

# Privacy-preserving collection and sharing of unbiased human voice data for automatic assessment of voice disorders

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## INTRO:

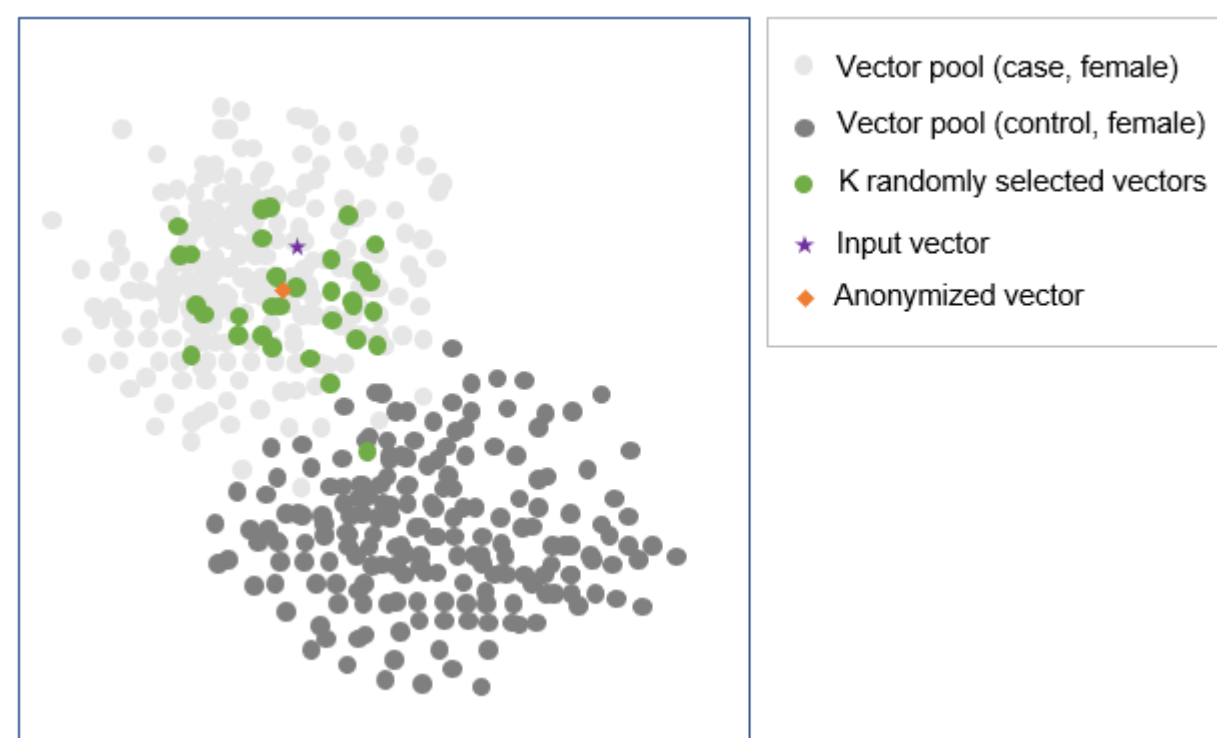
- We aim to explore the potential of utilizing privacy-preserving techniques for safely collecting and sharing human voice data from patients for automatic assessment of voice disorders.

## MOTIVATION:

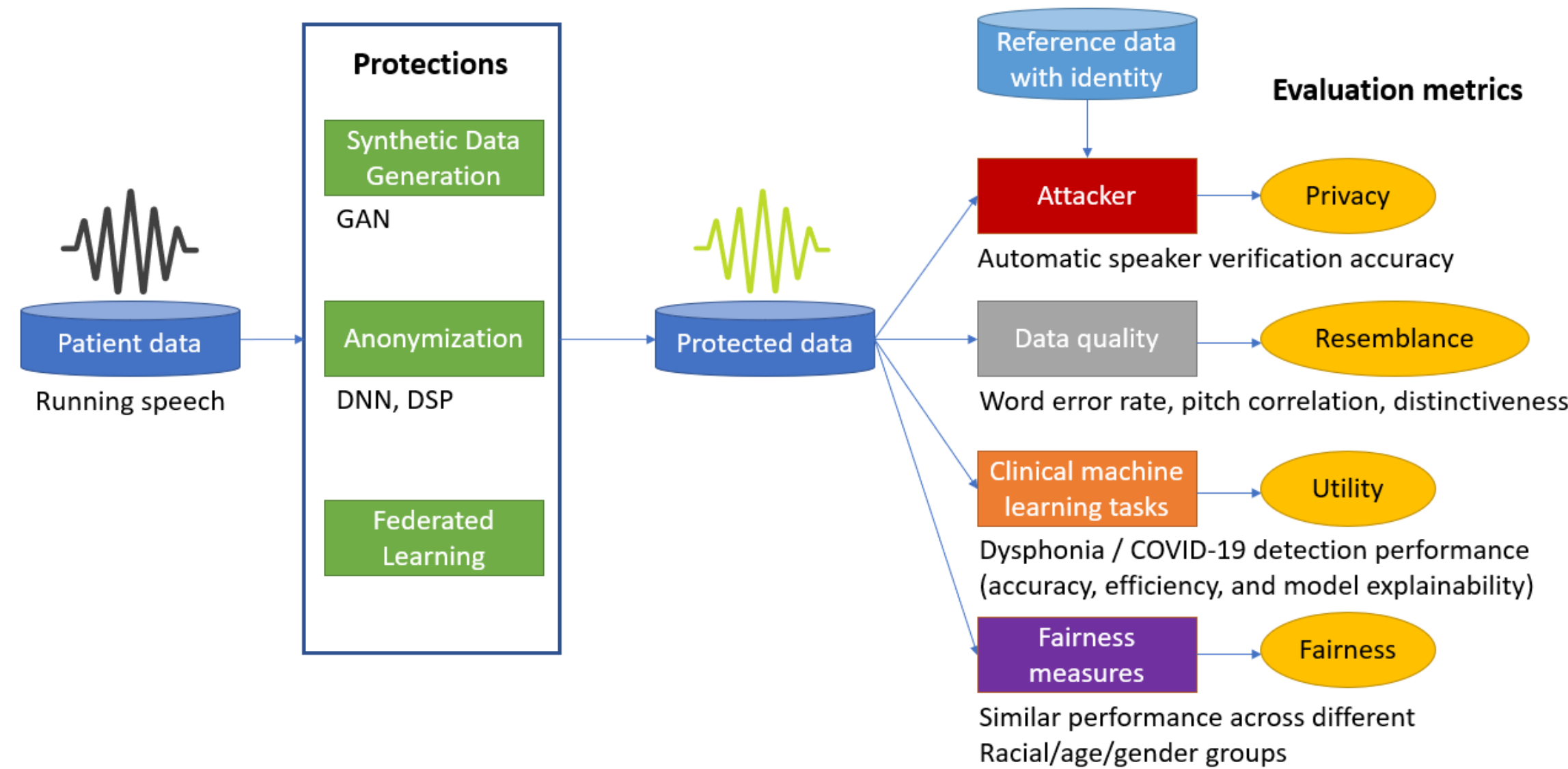
- Sharing voice data from patients with voice disorders/diseases is beneficial.
- Lack of voice data sharing in clinical settings due to privacy concerns.
- Anonymization techniques for human voice data could be used in this case.

## METHODS

- Evaluate the privacy risks of sharing voice data from patients
- Examine privacy-enhancing techniques for voice data sharing
- Datasets: (1) LibriSpeech dataset: 363 hours, 921 speakers. (2) Saarbruecken Voice Database: 2000 German-speaking individuals. (3) A dataset from Eye, Ear, Nose and Throat Hospital of Fudan University: 461 people.
- Illustration of the x-vector selection step in the anonymization process



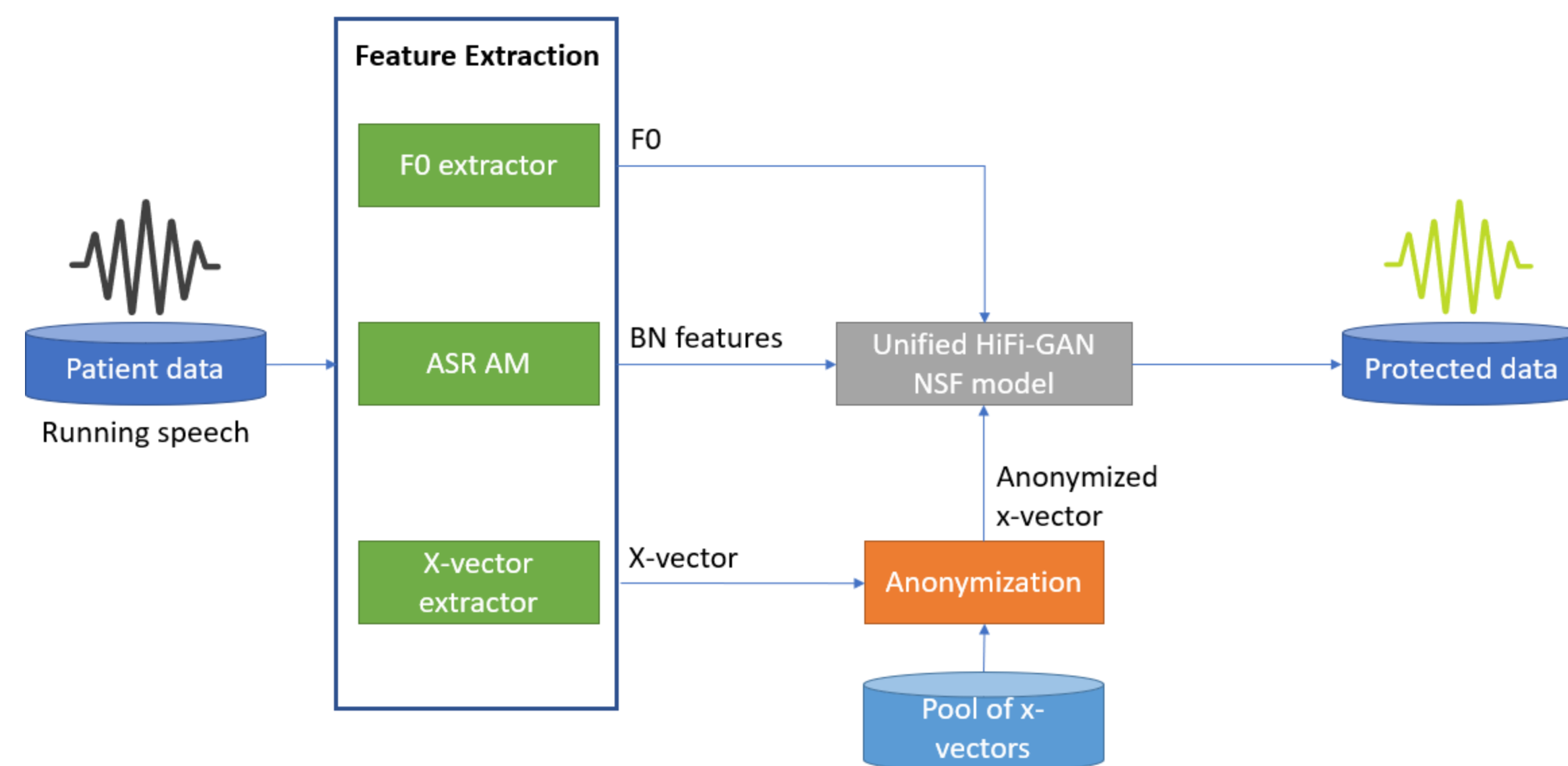
## METHODS – System Overview



An overview of the privacy-preserving voice data sharing system

GAN: generative adversarial net. DNN: deep neural net. DSP: digital signal processing.

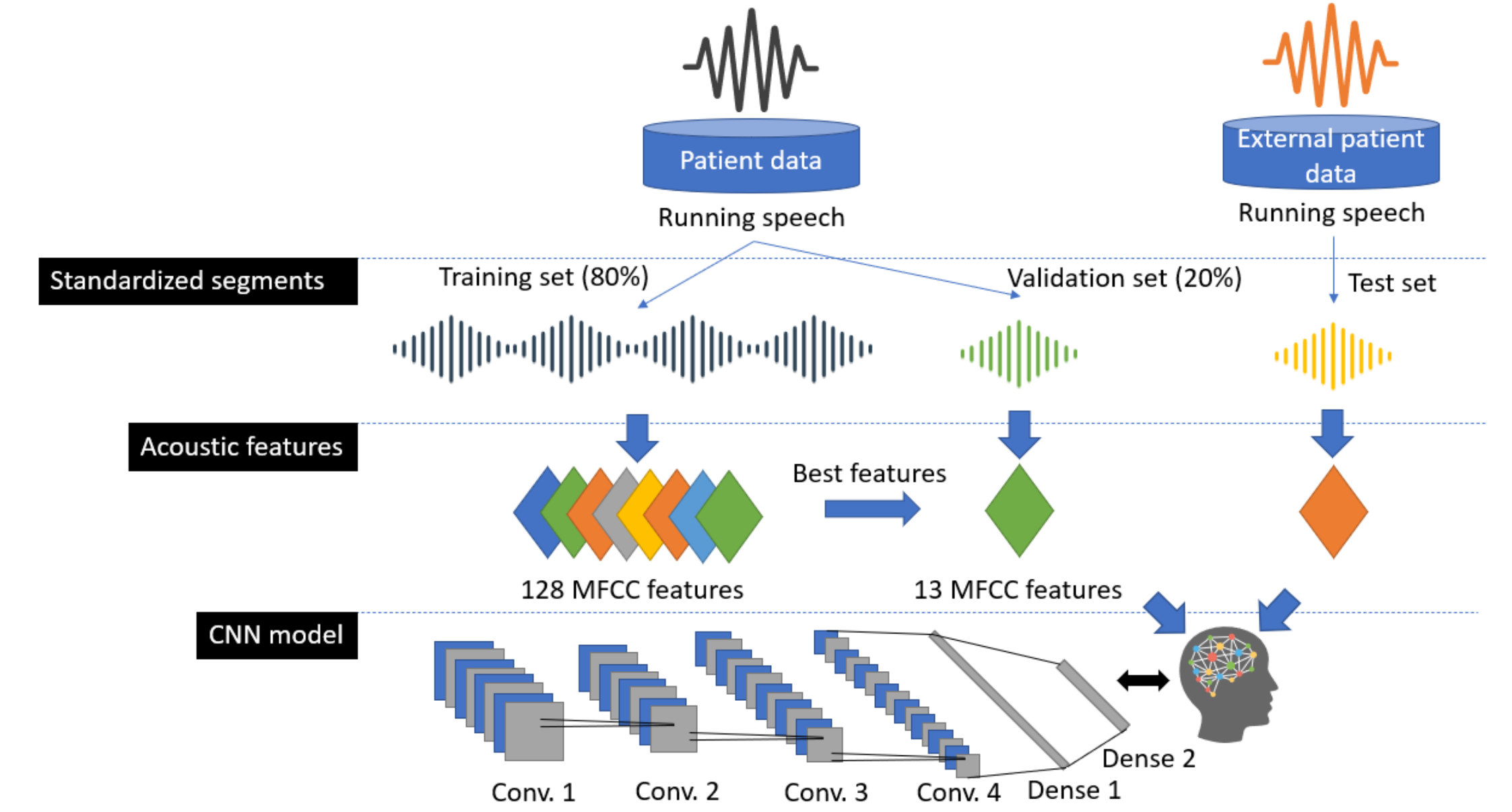
## METHODS – Anonymization Model



A DNN-based anonymization model for human voice data

F0: fundamental frequency. ASR: automatic speech recognition. AM: acoustic model. BN: bottleneck. X-vector: DNN embeddings. DNN: deep neural network. GAN: generative adversarial network. NSF: neural source-filter.

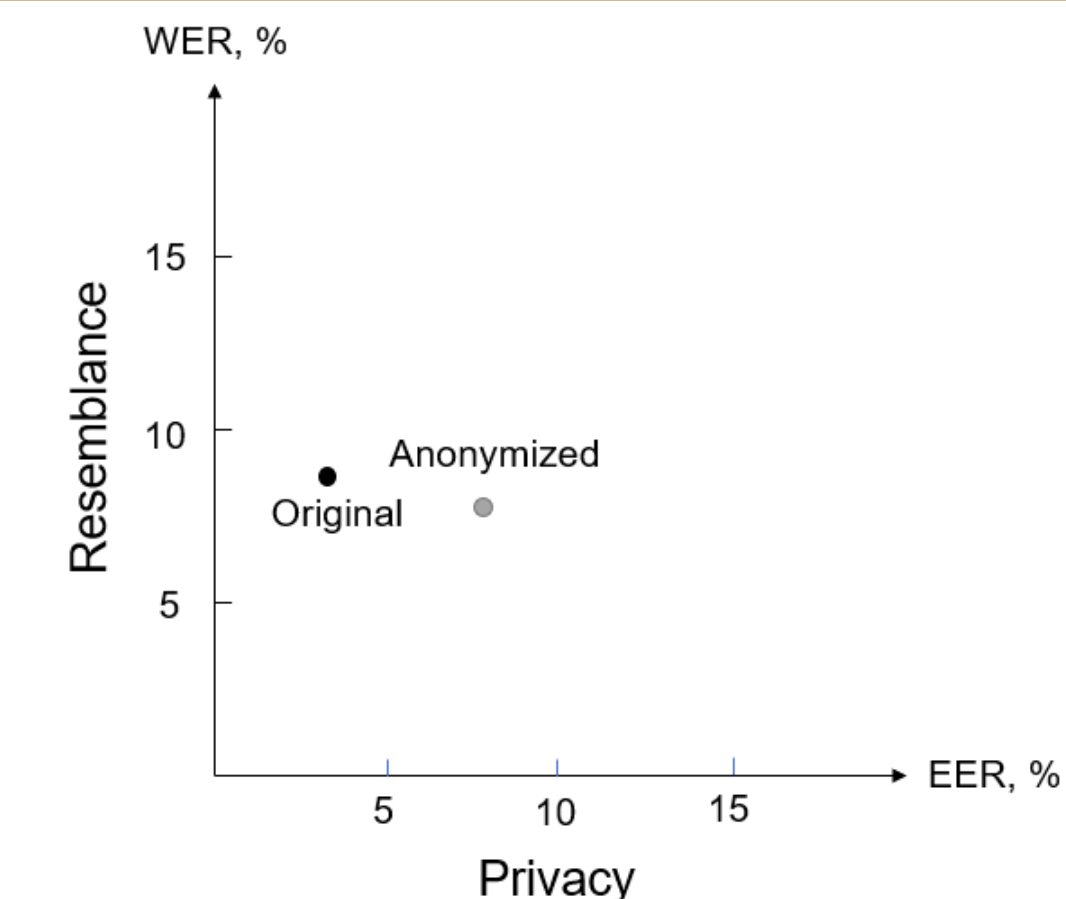
## METHODS – Learning Model



A learning model for dysphonia detection

CNN: convolutional neural net. MFCC: Mel-frequency cepstral coefficients.

## RESULTS – Anonymization



Results for resemblance (WER) and privacy (EER) metrics

WER, word error rate. EER: equal error rate.

## RESULTS – Learning

Ground truth	Patient data		Patient data	
	Normal	Dysphonia	Normal	Dysphonia
Normal	44	1	44	1
Dysphonia	4	44	2	46
	Prediction		Prediction	
	Normal	Dysphonia	Normal	Dysphonia

Performance evaluation of dysphonia detection

## REFERENCES

- Chen, Z., et al. Deep learning in automatic detection of dysphonia: Comparing acoustic features and developing a generalizable framework. *Int. J. Lang. Commun. Disord.* 1-16 (2022).
- Tomashenko, N., et al. The VoicePrivacy 2022 Challenge Evaluation Plan. *arXiv* 2203.12468 (2022).

Voice anonymization can be a promising approach to collecting and sharing more voice data while protecting the privacy of patients.