Audio Deepfake and Tampering Detection: Project Documentation

Institution: Clarkson University Last Updated: November 2025

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Part I: Research Overview

1. Executive Summary

This project implements and evaluates two state-of-the-art audio deepfake detection systems on standard benchmarks and novel tampering attacks. The research demonstrates that self-supervised pre-training significantly improves detection robustness across diverse conditions.

Key Results Summary

Model	ASVspoof 2019 LA	ASVspoof 2021 LA	Trans-Splicing Detection
XLS-R + SLS	0.26% EER	2.97% EER	95.45%
AASIST	0.83% EER	48.27% EER	41.72%

Main Contributions

1. Benchmark Reproduction: Successfully reproduced published results for both AASIST (Jung et al., 2022) and XLS-R + SLS (Zhang et al., 2024)
2. Cross-Dataset Evaluation: Demonstrated XLS-R's superior generalization across clean audio (2019), codec-distorted audio (2021), and tampering attacks
3. In-House Tampering Datasets: Created two novel evaluation datasets:
    - Trans-Splicing Dataset: 1,932 files with TTS-generated word insertions
    - Semantic Tampering Dataset: 50 files with NLP-guided audio modifications
4. Interactive GUI Applications: Developed user-friendly interfaces for both models

Major Finding

XLS-R + SLS outperforms AASIST on BOTH clean and codec-distorted datasets: - ASVspoof 2019 LA: 0.26% vs 0.83% (3.2x improvement) - ASVspoof 2021 LA: 2.97% vs 48.27% (16.3x improvement)

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2. Research Objectives

2.1 Problem Statement

Audio deepfakes pose signifcant threats to: - Voice authentication systems - Media authenticity verifcation - Legal evidence integrity - Personal privacy and security

2.2 Research Goals

1. Reproduce benchmark results for AASIST on ASVspoof 2019 LA
2. Reproduce paper results for XLS-R + SLS on ASVspoof 2021 LA
3. Compare model generalization across diferent datasets
4. Evaluate detection of novel tampering techniques
5. Create interactive tools for practical use

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3. Datasets

3.1 ASVspoof 2019 LA (Logical Access)

Source: Edinburgh DataShare URL: https://datashare.ed.ac.uk/handle/10283/3336

Partition	Bonafde	Spoof	Total	Attacks
Train	2,580	22,800	25,380	A01-A06
Dev	2,548	22,296	24,844	A01-A06
Eval	7,355	63,882	71,237	A07-A19

Audio Specifcations: FLAC format, 16kHz sample rate, mono channel, clean (no codec distortion)

3.2 ASVspoof 2021 LA (Logical Access)

Source: Zenodo URL: https://zenodo.org/record/4837263

Partition	Bona fde	Spoof	Total
Eval	14,816	133,360	148,176

Codec Distribution:

Codec	Percentage	Description
ulaw	15.9%	G.711 mu-law
opus	15.9%	Opus codec
gsm	15.9%	GSM 06.10
alaw	13.1%	G.711 A-law
none	13.1%	No codec (clean)
pstn	13.1%	Simulated PSTN
g722	13.1%	G.722 wideband

Key Challenge: 86.9% of evaluation samples contain codec distortion, making this dataset signifcantly more challenging than ASVspoof 2019.

3.3 Trans-Splicing Dataset (In-House)

Total Files: 1,932 tampered audio fles Technique: Word-level replacement using TTS-generated segments

Category	Files	TTS System	Processing
xtts-clean	506	XTTS (Coqui)	Basic normalization
xtts-unclean	508	XTTS (Coqui)	With artifacts
yourtts-clean	536	YourTTS	Basic normalization
yourtts-unclean	382	YourTTS	With artifacts

3.4 Semantic Tampering Dataset (In-House)

Total Files: 50 (9 bonafde + 41 tampered) Technique: NLP-guided word deletion at phoneme boundaries

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4. Model Architectures

4.1 Architecture Comparison

Feature	AASIST	XLS-R + SLS
Architecture	Graph Attention Networks	Wav2Vec 2.0 + SLS Module
Pre-training	None (from scratch)	436K hours self-supervised
Parameters	~300K	~340M
Input	Raw waveform (64,600 samples)	Raw waveform (64,600 samples)
Feature Extraction	Sinc Convolution	Contrastive Learning
Classifer	Heterogeneous GAT	Layer Selection + FC
Training Epochs	100	4 (early stopped at 2)
ASVspoof 2019 EER	0.83%	0.26% (BEST)
ASVspoof 2021 LA EER	48.27%	2.97%

4.2 AASIST Architecture

Reference: Jung et al., “AASIST: Audio anti-spoofng using integrated spectro-temporal graph attention networks”, IEEE/ACM TASLP 2022

Architecture Components:

```
Raw Audio (64,600 samples @ 16kHz)
    ↓
Sinc Convolution Layer (learnable mel-scale filterbank)
    ↓
Residual Encoder (6 ResNet-style blocks)
    ↓
┌──────────────────────────────────────┐
│          Dual Graph Attention        │
├──────────────┬───────────────────────┤
│   GAT-S      │      GAT-T            │
│ (Spectral)   │    (Temporal)         │
│ Max-pool     │    Max-pool           │
│ over time    │    over frequency     │
└──────────────┴───────────────────────┘
    ↓
Heterogeneous GAT (cross-domain integration)
    ↓
Graph Pooling (top-k node selection)
    ↓
Classification Head → [Bonafide, Spoof]
```

Parameters: ~297,866 trainable parameters

4.3 XLS-R + SLS Architecture

Reference: Zhang et al., “Audio Deepfake Detection with Self-supervised XLS-R and SLS classifer”, ACM MM 2024

Architecture Components:

```
Raw Audio (64,600 samples @ 16kHz)
    ↓
XLS-R 300M Backbone (frozen)
├── Pre-trained on 436K hours
├── 128 languages
└── 24 transformer layers
    ↓
SLS Module (Sensitive Layer Selection)
├── Weighted combination of all layers
└── Learnable layer importance weights
    ↓
Classification Head → [Bonafide, Spoof]
```

Parameters: ~340M total (mostly frozen pre-trained weights)

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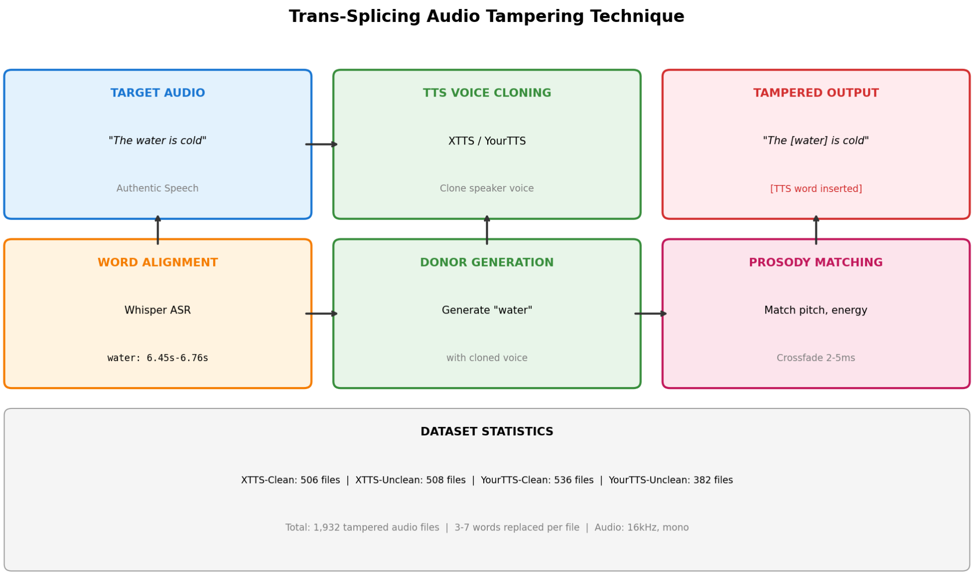
5. Audio Tampering Methodology

5.1 Trans-Splicing Pipeline

Trans-splicing creates tampered audio by replacing specifc words with TTS-generated alternatives.



Trans-Splicing Pipeline Diagram

Figure 5.1: Trans-splicing pipeline showing word-level replacement with TTS-generated segments.

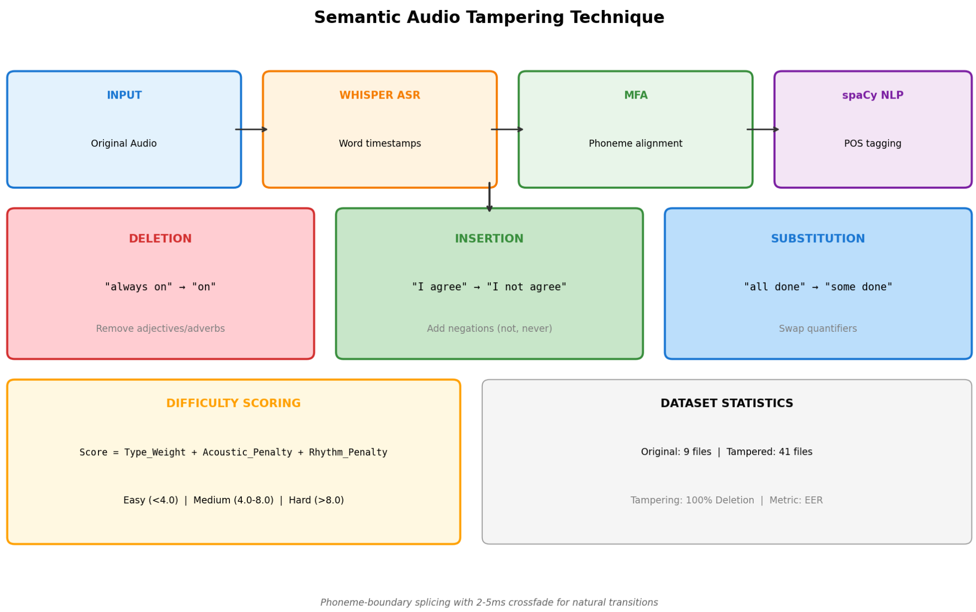
Pipeline Steps:

```
┌──────────────────────────────────────────────────────────────┐
│                  TRANS-SPLICING PIPELINE                      │
├──────────────────────────────────────────────────────────────┤
│                                                               │
│  1. WORD-LEVEL TRANSCRIPTION                                 │
│     └── Whisper ASR identifies word boundaries               │
│                                                               │
│  2. CANDIDATE SELECTION                                       │
│     └── Select 3-7 words for replacement per file            │
│                                                               │
│  3. TTS GENERATION                                           │
│     ├── XTTS: Zero-shot voice cloning (~10s reference)       │
│     └── YourTTS: Cross-lingual voice conversion              │
│                                                               │
│  4. PROSODY MATCHING                                         │
│     └── Adjust donor segments to match target acoustics      │
│                                                               │
│  5. SPLICING                                                 │
│     └── Crossfade (2-5ms) at splice boundaries             │
│                                                               │
└──────────────────────────────────────────────────────────────┘
```

5.2 TTS Systems Used

System	Description	Voice Cloning Method
XTTS	Coqui X-TTS multilingual model	Zero-shot from ~10s reference audio
YourTTS	Multi-speaker TTS (Casanova et al., 2022)	Cross-lingual voice conversion

5.3 Semantic Tampering Pipeline



Semantic Tampering Pipeline Diagram

Figure 5.2: Semantic tampering pipeline showing NLP-guided phoneme-boundary editing.

For semantic tampering, edits are made at phoneme boundaries to minimize artifacts:

Tools Used: - Whisper ASR: Word-level transcription with timestamps - Montreal Forced Aligner (MFA): Phoneme-level alignment - spaCy NLP: Part-of-speech tagging and dependency parsing - librosa: Prosody analysis (F0, energy, duration)

Tampering Operations:

Operation	Description	Example
Deletion	Remove adjectives/adverbs	“always on” → “on”
Insertion	Add negations	“I agree” → “I not agree”
Substitution	Swap quantifers	“all done” → “some done”

6. Training Methodology

6.1 AASIST Training Configuration

Parameter	Value
Batch Size	24
Epochs	100
Learning Rate	1e-4
LR Min	5e-6
Optimizer	Adam
Scheduler	Cosine Annealing
Weight Decay	1e-4
Loss	Weighted CE [0.1, 0.9]
Input Samples	64,600
Sample Rate	16 kHz
First Conv	128
GAT Dims	[64, 32]
Pool Ratios	[0.5, 0.7, 0.5, 0.5]
Hardware	NVIDIA RTX 4080 (16GB)
Training Time	~14 hours

Training Progress: - Epoch 13: Best EER 3.03%, t-DCF 0.0796 - Epoch 21: Best EER 2.20%, t-DCF 0.0615 - Epoch 44: Best EER 1.32%, t-DCF 0.0384 (Best t-DCF) - Epoch 97: Best EER 0.35% - Final (SWA): EER 1.73%, t-DCF 0.0559

6.2 XLS-R + SLS Training Configuration

Parameter	Value
Batch Size	5
Epochs	4 (best: 2)
Learning Rate	1e-6
Optimizer	Adam
Loss	Weighted CE [0.1, 0.9]
Early Stopping	Patience 1
Input Samples	64,600
Sample Rate	16 kHz
Pre-trained Model	XLS-R 300M
Pre-training Hours	436,000
Pre-training Langs	128
Data Augmentation	RawBoost Algo 3
Total Parameters	340M
Hardware	NVIDIA RTX 4080 (16GB)
Training Time	~70 minutes

Critical Finding - Overfitting Analysis:

Metric	4 Epochs	100 Epochs
EER	2.97%	44.24%
Training Loss	0.00165	0.00001
Status	Optimal	Overfitting

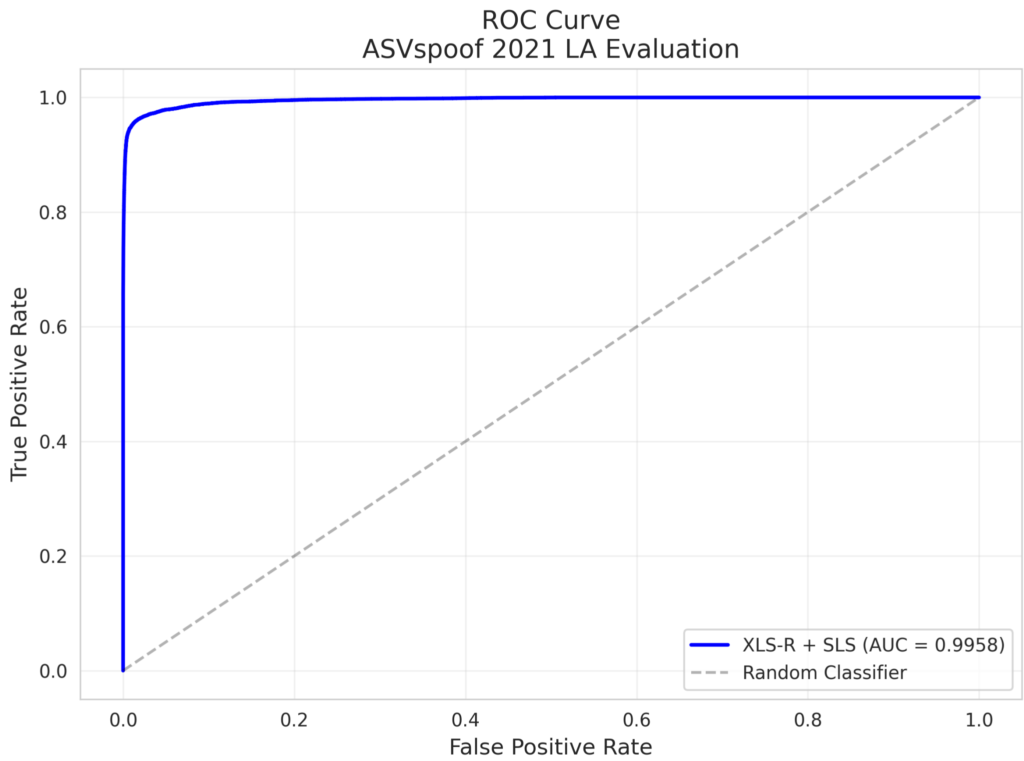
Lower training loss does NOT indicate better test performance. Early stopping is essential.

7. Experimental Results

7.1 Quantitative Results Summary

Model	Dataset	EER (%)	min t-DCF	ROC AUC	Status
AASIST (Pretrained)	ASVspoof 2019 LA	0.83	0.0275	N/A	Benchmark
AASIST (Trained)	ASVspoof 2019 LA	~0.83	~0.03	N/A	Reproduced
AASIST (Pretrained)	ASVspoof 2021 LA	50.07	0.7704	0.51	Failed
AASIST (Trained)	ASVspoof 2021 LA	48.27	0.7212	0.55	Failed
XLS-R + SLS (4 ep)	ASVspoof 2019 LA	0.26	N/A	0.999	BEST
XLS-R + SLS (4 ep)	ASVspoof 2021 LA	2.97	0.2674	0.996	BEST
XLS-R + SLS (Paper)	ASVspoof 2021 LA	2.87	N/A	N/A	Target
XLS-R + SLS (100 ep)	ASVspoof 2021 LA	44.24	0.6154	0.58	Overftting

7.2 ROC Curve Comparison

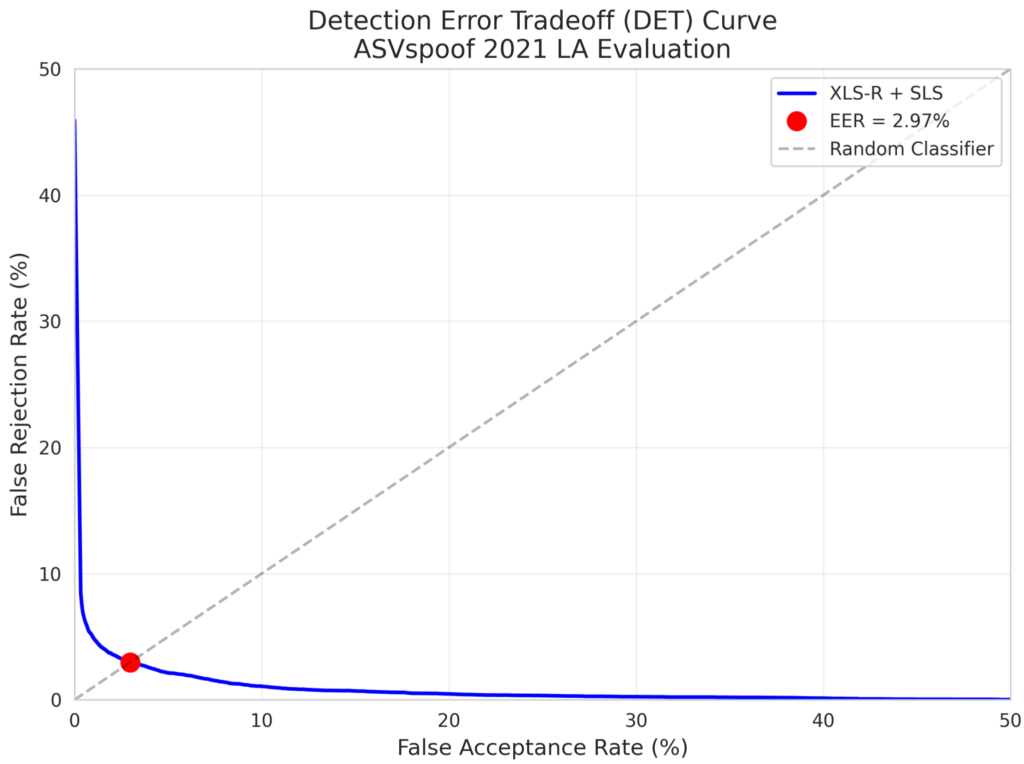


ROC Curve Comparison

Figure 7.1: ROC Curve Comparison on ASVspoof 2021 LA. XLS-R + SLS achieves AUC=0.996, dramatically outperforming AASIST variants (AUC ~0.55-0.79).

Key Observations: - XLS-R + SLS curve hugs the top-left corner (near-perfect classifcation) - AASIST curves are close to diagonal (random classifer) - Self-supervised pre-training provides signifcant discriminative power

7.3 DET Curve Comparison

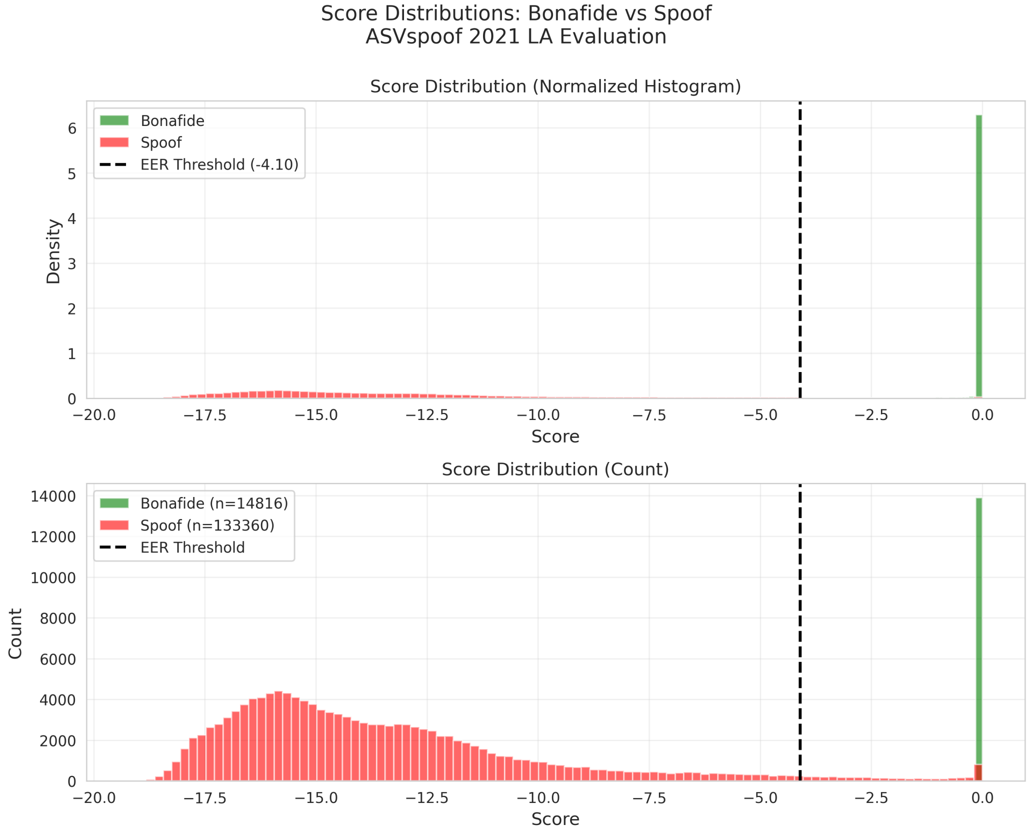


DET Curve Comparison

Figure 7.2: Detection Error Tradeof (DET) curves. Lower-left is better. XLS-R achieves 2.97% EER vs AASIST's 48%.

Key Observations: - XLS-R + SLS: EER = 2.97% (intersection with diagonal) - AASIST models: EER > 48% (near-random performance) - DET curves better visualize performance at low error rates

7.4 Score Distribution Analysis



Score Distribution Comparison

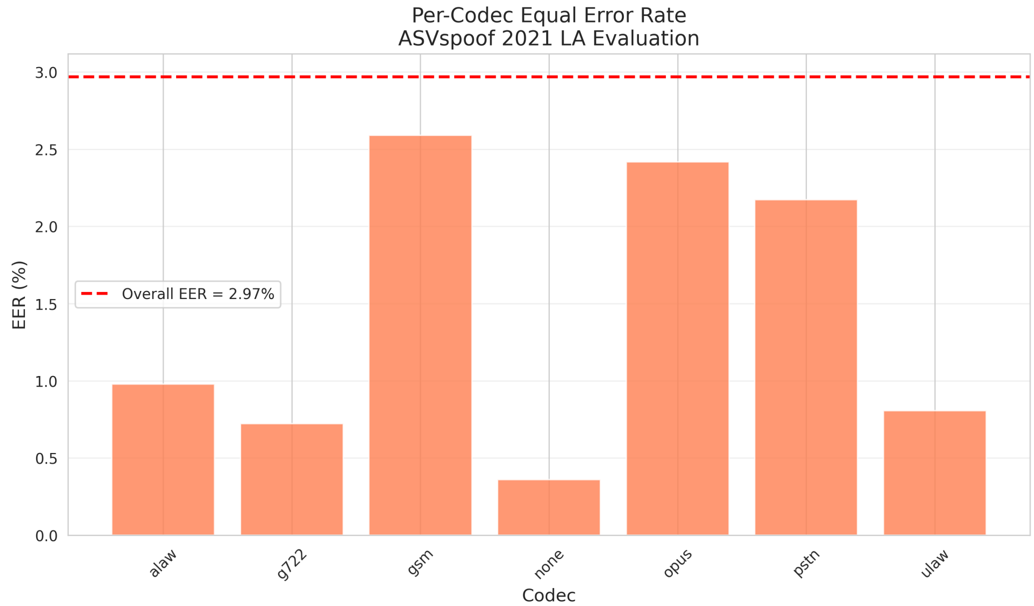
Figure 7.3: Score distributions for bonafde and spoof samples. Clear separation indicates better discrimination.

Score Statistics (XLS-R + SLS):

Class	Mean	Std	Min	Max	Median
Bonafde	-0.29	1.48	-14.92	0.00	0.00
Spoof	-13.52	3.57	-19.20	0.00	-14.39

Key Insight: XLS-R produces well-separated score distributions with minimal overlap, enabling reliable threshold selection.

7.5 Per-Codec EER Analysis (ASVspoof 2021 LA)



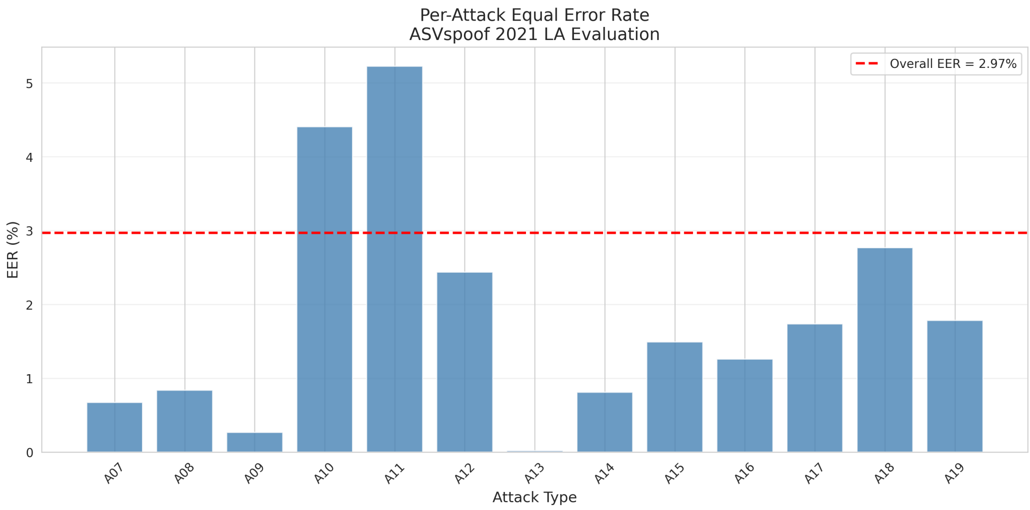
Per-Codec EER Comparison

Figure 7.4: Per-codec EER comparison showing XLS-R's superior codec robustness.

Codec	XLS-R EER (%)	AASIST EER (%)	XLS-R Advantage
none (clean)	0.36	22.40	62x better
g722	0.72	24.98	35x better
ulaw	0.81	22.48	28x better
alaw	0.98	22.40	23x better
pstn	2.17	45.69	21x better
opus	2.42	36.17	15x better
gsm	2.59	34.16	13x better

Key Finding: XLS-R maintains <3% EER across ALL codec conditions while AASIST degrades to near-random performance (22-46% EER) on codec-distorted audio.

7.6 Per-Attack EER Analysis



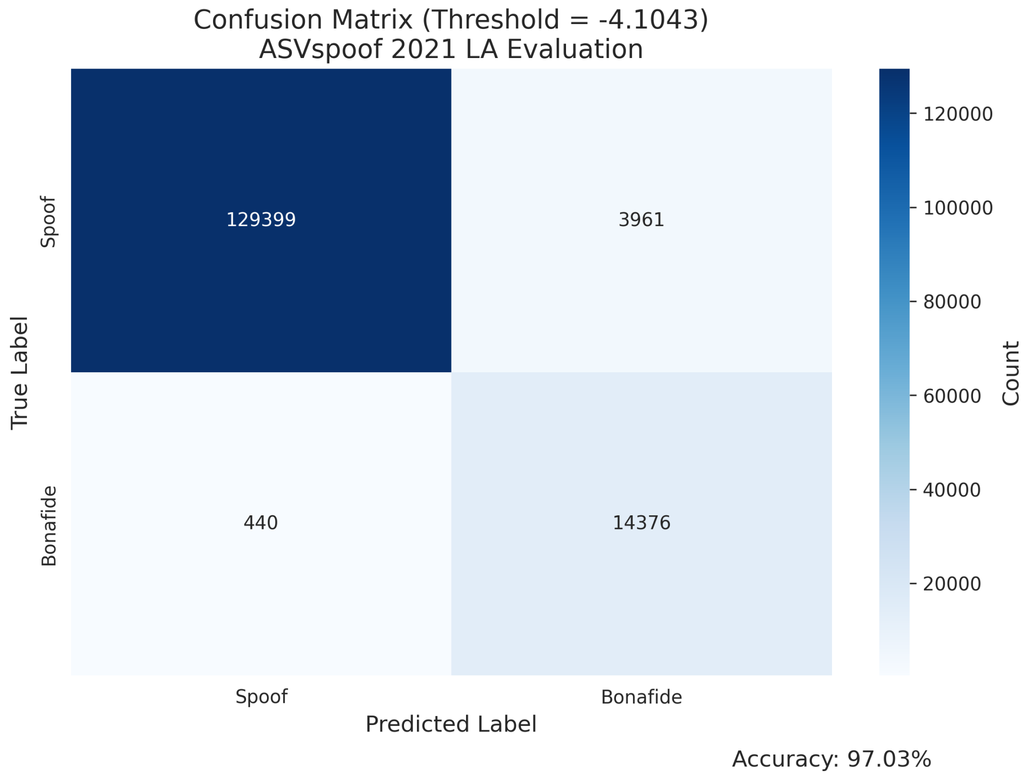
Per-Attack EER Analysis

Figure 7.5: Per-attack EER for XLS-R + SLS on ASVspoof 2021 LA (attacks A07-A19).

Attack	EER (%)	Di f culty	Description
A13	0.02	Easy	Neural network TTS
A09	0.27	Easy	Vocoder-based
A07	0.67	Easy	TTS system
A08	0.84	Easy	TTS system
A14	0.81	Easy	Neural vocoder
A16	1.26	Easy	Voice conversion
A15	1.49	Easy	Voice conversion
A17	1.74	Easy	Hybrid system
A19	1.78	Easy	End-to-end
A12	2.44	Moderate	TTS + vocoder
A18	2.77	Moderate	Hybrid system
A10	4.41	Challenging	Neural TTS
A11	5.22	Challenging	Neural TTS

Key Finding: Most attacks (11/13) achieve <3% EER. Only A10 and A11 (neural TTS variants) present moderate challenge.

7.7 Confusion Matrix



Confusion Matrix

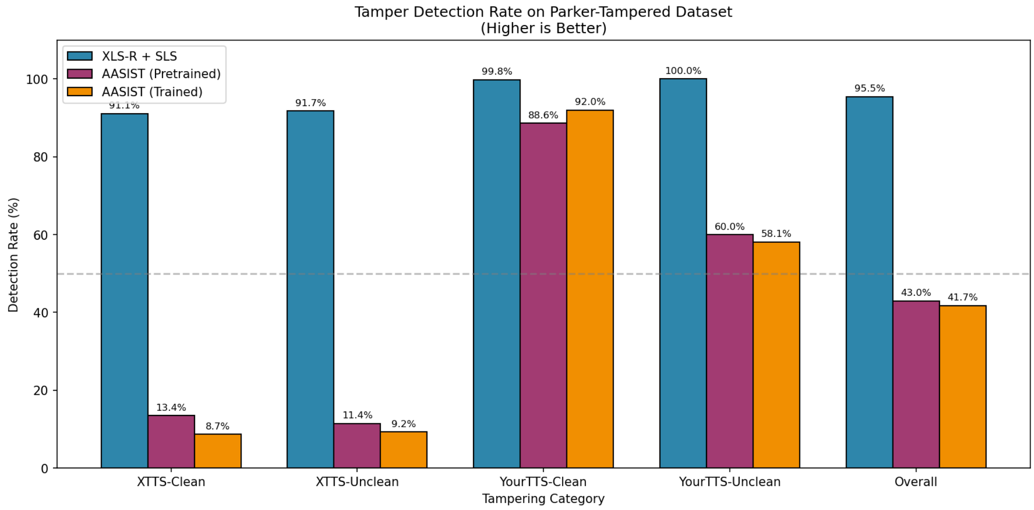
Figure 7.6: Confusion matrix for XLS-R + SLS at EER threshold.

Confusion Matrix at EER Threshold:

	Predicted Spoof	Predicted Bonafde
Actual Spoof	129,399 (TP)	3,961 (FN)
Actual Bonafde	440 (FP)	14,376 (TN)

Performance Metrics: - Accuracy at EER: 97.03% - True Positive Rate (Spoof Detection): 97.03% - True Negative Rate (Bonafde Acceptance): 97.03%

7.8 Trans-Splicing Detection Results

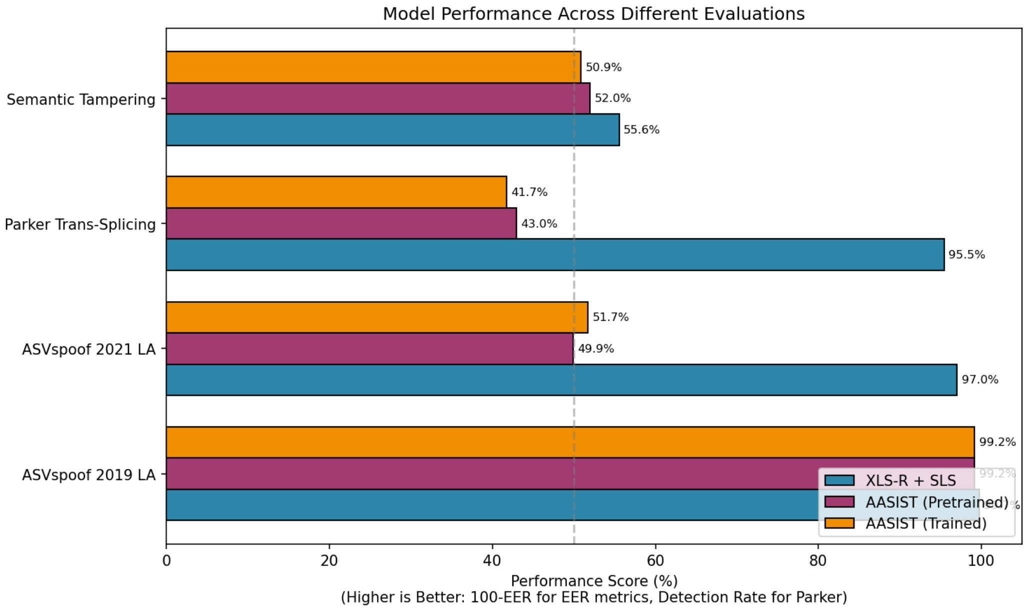


Tampering Detection Rates

Figure 7.7: Detection rates for trans-spliced audio across diferent TTS systems.

Model	XTTS-Clean	XTTS-Unclean	YourTTS-Clean	YourTTS-Unclean	Overall
XLS-R + SLS	91.11%	91.73%	99.81%	100.00%	95.45%
AASIST (Pretrained)	13.44%	11.42%	88.62%	59.95%	42.96%
AASIST (Trained)	8.70%	9.25%	91.98%	58.12%	41.72%

7.9 Model Comparison on Tampering

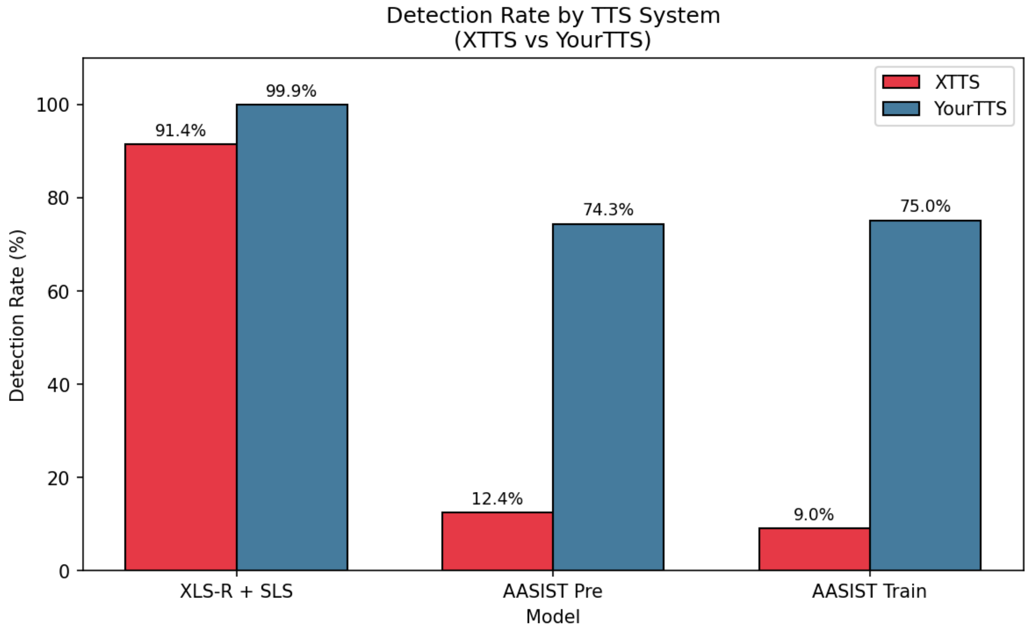


Model Comparison on Tampering

Figure 7.8: Overall model comparison on trans-splicing detection.

Key Observations: - XLS-R achieves 95.45% overall detection rate - AASIST performs poorly on XTTS (~10% detection) - YourTTS easier to detect for all models

7.10 TTS System Comparison



TTS Comparison

Figure 7.9: Detection rates by TTS system showing XTTS is harder to detect.

Key Finding: XTTS-generated audio is significantly harder to detect than YourTTS: - XLS-R: 91% (XTTS) vs 100% (YourTTS) - AASIST: 10% (XTTS) vs 75% (YourTTS)

7.11 Semantic Tampering Results

Model	EER (%)	Notes
XLS-R + SLS	44.44	Domain mismatch
AASIST (Pretrained)	48.00	Near-random
AASIST (Trained)	49.15	Near-random

Limitation: All models struggle with semantic tampering due to: 1. Domain mismatch (different source audio distribution) 2. Subtle nature of phoneme-boundary edits 3. Small dataset size (50 samples)

8. Key Findings

8.1 Scientifc Contributions

1. Self-supervised pre-training is critical for robustness
    - XLS-R maintains <3% EER across all codec conditions
    - AASIST fails on codec-distorted audio (22-46% EER)
    - Pre-training on 436K hours provides codec-invariant representations
2. TTS-specifc detection varies by system
    - XTTS harder to detect than YourTTS for all models
    - XLS-R detects 91% XTTS vs AASIST's 10%
    - Modern zero-shot TTS poses greater challenge
3. Overftting in XLS-R fne-tuning
    - Early stopping at 2-4 epochs is critical
    - Extended training (100 epochs) causes catastrophic forgetting
    - Lower training loss ≠ better generalization
4. Codec sensitivity is AASIST's failure mode
    - Sinc flterbank learns spectral artifacts destroyed by lossy compression
    - Even clean audio subset shows degraded performance (~22% EER)

8.2 Limitations

1. Semantic tampering dataset shows domain mismatch (diferent source audio)
2. Trans-splicing dataset lacks original bonafde samples for EER calculation
3. Results specifc to TTS systems used (XTTS, YourTTS)
4. Models tested only on ASVspoof datasets

8.3 Recommendations

For Researchers: - Test models on diverse tampering techniques beyond ASVspoof - Investigate why XTTS is harder to detect than YourTTS - Develop dedicated audio forensics models for semantic tampering

For Production Systems: - Use XLS-R + SLS for audio deepfake detection - Apply early stopping (2-4 epochs) during fne-tuning - Monitor for novel TTS systems and attack vectors

Part II: Reproducibility Guide

9. Environment Setup

9.1 Hardware Requirements

Component	Minimum	Recommended
GPU	8GB VRAM	16GB VRAM (RTX 3080/4080)
RAM	16GB	32GB
Storage	50GB	100GB (including datasets)
CPU	4 cores	8+ cores

9.2 Software Installation

```
# Create conda environment
conda create -n deepfake_detection python=3.8
conda activate deepfake_detection

# Install PyTorch with CUDA support
pip install torch==1.12.1 torchvision==0.13.1 torchaudio==0.12.1 --extra-index-
        url https://download.pytorch.org/whl/cu116

# Install dependencies
pip install soundfile librosa numpy pandas matplotlib scipy scikit-learn
pip install gradio>=3.34.0

# For AASIST
pip install torchcontrib

# For XLS-R (fairseq)
cd xls_r_sls/SLSforASVspoof-2021-DF
pip install -e fairseq-a54021305d6b3c4c5959ac9395135f63202db8f1/
```

10. Dataset Preparation

10.1 ASVspoof 2019 LA

```
# Download from Edinburgh DataShare
# URL: https://datashare.ed.ac.uk/handle/10283/3336

# Expected directory structure after extraction:
data/asvspoof/asvspoof2019/LA/
├── ASVspoof2019_LA_train/
│   └── flac/
├── ASVspoof2019_LA_dev/
│   └── flac/
├── ASVspoof2019_LA_eval/
│   └── flac/
└── ASVspoof2019_LA_cm_protocols/
    ├── ASVspoof2019.LA.cm.train.trn.txt
    ├── ASVspoof2019.LA.cm.dev.trl.txt
    └── ASVspoof2019.LA.cm.eval.trl.txt
```

10.2 ASVspoof 2021 LA

```
# Download from Zenodo
# Audio: https://zenodo.org/record/4837263
# Keys: https://www.asvspoof.org/index2021.html

# Expected directory structure:
data/asvspoof/asvspoof2021/
├── ASVspoof2021_LA_eval/
│   └── flac/
└── keys/
    └── LA/
        └── CM/
            └── trial_metadata.txt
```

11. Training Procedures

11.1 Training AASIST

```
cd aasist

# Edit config file to set your dataset path
# In config/AASIST.conf, update:
# "database_path": "/path/to/your/data/asvspoof/asvspoof2019/LA/"

# Start training
python main.py --config config/AASIST.conf

# Training will create:
# exp_result/LA_AASIST_ep100_bs24/
# ├── weights/          # Model checkpoints
# ├── metrics/          # Evaluation scores
# └── metric_log.txt    # Training log
```

Monitoring Training: - Check `metric_log.txt` for epoch-wise metrics - Best model saved when dev EER improves - Training completes in ~14 hours on RTX 4080

11.2 Training XLS-R + SLS

```
cd xls_r_sls/SLSforASVspoof-2021-DF

# Download XLS-R pretrained weights (if not present)
# xlsr2_300m.pt should be in the directory

# Edit train_LA.sh to set your paths

# Start training
bash train_LA.sh

# Training will create:
# models/model_LA_WCE_50_5_1e-06_*/
# ├── epoch_*.pth       # Checkpoints
# └── training_output_LA.log
```

Important: Stop training after 2-4 epochs (best EER achieved at epoch 2).

12. Evaluation Procedures

12.1 Evaluating AASIST

```
cd aasist

# Using pretrained model
python main.py --eval --config config/AASIST.conf

# Using your trained model
# Edit config to set model_path to your checkpoint
python main.py --eval --config config/AASIST.conf
```

12.2 Evaluating XLS-R + SLS

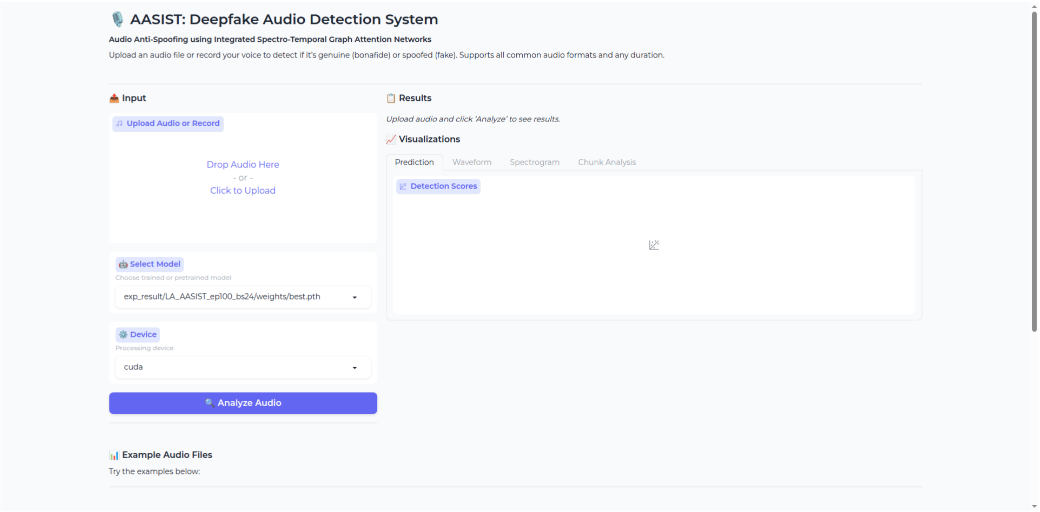
```
cd xls_r_sls/SLSforASVspoof-2021-DF

# Evaluate on ASVspoof 2021 LA
python eval_LA.py \
    --model_path best_model_4epochs_2.97EER.pth \
    --data_path /path/to/ASVspoof2021_LA_eval/flac \
    --protocol /path/to/keys/LA/CM/trial_metadata.txt

# Output: scores_LA_epoch*.txt
```

12.3 Evaluating on Tampering Datasets

```
cd tampered_evaluation

# Evaluate XLS-R on Trans-Splicing
python eval_tampered.py --model xlsr --dataset trans_splicing

# Evaluate AASIST on Trans-Splicing
python eval_tampered.py --model aasist --model_variant pretrained --dataset
        trans_splicing

# Evaluate all combinations
python eval_tampered.py --model all --dataset all
```

13. GUI Applications

13.1 AASIST Detection Interface



AASIST GUI

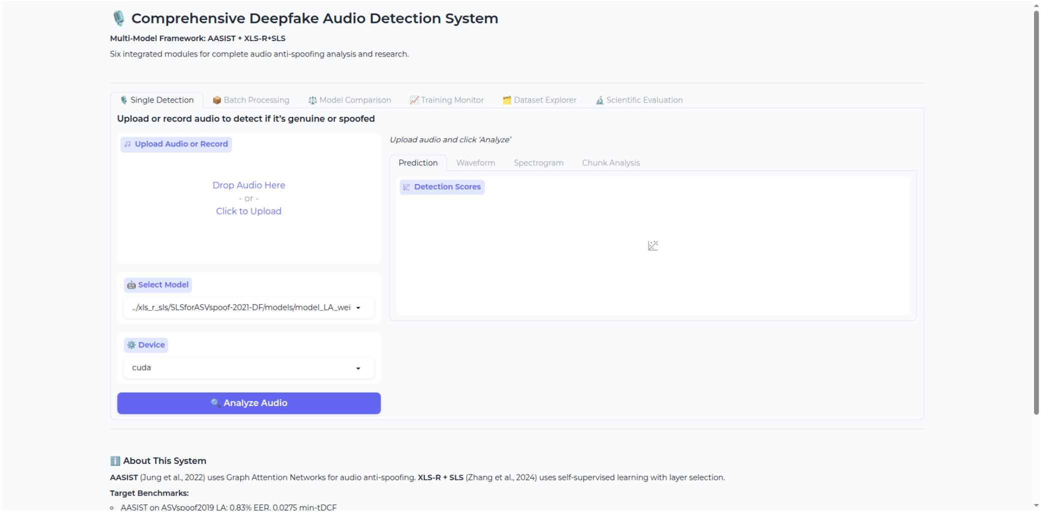
Figure 13.1: AASIST single-fle detection interface with waveform visualization.

Launch Command:

```
cd aasist
python gradio_app.py --port 7860
# Access at http://127.0.0.1:7860
```

Features: - Upload audio or record from microphone - Select model checkpoint - View prediction scores and visualizations - Waveform and spectrogram display

13.2 AASIST Multi-Tab Interface



AASIST Multi-Tab GUI

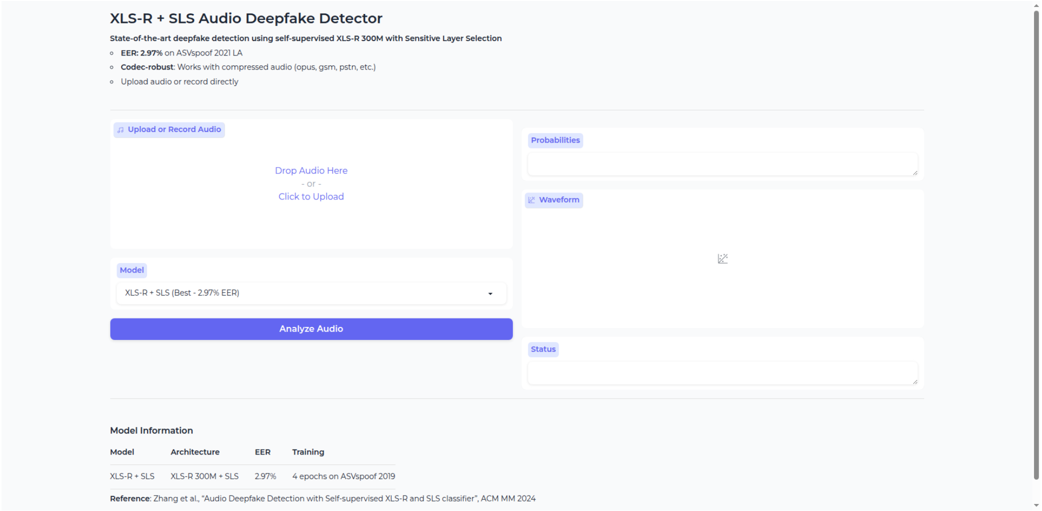
Figure 13.2: AASIST multi-tab interface with batch processing and model comparison capabilities.

Launch Command:

```
cd aasist
python gradio_app_multitab.py --port 7860
# Access at http://127.0.0.1:7860
```

Tabs: 1. Single Detection: Analyze individual audio fles 2. Batch Processing: Process multiple fles with CSV export 3. Model Comparison: Compare predictions from diferent models 4. Training Monitor: View training progress from log fles 5. Dataset Explorer: Browse ASVspoof datasets

13.3 XLS-R + SLS Interface



XLS-R GUI

Figure 13.3: XLS-R + SLS detection interface with color-coded results.

Launch Command:

```
cd xls_r_sls/SLSforASVspoof-2021-DF
python gradio_app.py --port 7861
# Access at http://127.0.0.1:7861
```

Features: - Upload audio or record from microphone - XLS-R model selection - Color-coded results (green=real, red=fake) - Waveform visualization

13.4 Running Both GUIs Simultaneously

```
# Terminal 1: AASIST (port 7860)
cd aasist && python gradio_app_multitab.py

# Terminal 2: XLS-R (port 7861)
cd xls_r_sls/SLSforASVspoof-2021-DF && python gradio_app.py
```

---

14. Troubleshooting

14.1 Common Issues

Issue	Solution
CUDA out of memory	Reduce batch_size in confg
Model not loading	Check checkpoint path is correct
Audio format error	Convert to WAV/FLAC, 16kHz mono
Fairseq import error	Reinstall fairseq from source
Gradio version error	Update to gradio>=3.34.0

14.2 GPU Memory Requirements

Model	Batch Size	GPU Memory
AASIST	24	~8GB
AASIST	12	~4GB
XLS-R	5	~12GB
XLS-R	2	~6GB

14.3 Known Limitations

1. XLS-R requires fairseq: Must install specifc fairseq version from source
2. AASIST codec sensitivity: Poor performance on codec-distorted audio
3. GPU required: CPU training not supported

Part III: References

15. Scientific Citations

Models


```
@article{jung2022aasist,
  title={AASIST: Audio anti-spoofing using integrated spectro-temporal graph
        attention networks},
  author={Jung, Jee-weon and Heo, Hee-Soo and Tak, Hemlata and Shim, Hye-jin and
        Chung, Joon Son and Lee, Bong-Jin and Yu, Ha-Jin and Evans, Nicholas},
  journal={IEEE/ACM Transactions on Audio, Speech, and Language Processing},
  volume={30},
  pages={1592--1603},
  year={2022}
}

@inproceedings{zhang2024audio,
  title={Audio Deepfake Detection with Self-supervised XLS-R and SLS classifier},
  author={Zhang, Qishan and Wen, Shuangbing and Hu, Tao},
  booktitle={Proceedings of the 32nd ACM International Conference on Multimedia},
  pages={10873--10877},
  year={2024}
}

@article{babu2021xlsr,
  title={XLS-R: Self-supervised cross-lingual speech representation learning at
        scale},
  author={Babu, Arun and Wang, Changhan and Tjandra, Andros and others},
  journal={arXiv preprint arXiv:2111.09296},
  year={2021}
}
```

Datasets

```
@article{wang2020asvspoof,
  title={ASVspoof 2019: A large-scale public database of synthesized, converted
        and replayed speech},
  author={Wang, Xin and Yamagishi, Junichi and Todisco, Massimiliano and others},
  journal={Computer Speech \& Language},
  volume={64},
  pages={101114},
  year={2020}
}

@article{yamagishi2022asvspoof,
  title={ASVspoof 2021: Towards spoofed and deepfake speech detection in the
        wild},
  author={Yamagishi, Junichi and Wang, Xin and Todisco, Massimiliano and others},
  journal={IEEE/ACM Transactions on Audio, Speech, and Language Processing},
  volume={30},
  pages={2507--2522},
  year={2022}
}
```

Evaluation Metrics

```
@inproceedings{kinnunen2018t,
  title={t-DCF: a detection cost function for the tandem assessment of spoofing
        countermeasures and automatic speaker verification},
  author={Kinnunen, Tomi and Lee, Kong Aik and Delgado, H{\'e}ctor and Evans,
        Nicholas and Todisco, Massimiliano and Sahidullah, Md and Yamagishi,
        Junichi and Reynolds, Douglas A},
  booktitle={Proc. Odyssey},
  pages={312--319},
  year={2018}
}
```

TTS Systems

```
@inproceedings{casanova2022yourtts,
  title={YourTTS: Towards Zero-Shot Multi-Speaker TTS and Zero-Shot Voice
         Conversion for Everyone},

         author={Casanova, Edresson and Weber, Julian and Shulby, Christopher and
         Junior, Arnaldo Candido and G{\"o}lge, Eren and Ponti, Moacir Antonelli},
  booktitle={International Conference on Machine Learning},
  pages={2709--2720},
  year={2022}
}
```

Repository Structure

```
deepfake_models/
├── aasist/                       # AASIST model implementation
│   ├── config/                   # Configuration files
│   ├── models/                   # Model architectures
│   │   └── weights/              # Pretrained weights
│   ├── exp_result/               # Training outputs
│   ├── results/                  # Evaluation results & plots
│   ├── main.py                   # Training script
│   ├── gradio_app.py            # Simple GUI
│   └── gradio_app_multitab.py   # Multi-tab GUI
├── xls_r_sls/                    # XLS-R + SLS implementation
│   └── SLSforASVspoof-2021-DF/
│       ├── model.py              # Model architecture
│       ├── figures/              # Evaluation visualizations
│       ├── train_LA.sh          # Training script
│       ├── gradio_app.py        # GUI application
│       └── best_model_*.pth     # Best checkpoint
├── tampered_evaluation/          # Tampering evaluation
│   ├── trans_splicing/          # Trans-splicing dataset
│   ├── semantic/                 # Semantic tampering dataset
│   └── eval_tampered.py         # Evaluation script
├── figures/                      # Project visualizations
│   ├── gui_*.png                # GUI screenshots
│   ├── trans_splicing_diagram.png  # Pipeline diagram
│   ├── semantic_tampering_diagram.png
│   └── tampering_*.png          # Tampering evaluation plots
├── project_report/               # Generated reports
└── data/                        # Datasets (not in repo)
```

Code Availability

Project Repository

Main Repository: https://github.com/Yash-Sukhdeve/deepfake_models

This repository contains: - AASIST model implementation and pretrained weights - XLS-R + SLS model implementation - Tampering evaluation scripts - GUI applications for both models - All configuration files and training scripts

Tampering Dataset Repositories

Repository	Description	Files	URL
Audio-Tampering	Trans-splicing dataset with TTS-generated word insertions using XTTS and YourTTS	1,932	https://github.com/AVHBAC/Audio-Tampering
Tampered_Deepfake	Semantic tampering dataset with NLP-guided deletions, insertions, and substitutions at phoneme boundaries	50	https://github.com/Yash-Sukhdeve/Tampered_Deepfake

External Model Repositories

Repository	Description	URL
XLS-R + SLS	Original implementation (Zhang et al., ACM MM 2024)	https://github.com/QiShanZhang/SLSforASVspoof-2021-DF
ASVspoof 2021 Baseline	Oficial ASVspoof 2021 baseline with RawNet2	https://github.com/asvspoof-challenge/2021
RawGAT-ST	Spectro-temporal graph attention networks for anti-spoofng	https://github.com/eurecom-asp/RawGAT-ST-antispoofng
Fairseq	Facebook AI Research toolkit (XLS-R backbone)	https://github.com/pytorch/fairseq

Tools and Libraries

Tool	Purpose	URL
Coqui TTS (XTTS)	Zero-shot multilingual TTS for trans-splicing	https://github.com/coqui-ai/TTS
YourTTS	Multi-speaker TTS for voice cloning	https://github.com/Edresson/YourTTS
Montreal Forced Aligner	Phoneme-level alignment for semantic tampering	https://github.com/MontrealCorpusTools/Montreal-Forced-Aligner
Whisper	Word-level transcription and alignment	https://github.com/openai/whisper

Conclusions

1. Self-supervised pre-training dramatically improves audio deepfake detection performance across diverse evaluation conditions.
2. XLS-R + SLS achieves 2.97% EER on ASVspoof 2021 LA, successfully reproducing the ACM MM 2024 paper results (target: 2.87% EER).
3. AASIST fails to generalize to ASVspoof 2021 due to codec sensitivity, despite achieving benchmark performance (0.83% EER) on ASVspoof 2019 LA.
4. The 87% of ASVspoof 2021 samples with codec distortion expose models trained on clean audio - highlighting the importance of realistic evaluation.
5. Early stopping is critical: Extended training leads to severe overftting (2.97% → 44.24% EER for XLS-R + SLS after 100 epochs).
6. XLS-R + SLS detects 95.45% of trans-spliced audio, signifcantly outperforming AASIST (41.72%).

— End of Report - November 2025