





## A Preliminary Case Study on Long-Form Inthe-Wild Audio Spoofing Detection

Xuechen Liu, Xin Wang, *Junichi Yamagishi*BIOSIG 2024
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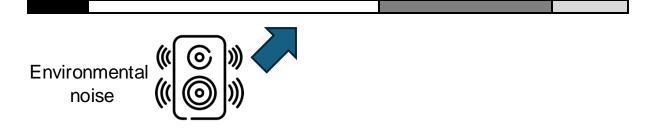
### **Our Objective**

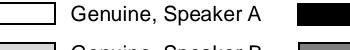
- Audio deepfakes pose a significant threat, with real-world cases of fraud and misinformation on the rise
- So far, we have focused on short-duration (short-form), acoustically-clean and singlespeaker audio waveforms
- Longer durations and partially-spoofed audio have been addressed
- Our goal is to take a step towards realistic conditions, with longer duration (long-form), acoustically-complex, and multi-speaker audios

#### Previous approaches

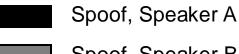
(Liu et al, 2023; Yi et al, 2022) (Zhang et al, 2023)





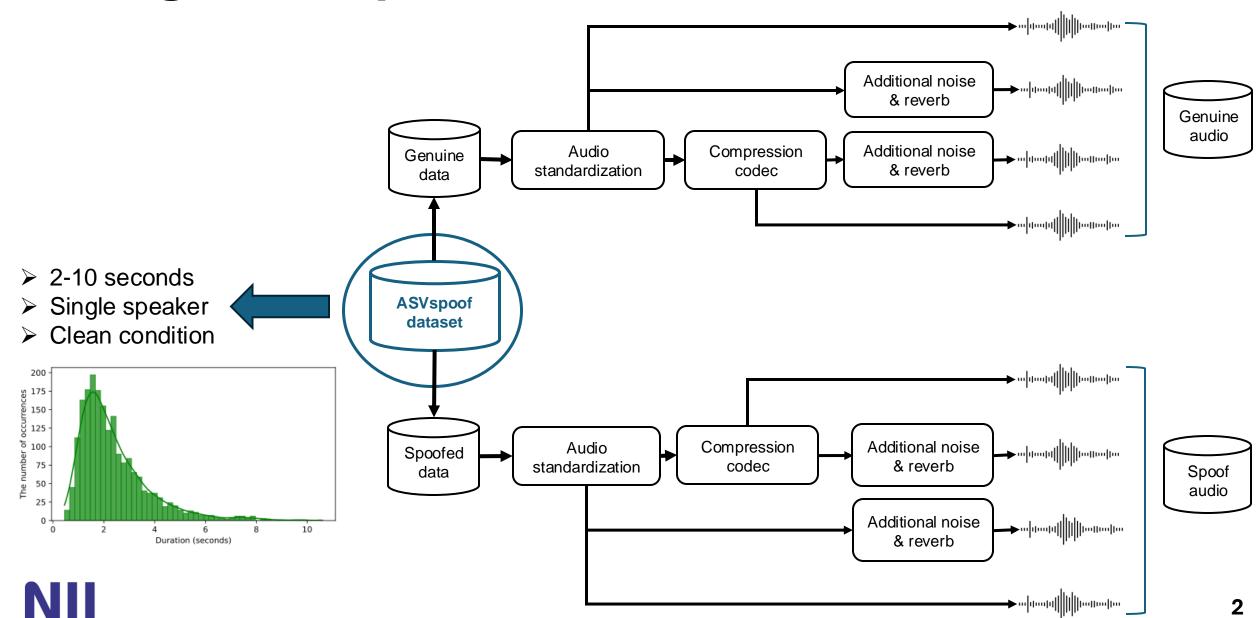


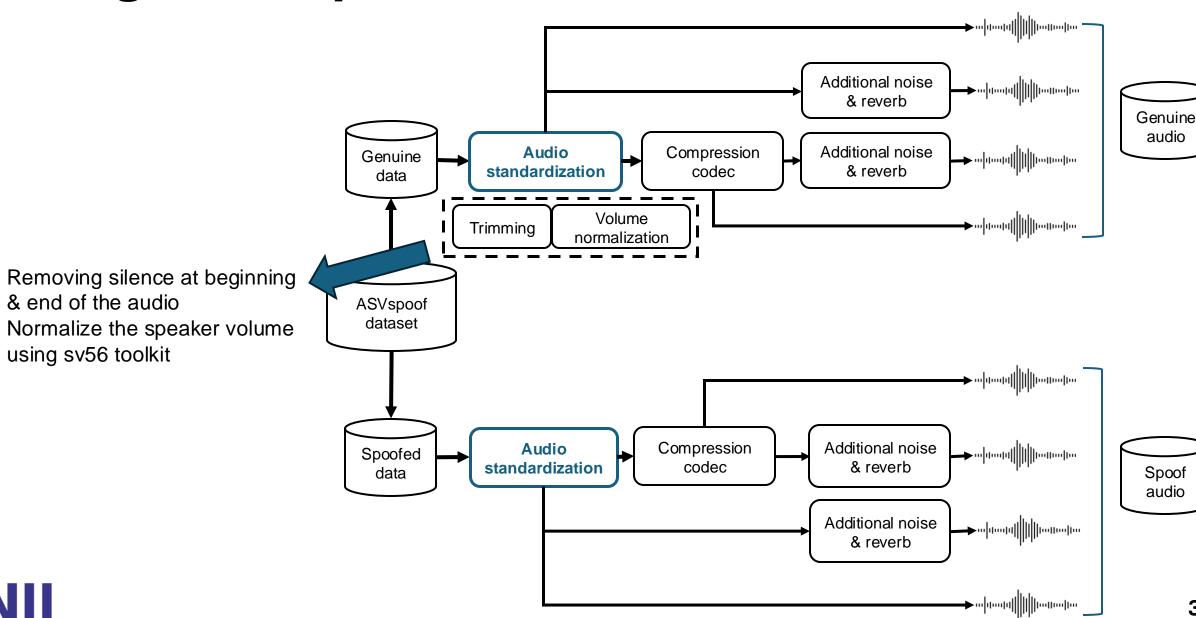




Spoof, Speaker B





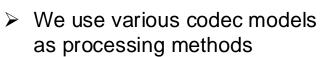




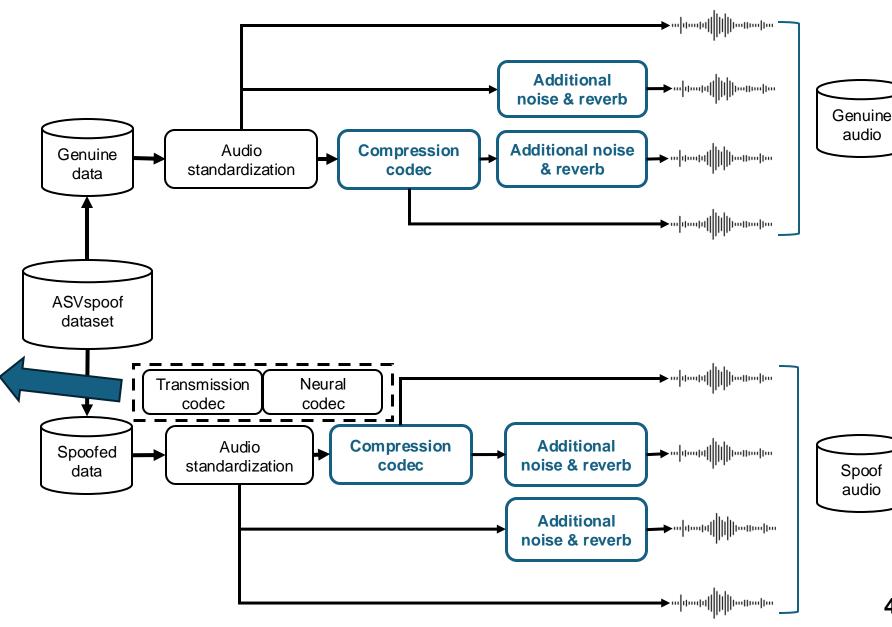
& end of the audio

using sv56 toolkit

audio

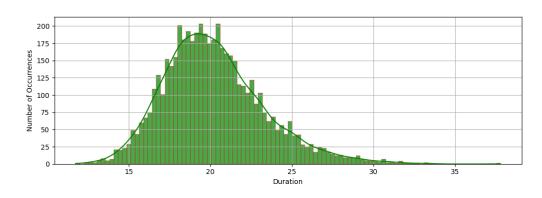


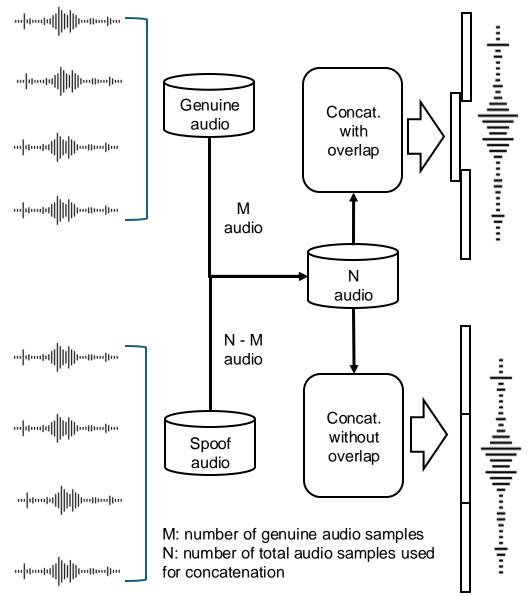
- Transmission codec: mp3, opus, a-law.....
- Neural codec: EnCodec, Soundsteam, FACodec...
- Additions: RIR & MUSAN





- > Generated audio via concatenation, with optionally overlap
- Usually, 15-30 seconds long
- Multiple speakers in the same audio
- Mixed amount of genuine and spoofed content
- Varying amount of genuine vs. spoof ratio, so purelygenuine and purely-spoofed audios are also there

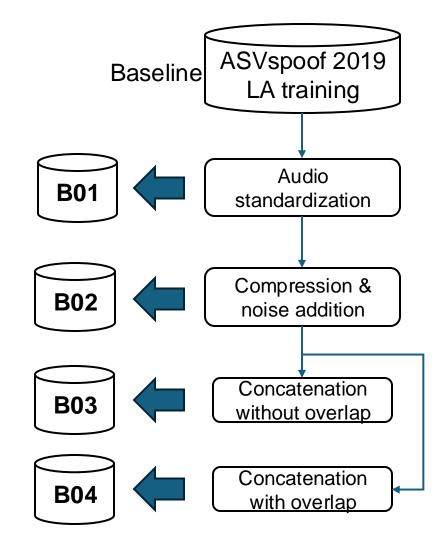






### **Experimental Setup**

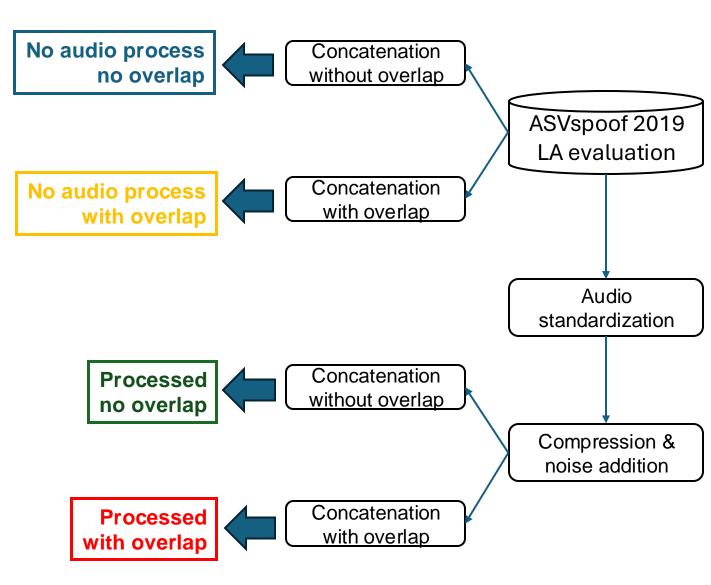
- We use state-of-the-art end-to-end audio deepfake detector called AASIST
- We developed multiple training sets
  - Baseline: The original ASVspoof 2019 LA training data (short-form, clean, single-speaker)
  - B01: Baseline + audio standardization
  - ▶ B02: B01 + audio processing
  - ➤ B03: B02 + long-form audio concatenation
  - B04: B02 + long-form audio concatenation, w/ overlap
- Evaluation audio are generated via same functions, with different placements
  - No audio process, no overlap
  - No audio process, with overlap
  - Processed, no overlap
  - Processed, with overlap





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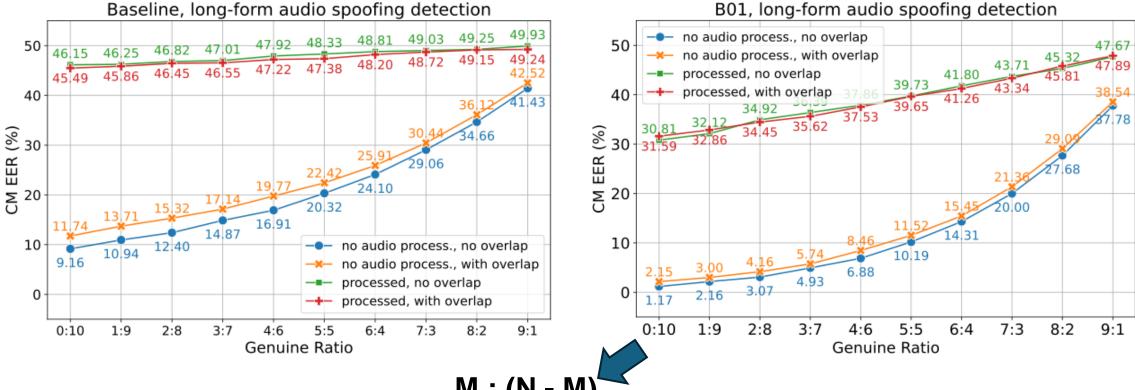
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#### Results

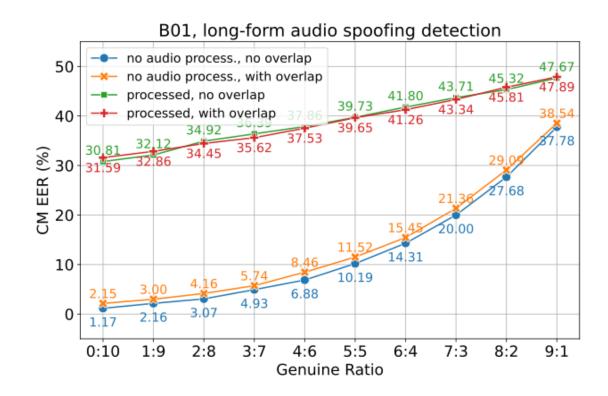
- Training on short, clean speech is not enough for detecting complex spoofed audios
- Performance drops as the amount of genuine content in the long-form audio increases

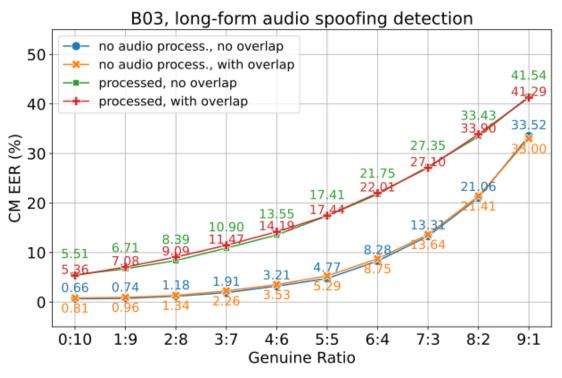




#### Results

Further improvement on training set improves performance, especially for highly-spoofed audio

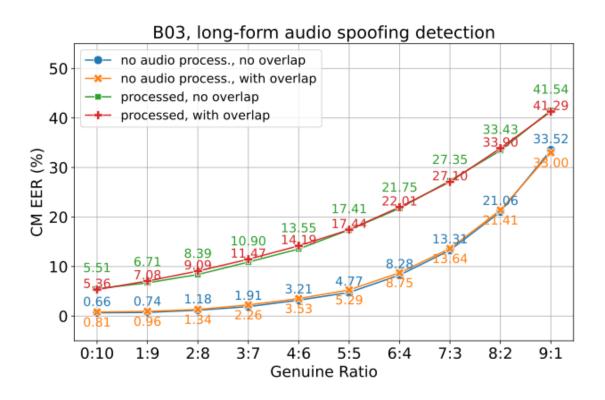


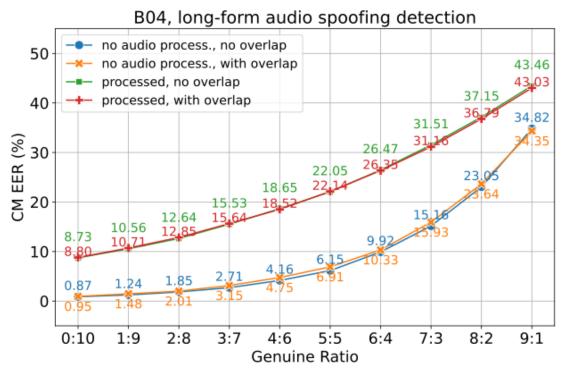




#### Results

Overlapping the adjacent in long-form audio in the training set slightly worsens the performance

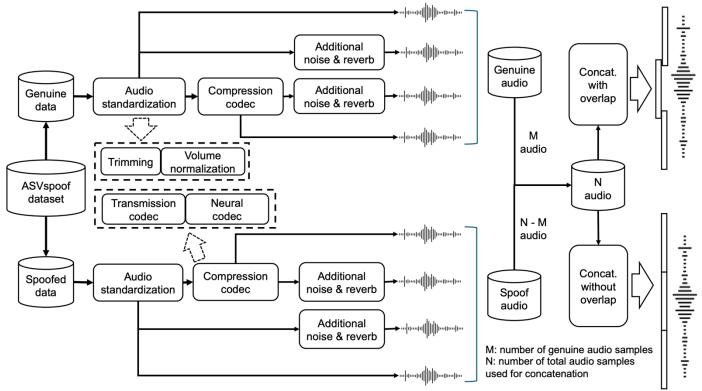






#### **Main Take-Aways**

- Short-form detection models are insufficient for more challenging scenarios posed by audio DeepFake technologies
- We have proposed a new pipeline on generating longer duration
  - 15-30 seconds
  - Varying amount of spoofed content
  - Multi-speaker presence
- Long-form training data improves detection accuracy for complex audio spoofing task
- Future work will explore larger datasets and more complex models









# **Thanks for Listening!**