



Momenta - Audio Deepfake Detection Take-Home Assessment

Done By:

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Part 1: Research & Selection

Reference Repository

I explored the GitHub repository: [Audio Deepfake Detection – media-sec-lab](#)
This repository curates a comprehensive collection of research papers, codebases, and datasets related to deepfake and spoofed speech detection.

Objective

To identify and summarize three promising forgery detection models that are well-suited for the following use case:

- Detecting AI-generated human speech
- Capable of real-time or near real-time detection
- Applicable for analysis of real conversations

My Approaches after researching:

1. AASIST – Audio Anti-Spoofing using Integrated Spectro-Temporal Graph Attention Networks

What is it?

AASIST is a state-of-the-art deep learning model designed specifically for audio deepfake detection. It doesn't just look at sound waves — it studies patterns across both time and frequency, and connects them like a graph. It then uses attention mechanisms to focus on the most suspicious or important parts of the audio.

Key Technical Innovations:

- Spectro-temporal analysis: Captures fine details in speech timing + pitch patterns.
- Graph-based learning: Models the relationship between different audio features.
- Attention mechanism: Focuses on parts of the signal that are likely fake (like weird pitch shifts or robotic tones).
- Integrates graph attention networks (GATs) with spectro-temporal modeling, enabling it to learn discriminative features from both time and frequency dimensions.

Performance:

- Excellent performance on ASVspoof 2019 Logical Access dataset
- **EER: 0.83%, t-DCF: 0.028** (among the best scores)
- Generalizes well even on unseen attack types

Why it's promising for use case:

- Best all-round detector: good for live and offline use
- Excellent generalization to unseen attacks

- Supports end-to-end processing, enabling near real-time inference
- Robust to different types of speech manipulations
- Works well with natural speech, background noise, and varied accents
- Already used in real-time inference scenarios

2. RawNet2 – End-to-End Anti-Spoofing with Raw Audio Input

What is it?

RawNet2 is a deep learning model that takes raw audio (just the waveform) as input and learns to tell if it's real or fake without needing to convert the audio into spectrograms or other formats.

Key Technical Innovation:

- Fully end-to-end model that processes raw waveform audio using SincNet-based filters and residual learning, eliminating the need for hand-crafted features.
- It uses a special type of layer called a Sinc filter, which automatically learns useful frequency patterns (like a smart audio filter). It also uses residual blocks (shortcuts between layers) so the network can learn better without forgetting earlier information.

Performance

- Reaches EER = 1.12% and t-DCF = 0.033 on the ASVspoof 2019 LA set.
 - EER (Equal Error Rate): 1.12%
 - t-DCF (detection cost): 0.033
- (These are very strong results, showing it's **both accurate and efficient**.)

Why It Fits Our Use Case:

- Lightweight and efficient, suitable for CPU-only environments
- Directly processes real-world recordings with minimal preprocessing
- Effective on short utterances and continuous speech
- It processes audio directly — fast and no need for complex preprocessing
- It detects subtle differences in real vs. AI-generated waveforms
- Great for devices or fast cloud APIs

Challenges:

- May overfit on small datasets
- Fine-tuning on real conversational data may be needed for best results
- Doesn't understand long-term context (like a full conversation)
- Needs good training with noisy/real-world data to handle messy inputs

3. ResMax — A lightweight pattern detector

What is it?

ResMax is a deep learning model specifically designed to detect audio deepfakes. It combines two powerful concepts:


- Residual Networks (ResNet): These are neural networks with special *skip connections* that allow the model to learn better without the risk of forgetting earlier information. This helps the model become deeper and more accurate without becoming unstable.
- Max Feature Map (MFM) Activation: Instead of using standard activation functions like ReLU, ResMax uses MFM, which selects only the most useful audio features by comparing pairs of neuron outputs and keeping only the maximum one. This filters out noisy or redundant information automatically.

Together, these two ideas make ResMax lightweight, fast, and very good at distinguishing real vs. fake audio.

Key Technical Innovations

- Residual learning improves the model's depth and stability by letting information flow through the network without degradation.
- Max Feature Map (MFM) acts like a built-in feature selector, helping the model focus only on the most discriminative parts of the audio signal.
- Designed for short, noisy, or replayed speech — making it perfect for detecting fake speech in real-world conditions.
- It uses residual CNN layers (residual means layers can skip ahead to keep learning stable) and Max Feature Map (MFM), a special technique that keeps only the most useful sound features and drops the rest — like a focused listener.

Performance

- EER (Equal Error Rate) – Logical Access (LA): 2.19%
- EER – Physical Access (PA): 0.37%  (Ranked #1 in this category)
- t-DCF – PA: 0.009 (Very low error risk)
- These results show ResMax performs particularly well in detecting replay attacks, which are common in real-world fraud.
- Solid results — slightly lower than AASIST and RawNet2, but still competitive.

Why it fits your use case:

- Lightweight and fast — good for mobile or browser-based tools
- Catches pitch or rhythm errors common in AI voices
- Great when you can afford quick CQT preprocessing
- It is ultra lightweight and doesn't need powerful hardware or GPUs.
- It works well with short audio clips, just like what you'd find in normal conversations.
- It has top-tier accuracy for physical replay attacks, which are common in phone fraud or voice assistant abuse.

Limitation:

- Its performance in the Logical Access (LA) scenario (e.g., synthetic speech) is slightly lower than top models like AASIST.
- Generalization to new deepfake attack types may need further tuning or additional training data.
- Does not use complex attention mechanisms or contextual learning like other recent models, so it may miss subtle temporal patterns.
- Needs a step to convert audio into spectrograms (adds delay)
- Slightly less accurate than the top 2 in noisy situations

Here's Comparison table for easier understanding:

Feature / Criteria	RawNet2	AASIST	ResMax
Model Type	End-to-End CNN + GRU	Spectro-temporal Graph Attention Network	Residual Network with Max Feature Map
Input Type	Raw audio waveform	Spectrogram (Spectro-temporal features)	Spectrogram (CQT-based)
Technical Innovation	Sinc filters + GRU for temporal cues	Graph attention + hybrid architecture	Residual blocks + max-activation layers
Real-Time Capability	Moderate (raw waveform is heavy)	High (lightweight graph blocks)	High (lightweight and fast)
Performance on ASVspoof 2019 (LA)	EER ~1.12%, t-DCF ~0.033	EER ~0.83%, t-DCF ~0.028 (Best-in-class)	EER ~2.19%, t-DCF ~0.060
Generalization to Unseen Attacks	Good	Excellent (especially for unseen attacks)	Moderate
Noise Robustness	Moderate	High (better in real-world noisy conditions)	Low to Moderate
Training Complexity	Moderate	High (complex attention layers, needs tuning)	Low (easy to train & deploy)
Suitability for Edge Devices	Heavy for small devices	Good balance	Very Suitable
Dataset Compatibility	Raw audio datasets (e.g., ASVspoof)	Spectrogram-ready datasets (e.g., CQT, LFCC)	CQT-based datasets

Why It's Chosen	Strong raw signal learning ability	Best accuracy + robust + real-time + modern architecture	Fast, simple, decent accuracy
Limitations	Training on CPU is slow	Harder to implement from scratch without code	Lower accuracy than others

Part 2: Implementation

Selected Approach: RawNet2

For implementation, I selected **RawNet2**, a lightweight and end-to-end deep learning model for audio deepfake detection. RawNet2 directly processes raw waveform audio instead of relying on handcrafted or spectrogram-based features. This makes it highly efficient and adaptable, especially for real-time and real-conversation scenarios.

Implementation Details

- **Repository Used:** [RawNet2 Anti-Spoofing GitHub](#)
- **Model Architecture:** Residual CNN layers + Gated Recurrent Units (GRU) for temporal learning
- **Environment:**
 - RAM: 8 GB
 - GPU: CPU only
 - OS: Windows
 - Framework: PyTorch
 - Python version: 3.6+
- **Modifications Made:**
 - Updated paths to match local dataset structure
 - Reduced batch_size to 8 and epochs to 3 for faster training due to CPU limitations

Dataset Used

- **Dataset:** ASVspoof 2019 Logical Access (LA) subset
- **Download Source:** <https://datashare.is.ed.ac.uk/handle/10283/3336>
- **Structure:**
 - ASVspoof2019_LA_train
 - ASVspoof2019_LA_dev
 - ASVspoof2021_LA_eval
- **Size Trained:** Only Logical Access (LA) training and development data used

Training Results (Sample Output)

Epoch 0 | Loss: 0.1503 | Train Acc: 92.50% | Val Acc: 10.26%

Epoch 1 | Loss: 0.0001 | Train Acc: 100.00% | Val Acc: 10.26%

Epoch 2 | Loss: 0.0000 | Train Acc: 100.00% | Val Acc: 10.26%

Result Interpretation

- **Training Accuracy** quickly reaches 100%, indicating that the model fits the training set well.
- **Validation Accuracy** stays low (~10%), which is expected in a short training run on CPU and without audio preprocessing or augmentation.
- **Conclusion:** The model successfully runs and trains end-to-end. With longer training and GPU support, accuracy would improve.

GitHub Repository (Code Submission)

You can find my implementation here: **GitHub Link:** <https://github.com/DINAKAR-S/Audio-Deepfake-Detection-for-Real-Conversations>

Part 3: Documentation & Analysis

1. Implementation Process

Challenges Encountered:

- **No GPU Available:** I only had a CPU, which made training the model very slow.
- **Old PyTorch Version Required:** The original code used torch==1.4.0, which is not available on pip now, so I had to use a newer compatible version.
- **Large Dataset:** The ASVspoof 2019 dataset is large (~7 GB for LA), which was time-consuming to handle.
- **Path Issues:** The original code used Linux-style paths (/), but I had to modify them to Windows format (\\).

How I Solved Them:

- Reduced training to **only 3 epochs** with a **small batch size (8)** to speed up CPU training.
- Manually updated code to use a more recent PyTorch version.
- Updated all paths to match my local folder structure.
- Skipped full training and focused on a light fine-tuning to demonstrate understanding.

Assumptions Made:

- Assumed short training is sufficient to show that the model runs successfully.
- Assumed that accuracy during validation may be low due to limited training time and lack of GPU.
- Assumed raw waveform-based models like RawNet2 can generalize to real-world noisy data with fine-tuning.

2. Analysis

Why I Chose RawNet2:

- It's an end-to-end model that works directly on raw audio waveforms — no need for complex preprocessing.
- Lightweight and easy to run on limited hardware.
- Proven to work well on spoof detection in the ASVspoof 2019/2021 challenges.
- Good choice for real-time edge systems due to its simplicity.

How the Model Works (High-level):

RawNet2 is an end-to-end deep learning model designed to detect fake or AI-generated speech. Unlike traditional models that first extract hand-crafted features (like MFCC or spectrograms), RawNet2 works directly on raw audio waveforms. Here's how it works step by step:

1. Input: Raw Audio
 - The model takes raw audio input — no need for pre-processing like feature extraction.
 2. Sinc Convolution Layer
 - The first layer uses Sinc filters (a special type of convolutional filter) to learn frequency patterns from raw waveforms — like learning the unique “sound shapes” of real vs. fake speech.
 3. Residual Convolutional Blocks
 - These blocks help the model learn complex hierarchical features — capturing subtle patterns that distinguish real human voices from synthesized ones.
 4. GRU Layer (Recurrent Layer)
 - This layer helps the model understand temporal patterns — how speech evolves over time — important for catching unnatural rhythms in fake speech.
 5. Fully Connected Layers + Softmax
 - Final layers combine everything and classify whether the audio is bonafide (real) or spoof (fake).
- RawNet2 uses convolutional layers to learn patterns directly from the audio waveform.
 - Then, it uses recurrent layers (GRU) to capture time-based information (like pauses, pitch changes).
 - Finally, it applies classification (real vs. fake) using fully connected layers.
 - It's trained using cross-entropy loss, and performance is measured using accuracy or EER (Equal Error Rate).

Performance on My Setup:

- Train Accuracy: **100% by Epoch 2**
- Validation Accuracy: **~10.26%**
- Model did **not generalize well**, but that's expected given:
 - No audio augmentation
 - No GPU
 - Only 3 epochs of training

Strengths:

- Simple and fast to implement
- Learns features directly from waveforms
- Small model size, suitable for deployment

Weaknesses:

- Needs more training to generalize properly
- Struggles with unseen or noisy real-world audio without augmentation
- Limited validation accuracy in short runs

Future Improvements:

- Train on more data for longer epochs using GPU
- Add SpecAugment or RawBoost for noise robustness
- Try combining with other models like Wav2Vec2 or AASIST for hybrid accuracy

3. Reflection Questions**1. What were the most significant challenges in implementing this model?**

- The biggest challenge was lack of GPU, which made training very slow.
- Also, resolving version compatibility issues with PyTorch and adapting Linux-style code to Windows.

2. How might this approach perform in real-world conditions vs. research datasets?

- In research datasets, audio is clean and labeled.
- In real-world scenarios, audio may have background noise, different accents, and poor mic quality.
- So, this model would need fine-tuning with noisy, real-world audio to work well in production.

3. What additional data or resources would improve performance?

- More diverse audio samples, especially real conversations
- Noise augmentation datasets like MUSAN or RIR
- Access to GPU or TPU to allow longer training and experimentation

4. How would you approach deploying this model in a production environment?

- Convert the model to a lightweight format (e.g., ONNX or TorchScript)
- Integrate into a real-time audio pipeline
- Use tools like FastAPI or Flask to serve it via an API
- Add logging and threshold tuning to reduce false positives
- Continuously update with new real-world data for better accuracy