SPEECH UNDERSTANDING

K.K.N Shyam Sathvik

Neermita Bhattacharya

B22EE036, B22CS092

AUDIO FORENSICS

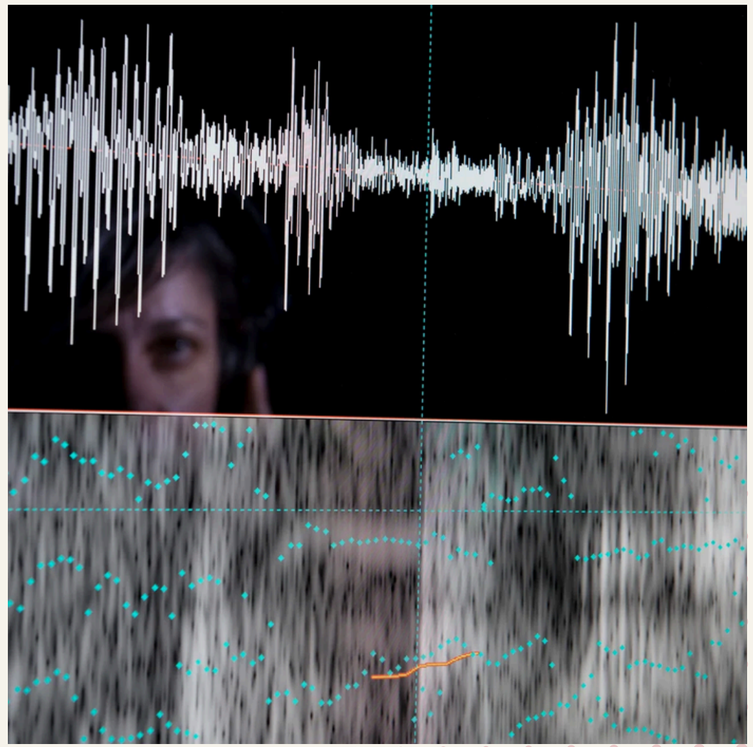
Audio forensics is the scientific analysis of audio recordings to determine their authenticity, improve intelligibility, and identify potential manipulations, often used in legal proceedings to present evidence as part of a criminal investigation or civil case. It involves using specialized techniques to verify if an audio recording is genuine and can be trusted as evidence.

INTRODUCTION

Audio forensics is a large field encompassing various tasks such as authentication, enhancement, speaker identification and recognition, lie detection, etc.

We discuss two aspects-

Lie Detection and Deepfake detection



https://www.scientificamerican.com/article/voice-analysis-should-be-used-with-caution-in-court/

IMPORTANCE

Lie Detection

Lie detection is crucial to solving crimes, ensuring public safety, and maintaining ethical standards.

Deep Fake Detection

DeepFake detection is crucial to prevent identity theft, fraud, misinformation, and security threats.

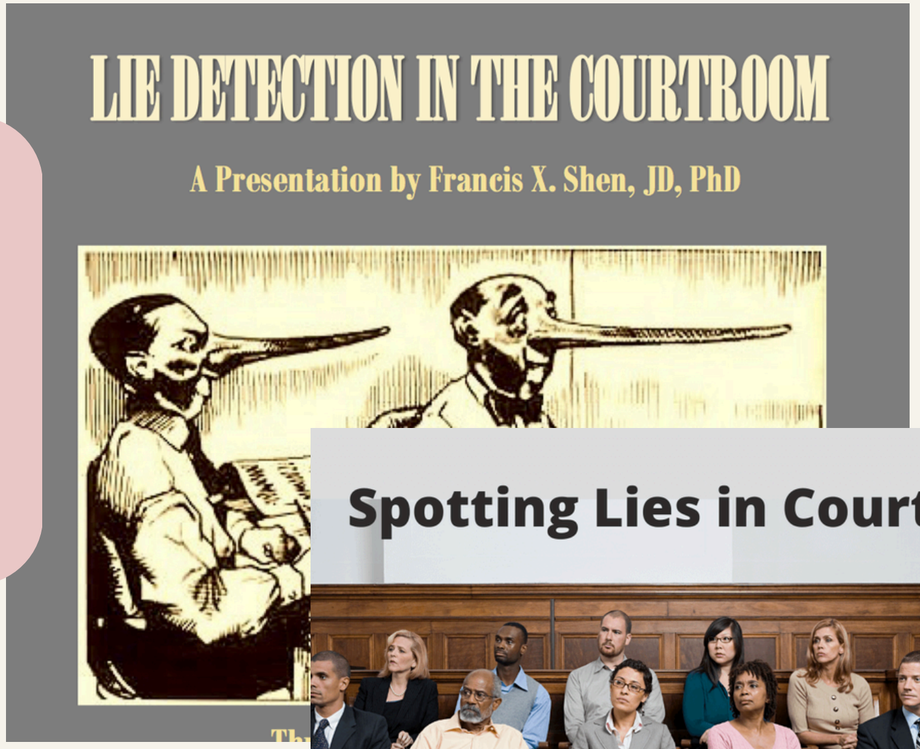
LIE DETECTION

What are the methods?

In general, we can detect deception from -

- Shortened length of speech
- Flushed face
- Changing frequencies
- Avoidant eye contact
- Change in pupil's diameter
- Increase in blood pressure
- Increased pause time

These are all a mix of physiological, behavioral and verbal analyses!



https://www.paulekman.com/blog/spotting-lies-in-court/

WHY IS VERBAL ANALYSIS SO POPULAR?

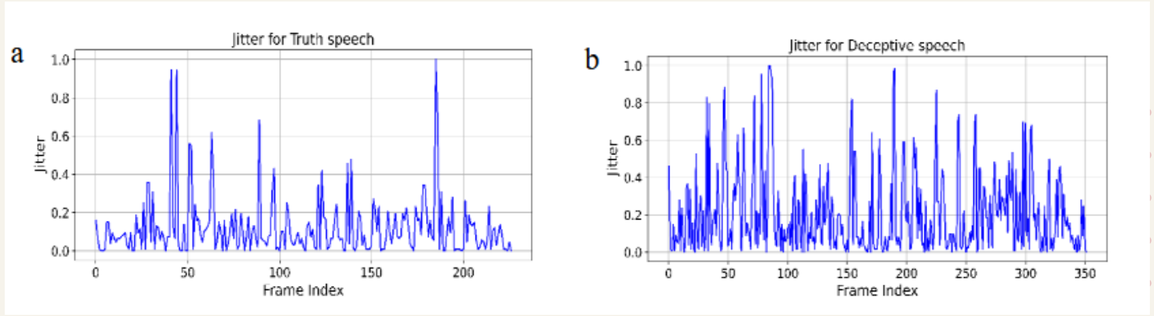
- Physiological analysis techniques are mainly invasive procedures. Polygraphs - utilize blood pressure cuffs, rubber tubes and metal plates on fingertips to measure the respiratory rate, blood pressure, electrodermal activity and heart rate.
- EEGs are also invasive, where electrodes are attached to the scalp to to measure brain activities.
- People have found ways to cheat the system by using antiperspirants and sedatives.
- Tone of a person's voice expresses emotions very well. Changes in sound pressure, frequency, speed can be utilized non-invasively.

CURRENT STATE-OF-THE-ART METHODOLOGIES

Computer-based lie detection

- Support Vector Machines (SVM)
- Decision Trees
- Neural Networks
- Random Forests (RFs)
- Deep Neural Networks (DNN)
- Convolutional Neural Networks (CNN)
- LSTMs, RNNs

They analyze features such as:
Speech patterns, Voice stress
Acoustic features in speech (mean and std dev of pitch, MFCCs, jitter, harmonic-to-noise ratio)

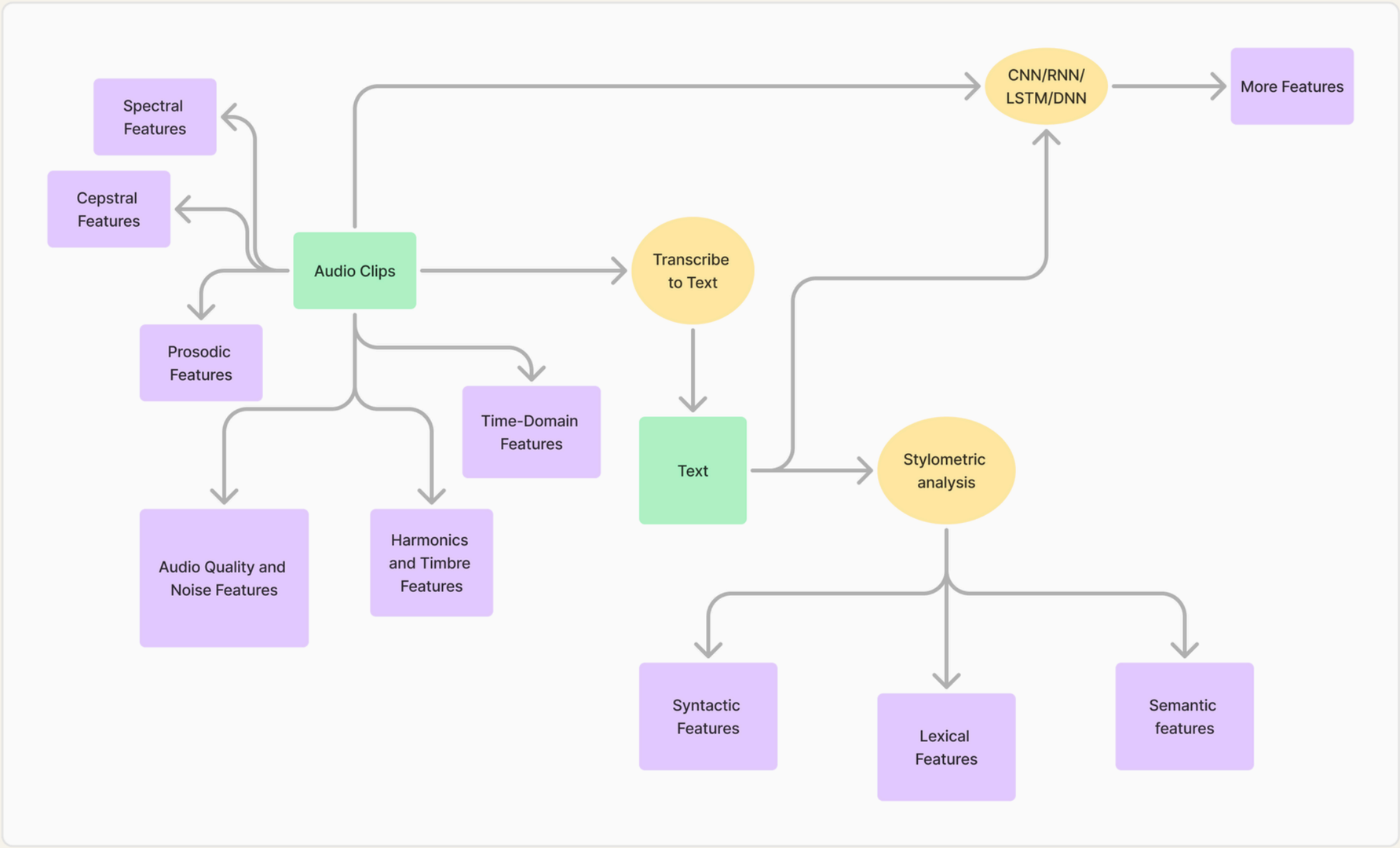


https://ijcsm.researchcommons.org/ijcsm/vol5/iss2/7/

METHODS

Study	Method	Dataset	Strengths	Limitation	Metric	Value
https://iopscience.iop.org/article/10.1088/1742-6596/1921/1/012028	MFCC and MFCC mean features, PCA + SVM	RLDD	Non-invasive, discriminative features	Only MFCC and MFCC mean as features	Accuracy	81% and 78% using polynomial and Gaussian kernels respectively.
https://www.scitepress.org/Papers/2020/90387/90387.pdf	MFCC sequence + padding, LSTM	Custom (interviews in Brazilian Portugese)	Used temporal information	Only focused on stress detection	Accuracy	72.5%
https://www.mdpi.com/1424-8220/22/3/1228	Spectrogram + handcrafted features, Hybrid CNN-MLP	RLDD, RODeCAR	Using spectrogram + handcrafted features + Kolmogorov-Smirnov test.	RODeCAR had poor audio quality, computational costs of CNN-MLP	Unweighted Accuracy	63.7% (RLDD), 62.4% (RODeCAR)
https://www.nowpublishers.com/article/Details/SIP-169	openSMILE + BERT + BLSTM + attention at word level and sentence level + late fusion	Daily Deceptive Dialogues corpus of Mandarin	Multimodal features + temporal information	Computational cost, Dataset imbalance in implicature labels	Unweighted Average Recall, Deception & Truth UAR, w-FI score	80.61% UAR, DUAR 80.34, TUAR 80.87 79.95% w-FI score

WHAT NEXT?


Spectral Features
Cepstral Features
Audio Clips
Prosodic Features
Time-Domain Features
Audio Quality and Noise Features
Harmonics and Timbre Features
CNN/RNN/ LSTM/DNN
More Features
Transcribe to Text
Text
Stylometric analysis
Syntactic Features
Lexical Features
Semantic features

ON TO DEEPFAKE DETECTION!

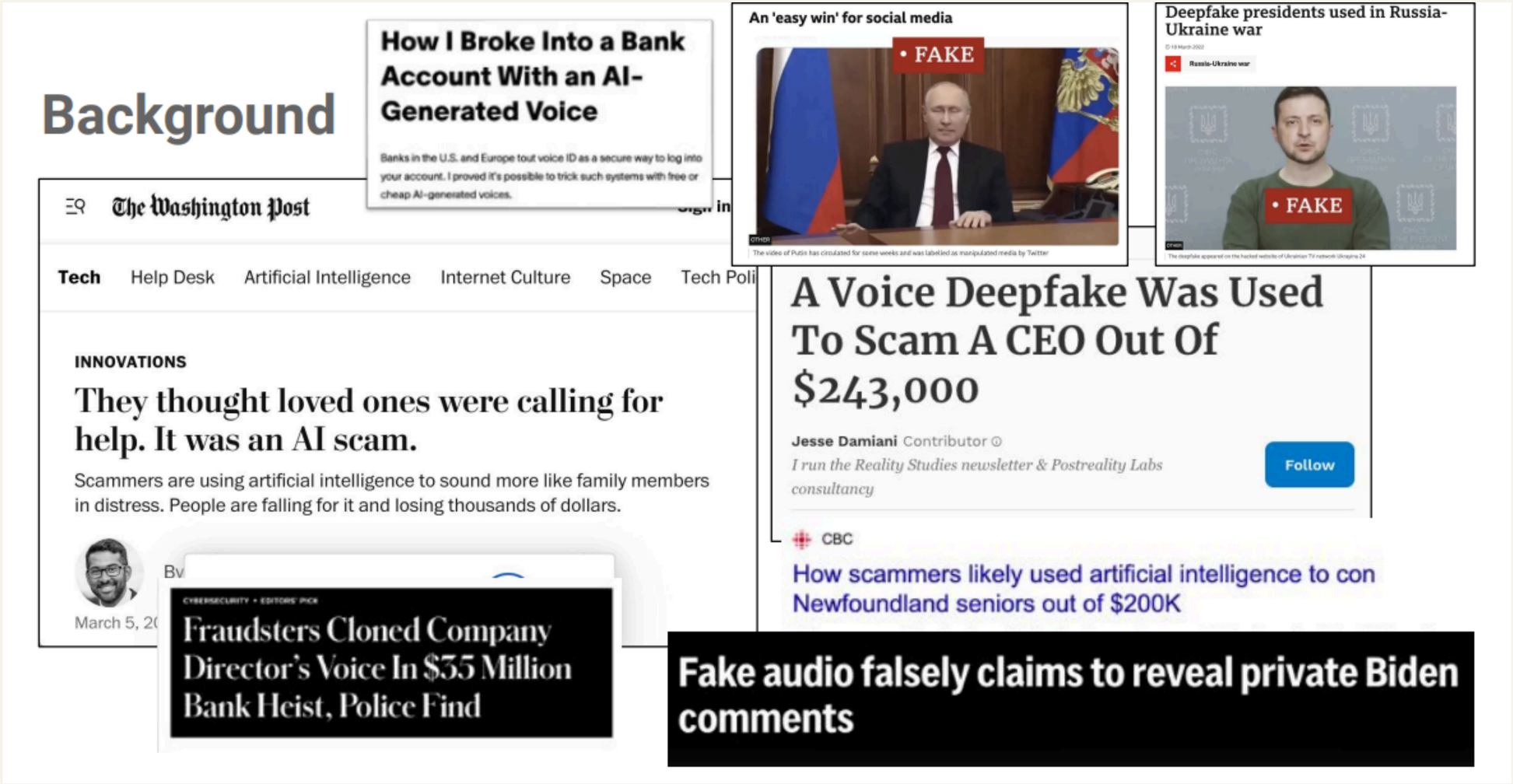
DEEPFAKE DETECTION

What does it mean?
Why is it important in the real world?

- **Fraud Prevention**
- **Misinformation Control**
- **Security**
- **Trust in Media**
- **Legal and Compliance**
- **Identity Theft prevention**
- **Intellectual Property Protection**

Audio deepfakes use AI to synthesize human voices, mimicking speech patterns, tone, and emotions with high accuracy.

Why is deepfake detection important in the real world?



https://www.washingtonpost.com/technology/2023/03/05/ai-voice-scam/
https:/www.forbes.com/sites/jessedamiani/2019/09/03/a-voice-deepfake-was-used-to-scam-a-ceo-out-of-243000/?sh=1081d7802241
https://apnews.com/article/fact-check-biden-audio-banking-fake-746021122607

DIFFERENT KINDS OF DEEPFAKES

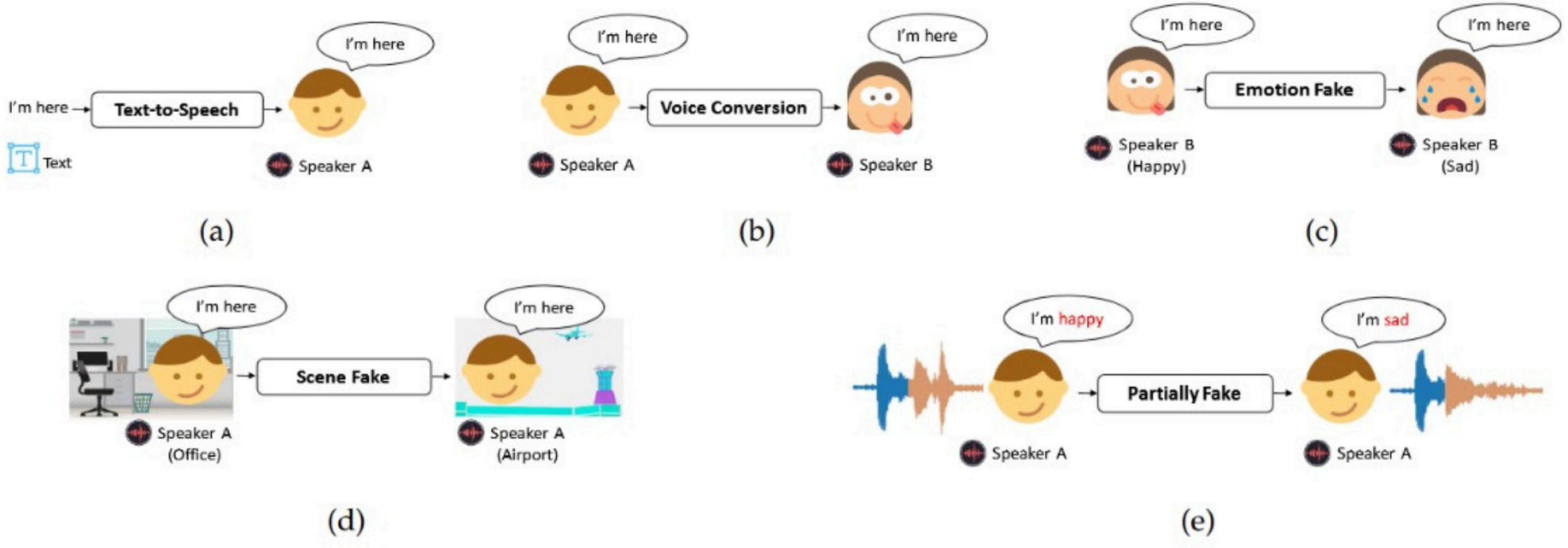


Fig. 2. Five kinds of deepfake audio: (a) text-to-speech, (b) voice conversion, (c) emotion fake, (d) scene fake, (e) partially fake.

SOURCES OF DEEPFAKES

- Text-to-Speech (TTS): Synthesizes natural-sounding speech from text using deep neural networks.
- Voice Conversion (VC): Clones a person's voice by altering the timbre and prosody while keeping the content intact.
- Emotion Fake: Alters the emotional tone of speech while keeping other attributes like speaker identity and content unchanged.
- Scene Fake: Manipulates the acoustic scene of the audio (e.g., changing a background from an office to an airport).
- Partially Fake: Modifies specific parts of an audio clip, such as changing a few words while keeping the rest of the audio intact.

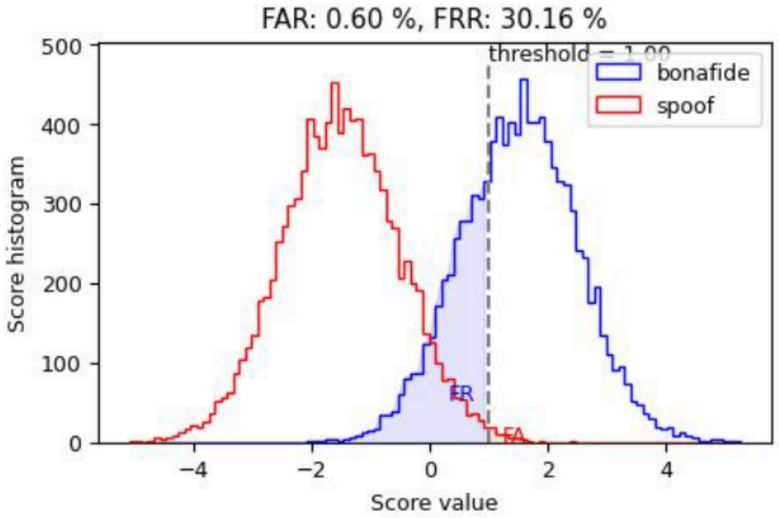
DATASETS

Generated using VC and TTS algorithms

- **ASVspoof2019**
- **ASVspoof2021 : DF evaluation set is generated by more than hundreds of different TTS and VC spoofing attack algorithms**
- **WaveFake: 6 different GAN-based TTS algorithms across two languages, English and Japanese**
- **Chinese Fake Audio Detection (CFAD): Mandarin**
- **Multi-Language Audio Anti-spoofing (MLAAD): 54 models & 23 languages**

PERFORMANCE METRICS

- False rejection rate (FRR)
- False acceptance rate (FAR)



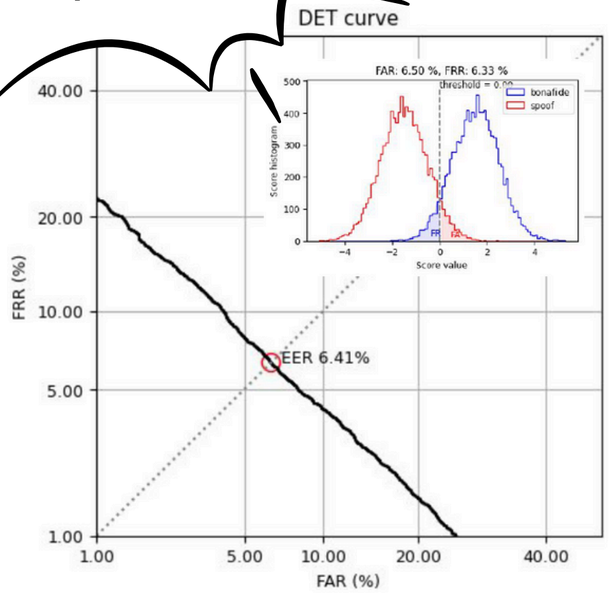
ERR most commonly used and reported !

Evaluation metrics

Detection error trade-off (DET) curve (Martin 1997)

Equal error rate (EER)

- Choose the operating point (threshold) so that FAR is **roughly** equal to FRR
- We don't need to specify the threshold manually



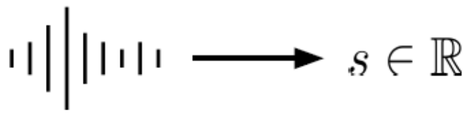
EER measures discrimination, but not calibration. See more in (Van Leeuwen 2007)

TASK DEFINITION

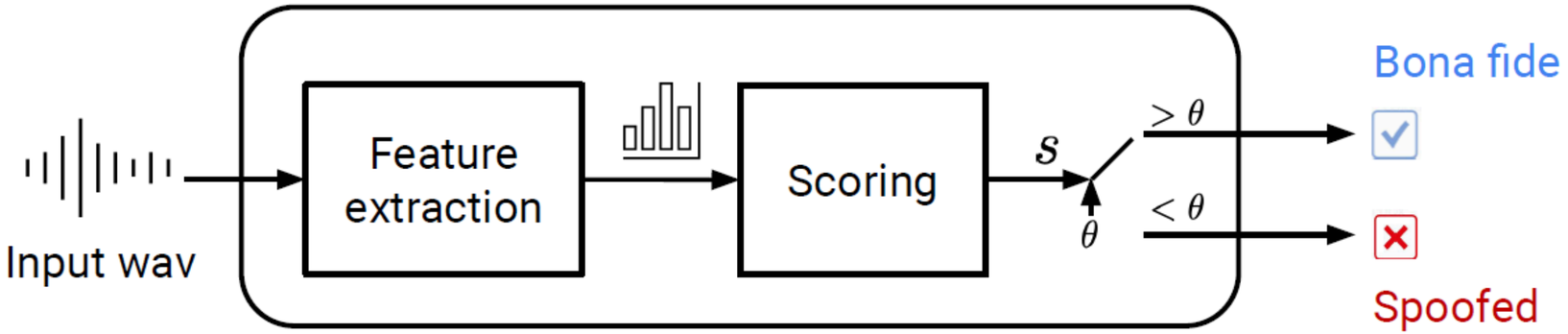
Feature based Classification

A binary classification task

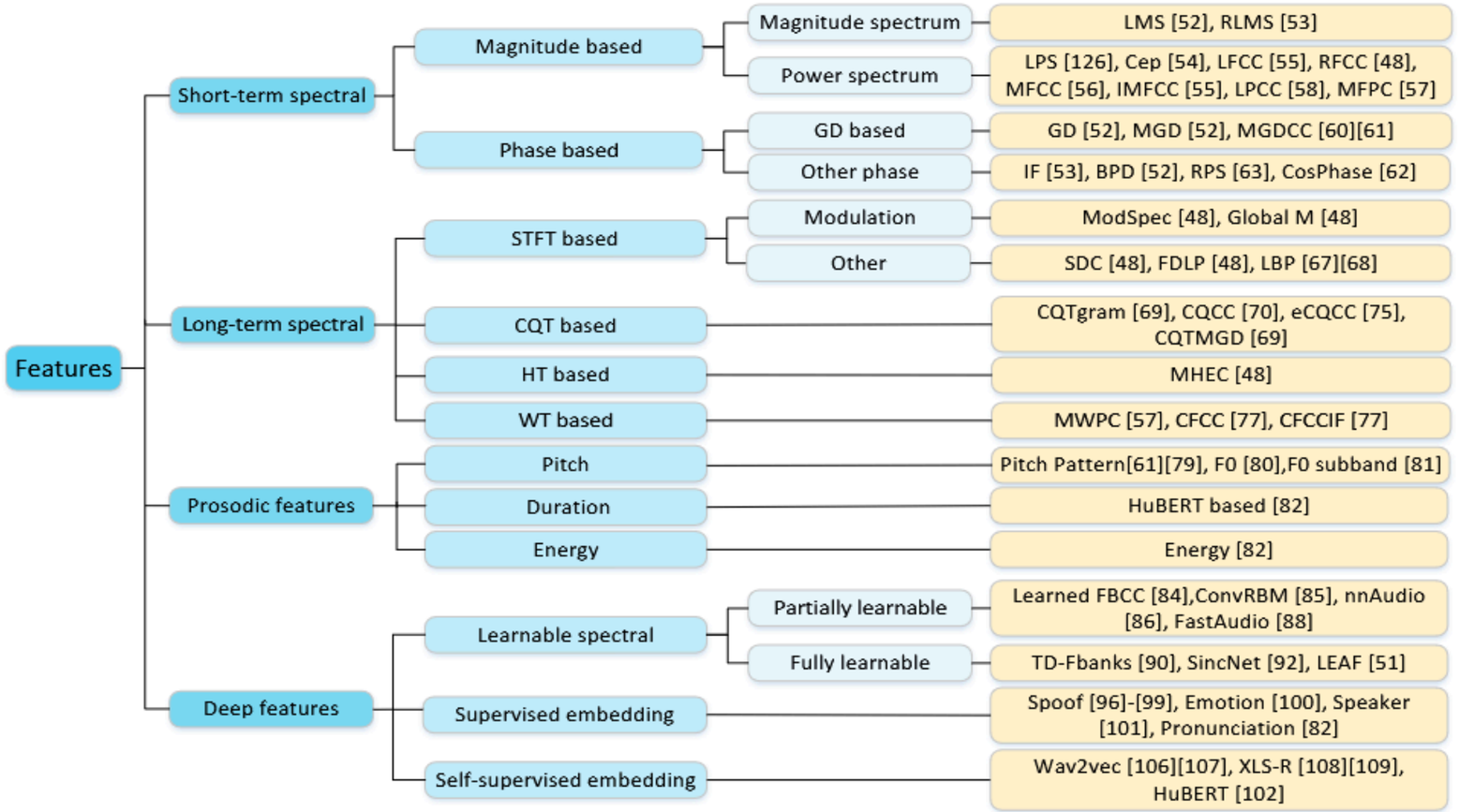
- Feature extraction: front end
- Scoring: back end
- Decision



How likely the input waveform is bona fide



DIFFERENT TYPES OF FEATURES

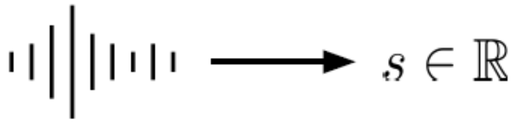


TASK DEFINITION

Feature based Binary Classification

A binary classification task

- Feature extraction: front end
- Scoring: back end
- Decision



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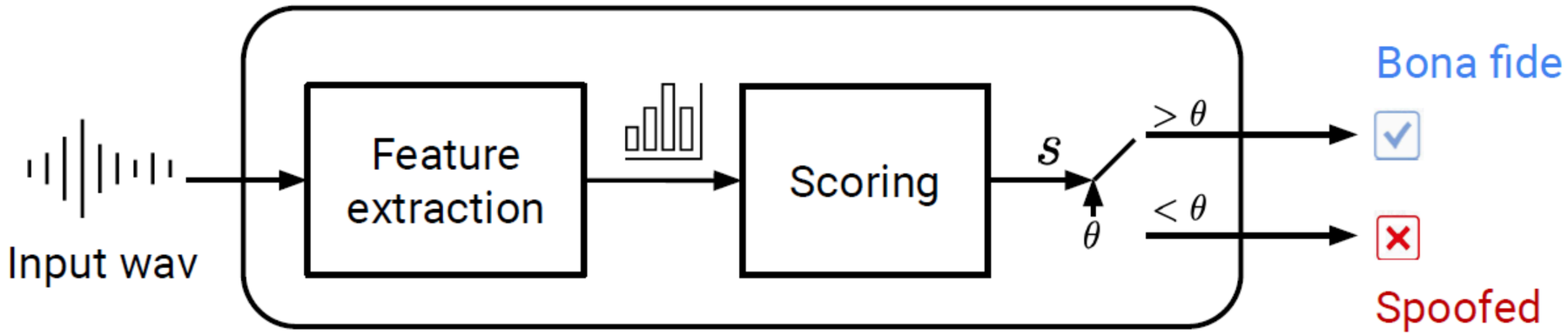
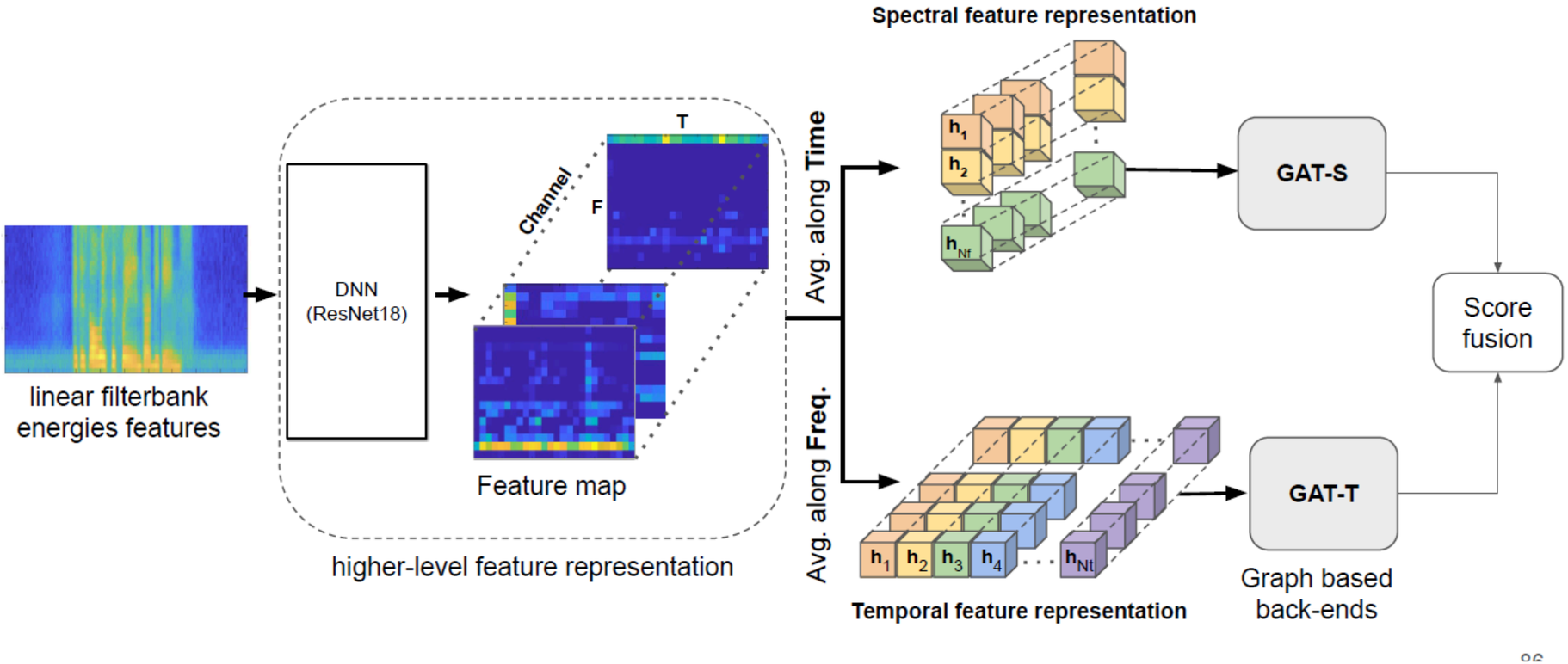


TASK DEFINITION 02

Graph attention network for anti-spoofing

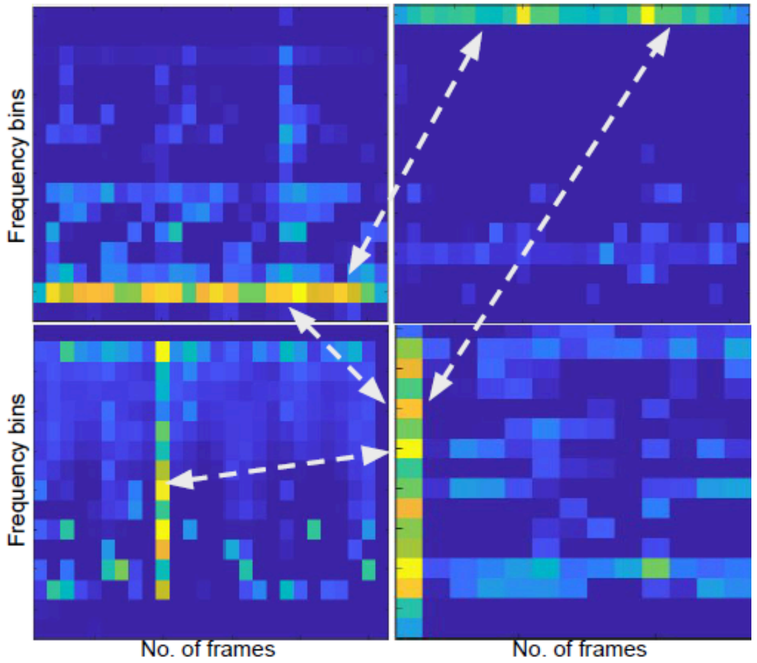


TASK DEFINITION 02

Graph attention network for anti-spoofing

GNN to model relationship between spectral and temporal representation

- Spoofing artefacts lie in **specific spectral subbands or temporal frames**[Yang 2019, Tak 2020, Chettri 2020,Tak 2021]
- modelling the relationship between the evidence spanning different **sub-bands and temporal intervals**
- to leverage the potential of **GNNs** for **modeling relationships** in spectral and temporal domain[Velickovic 2018]

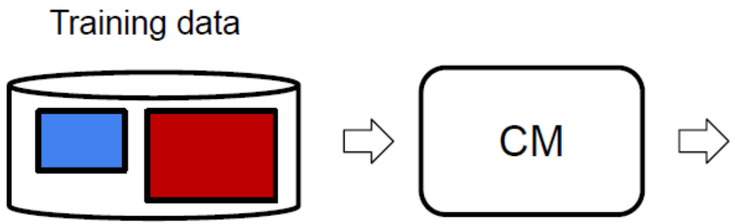


feature-map representations from deep residual network

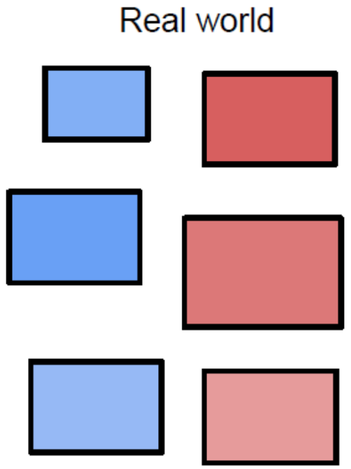
PROBLEMS

Why is anti-spoofing difficult

Unseen variabilities real world test data



We need more powerful tools to extract features and compute score



- Speakers
- Unseen attacks
- Channels
- Languages
- …

Problem

To collect huge labelled data is time-consuming

45

TASK DEFINITION 03

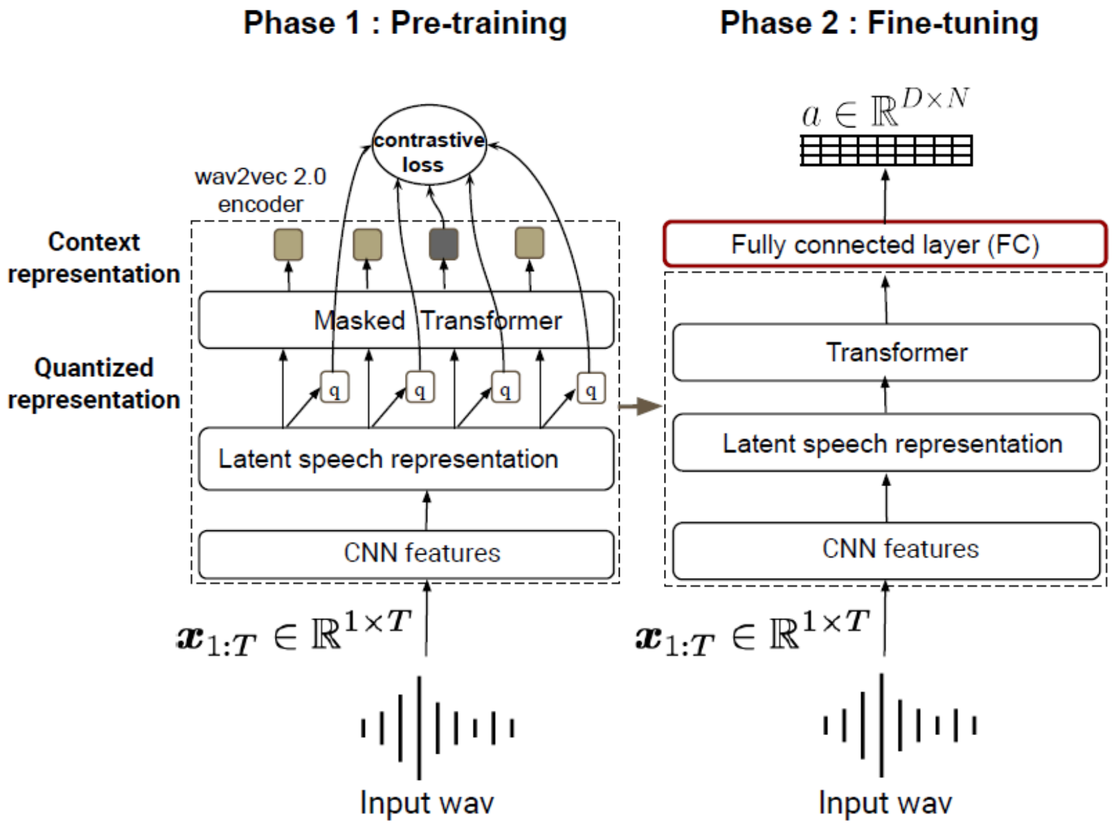
Self-supervised learning for speech anti-spoofing

SSL framework

Two stages in the framework:

1. Use SSL to pre-train an upstream model for general purpose task.

2. Downstream task uses the learned representation from a pre-trained model (fixed) or fine-tune the pre-trained model for specific downstream task.



CURRENT STATE-OF-THE-ART METHODOLOGIES

Publication		Data augmentation	Feature	Classifier	Loss funcion	# Params	ASVspoof			Access-ibility
							19-LA	21-LA	21-DF	
[291]	INTERSPEECH'21	w/o	Mel-Spec on 0-4kHz	SE-ResNet-18	AM-Softmax	1.1M	1.14	-	-	No
[204]	INTERSPEECH'21	channel masking	RawNet2*	GAT	CE	440K	1.06	6.92	-	Yes[1]
[71]	INTERSPEECH'21	channel masking	SincNet	Raw PC-DARTS	MSE	24.4M	1.77	6.43	-	Yes[2]
[87]	SPL'21	mix-up	E2E: CNN→ResNet→MLP		CE	350M	1.64	-	-	Yes[3]
[65]	ICASSP'22	w/o	FastAudio	ECAPA-TDNN	CE	Unknown	1.54	-	-	Yes[4]
[119]	DSP'22	w/o	L-VQT	DenseNet	CE	338K	2.19	-	-	No
[212]	ICPR'22	w/o	RawNet2+(CQT →ECAPA-TDNN)	CNN→MLP	CE	7.19M	1.11	-	-	Yes[5]
[114]	INTERSPEECH'22	w/o	wav2vec2.0-XLSR	MLP	CE	317M	0.31	-	-	No
[59]	INTERSPEECH'22	w/o	wav2vec2.0-960	MLP	CE	Unknown	0.40	-	-	No
[39]	INTERSPEECH'22	frequency masking	CQT-Spec	LCNN	CE	135K	1.35	-	-	No
[227]	ODYSSEY'22	w/o	wav2vec2.0-XLSR	Bi-LSTM →MLP	CE	317M	1.28	6.53	4.75	No
[209]	ODYSSEY'22	RawBoost	wav2vec2.0-XLSR	AASIST	CE	Unknown	-	**0.82**	**2.85**	Yes[6]
[144]	DDAM'22	RawBoost	ImageNet + Jitter + Shimmer	MLP	AM-Softmax	Unknown	0.87	10.06	27.08	No
[217]	DDAM'22	w/o	wav2vec2.0-Large	DARTS	Unknown	Unknown	1.08	-	7.89	No
[92]	ICASSP'22	w/o	RawNet2	GAT	CE	297K	0.83	5.59	-	Yes[7]
[117]	SPL'22	w/o	LFCC	OCT	Focal loss	250K	1.06	-	-	No
[132]	APSIPA'22	adding noise, RIRs	wav2vec2.0	LCNN	CE	Unknown	0.24	-	-	No
[100]	MAD'23	w/o	Mel-spec + Spec-Env + Spec-Contrast	Transformer →CNN	CE	603K	0.95	-	-	No
[218]	INTERSPEECH'23	w/o	Duration + pronunciation + wav2vec2.0-XLSR	LCNN →Bi-LSTM →MLP	CE	Unknown	1.58	-	-	No
[151]	SPL'23	w/o	(LFCC →ResNet) + (CQT-Spec →ResNet)	GRL →MLP	CE	Unknown	0.80	-	-	Yes[8]
[139]	ICASSP'23	w/o	RawNet2	Rawformer	CE	370K	0.59	4.98	4.53	Yes[9]
[158]	ICASSP'23	FIR filter	wav2vec2.0-XLSR	MLP	OC-Softmax	300M	-	3.54	6.18	No
[32]	ICASSP'23	time & frequency masking	LFB-Spec	GCN	CE	Unknown	0.58	-	-	No
[276]	ALGORITHM'23	RawRoost	wav2vec 2.0	Transformer	CE	Unknown	-	1.18	4.72	No
[101]	ICASSP'24	FIR filter, codec, noises, shift	SDC + Bi-LSTM	Auto-encoder →SE-ResNeXT	CE	Unknown	**0.22**	3.50	3.41	No

ROOM FOR IMPROVEMENT

Best CM performance on unseen test set

Q : What is the **Best CM** performance on **in the wild dataset**[Muller 2022] ?

In the wild dataset is more challenging

- more diverse acoustic characteristics
- fake audios are generated using publicly available sources such as social networks and popular video sharing platforms
- 50 English-speaking celebrities and politicians

➔ **10.46% EER** on in the wild dataset

The best CM system is not well generalised to an unseen test set.

References: Interspeech 2023

IIT Jodhpur | 2025

THANK YOU