Audio denoising in the wild

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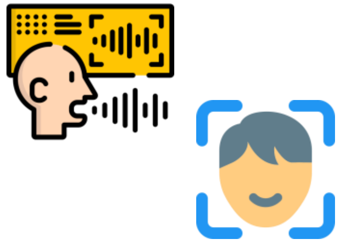
INTRODUCTION

- premise
- main purposes
- basic concepts

audio-related tasks are **very popular** thanks to the amount of existing voice assistants

among all, the most common are **speaker recognition** and **speech recognition**



there are numerous problems for these tasks, **background noise** is one of the main ones [1]

the **primary objective** is the creation of a system for the background noise removal

subsequently verify the possible positive impact of this removal on the performance of a speaker recognition system through an **integrated training**

the **main idea** is to create a noise removal system that includes the following features

neural architecture

limited data pre-processing

robustness to noise intensity and duration of the audio signal

- resources
- procedure

DATASETS

different resources

clean audio sources

noise source

audio quality evaluation

SIWIS [2]

VoxCeleb 2 [3] ($\frac{1}{3}$ test set)

MUSAN [4]

DEMAND [5]

Additive mixing using **different** SNRs the objective is the creation of 3 **distinct** dataset for the model training

SIWIS

VoxCeleb 2

SIWIS+VoxCeleb 2

- 16 kHz re-sampled
- 2.5, 7.5, 12.5 and 17.5 SNR noise addiction
- 1 second sliding window
- rebalance through oversampling
- ark, scp storing format

METHODOLOGICAL APPROACH

- models
- experimental setup
- pipeline details

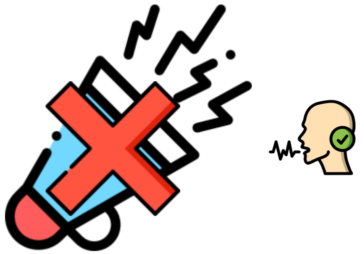
two models
with two tasks

WaveNet for the
denoising task [6]

Implemented **from scratch** using
PyTorch and trained on the 3
different datasets

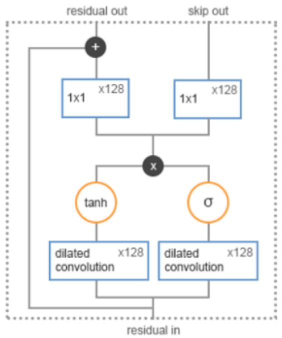
Thin ResNet-34 for the
speaker verification task [7]

pre-trained on VoxCeleb 1
and VoxCeleb 2 train sets

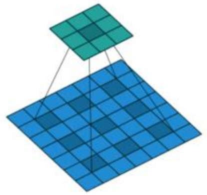


WaveNet characteristics

- **raw** audio as input data

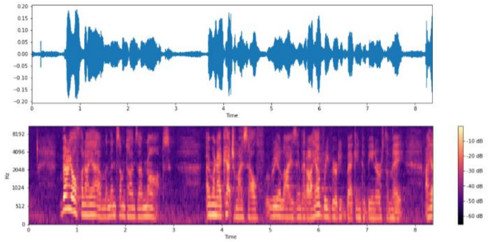


- **G**ated **A**ctivation **U**nits (residual blocks)
- non-causal, **dilated** convolutions

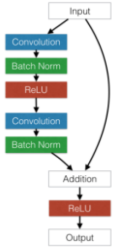


- symmetrical 3 x 1 convolutions
- **real value** output with 1 : 1 ratio respect to input
- energy conserving loss $\mathcal{L}(\hat{s}_t) = |s_t - \hat{s}_t| + |b_t - \hat{b}_t|$

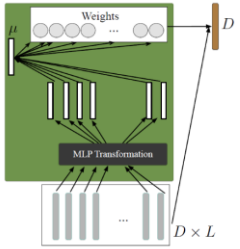
Thin ResNet-34 characteristics



- **Mel spectrogram** as input
- classical residual blocks



- thin because has **¼ filters** compared to normal counterpart
- **S**elf-**A**ttemptive **P**ooling layer



- 1 x 512 embedding dimension
- angular prototypical loss

$$L_P = -\frac{1}{N}\sum_{j=1}^{N} \log \frac{e^{S_{j,j}}}{\sum_{k=1}^{N} e^{S_{j,k}}}$$

experimental setup

WaveNet

- 3 models (1 for dataset)
- 30 GAUs conv. blocks with 128 filters
- 3 stacks (1 to 512 dilation factor)
- 2048 and 256 filters on final conv layers
- 6.3 mln parameters
- scheduled Adam optimizer
- training and fine-tuning procedure with **variable** n. of epochs

Thin ResNet-34

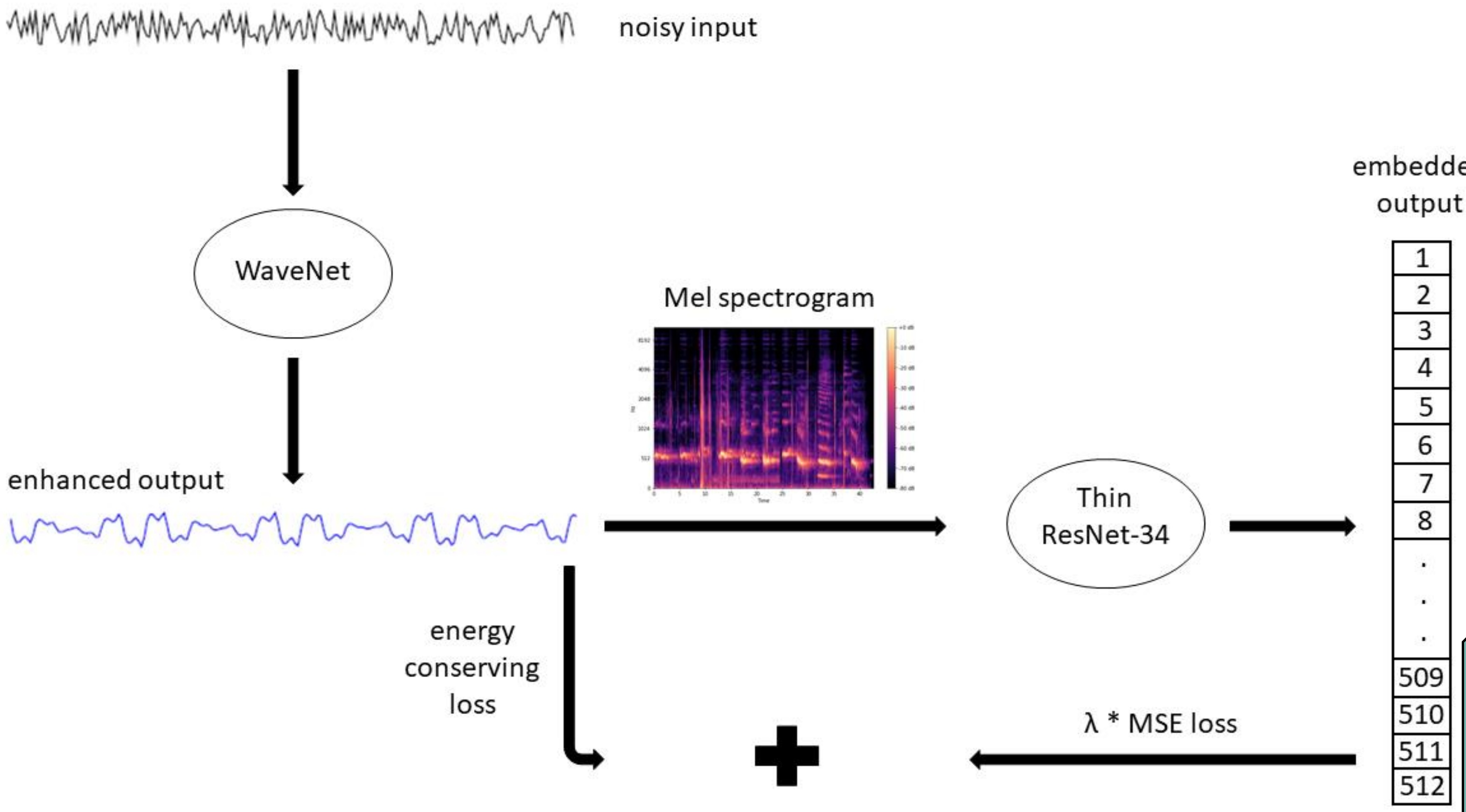
- pre-trained with ~500 epochs and scheduled Adam optimizer
- 34 residual conv. blocks
- 1.4 mln parameters
- used as component for the fine-tuning procedure with the WaveNets

pipeline

WaveNet init

first training

fine-tuning **stacking** with Thin ResNet-34

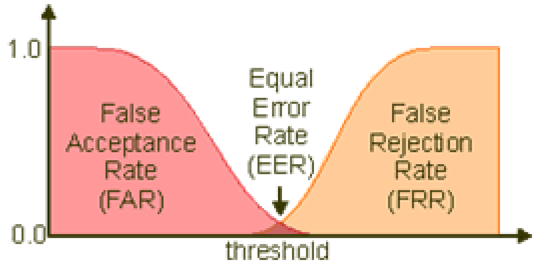


RESULTS

- measures
- speaker verification
- denosing

two types of measures

speaker verification quality



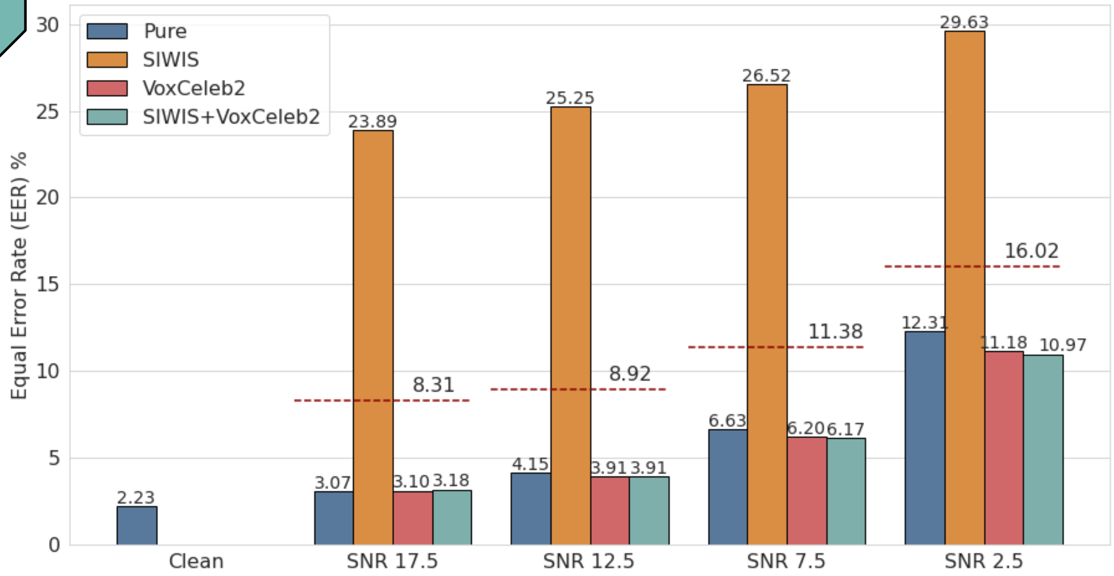
Equal Error Rate (**EER**)

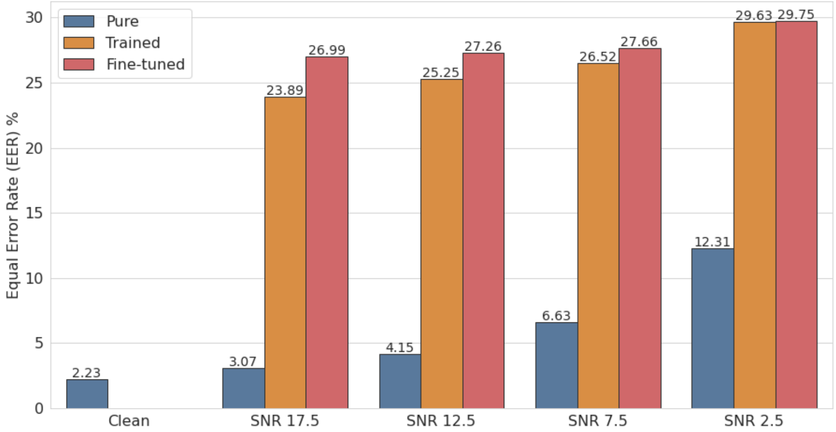
audio enhancement quality

objective quality measures [8]

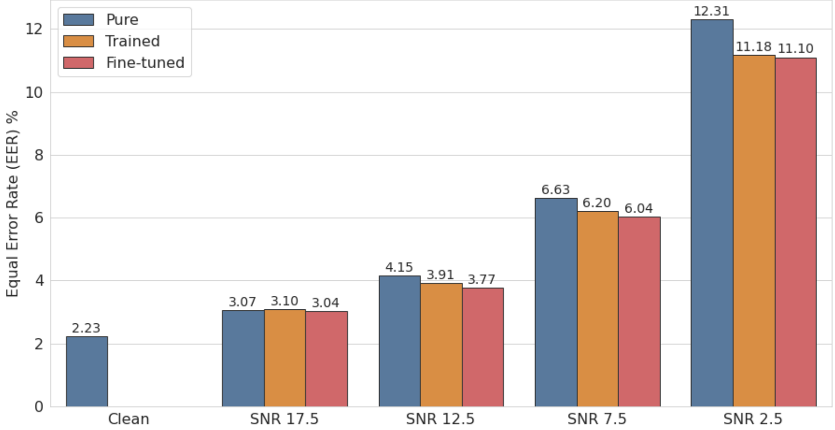
- signal distortion (**SIG**)
- background noise distortion (**BAK**)
- overall quality (**OVL**)
- perceptual evaluation of speech quality (**PESQ**)
- segmental signal-to-noise ration (**SSNR**)

first training performance

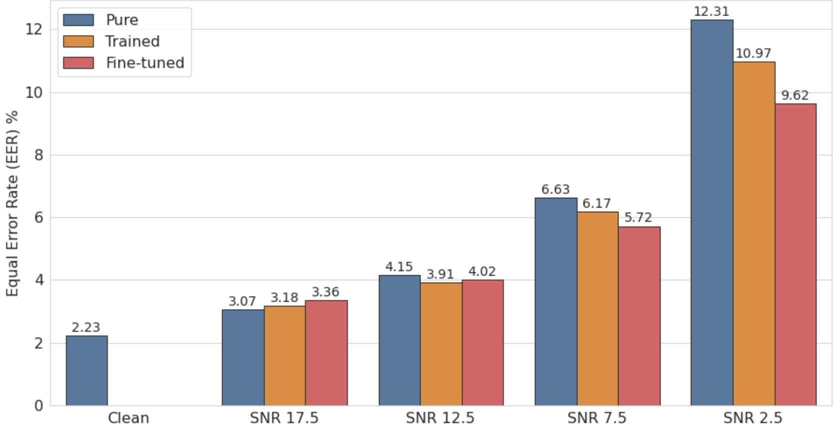




SIWIS

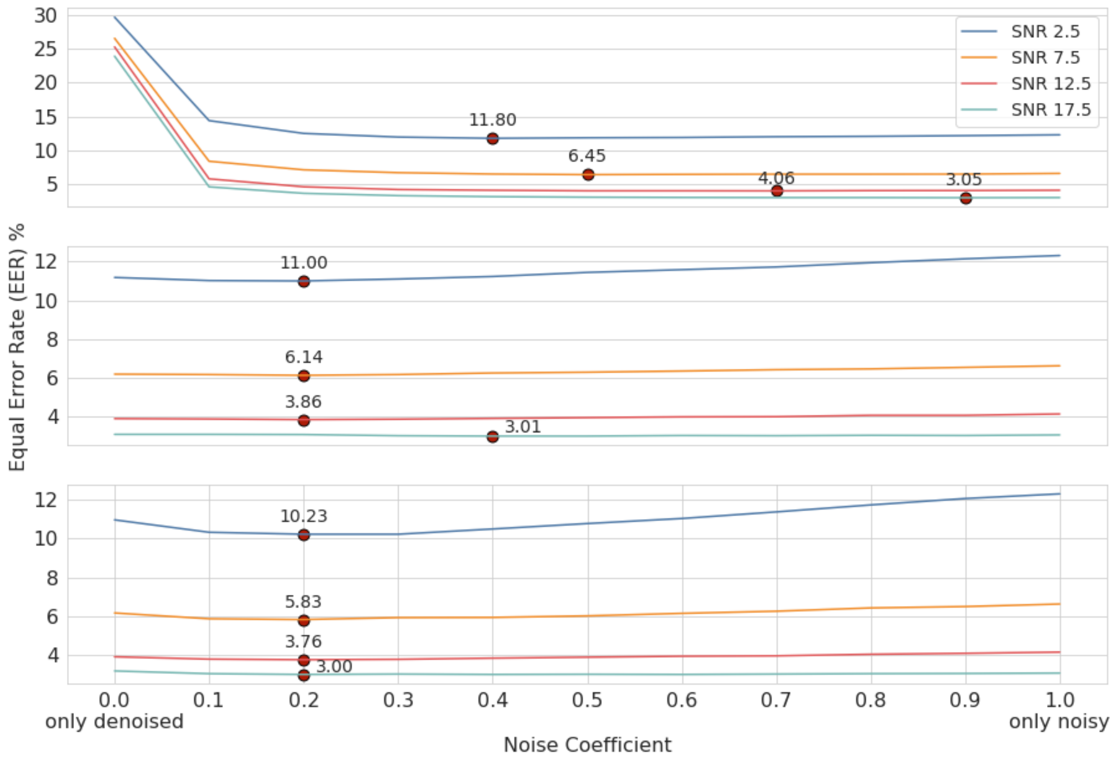


VoxCeleb

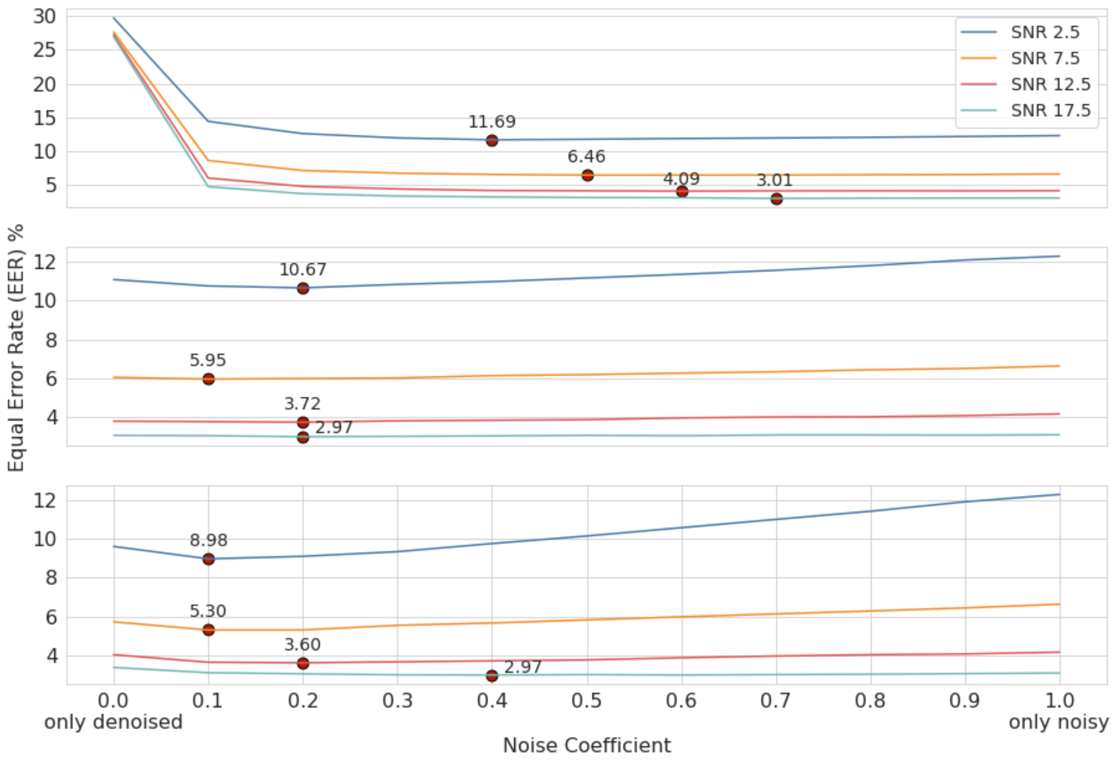


SIWIS + VoxCeleb

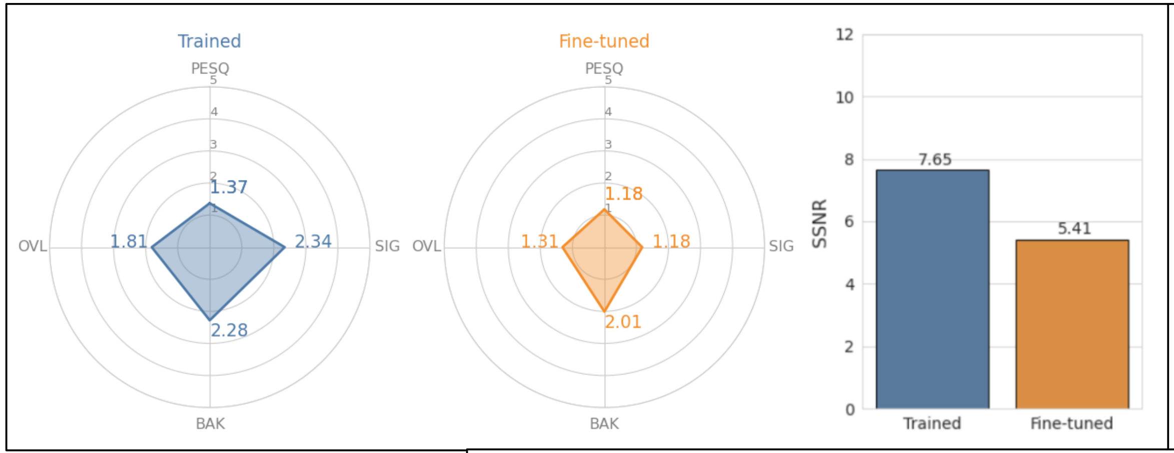
first training



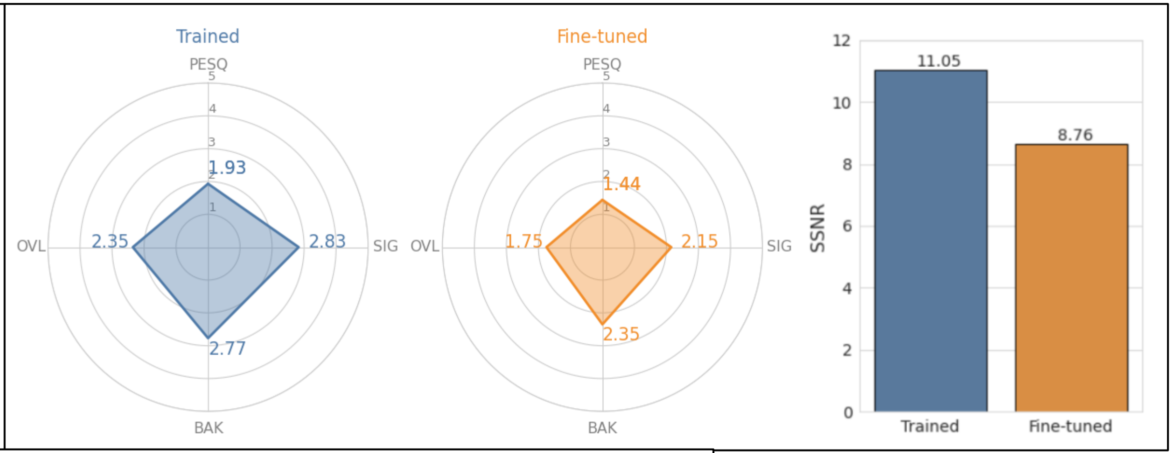
fine tuning

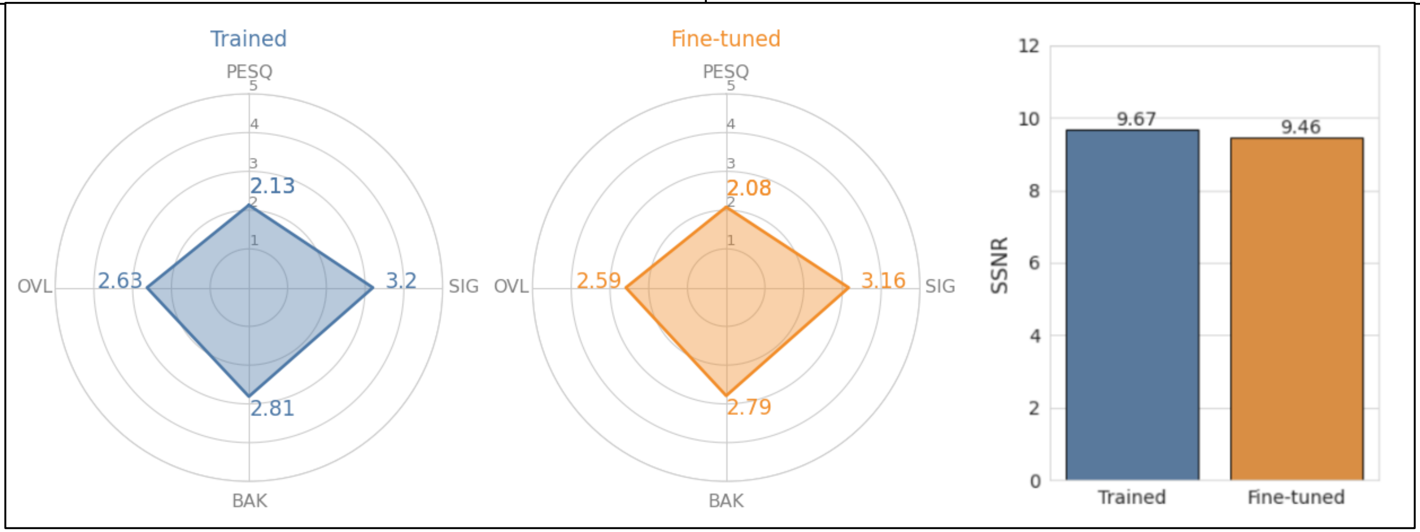


SIWIS



VoxCeleb





SIWIS+VoxCeleb

DISCUSSION

some considerations on the obtained results

1. as expected, the **greater** the SNR, the **greater** the classification error
2. the **larger** and more varied the dataset, the **better** the performance
3. fine-tuning brought a real **benefit** to performance
4. the mixing procedure is **effective** for each model, for each SNR, both before and after the fine-tuning
5. audio quality **degrades** for each model
6. an improvement in classification **does not necessarily coincide** with an improvement in audio quality

CONCLUSIONS

- final considerations
- future work

in conclusion...

there is a **real improvement** in performance

the stacking strategy has shown **encouraging results**

despite the limited resources, the modesty of the results **bodes well**

possible improvements...

more computational resources

use of **generative models** (CycleGANs)

improve denoising by classifying the type of noise

try to apply denoising techniques on **non-audio signals** (i.e. electrocardiogram)

THANK YOU

REFERENCES

[1] N. Singh, A. Agrawal, and R. A. Khan. “Automatic Speaker Recognition: Current Approaches and Progress in Last Six Decades”. In: Global Journal of Enterprise Information System 9.3 (2017), pp. 45–52.

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[3] A. Nagrani, J. S. Chung, and A. Zisserman. “VoxCeleb: a large-scale speaker identification dataset”. In: (2017).

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[5] C. Valentini-Botinhao. “Noisy speech database for training speech enhancement algorithms and TTS models”. In: (2017).

[6] D. Rethage, J. Pons, and X. Serra. “A Wavenet for Speech Denoising”. In: (2017).

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Dataset	Train set split	Test set split
SIWIS	90 %	10 %
VoxCeleb2	70 %	30 %

Dataset	Portion	n. of samples	avg. samples per speaker
SIWIS	train	7,344	~ 333
	test	816	~ 37
VoxCeleb2	train	8,448	~ 71
	test	2,113	~ 17
SIWIS + VoxCeleb2	train	15,792	~ 112
	test	2,929	~ 21

Dataset	Portion	n. of samples	avg. samples per speaker
SIWIS	train	7,344	~ 333
	test	816	~ 37
VoxCeleb2	train	9,027	~ 76
	test	2,287	~ 19
SIWIS + VoxCeleb2	train	25,334	~ 180
	test	5,482	~ 39

Model	n. of epochs training	n. of epochs fine-tuning
SIWIS	75	83
VoxCeleb	92	66
SIWIS+VoxCeleb	87	82