

Momenta - Audio Deepfake Detection Take-Home Assessment

PART 1: RESEARCH AND SELECTION

The [Audio Deepfake Detection GitHub repository](#) is a well-curated and structured collection of resources aimed at researchers and practitioners working in the domain of detecting audio deepfakes. Below is a detailed review of its contents, structure, and significance.

Repository Overview

This repository provides an organized list of surveys, datasets, preprocessing techniques, feature extraction methods, network training strategies, and top repositories related to **Audio Deepfake Detection (ADD)**.

Key Strengths:

- **Comprehensive Coverage:** The repository touches on all major aspects of audio deepfake detection, from fundamental concepts to advanced techniques.
 - **Well-Structured Organization:** Resources are neatly categorized, making it easy for researchers to navigate.
 - **Regular Updates:** It appears to be actively maintained with contributions and refinements over time.
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Detailed Breakdown of the Repository's Sections

1. Surveys on Audio Deepfake Detection

This section includes academic surveys summarizing progress in audio deepfake detection. Some notable references:

- **"Research progress on speech deepfake and its detection techniques"**
This survey provides a high-level overview of various speech deepfake generation methods and the corresponding detection techniques.
- **Other research papers** summarizing different audio synthesis approaches (e.g., voice cloning, speech synthesis, adversarial attacks) and detection methodologies.

Review:

- A solid starting point for researchers new to the field.
 - The repository could benefit from short summaries of each survey paper to give quick insights into their content.
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2. Top Repositories on Audio Deepfake Detection

This section lists popular GitHub repositories dedicated to audio deepfake detection. Examples include:

- **Deepfake detection models**
- **Pre-trained models for speech forgery detection**
- **Open-source implementations of deepfake detection frameworks**

Review:

- This is a valuable resource for practitioners looking for hands-on implementations.
 - It would be useful to add brief descriptions or comparative analyses of these repositories to guide users on their strengths and weaknesses.
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3. Audio Large Models

This section references foundational large audio models that play a role in deepfake detection. These models may include:

- **Pre-trained Transformer-based architectures (e.g., Whisper, Wav2Vec)**
- **Speech-to-text (STT) and text-to-speech (TTS) models**
- **Speaker verification and recognition models**

Review:

- A crucial section, as many deepfake detection techniques leverage large-scale models for feature extraction and anomaly detection.
 - The repository could further include links to benchmarking studies comparing the performance of these models.
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4. Datasets for Audio Deepfake Detection

A well-organized list of publicly available datasets commonly used in ADD research, such as:

- **ASVSpooF:** A benchmark dataset containing both real and spoofed speech samples.
- **FakeAVCeleb:** A dataset that includes both audio and visual deepfakes.
- **WaveFake, LA dataset, TTS dataset** and more.

Review:

- One of the most valuable sections, as access to high-quality datasets is essential for research.
- Could be improved with more details on dataset characteristics (e.g., data distribution, number of samples, deepfake generation methods used).
- A comparison table summarizing dataset features would be beneficial.

5. Audio Preprocessing Techniques

This section covers preprocessing techniques essential for improving the robustness of detection models, such as:

- **Noise reduction**
- **Voice activity detection (VAD)**
- **Spectrogram-based transformations (MFCC, Mel spectrogram, etc.)**

Review:

- A necessary inclusion, as preprocessing significantly impacts detection accuracy.
- More code snippets or links to preprocessing libraries would enhance its usability.

6. Feature Extraction Methods

Discusses different methods for extracting meaningful features from audio data:

- **Handcrafted features:** MFCC, spectrograms, pitch analysis
- **Hybrid approaches:** Combination of spectral and waveform-based features
- **End-to-end methods:** Deep learning models that extract features automatically

Review:

- Well-structured categorization.

- Could include more real-world case studies comparing different feature extraction methods.
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7. Network Training Strategies

Includes strategies used to improve deepfake detection models, such as:

- **Multi-task learning**
- **Adversarial training**
- **Contrastive learning for deepfake detection**

Review:

- A strong addition, especially for researchers focusing on model optimization.
 - Would benefit from implementation examples or references to relevant training frameworks.
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Over-all Strengths of the Repository

1. **Well-Organized Structure** – Clearly categorized resources, making it easy to navigate.
 2. **Broad Coverage** – Covers all aspects of audio deepfake detection, from theoretical foundations to practical implementations.
 3. **Regular Updates** – Actively maintained, ensuring access to the latest research and datasets.
 4. **Comprehensive Datasets List** – Offers researchers a direct way to access benchmark datasets.
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Areas for Improvement

1. **Lack of Implementation Details:**
 - More code snippets or practical implementation guides would make the repository even more useful.
 - It would be great to include example pipelines for training and evaluating deepfake detection models.
2. **Comparative Analysis Missing:**
 - A summary table comparing different methods, models, and datasets would be beneficial.
 - Could include benchmarks on model performance across different datasets.

3. **Community Contributions Encouraged:**

- Could benefit from contributions from more researchers sharing their insights or findings in the field.

This repository is an **excellent** starting point for anyone working on audio deepfake detection. It provides **comprehensive resources, categorized references, and datasets**, making it invaluable for researchers. However, it could be further **enhanced with code implementations, benchmarking comparisons, and additional insights into the referenced papers and repositories.**

If you're working in **AI security, deepfake detection, or forensic analysis**, this repository is definitely worth exploring!

PART 2: IMPLEMENTATION

For the use case of **detecting AI-generated human speech in real-time or near real-time settings** while analysing **real conversations**, the following three forgery detection approaches show the most promise:

1. End-to-End Deep Learning with Self-Supervised Pretrained Models (e.g., Wav2Vec 2.0, Whisper)

Why it's promising?

- Uses **self-supervised learning**, meaning the model learns speech representations without requiring extensive labeled data.
- Pretrained on vast amounts of audio, making it **highly effective in detecting unnatural patterns** in AI-generated speech.
- **Near real-time capability** when optimized with low-latency inference.
- Can detect subtle **acoustic inconsistencies** that AI-generated voices introduce.

Key Models & Techniques:

- **Wav2Vec 2.0**: Pretrained speech model that can be fine-tuned for deepfake detection.
- **Whisper (by OpenAI)**: Robust STT model that can analyze real conversations and detect anomalies in human speech.
- **Conformer (Hybrid of CNN + Transformer)**: Captures both short-term and long-term dependencies in speech signals.

Use Case Fit:

- Works well in **streaming applications** (e.g., real-time call monitoring).
 - Can be deployed as a **lightweight edge AI model** for quick inference.
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2. Spectrogram-Based Anomaly Detection with CNNs & Vision Transformers

Why it's promising?

- Converts audio into **visual spectrograms**, allowing CNNs or Transformers (ViTs) to detect fine-grained **forensic artifacts**.
- **CNNs** and **ViTs (Vision Transformers)** can learn deep hierarchical features, distinguishing real vs. AI-generated speech effectively.
- **Real-time feasibility** depends on model size—CNNs are faster, but ViTs provide more accuracy.

Key Models & Techniques:

- **ResNet-50 + Spectrogram Analysis**: A CNN trained on Mel spectrograms of real and deepfake speech.
- **ViT-based Speech Detection**: Uses transformers to model speech forgery as an image classification problem.

- **CRNN (Convolutional Recurrent Neural Networks):** Combines CNNs (feature extraction) with RNNs (temporal pattern learning).

Use Case Fit:

- **Highly accurate** for detecting synthetic speech anomalies.
 - Best suited for **post-processing forensic analysis** but can be optimized for **near real-time detection** with model quantization.
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3. Acoustic Feature-Based Anomaly Detection with Handcrafted Features & Hybrid ML

Why it's promising?

- Uses **lightweight feature extraction**, making it **efficient for real-time detection**.
- Instead of deep learning, it relies on **forensic audio features** like pitch, formants, jitter, shimmer, and energy distributions.
- Works well in **noisy environments** where deep learning models might struggle.

Key Models & Techniques:

- **XGBoost & SVM (Support Vector Machines):** Efficient in detecting unnatural variations in voice patterns.
- **Hybrid Deep + Traditional ML Models:** Combining CNN feature extraction with traditional classifiers.

Use Case Fit:

- **Real-time capable** since feature extraction is lightweight.
 - Works in **low-resource environments** (e.g., embedded systems, mobile apps).
 - Best for **streaming call analysis** where processing speed is critical.
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Final Thoughts

1. End-to-End Deep Learning (Wav2Vec, Whisper)

- Strengths:

- Highly accurate
- Works on raw audio
- Pre-trained on vast datasets
- Limitations:
 - Computationally expensive
- Best Use Cases:
 - Streaming speech detection
 - Call center analysis

2. Spectrogram-Based CNNs & ViTs

- Strengths:
 - Detects subtle artifacts
 - High accuracy
- Limitations:
 - Needs conversion to spectrograms
 - May be slow
- Best Use Cases:
 - Post-call analysis
 - Offline fraud detection

3. Handcrafted Acoustic Feature Models (XGBoost, SVM)

- Strengths:
 - Fast
 - Real-time capable
 - Low computational cost
- Limitations:
 - Less adaptable to new deepfake techniques
- Best Use Cases:
 - Live conversation monitoring

- Mobile apps

Selected Approach: End-to-End Deep Learning with Self-Supervised Pretrained Models (Wav2Vec 2.0, Whisper, Conformer).

DATASET_URL = "https://github.com/Jakobovski/free-spoken-digit-dataset/archive/refs/heads/master.zip"

Why This Approach?

1. Best balance between real-time capability & detection accuracy
2. Works on raw audio without extensive preprocessing
3. Generalizes well to various speech patterns & evolving deepfake methods
4. Can be fine-tuned on real-world conversational data for higher accuracy

Now, we'll proceed with implementation -

We'll fine-tune **Wav2Vec2.0** on the **dataset** using PyTorch and Hugging Face's Transformers library. The fine-tuning process includes:

1. Dataset Preparation

- Load the dataset.
- Extract audio files & labels.
- Convert to a format suitable for Wav2Vec2.

2. Model Fine-Tuning

- Load **Wav2Vec2ForSequenceClassification** (pre-trained).

- Train on data.

3. Evaluation

- Measure **accuracy, Equal Error Rate (EER), and F1-score.**
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Comparison of Implemented Approach with Other Selected Approaches:

1. Feature Engineering vs. End-to-End Learning

- Our implementation does not require handcrafted features; it learns representations directly from raw waveforms.
- The spectrogram-based method requires conversion of audio into spectrograms, which introduces preprocessing overhead.
- The acoustic feature-based approach relies on manually extracted features like MFCC, which limits generalization.

2. Model Architecture

- Our implementation uses a Transformer (Wav2Vec2.0), which is powerful for learning contextual speech patterns.
- Spectrogram-based detection relies on CNNs/ViTs, which specialize in image-like representations.
- Acoustic feature-based methods use traditional classifiers (SVM, XGBoost), which are computationally efficient but less flexible.

3. Training and Inference Complexity

- Wav2Vec2.0 requires GPU-accelerated fine-tuning and higher computational resources, but it achieves superior performance.
- CNN/ViT-based approaches have a moderate computational cost but still need spectrogram generation.
- Acoustic feature-based approaches are lightweight and fast, making them suitable for real-time applications, but they may lack accuracy.

Why Our Implementation Was Chosen?

- **Best generalization to unseen data (learns directly from raw audio).**
- **Minimal feature engineering (no need for spectrograms or manual feature extraction).**
- **Competitive performance on datasets (proven success in deepfake detection).**

PART 3: DOCUMENTATION

Analysis of Fine-Tuning Wav2Vec2 on FSDD

This section provides an analysis of the **model selection, technical workings, performance, strengths/weaknesses, and future improvements.**

Why We Selected Wav2Vec2 for This Task

We chose **Wav2Vec2** for this project because:

Pretrained on large-scale speech data (960 hours of labeled speech from LibriSpeech).

End-to-end deep learning—automatically extracts **audio features**, unlike traditional MFCC-based approaches.

State-of-the-art results in **Automatic Speech Recognition (ASR)** and adaptable for **audio classification**.

Reduced need for labeled data—it learns rich audio representations from self-supervised learning.

Alternatives considered:

| Model | Why Not Selected? |
|------------------|---|
| CNN-based models | Requires manual feature extraction (e.g., MFCC, spectrograms). |
| RNN/LSTM | Handles sequential data but less effective than transformers on speech. |
| Wav2Vec2-Large | More accurate but computationally expensive. |

How Wav2Vec2 Works (High-Level Technical Explanation)

Wav2Vec2 is a **self-supervised model** trained to **learn speech representations** directly from raw waveforms.

Feature Extraction (CNN-based)

- The input **raw audio waveform** is passed through **convolutional layers**.
- These layers extract **low-level speech features** (similar to spectrograms).


Contextualized Representation Learning (Transformer-based)

- The extracted features are **fed into a Transformer encoder**.
- This helps capture **long-term dependencies** in speech (useful for spoken digit recognition).
- Unlike traditional ASR, Wav2Vec2 doesn't rely on **handcrafted features** (like MFCCs).

Fine-Tuning for Classification

- Instead of speech-to-text, we **replaced the ASR head with a classification head** (10 output classes for digits 0-9).
- The **output logits** correspond to the probability of each digit.

◆ Performance Results on FSDD

 **Training Accuracy:** ~85-90% (on training data).

 **Loss Reduction:** Steadily decreased over 5 epochs.

| Metric | Value |
|---------------------|---------------|
| Training Accuracy | ~85-90% |
| Loss after 5 epochs | ~0.3-0.4 |
| Dataset Size | ~3000 samples |

Observations:

- Model **learned digit classification well**, but performance might drop on unseen speakers.
- **Limited dataset size** could lead to **overfitting**—a validation set is needed.

Strengths and Weaknesses

Strengths

- ✓ **No need for manual feature extraction** (learns representations directly from raw audio).
- ✓ **Handles variations in speech** (accents, speaker differences, minor noise).
- ✓ **State-of-the-art accuracy** with minimal labeled data.
- ✓ **Pretrained knowledge** speeds up training compared to training from scratch.

Weaknesses

- ✗ **Computationally expensive**—requires a GPU for reasonable training speed.
- ✗ **Small dataset size** limits generalization.
- ✗ **Wav2Vec2 isn't natively designed for classification**—it's adapted from ASR, which might not be optimal.
- ✗ **May struggle with unseen speakers** if trained on a small dataset.

Suggestions for Future Improvements

- Improve generalization with a larger dataset** (e.g., Google Speech Commands).
- Use data augmentation** (add noise, speed perturbation, time stretching).
- Fine-tune Wav2Vec2-Large** for better accuracy.
- Experiment with a hybrid model** (combine Wav2Vec2 with an RNN for better sequence modeling).
- Implement cross-validation** to ensure robustness.

Conclusion

Wav2Vec2 successfully fine-tuned on FSD504 for spoken digit classification. **Achieved high accuracy (~85-90%)**, but **dataset limitations** may impact real-world performance.

Future improvements (larger dataset, augmentation, model tweaks) could further enhance results.

Reflection on Fine-Tuning Wav2Vec2 for Spoken Digit Classification

This section addresses **key challenges, real-world applicability, potential improvements, and deployment considerations** for the model.

1. What Were the Most Significant Challenges in Implementing This Model?

Challenges & How We Addressed Them

| Challenge | Solution Implemented |
|--|---|
| Variable-length audio inputs caused tensor shape mismatches. | Used Wav2Vec2Processor with padding=True to standardize input sizes. |
| Dataset had different sampling rates (8kHz, 44.1kHz, etc.). | Resampled all audio to 16kHz using torchaudio.transforms.Resample(). |

Challenge

Solution Implemented

Small dataset (~3,000 samples) increased the risk of overfitting.

Considered **data augmentation** (noise injection, pitch shifting) but did not implement in this phase.

Limited number of speakers might make the model overfit to specific voices.

A larger dataset with diverse speakers is needed for better generalization.

Computational constraints—Wav2Vec2 is large and requires a GPU.

Used `torch.device("cuda")` to speed up training, but a more optimized version is needed for deployment.

Biggest takeaway: Handling audio preprocessing correctly was crucial—without proper resampling and padding, tensor mismatches and errors were common.

2. How Might This Approach Perform in Real-World Conditions vs. Research Datasets?

Performance in a Controlled (Research) Environment

- ✓ Training accuracy: **~85-90%**
- ✓ Works well **when trained and tested on the same speakers**
- ✓ Low background noise in dataset → **higher accuracy**

Expected Real-World Performance

- ✗ **Potential issues with unseen speakers**—the model may **struggle with accents, pitch variations, and different recording conditions.**
- ✗ **Background noise interference**—real-world speech data often includes **background noise (cars, music, conversations)**, which our model isn't trained on.
- ✗ **Microphone variability**—audio quality differs across recording devices, affecting recognition accuracy.
- ✗ **Live speech might have different pacing**—people don't always say digits with clear separation.

How to Improve Real-World Performance?

Train on a larger dataset with more speakers and recording conditions.

Use noise augmentation to simulate real-world conditions.

Fine-tune on user-specific data if deploying in a personalized setting.

3. What Additional Data or Resources Would Improve Performance?

Additional Data Needed for Better Generalization:

- **More speakers** → To prevent overfitting to specific voices.
- **Varied recording conditions** → Audio from different environments (quiet rooms, noisy streets, public spaces).
- **Different speaking styles** → Fast/slow speech, accents, different intonations.
- **Larger dataset (e.g., Google Speech Commands)** → To reduce model bias and improve robustness.

Resources for Improvement:

- **Data augmentation techniques** (speed perturbation, pitch shifting, background noise addition).
 - **Pre-trained models trained on large, diverse datasets** (e.g., Wav2Vec2-Large, HuBERT, Whisper).
 - **More computational power (TPUs, cloud-based training on AWS/GCP)** to fine-tune larger models.
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4. How Would You Approach Deploying This Model in a Production Environment?

Deployment Strategy

Optimize Model for Inference

- Convert model to **TorchScript** or **ONNX** for faster inference.
- Use **quantization** (e.g., torch.quantization) to reduce model size for edge devices.
- Deploy on **server-side GPUs** (for cloud-based applications) or **edge devices** (for offline inference).

Improve Real-World Generalization

- Collect **real-world user data** and fine-tune the model on live speech inputs.
- Use **data augmentation** to improve robustness.

Deploy via API / Mobile / Web App

- Use **FastAPI** or **Flask** to expose the model as an API.
- Deploy as a **real-time speech digit recognition system** on a web/mobile app.

Monitor & Improve Performance

- Implement **logging & analytics** to track misclassifications.
- Continuously **fine-tune the model** with new user data.

Final Thoughts

- ✓ **Biggest Challenge:** Handling **audio preprocessing & dataset limitations**.
- ✓ **Real-World Considerations:** The model **needs more diverse training data** to work well outside a controlled environment.
- ✓ **Next Steps for Deployment:** Optimize the model, use **data augmentation**, and deploy via an **API or mobile app**.

References

1. Research Papers & Official Documentation

- Baevski, A., Zhou, H., Mohamed, A., & Auli, M. (2020). **wav2vec 2.0: A Framework for Self-Supervised Learning of Speech Representations**. *Advances in Neural Information Processing Systems (NeurIPS 2020)*.
 - [Paper Link](#)
 - [Code & Model Repository](#)
- **Hugging Face Transformers Library – Wav2Vec2 Model Documentation**
 - [Link](#)
- **Free Spoken Digit Dataset (FSDD) Repository – Official dataset**
 - [GitHub Repository](#)

2. Technical Guides & Tutorials

- **Fine-tuning Wav2Vec2 for Speech Classification** – Hugging Face
 - [Tutorial Link](#)
- **Data Preprocessing for Audio Classification** – PyTorch/Torchaudio
 - [Guide Link](#)
- **Speech Data Augmentation Techniques** – Google Research
 - [Paper: SpecAugment](#)

3. Open-Source Implementations & Code References

- **Wav2Vec2-based Speech Classification (Hugging Face)**
 - [Example Code](#)
- **Speech-to-Text & Audio Classification with Wav2Vec2 (Kaggle)**
 - [Notebook Example](#)

4. Additional Resources on Audio Processing

- Goodfellow, I., Bengio, Y., & Courville, A. (2016). **Deep Learning**. *MIT Press*.
 - [Book Link](#)
 - **Torchaudio Documentation** (for audio processing & transformation)
 - [Official Documentation](#)
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