the urgent need for the development of more robust and reliable detection algorithms.

Additionally, it is noteworthy that, compared to speech foundation models, the accuracy of all five traditional detection models on the AudioGen dataset, which consists of synthesized environmental sounds, remains relatively low. Specifically, LFCC-LCNN, Spec.+ResNet, RawNet2, RawGATST, and AASIST achieve accuracies of 0.46, 0.68, 0.26, 0.24, and 0.69, respectively. In contrast, Whisper-small, Whisper-large, Wave2Vec2, HuBERT, and Wave2VecBERT attain significantly higher accuracies of 0.8, 0.84, 0.99, 1.0, and 0.97, respectively. This discrepancy may be due to traditional detection models being trained exclusively on speech data, which limits their generalization to audio from different distributions. In comparison, foundation models demonstrate greater robustness to out-of-distribution audio samples. An exception to this is CLAP, which is an audio foundation model pre-trained on a variety of environmental audio-text pairs and only achieves an accuracy of 0.25 on AudioGen. Similar to previous results, it's possibly due to the fact that its full-weight fine-tuning on speech data may have compromised its ability to effectively recognize environmental sounds, resulting in poor performance.

4.2.3 Can generalizability increase with model size?

Building on the observation that Whisper-large consistently outperforms Whisper-small, we extend our analysis with controlled experiments on the entire Whisper model family. Specifically, the Whisper family comprises five different model sizes: Whisper-tiny, Whisper-base, Whisper-small,

Table 5: Generalization across existing audio deepfake datasets. All Whisper models are trained/fine-tuned on the Wavefake training set. Green and orange indicate the best and second-best performance, respectively.

Model	Wavefake			LibriSeVoc			In-the-wild		
	Accuracy	AUROC	EER(%)	Accuracy	AUROC	EER(%)	Accuracy	AUROC	EER(%)
Whisper-tiny	0.9839	0.9985	1.603	0.8557	0.9307	14.426	0.498	0.5	50.203
Whisper-base	0.9908	0.9996	0.916	0.9163	0.9734	8.368	0.7398	0.8124	26.024
Whisper-small	0.9935	0.9997	0.649	0.9345	0.9837	6.551	0.821	0.9025	17.899
Whisper-medium	0.9962	0.9999	0.381	0.944	0.985	5.604	0.8572	0.9288	14.277
Whisper-large	0.9962	0.9992	0.381	0.9572	0.9901	4.279	0.8848	0.9552	11.518

Whisper-medium, and Whisper-large. Table 4 presents the number of model parameters of them. Specifically, each model is fine-tuned on the Wavefake training dataset using the same hyperparameters. Our results show that as model size increases, the generalizability of the models improves as well.

Table 5 presents the detection performance of the Whisper models across the Wavefake, LibriSeVoc, and In-the-wild datasets. First, Whisper-tiny, despite its smaller size, still outperforms or achieves comparable detection performance to traditional detection models (recall Table 2) on the LibriSeVoc test set. This again validates the finding that foundation models exhibit stronger generalizability for audio deepfake detection tasks, even in their smallest configurations.

Second, as the model size increases from Whisper-tiny to Whisper-large, both accuracy and AUROC improve significantly across the LibriSeVoc and In-the-wild datasets. Whisper-large achieves an accuracy of 95.72% and an AUROC of 0.9901 on LibriSeVoc, surpassing Whisper-tiny by 10.07% in accuracy. A more evident pattern can be observed on the In-the-wild dataset, where Whisper-large outperforms Whisper-tiny by 38.48% in accuracy. Furthermore, the Equal Error Rate (EER) decreases as the model size increases, indicating that larger models are not only more accurate but also better at minimizing both false positives and false negatives.

Table 4: Whisper model sizes.

Model	#Params
Whisper-tiny	39M
Whisper-base	74M
Whisper-small	244M
Whisper-medium	769M
Whisper-large	1550M

Table 6: Evaluation on SONAR dataset. Green and orange indicate the best and second-best performance, respectively.

(a) Accuracy (\uparrow).

Model	PromptTTS2	NaturalSpeech3	VALL-E	VoiceBox	FlashSpeech	AudioGen	xTTS	Seed-TTS	OpenAI	Average
Whisper-tiny	0.8000	0.3438	0.6947	0.6442	0.4661	0.73	0.6517	0.5067	0.0833	0.5467
Whisper-base	0.8400	0.4375	0.6947	0.6731	0.6017	0.6800	0.6550	0.4800	0.1117	0.5749
Whisper-small	0.8800	0.5625	0.7158	0.7404	0.5678	0.8000	0.8050	0.5983	0.1883	0.6509
Whisper-medium	0.96	0.6250	0.7895	0.8077	0.7119	0.8000	0.8400	0.5517	0.2183	0.7005
Whisper-large	1.000	0.6562	0.7895	0.7885	0.7288	0.8400	0.9033	0.5933	0.2900	0.7322

(b) AUROC (\uparrow).

Model	PromptTTS2	NaturalSpeech3	VALL-E	VoiceBox	FlashSpeech	AudioGen	xTTS	Seed-TTS	OpenAI	Average
Whisper-tiny	0.9136	0.2998	0.7436	0.7144	0.4886	0.7660	0.7239	0.5033	0.0454	0.5776
Whisper-base	0.9296	0.4326	0.7512	0.7482	0.6548	0.7505	0.7167	0.5152	0.041	0.6155
Whisper-small	0.9776	0.5762	0.8050	0.8400	0.6446	0.8284	0.8915	0.6326	0.108	0.7004
Whisper-medium	0.9984	0.6279	0.886	0.8578	0.7950	0.8640	0.9215	0.5858	0.1567	0.7437
Whisper-large	1.0000	0.6992	0.9063	0.8552	0.7933	0.8926	0.969	0.6558	0.2327	0.7782

(c) EER(%) (\downarrow).

Model	PromptTTS2	NaturalSpeech3	VALL-E	VoiceBox	FlashSpeech	AudioGen	xTTS	Seed-TTS	OpenAI	Average
Whisper-tiny	20.000	65.625	30.526	35.577	53.390	27.000	34.833	49.333	91.667	45.328
Whisper-base	16.000	56.250	30.526	32.692	36.831	32.000	34.500	52.000	88.833	42.811
Whisper-small	12.000	43.750	28.421	25.962	43.220	20.000	19.500	40.667	81.167	34.965
Whisper-medium	4.000	37.500	21.053	19.231	28.814	20.000	16.000	44.833	78.167	29.955
Whisper-large	0.000	34.375	21.053	21.154	27.119	16.000	9.667	40.167	71.000	26.726

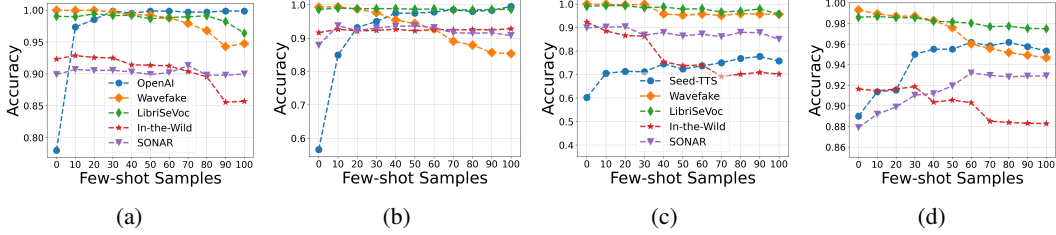


Figure 2: Performance of few-shot fine-tuning for Wave2Vec2BERT and HuBERT with a varying number of few-shot audio samples from OpenAI and Seed-TTS, respectively. (a) Fine-tune Wave2Vec2BERT on OpenAI. (b) Fine-tune HuBERT on OpenAI; (c) Fine-tune Wave2Vec2BERT on Seed-TTS; and (d) Fine-tune HuBERT on Seed-TTS.

We also evaluate the Whisper family on the proposed SONAR dataset. Table 6a, Table 6b, Table 6c present the corresponding Accuracy, AUROC, and EER(%). A similar trend can also be observed. In Table 6a, the accuracy of the Whisper models shows a clear upward trend as the model size increases from Whisper-tiny to Whisper-large. Whisper-tiny achieves an average accuracy of 0.5467, while Whisper-large reaches the highest average accuracy of 0.7322. Notably, Whisper-large performs best on almost all datasets, particularly with TTS models such as PromptTTS2, NaturalSpeech3, VALL-E, and OpenAI, highlighting its better generalizability. Additionally, Whisper-large’s performance is higher on challenging datasets like Seed-TTS and OpenAI, which are known for their high-quality synthesis. The smaller models (e.g., Whisper-tiny and Whisper-base), on the other hand, struggle to generalize effectively, particularly on datasets such as OpenAI, where the accuracy drops to 0.0833 for Whisper-tiny.

The results highlight the scalability of the Whisper models: larger models demonstrate better generalization across diverse test sets, underscoring the importance of model capacity in tackling challenging out-of-distribution data, such as audio generated by advanced TTS models.

4.2.4 On the effectiveness and efficiency of few-shot fine-tuning to improve generalization

Despite the challenges in generalizing across different datasets, we investigate whether there exist efficient solutions that can enhance models’ detection performance on those challenging subsets from SONAR dataset. To this end, we conduct a case study on Wave2Vec2BERT and HuBERT, as these models perform relatively poorly on the OpenAI and SeedTTS datasets but demonstrate competitive performance on other subsets. Specifically, we generate 100 additional fake audio samples using the OpenAI TTS API and randomly select another 100 fake audio samples from the SeedTTS test set for few-shot fine-tuning. Our study yields several interesting findings.

Figures 2a and 2b present the results of fine-tuning Wave2Vec2BERT and HuBERT using varying numbers of samples from OpenAI. Before fine-tuning, Wave2Vec2BERT and HuBERT only achieve accuracies of 0.7833 and 0.5658, respectively. Notably, with only 10 shots of fake speech data, Wave2Vec2BERT reaches an accuracy of approximately 0.97, while HuBERT’s accuracy increases significantly to approximately 0.85. Importantly, the models’ generalization to other datasets remains unchanged, demonstrating the effectiveness and efficiency of few-shot fine-tuning. However, as the number of fine-tuning samples increases, HuBERT’s test accuracy on the WaveFake test set shows a declining trend, which is also observed for Wave2Vec2BERT.

It is important to note, however, that the efficiency and effectiveness of few-shot fine-tuning may vary across different datasets. As illustrated in Figures 2c and 2d, which depict the fine-tuning results for Wave2Vec2BERT and HuBERT on Seed-TTS, the improvement in accuracy is less pronounced compared to the results on the OpenAI dataset. While the accuracy of both Wave2Vec2BERT and HuBERT does improve on Seed-TTS, the gains are not as significant as those observed for the OpenAI dataset. Additionally, the detection performance on other datasets decreases more noticeably when fine-tuning on Seed-TTS compared to OpenAI.

These findings suggest that the effectiveness of few-shot fine-tuning may depend on the specific characteristics of the dataset. Moreover, this also highlights its potential for tailored applications, such as personalized detection systems for a specific entity or individual, to enable more customized and practical applications.

5 Discussion

AI-synthesized audio detection methods must be evaluated on diverse and advanced benchmarks.

In our evaluation using the proposed dataset, most models perform well on standard TTS tools but suffer significant degradation when tested on the fake audios generated by the most advanced tool such as Voice Engine released by OpenAI. Therefore, we advocate for future research in audio deepfake detection to prioritize benchmarking against the latest and most advanced TTS technologies, which will lead to more robust and reliable detectors, as relying on high detection rates from outdated tools may create a false sense of generalization. Additionally, there is an urgent need to develop larger-scale training datasets comprising fake audio generated by cutting-edge TTS models to keep pace with rapid advancements in TTS technology and mitigate associated risks.

Limitations and future work. While our primary goal in proposing this dataset is to facilitate comprehensive evaluation, it remains relatively small in size and is primarily focused on English. A more in-depth analysis of detection performance across different languages and gender representations is crucial for a more comprehensive evaluation. These aspects are essential for future research to enhance the dataset’s applicability and generalizability. For future work, we also plan to: (1) incorporate additional AI-audio detection models, including those targeting advanced audio editing techniques designed to bypass detection systems; (2) explore innovative methods to further improve generalizability; and (3) address realistic challenges and risks in deploying the proposed method in real-world scenarios, such as evaluating the robustness of models against common or adversarial corruptions. These efforts will contribute to the development of more effective strategies to combat AI-generated audio threats.

Data license considerations. Since our dataset is sourced from various models, each may be subject to different distribution licenses and usage restrictions. Throughout the data collection process, we ensured strict adherence to all relevant usage policies. We have also made the dataset accessible to everyone, either directly via the provided link or indirectly through the original sources. However, as these policies are frequently refined and updated, we will ensure that our published dataset remains in full compliance with the latest regulations. Additionally, we will reference the usage policies of the respective API providers to ensure that users are informed of any potential restrictions.

6 Conclusion

In this paper, we presented SONAR, a framework providing a comprehensive evaluation for distinguishing state-of-the-art AI-synthesized auditory content. SONAR introduces a novel evaluation dataset sourced from 9 diverse audio synthesis platforms, including leading TTS service providers and state-of-the-art TTS models. To the best of our knowledge, SONAR is the first platform that provides uniform, comprehensive, informative, and extensible evaluation of deepfake audio detection models. Leveraging SONAR, we conducted extensive experiments to analyze the generalizability limitations of current detection methods. We found that foundation models demonstrate stronger generalization capabilities, given their massive model size scale and pertaining data. We further explored the potential of few-shot fine-tuning to improve generalization and demonstrated its efficiency and effectiveness. We envision that SONAR will serve as a valuable benchmark to facilitate research in AI-audio detection and highlight directions for further improvement.

References

- [1] Apoorv Vyas, Bowen Shi, Matthew Le, Andros Tjandra, Yi-Chiao Wu, Baishan Guo, Jiemin Zhang, Xinyue Zhang, Robert Adkins, William Ngan, et al. Audiobox: Unified audio generation with natural language prompts. *arXiv preprint arXiv:2312.15821*, 2023.
- [2] Zhen Ye, Zeqian Ju, Haohe Liu, Xu Tan, Jianyi Chen, Yiwen Lu, Peiwen Sun, Jiahao Pan, Weizhen Bian, Shulin He, et al. Flashspeech: Efficient zero-shot speech synthesis. *arXiv preprint arXiv:2404.14700*, 2024.
- [3] 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 *International Conference on Machine Learning*, pages 2709–2720. PMLR, 2022.
- [4] Chengyi Wang, Sanyuan Chen, Yu Wu, Ziqiang Zhang, Long Zhou, Shujie Liu, Zhuo Chen, Yanqing Liu, Huaming Wang, Jinyu Li, et al. Neural codec language models are zero-shot text to speech synthesizers. *arXiv preprint arXiv:2301.02111*, 2023.

- [5] Nicolas M Müller, Pavel Czempin, Franziska Dieckmann, Adam Froghyar, and Konstantin Böttinger. Does audio deepfake detection generalize? *arXiv preprint arXiv:2203.16263*, 2022.
- [6] Yongyi Zang, You Zhang, Mojtaba Heydari, and Zhiyao Duan. Singfake: Singing voice deepfake detection. In *ICASSP 2024-2024 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 12156–12160. IEEE, 2024.
- [7] 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 2022-2022 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pages 6367–6371. IEEE, 2022.
- [8] Hemlata Tak, Jose Patino, Massimiliano Todisco, Andreas Nautsch, Nicholas Evans, and Anthony Larcher. End-to-end anti-spoofing with rawnet2. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6369–6373. IEEE, 2021.
- [9] Hemlata Tak, Jee-weon Jung, Jose Patino, Madhu Kamble, Massimiliano Todisco, and Nicholas Evans. End-to-end spectro-temporal graph attention networks for speaker verification anti-spoofing and speech deepfake detection. *arXiv preprint arXiv:2107.12710*, 2021.
- [10] Galina Lavrentyeva, Sergey Novoselov, Andzhukaev Tseren, Marina Volkova, Artem Gorlanov, and Alexandr Kozlov. Stc antispoofing systems for the asvspoof2019 challenge. *arXiv preprint arXiv:1904.05576*, 2019.
- [11] Matthew Le, Apoorv Vyas, Bowen Shi, Brian Karrer, Leda Sari, Rashel Moritz, Mary Williamson, Vimal Manohar, Yossi Adi, Jay Mahadeokar, et al. Voicebox: Text-guided multilingual universal speech generation at scale. *Advances in neural information processing systems*, 36, 2024.
- [12] Jonathan Shen, Ruoming Pang, Ron J Weiss, Mike Schuster, Navdeep Jaitly, Zongheng Yang, Zhifeng Chen, Yu Zhang, Yuxuan Wang, Rj Skerrv-Ryan, et al. Natural tts synthesis by conditioning wavenet on mel spectrogram predictions. In *2018 IEEE international conference on acoustics, speech and signal processing (ICASSP)*, pages 4779–4783. IEEE, 2018.
- [13] Yi Ren, Yangjun Ruan, Xu Tan, Tao Qin, Sheng Zhao, Zhou Zhao, and Tie-Yan Liu. FastSpeech: Fast, robust and controllable text to speech. *Advances in neural information processing systems*, 32, 2019.
- [14] Naihan Li, Shujie Liu, Yanqing Liu, Sheng Zhao, and Ming Liu. Neural speech synthesis with transformer network. In *Proceedings of the AAAI conference on artificial intelligence*, volume 33, pages 6706–6713, 2019.
- [15] Jaehyeon Kim, Jungil Kong, and Juhee Son. Conditional variational autoencoder with adversarial learning for end-to-end text-to-speech. In *International Conference on Machine Learning*, pages 5530–5540. PMLR, 2021.
- [16] Yanqing Liu, Ruiqing Xue, Lei He, Xu Tan, and Sheng Zhao. Delightfultts 2: End-to-end speech synthesis with adversarial vector-quantized auto-encoders. *arXiv preprint arXiv:2207.04646*, 2022.
- [17] Erica Cooper, Cheng-I Lai, Yusuke Yasuda, Fuming Fang, Xin Wang, Nanxin Chen, and Junichi Yamagishi. Zero-shot multi-speaker text-to-speech with state-of-the-art neural speaker embeddings. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6184–6188. IEEE, 2020.
- [18] Zhizheng Wu, Junichi Yamagishi, Tomi Kinnunen, Cemal Hanilçi, Mohammed Sahidullah, Aleksandr Sizov, Nicholas Evans, Massimiliano Todisco, and Hector Delgado. Asvspoof: the automatic speaker verification spoofing and countermeasures challenge. *IEEE Journal of Selected Topics in Signal Processing*, 11(4):588–604, 2017.
- [19] Andreas Nautsch, Xin Wang, Nicholas Evans, Tomi H Kinnunen, Ville Vestman, Massimiliano Todisco, Héctor Delgado, Md Sahidullah, Junichi Yamagishi, and Kong Aik Lee. Asvspoof 2019: spoofing countermeasures for the detection of synthesized, converted and replayed speech. *IEEE Transactions on Biometrics, Behavior, and Identity Science*, 3(2):252–265, 2021.
- [20] Massimiliano Todisco, Xin Wang, Ville Vestman, Md Sahidullah, Héctor Delgado, Andreas Nautsch, Junichi Yamagishi, Nicholas Evans, Tomi Kinnunen, and Kong Aik Lee. Asvspoof 2019: Future horizons in spoofed and fake audio detection. *arXiv preprint arXiv:1904.05441*, 2019.
- [21] Joel Frank and Lea Schönherr. Wavefake: A data set to facilitate audio deepfake detection. *arXiv preprint arXiv:2111.02813*, 2021.
- [22] Chengzhe Sun, Shan Jia, Shuwei Hou, and Siwei Lyu. Ai-synthesized voice detection using neural vocoder artifacts. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 904–912, 2023.
- [23] Xin Wang and Junichi Yamagishi. Investigating self-supervised front ends for speech spoofing countermeasures. *arXiv preprint arXiv:2111.07725*, 2021.

- [24] 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. *arXiv preprint arXiv:2202.12233*, 2022.
- [25] Piotr Kawa, Marcin Plata, Michał Czuba, Piotr Szymański, and Piotr Syga. Improved deepfake detection using whisper features. *arXiv preprint arXiv:2306.01428*, 2023.
- [26] Alexei Baevski, 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*, 33:12449–12460, 2020.
- [27] Edresson Casanova, Kelly Davis, Eren Gölge, Görkem Gökner, Iulian Gulea, Logan Hart, Aya Aljafari, Joshua Meyer, Reuben Morais, Samuel Olayemi, et al. Xtts: a massively multilingual zero-shot text-to-speech model. *arXiv preprint arXiv:2406.04904*, 2024.
- [28] Felix Kreuk, Gabriel Synnaeve, Adam Polyak, Uriel Singer, Alexandre Défossez, Jade Copet, Devi Parikh, Yaniv Taigman, and Yossi Adi. Audiogen: Textually guided audio generation. *arXiv preprint arXiv:2209.15352*, 2022.
- [29] Philip Anastassiou, Jiawei Chen, Jitong Chen, Yuanzhe Chen, Zhuo Chen, Ziyi Chen, Jian Cong, Lelai Deng, Chuang Ding, Lu Gao, et al. Seed-tts: A family of high-quality versatile speech generation models. *arXiv preprint arXiv:2406.02430*, 2024.
- [30] Yichong Leng, Zhifang Guo, Kai Shen, Xu Tan, Zeqian Ju, Yanqing Liu, Yufei Liu, Dongchao Yang, Leying Zhang, Kaitao Song, et al. Prompttts 2: Describing and generating voices with text prompt. *arXiv preprint arXiv:2309.02285*, 2023.
- [31] Zeqian Ju, Yuancheng Wang, Kai Shen, Xu Tan, Detai Xin, Dongchao Yang, Yanqing Liu, Yichong Leng, Kaitao Song, Siliang Tang, et al. Naturalspeech 3: Zero-shot speech synthesis with factorized codec and diffusion models. *arXiv preprint arXiv:2403.03100*, 2024.
- [32] Heiga Zen, Viet Dang, Rob Clark, Yu Zhang, Ron J Weiss, Ye Jia, Zhifeng Chen, and Yonghui Wu. Libritts: A corpus derived from librispeech for text-to-speech. *arXiv preprint arXiv:1904.02882*, 2019.
- [33] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.
- [34] Loïc Barrault, Yu-An Chung, Mariano Coria Meglioli, David Dale, Ning Dong, Mark Duppenthaler, Paul-Ambroise Duquenne, Brian Ellis, Hady Elsahar, Justin Haaheim, et al. Seamless: Multilingual expressive and streaming speech translation. *arXiv preprint arXiv:2312.05187*, 2023.
- [35] Wei-Ning Hsu, Benjamin Bolte, Yao-Hung Hubert Tsai, Kushal Lakhota, Ruslan Salakhutdinov, and Abdelrahman Mohamed. Hubert: Self-supervised speech representation learning by masked prediction of hidden units. *IEEE/ACM transactions on audio, speech, and language processing*, 29:3451–3460, 2021.
- [36] Benjamin Elizalde, Soham Deshmukh, Mahmoud Al Ismail, and Huaming Wang. Clap learning audio concepts from natural language supervision. In *ICASSP 2023-2023 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 1–5. IEEE, 2023.
- [37] Alec Radford, Jong Wook Kim, Tao Xu, Greg Brockman, Christine McLeavey, and Ilya Sutskever. Robust speech recognition via large-scale weak supervision. In *International conference on machine learning*, pages 28492–28518. PMLR, 2023.
- [38] Piotr Kawa, Marcin Plata, and Piotr Syga. Specrnet: Towards faster and more accessible audio deepfake detection. In *2022 IEEE International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom)*, pages 792–799. IEEE, 2022.
- [39] Piotr Kawa, Marcin Plata, and Piotr Syga. Attack agnostic dataset: Towards generalization and stabilization of audio deepfake detection. *arXiv preprint arXiv:2206.13979*, 2022.
- [40] Kundan Kumar, Rithesh Kumar, Thibault De Boissiere, Lucas Gestin, Wei Zhen Teoh, Jose Sotelo, Alexandre De Brebisson, Yoshua Bengio, and Aaron C Courville. Melgan: Generative adversarial networks for conditional waveform synthesis. *Advances in neural information processing systems*, 32, 2019.
- [41] Geng Yang, Shan Yang, Kai Liu, Peng Fang, Wei Chen, and Lei Xie. Multi-band melgan: Faster waveform generation for high-quality text-to-speech. In *2021 IEEE Spoken Language Technology Workshop (SLT)*, pages 492–498. IEEE, 2021.
- [42] Jungil Kong, Jaehyeon Kim, and Jaekyoung Bae. Hifi-gan: Generative adversarial networks for efficient and high fidelity speech synthesis. *Advances in neural information processing systems*, 33:17022–17033, 2020.
- [43] Ryuichi Yamamoto, Eunwoo Song, and Jae-Min Kim. Parallel wavegan: A fast waveform generation model based on generative adversarial networks with multi-resolution spectrogram. In *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 6199–6203. IEEE, 2020.

- [44] Ryan Prenger, Rafael Valle, and Bryan Catanzaro. Waveglow: A flow-based generative network for speech synthesis. In *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 3617–3621. IEEE, 2019.
- [45] Keith Ito and Linda Johnson. The lj speech dataset. <https://keithito.com/LJ-Speech-Dataset/>, 2017.
- [46] Aaron Van Den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, Koray Kavukcuoglu, et al. Wavenet: A generative model for raw audio. *arXiv preprint arXiv:1609.03499*, 12, 2016.
- [47] Nal Kalchbrenner, Erich Elsen, Karen Simonyan, Seb Noury, Norman Casagrande, Edward Lockhart, Florian Stimberg, Aaron Oord, Sander Dieleman, and Koray Kavukcuoglu. Efficient neural audio synthesis. In *International Conference on Machine Learning*, pages 2410–2419. PMLR, 2018.
- [48] Nanxin Chen, Yu Zhang, Heiga Zen, Ron J Weiss, Mohammad Norouzi, and William Chan. Wavegrad: Estimating gradients for waveform generation. *arXiv preprint arXiv:2009.00713*, 2020.
- [49] Zhifeng Kong, Wei Ping, Jiaji Huang, Kexin Zhao, and Bryan Catanzaro. Diffwave: A versatile diffusion model for audio synthesis. *arXiv preprint arXiv:2009.09761*, 2020.

A Appendix

A.1 Broad Impacts

Societal Risks. The rapid advancement of AI-generated content (AIGC) in audio and speech poses significant societal risks as it becomes more prevalent in audio and speech generation. As our work in benchmarking AI-synthesized audio detection demonstrates, the line between AI-generated audio and human speech is increasingly blurring, making it difficult for individuals to distinguish between synthetic and authentic voices. This raises serious concerns about spreading misinformation and fabricating narratives. AI-generated speeches could be used to impersonate public figures, spread false information, or even incite unrest by delivering provocative messages that appear authentic. For example, deepfake audios of political figures can be created to falsely represent their opinions or statements, potentially influencing public perception and affecting democratic processes.

Moreover, these technologies could be exploited to damage reputations or cause legal issues for individuals or organizations through fake endorsements or harmful statements. It is crucial for academia and industry to develop robust detection methods and ethical guidelines to prevent misuse of this technology and to educate the public about its capabilities and associated risks.

Positive Impacts. On the positive side, AI-synthesized audio/speech has the potential to revolutionize content creation in various sectors, including education, entertainment, and accessibility. In education, AI-synthesized audios and speeches enables production of customized content that meets diverse learning needs and languages, improving access and inclusivity. For entertainment, they can offer novel experiences by generating dynamic dialogues in games or virtual reality, enriching user engagement and creativity.

Furthermore, AI-synthesized audios and speeches also enhances accessibility by producing speech in various languages or dialects, bridging communication gaps and making information more accessible to non-native speakers or those with liabilities. Additionally, the technology can help preserve lesser-spoken languages and dialects at risk of extinction by creating archives of AI-generated speeches and narratives.

In conclusion, while AI-synthesized audios and speeches offer exciting opportunities for content creation and accessibility, it is essential to address the ethical and societal challenges associated with its use. Collaborative efforts among researchers, developers, and policymakers are crucial to leveraging AI-synthesized audio and speech benefits responsibly while mitigating its risks, ensuring the technology serves to enhance human communication and creativity positively and responsibly.

A.2 Implementation Details

Table 7 presents the hyperparameters for training AASIST, RawNet2, RawGAT-ST, LCNN, and Spec.+ResNet. We train AASIST, RawNet2, and RawGAT-ST with a learning rate of 0.0001 and LCNN and Spec.+ResNet with a learning rate of 0.0003. The batch size for AASIST, RawNet2, RawGAT-ST, LCNN, and Spec.+ResNet are 64, 256, 32, 512, and 256, respectively. All input audios

Table 7: Hyperparameters

config	value
optimizer	Adam
optimizer momentum	$\beta_1 = 0.9, \beta_2 = 0.999$
weight decay	$1\text{e-}4$
epochs	40
warmup epochs	0
scheduler	cosine decay

are resampled to a 16kHz sampling rate and converted into raw waveforms consisting of 64,000 samples (approximately 4 seconds). Audios longer than 4 seconds are randomly trimmed, while those shorter than 4 seconds are repeated and padded to meet the 4-second duration.

For the foundation models, two linear layers are added after the encoder’s output, with the hidden layer dimension matching the dimension of the encoder’s output. We fine-tune all foundation models on the Wavefake training dataset for 3 epochs using the Adam optimizer with a learning rate of 0.00001 and a weight decay of 0.0005.

For few-shot fine-tuning, models are fine-tuned for 30 epochs with a learning rate of 0.00001 and a weight decay of 0.00005.