# RuHuman: A Resilient Multimodal AI-Powered Audio Verification System

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ECE202A Embedded Systems @ UCLA

# Motivation and Objectives

- Audio deep fakes are becoming more easily spoofable with the advent of generative AI.
  - Growing number in deep fake crimes
- RuHuman evaluates existing audio liveness detection systems that exploit multiple audio modalities.
- The Objectives of this RuHuman Are:
  - Evaluating different audio liveness detector architectures against state of the art voice cloners.
  - Developing a user interface to make gateway devices (e.g. phone) easily verify with their microphones

Mom warns of AI voice cloning scam

119K views • 8 months ago

Good Morning America

ABC News' Erielle Reshef shares an urgent warning from

# Previous/Related Work

- ASVSpoof  is a dedicated challenge that to develop audio spoofing classifiers. Three main challenges are PA, LA, and DF (RuHuman focuses on LA).
- Researchers take advantage of various encodings (STFT, MFCC, CQCC) to augment the training resolution of the audio sample.
- UCLA NESL developed ResNet models with different embeddings and performed model fusion to minimize ASV/CM loss metrics in ASVSpoof 2019.

ASVspoof

Automatic Speaker Verification and Spoofing Countermeasures Challenge

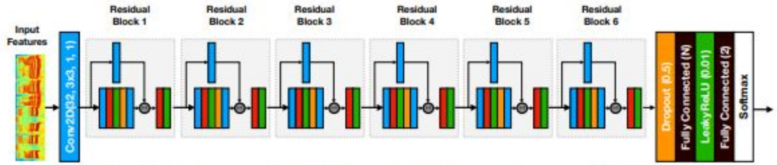
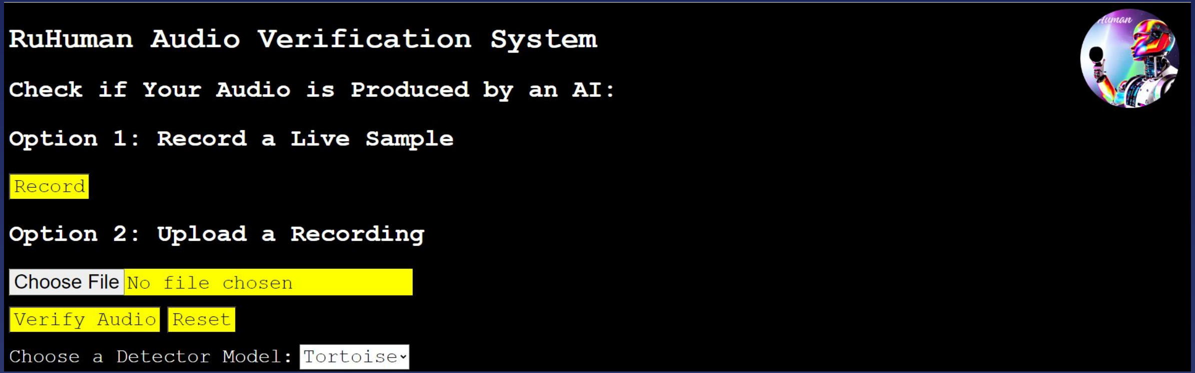


Figure 1: *Model architecture for the Spec-ResNet model. Detailed structure of residual blocks is shown in* 2.

# Novelty of Project

- Datasets used for training in ASVSpoof2019 LA challenge were in a controlled environment, insusceptible to ‘out in the wild’ samples
- RuHuman investigates the performance of different detector architectures when additive noise is mixed in with the suspected audio sample.
- Additionally, RuHuman implements an interactive user interface that allow for a wide range of computing (from a cell phone to a computer workstation) to access multiple detector models with just an HTTP Post Request.



**RuHuman Audio Verification System**

**Check if Your Audio is Produced by an AI:**

**Option 1: Record a Live Sample**

**Option 2: Upload a Recording**

Choose a Detector Model: Tortoise

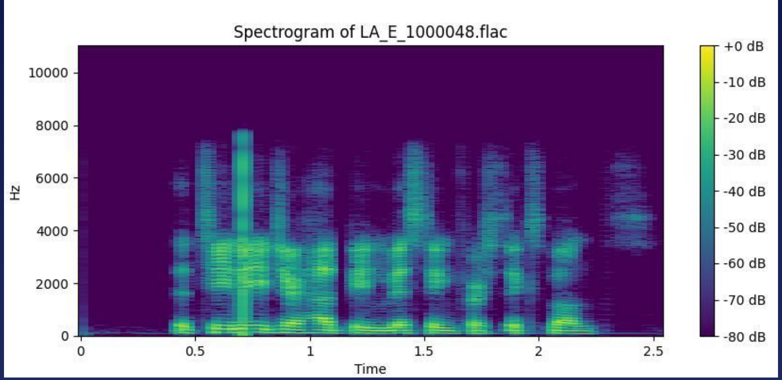
# Background: Audio Feature Extractions

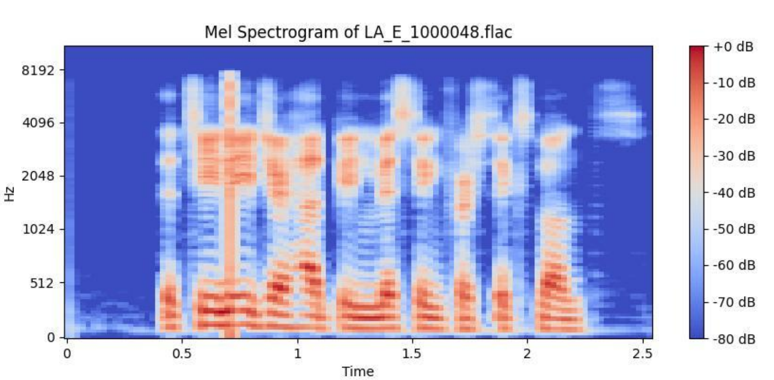
**STFT** (Short-Time Fourier Transform): Compute FFT over a window, use log to plot Spectrogram.

**LFCC** (Linear-Frequency Cepstral Coefficients): Map frequency powers through a linear filter bank then take DCT of log of filter coefficients

**MFCC** (Mel-Frequency Cepstral Coefficients): Map frequency powers through a mel filter bank (tuned for humans), then take DCT of coefficients.

**CQCC** (Constant Q Cepstral Coefficients): Uses CQT basis for cepstrum. More spectro/temporal resolution at low/high frequencies.





# Overview of Voice Cloners

- **Tortoise:** A voice cloner using Autoregressive Diffusive decoder with DDPM noise schedulers.
    - Pre-trained on 49,000 hours of audio clips from podcasts/videos.
- **Apple Personal Voice:** A proprietary personalized voice synthesizer that is trained by using 15 mins of live utterance
    - Trained locally on iOS device, use text to speech to synthesize audio.
    - Aside: Not easily exportable, must use screen recorder to grab audio.

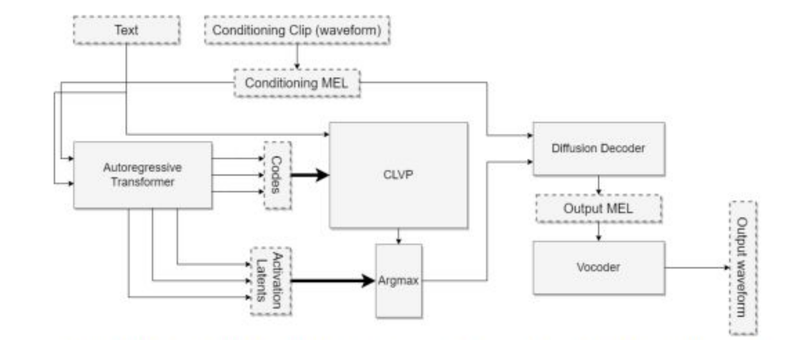
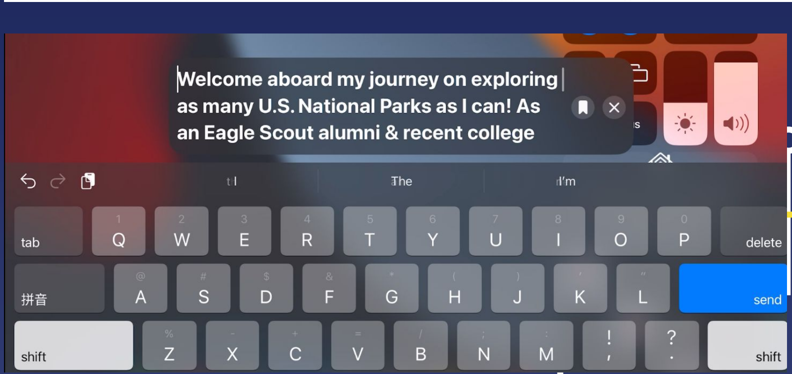


Figure 1: TorToise-v2 architectural design diagram. Inputs of text and a reference audio clip (for speaker cloning) flow through a series of decoding and filtering networks to produce high-quality speech.



Welcome aboard my journey on exploring as many U.S. National Parks as I can! As an Eagle Scout alumni & recent college

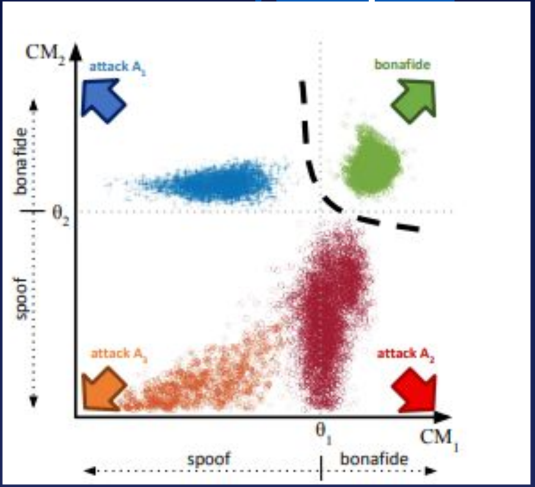
# Overview of Voice Detectors

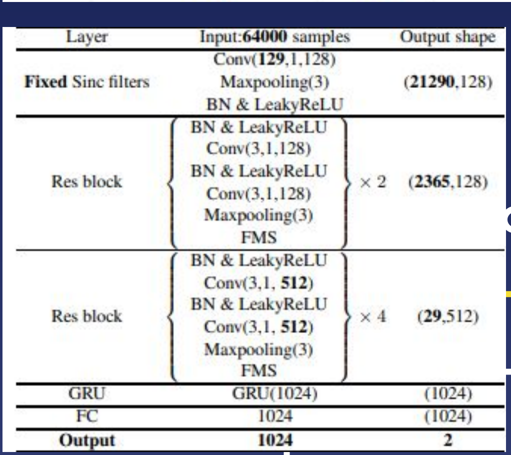
**Baseline ASVSpoof Models:**

- **LFCC-GMM:** A Two-Class Gaussian Mixture Model with LFCC input. 70-Channel Linear Filters. Outputs LLR between bonafide & spoof.
- **CQCC-GMM:** A Two-Class Gaussian Mixture Model with CQCC input. Features are 1st 19 Coeff. Outputs LLR between bonafide & spoof.
- **RawNet2:** An End to End Neural Network using mel sinc filters. Outputs two-class likelihood between bonafide and spoof.
- All Baseline models trained with ASVSpoof2019 Training Set (~25380 Samples, 20/107 Distinct Speakers from total set)

**In the Wild Models:**

- **Tortoise:** An Audio Mini Encoder Classifier. Outputs probability on whether an audio sample was generated by TortoiseTTS.
  - Trained on same data used by detector (49,000 hours of podcasts/videos from internet).

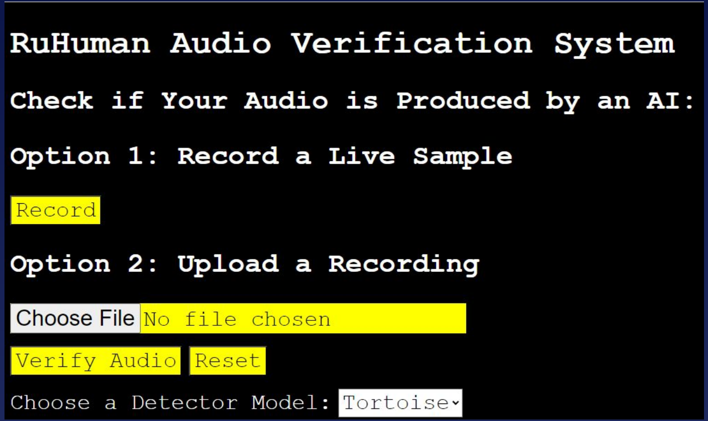




| Layer | Input:**64000** samples | | Output shape |
|---|---|---|---|
| **Fixed** Sinc filters | Conv(**129**,1,128)<br>Maxpooling(3)<br>BN & LeakyReLU | | (**21290**,128) |
| Res block | BN & LeakyReLU<br>Conv(3,1,128)<br>BN & LeakyReLU<br>Conv(3,1,128)<br>Maxpooling(3)<br>FMS | × 2 | (**2365**,128) |
| Res block | BN & LeakyReLU<br>Conv(3,1, **512**)<br>BN & LeakyReLU<br>Conv(3,1, **512**)<br>Maxpooling(3)<br>FMS | × 4 | (**29**,512) |
| GRU | GRU(1024) | | (1024) |
| FC | 1024 | | (1024) |
| **Output** | **1024** | | **2** |

# Overview of User Interface

- Web Server Implemented in Python Flask to serve many gateway devices that have internet access.
- Users can verify their audio sample in 2 ways:
  - **1.** Users record a live sample client-side by using *getUserMedia()* from Javascript, which then is saved to a blob.
  - **2.** Users upload a pre-recorded audio file from their device to the HTML form to post.
- Users upload data via HTTP request post to server.
- File is stored and pass through detector via refactored callable Python functions (GMMs: *matlab.engine*)
- Dashboard displays uploaded audio (verifying it's on the server), in addition to visualizing it's encodings with *librosa* and outputting metrics of verification.



RuHuman Audio Verification System

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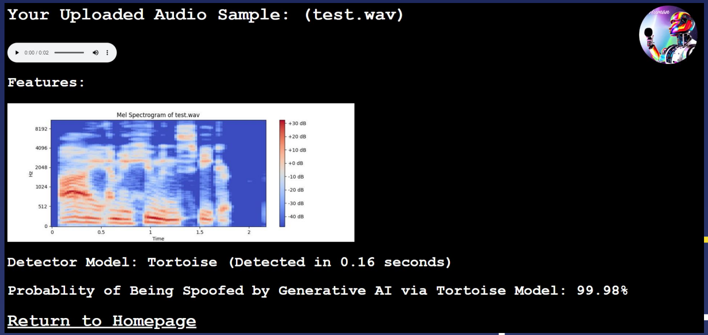

Your Uploaded Audio Sample: (test.wav)

Features:

Detector Model: Tortoise (Detected in 0.16 seconds)

Probablity of Being Spoofed by Generative AI via Tortoise Model: 99.98%

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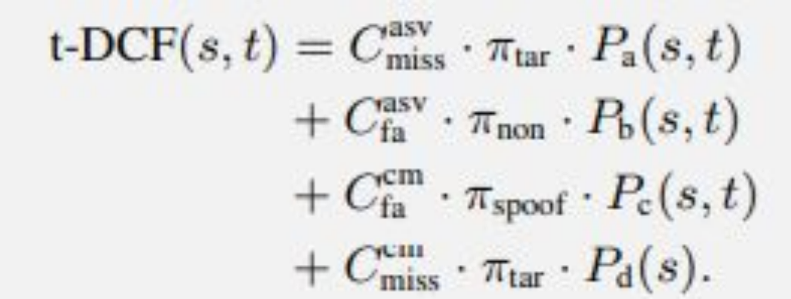
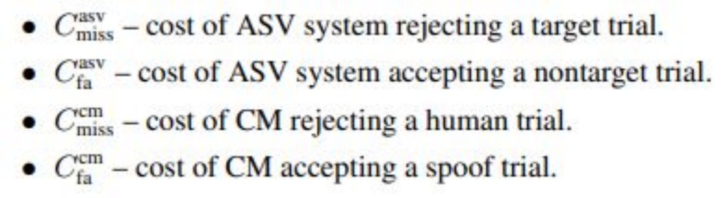
# Metrics of Evaluation

- **t-DCF:** A custom cost function that weighs between predefined ASV scores (from organizers), speaker priors, and CM scores provided by the detector architecture.
- **EER:** The likelihood threshold at which the miss rate and the false alarm rate equate.
- **Computation Time:** The duration for a single audio sample to be verified.
    - Ideally in a live setting should be less than duration of the sample.
- Objective is to minimize all metrics for accuracy and efficiency in live settings.



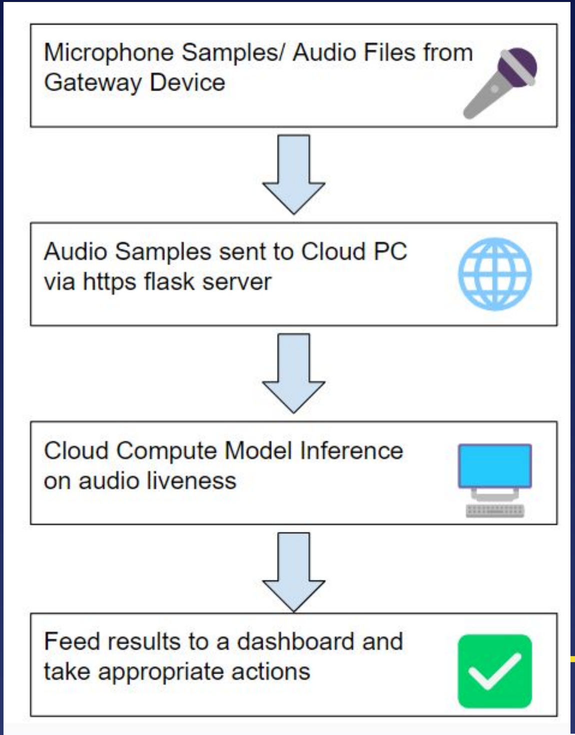
$$\begin{aligned}\text{t-DCF}(s,t) = {} & C^{\text{asv}}_{\text{miss}} \cdot \pi_{\text{tar}} \cdot P_{\text{a}}(s,t) \\ & + C^{\text{asv}}_{\text{fa}} \cdot \pi_{\text{non}} \cdot P_{\text{b}}(s,t) \\ & + C^{\text{cm}}_{\text{fa}} \cdot \pi_{\text{spoof}} \cdot P_{\text{c}}(s,t) \\ & + C^{\text{cm}}_{\text{miss}} \cdot \pi_{\text{tar}} \cdot P_{\text{d}}(s).\end{aligned}$$



- $C^{\text{asv}}_{\text{miss}}$ – cost of ASV system rejecting a target trial.
- $C^{\text{asv}}_{\text{fa}}$ – cost of ASV system accepting a nontarget trial.
- $C^{\text{cm}}_{\text{miss}}$ – cost of CM rejecting a human trial.
- $C^{\text{cm}}_{\text{fa}}$ – cost of CM accepting a spoof trial.

# Technical Approach

- **Phase 1: Investigation of Additive Noise Sources** (ASVSpoof Submissions Only)
  - Work with each baseline detector to produce metrics on the ASVSpoof2021 Evaluation Set (181,566 samples, 67 Distinct Speakers, 37 F, 30 M).
  - Inject each audio sample in the evaluation set with additive white gaussian noise (SNR = 50).
  - Recompute metrics with infected evaluation set and compare scores.
- **Phase 2: Deployment of User Interface**
  - Send/receive audio from client/gateway with multiple upload options.
  - Refactor detectors to be callable functions with audio path argument.
  - Show audio features and results on dashboard.



Microphone Samples/ Audio Files from Gateway Device

Audio Samples sent to Cloud PC via https flask server

Cloud Compute Model Inference on audio liveness

Feed results to a dashboard and take appropriate actions

# Primary Metric Metric: t-DCF & EERs

| Detector Architecture (Normal) | Pooled t-DCF | Pooled EER (%) |
|---|---|---|
| Baseline LFCC-GMM (MATLAB) | 0.5758 | 19.30 |
| Baseline CQCC-GMM (MATLAB) | 0.4964 | 15.62 |
| Baseline RawNet2 (Python) | 0.4255 | 9.49 |

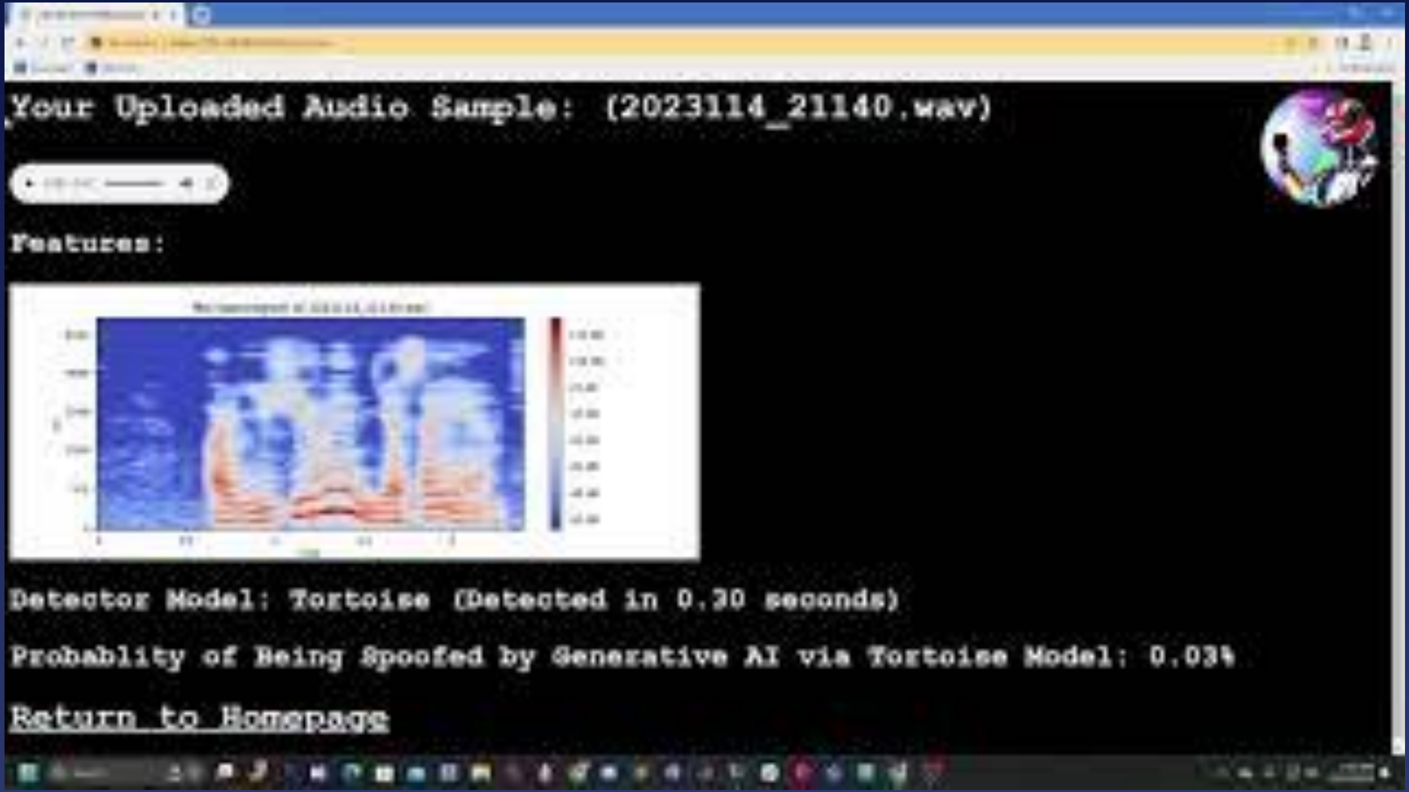
| Detector Architecture (AWGN) | Pooled t-DCF | Pooled EER (%) |
|---|---|---|
| Baseline LFCC-GMM (MATLAB) | 0.8527 | 41.33 |
| Baseline CQCC-GMM (MATLAB) | 0.7609 | 31.99 |
| Baseline RawNet2 (Python) | 0.3317 | 7.23 |

# Secondary Metric: Computation Time

| Detector Architecture | Average Computation Time per Sample (s) |
|---|---|
| Tortoise Audio Mini Encoder (Python) | 0.22 |
| Baseline LFCC-GMM (MATLAB) | 0.18 |
| Baseline CQCC-GMM (MATLAB) | 0.27 |
| Baseline RawNet2 (Python) | 0.30 |

**on average each sample was approximately 3-5 seconds long*

# Demo



Your Uploaded Audio Sample: (2023114_21140.wav)

Features:

Detector Model: Tortoise (Detected in 0.30 seconds)

Probablity of Being Spoofed by Generative AI via Tortoise Model: 0.03%

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# Conclusion & Future Directions

## Conclusion:

- Primary evaluation from phase 1 indicates that additive noise can be injected to GMMs enhance a plausible spoofing attack to being successful.
    - Metrics actually went lower for RawNet2, perhaps the initial layer of Mel Sinc Filters mitigated the effect of AWGN.
- All detectors were able to detect an audio samples within a second, making them usable for liveness detection.
- User Interface was deployed and easily accessible from gateway devices.

## Future Directions:

- Preprocess audio samples with denoising to isolate speaker from noise before being sent to spoof detection model.
- Perform embedded actions on classifier outputs (e.g. turn a light red/green)
- Audio spoofing detection can be fused with other modalities of liveness detection (i.e. video deep fake detection) for a complete system. May experiment with this pipeline over winter break on a separate branch.

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# Thanks for Listening!
# Any Questions?