Mobile Health
Lecture 6
Audio Signal and Health (Part 2)

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Coronary Heart Disease and Voice

- In Coronary Heart Disease, plaque builds in arteries (which carry oxygen to the heart) and restricts flow.
- These changes can induce respiration changes, irregular breathing and increased muscle tension in the vocal tract.
- Participant's voice while sustaining vowels was analyzed.

Feature: Average Fundamental Frequency

- Fundamental frequency (FF) is the rate of vocal fold vibration
  - FF: lowest frequency of a periodic waveform.
  - The approximate frequency of the ~periodic structure of voiced speech signals

Segment of a speech signal, with the period length *L*, and fundamental frequency *F0=1/L*.

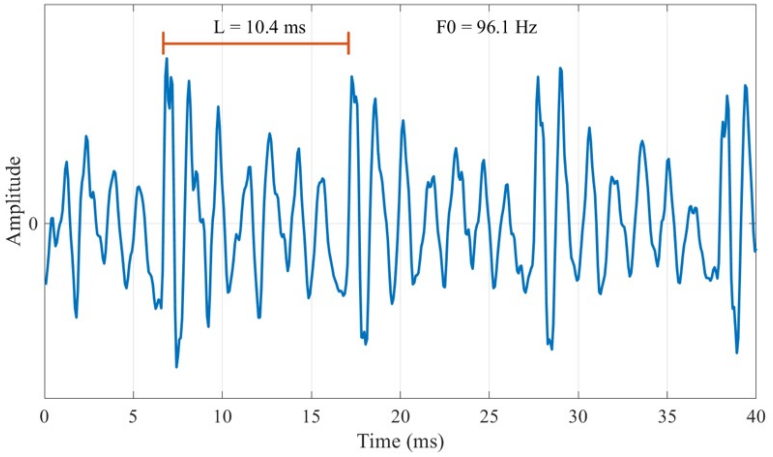

Figure from
https://wiki.aalto.fi/pages/viewpage.action?pageId=149890776

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Jitter and Shimmer

- Amount of variation in period length and amplitude are known respectively as *jitter* and *shimmer*.
- They are perceived as roughness, breathiness, or hoarseness in a speaker's voice.

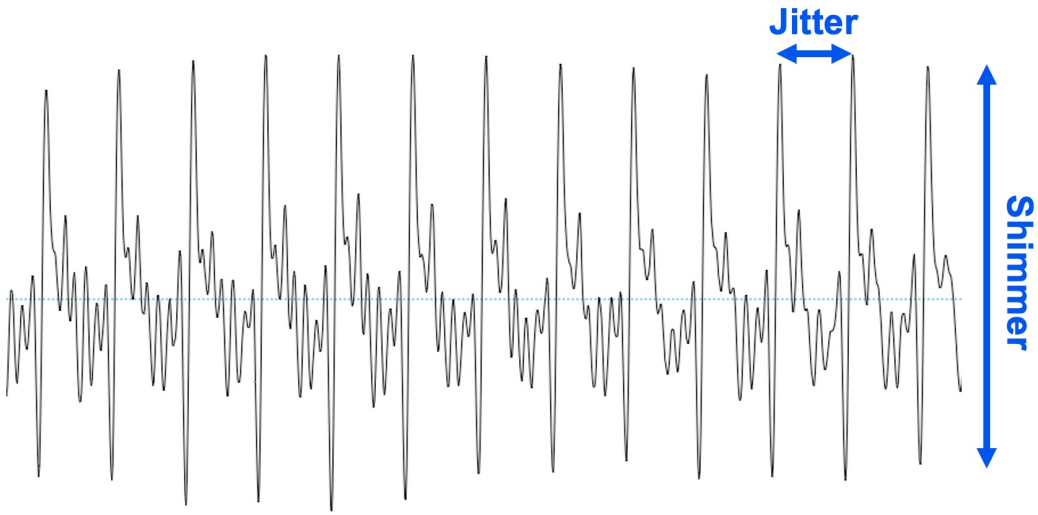

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Figure from https://wiki.aalto.fi/display/ITSP/Jitter+and+shimmer

Features: Absolute Jitter

- Absolute Jitter is the period to period variability of the pitch period
- Jitter in essence measures the changes in distance between peaks

$$\text{Jita} = \frac{1}{N-1} \sum_{i=1}^{N-1} \left| T^{(i)} - T^{(i+1)} \right|$$

Feature: Shimmer

- Measures the differences between amplitudes of the max peaks in periods

Results (male group)

Parameters	Control Group (mean ± SD)	CHD Group (mean ± SD)
Jita (μsec)	116.56±41.09	68.45±27.88
Jitt (%)	1.35±0.509	0.86±0.41
RAP (%)	0.80±0.30	0.54±0.30
PPQ (%)	0.81±0.30	0.53±0.31
sPPQ (%)	1.19±0.52	0.76±0.28
ShdB (dB)	0.73±0.25	0.45±0.16
Shim (%)	8.056±2.59	4.98±1.59
APQ (%)	5.87±1.76	3.70±1.14
sAPQ (%)	8.69±3.23	6.32±2.30

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Table from V. Pareek and R. K. Sharma, "Coronary heart disease detection from voice analysis," 2016 IEEE (SCEECS), Bhopal, India, 2016.

Parkinson’s

- **Parkinson's disease** is a brain disorder that leads to shaking, stiffness, and difficulty with walking, balance, and coordination.
- Hypokinetic dysarthria (HD) occurs in 90% of Parkinson’s disease (PD) patients.
- HD is characterized by rigidity, bradykinesia, and **reduced muscular control of the larynx**, articulatory organs, and **other physiological support mechanisms of human speech production**. The following speech flaws have been observed**: increased acoustic noise, reduced intensity of voice, harsh and breathy voice quality, increased voice nasality, monopitch, monoloudness, and speech rate disturbances**.

Parkinson's diagnosis via voice: Shimmer works

Vowel	Feature	ρ	MI	p	ACC [%]	SEN [%]	SPE [%]	TSS
a (s)	F_2 (99p)	–0.0219	0.7540	0.8029	65.41	66.67	63.27	1.65
e (s)	BW_2 (1p)	–0.0045	0.5826	0.9609	68.42	69.05	67.35	1.71
i (s)	IMF-SNR$_{\mathrm{TKEO}}$ (ir)	–0.0865	0.3564	0.3216	68.42	72.62	61.22	1.68
o (s)	IMF-SNR$_{\mathrm{SE}}$ (1p)	0.0946	0.5631	0.2781	68.42	72.62	61.22	1.68
u (s)	IMF-SNR$_{\mathrm{SEO}}$ (std)	–0.0568	0.6674	0.5152	67.67	67.86	67.35	1.70
a (l)	IMF-SNR$_{\mathrm{SEO}}$ (1p)	0.0897	0.3127	0.3037	63.16	64.29	61.22	1.62
e (l)	IMF-GNE (median)	–0.0747	0.4386	0.3920	63.91	63.10	65.31	1.64
i (l)	IMF-NSR$_{\mathrm{SE}}$ (1p)	0.0438	**0.7679**	0.6161	62.41	60.71	65.31	1.62
o (l)	F_0 (ir)	–0.0292	0.6948	0.7388	66.92	71.43	59.18	1.65
u (l)	IMF-GNE (99p)	–0.0309	0.2310	0.7247	68.42	71.43	63.27	1.69
a (ll)	jitter (RAP)	–0.0568	0.4549	0.5152	69.92	73.81	63.27	1.70
e (ll)	IMF-NSR$_{\mathrm{RE}}$ (std)	–0.2911	0.6768	0.0008	66.92	66.67	67.35	1.69
i (ll)	IMF-CPP (median)	–0.1790	0.7071	0.0399	67.67	70.24	63.27	1.68
o (ll)	IMF-SNR$_{\mathrm{SE}}$ (1p)	–0.0345	0.6136	0.6935	62.41	69.05	51.02	1.55
u (ll)	IMF-NSR$_{\mathrm{SE}}$ (ir)	–0.2010	0.6654	0.0211	69.17	71.43	65.31	1.71
a (ls)	IMF-NSR$_{\mathrm{SE}}$ (median)	0.0930	0.7455	0.2865	64.66	67.86	59.18	1.63
e (ls)	IMF-NSR$_{\mathrm{TKEO}}$ (std)	–0.1636	0.6317	0.0605	66.17	63.10	71.43	1.69
i (ls)	shimmer (local, dB)	**–0.4064**	0.7633	**0.0000**	**72.18**	**75.00**	**67.35**	**1.75**
o (ls)	IMF-FD (median)	–0.2119	0.7276	0.0150	66.17	70.24	59.18	1.64
u (ls)	HNR (median)	0.2976	0.6768	0.0006	65.41	70.24	57.14	1.62

Z. Smekal, J. Mekyska, Z. Galaz, Z. Mzourek, I. Rektorova and M. Faundez-Zanuy, "Analysis of phonation in patients with Parkinson's disease using empirical mode decomposition," 2015 International Symposium on Signals, Circuits and Systems (ISSCS), 2015

OpenSmile Toolkit and Features

Audio features (low-level)

The following (audio-specific) low-level descriptors can be computed by openSMILE:

- Frame Energy
- Frame Intensity / Loudness (approximation)
- Critical Band spectra (Mel/Bark/Octave, triangular masking filters)
- Mel-/Bark-Frequency-Cepstral Coefficients (MFCC)
- Auditory Spectra
- Loudness approximated from auditory spectra
- Perceptual Linear Predictive (PLP) Coefficients
- Perceptual Linear Predictive Cepstral Coefficients (PLP-CC)
- Linear Predictive Coefficients (LPC)
- Line Spectral Pairs (LSP, aka. LSF)
- Fundamental Frequency (via ACF/Cepstrum method and via Subharmonic-Summation (SHS))
- Probability of Voicing from ACF and SHS spectrum peak
- Voice-Quality: Jitter and Shimmer
- Formant frequencies and bandwidths
- Zero and Mean Crossing rate
- Spectral features (arbitrary band energies, roll-off points, centroid, entropy, maxpos, minpos, variance (= spread), skewness, kurtosis, slope)
- Psychoacoustic sharpness, spectral harmonicity
- CHROMA (octave-warped semitone spectra) and CENS features (energy-normalised and smoothed CHROMA)
- CHROMA-derived features for Chord and Key recognition
- F0 Harmonics ratios

Heart Auscultation

One heartbeat consists of two sounds, commonly known as: “Lub” and “Dub”.

“Lub” = turbulence from closure of **mitral** and **tricuspid** valves
“Dub” = turbulence from closure of **aortic** and **pulmonic** valves

Trainee doctors from USA, UK, and Canada could only diagnose the heart pathology **correctly in 23% of cases** [1]

[1] S. Mangione, “Cardiac auscultatory skills of physicians-in-training: a comparison of three English- speaking countries,” Am. J. Med., vol. 110, no. 3, pp. 210–216, Feb. 2001.

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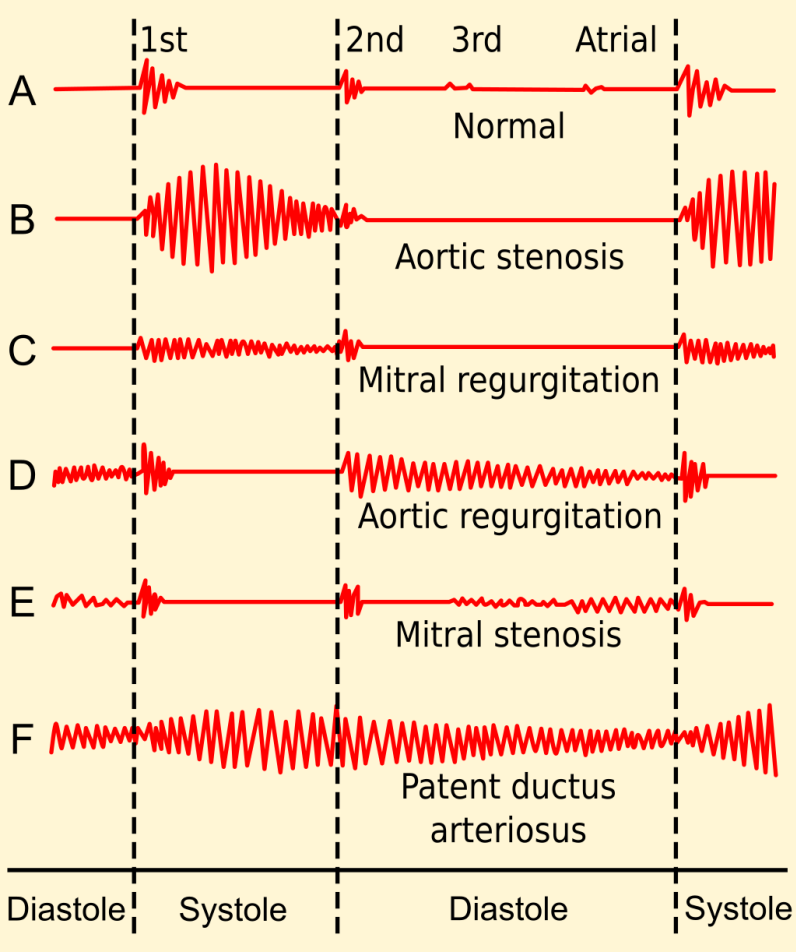
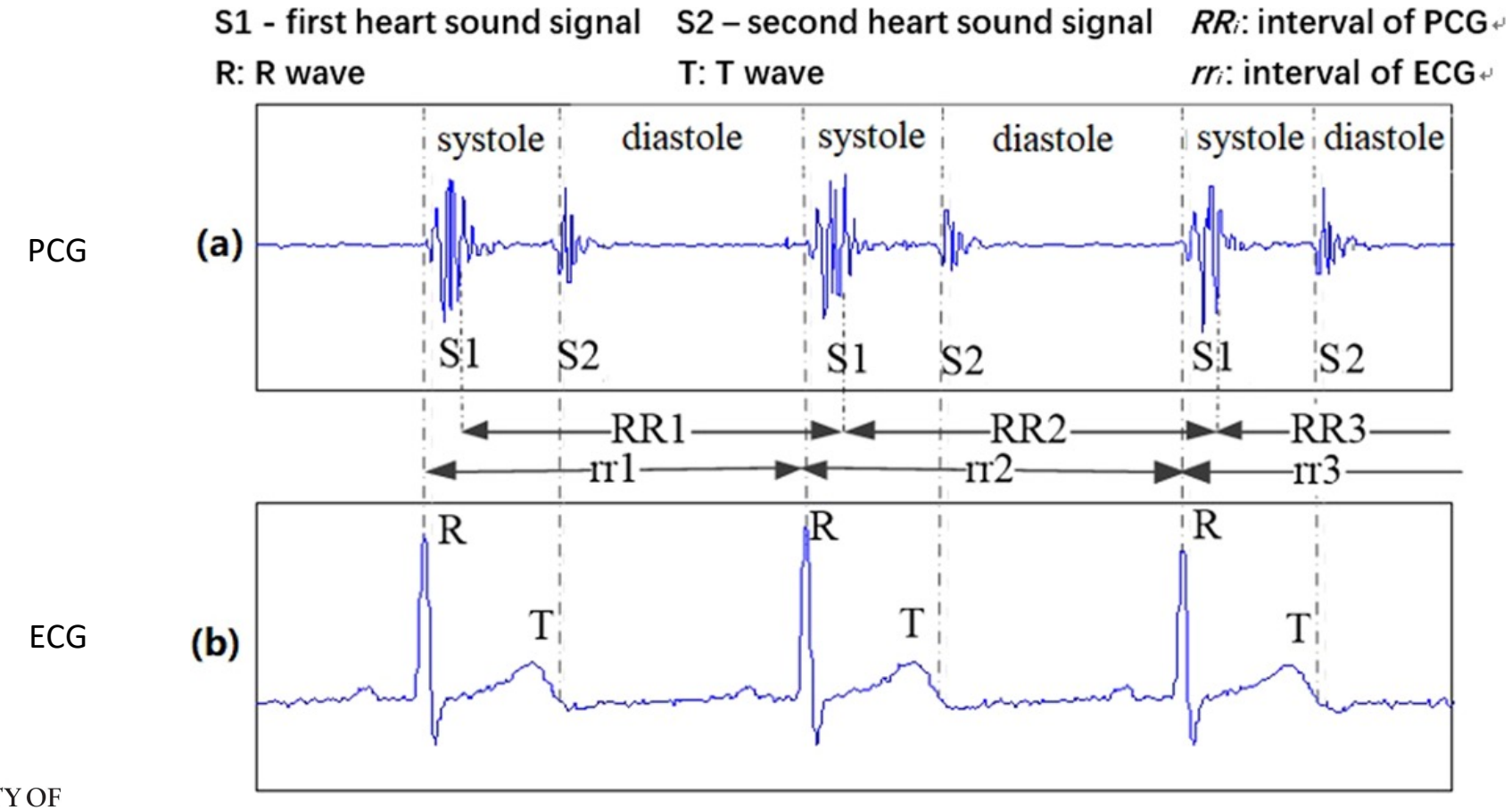
Hear Pathology Diagnosis through Audio Data



Alignment of ECG and Audio



DFT of S1 and S2 components

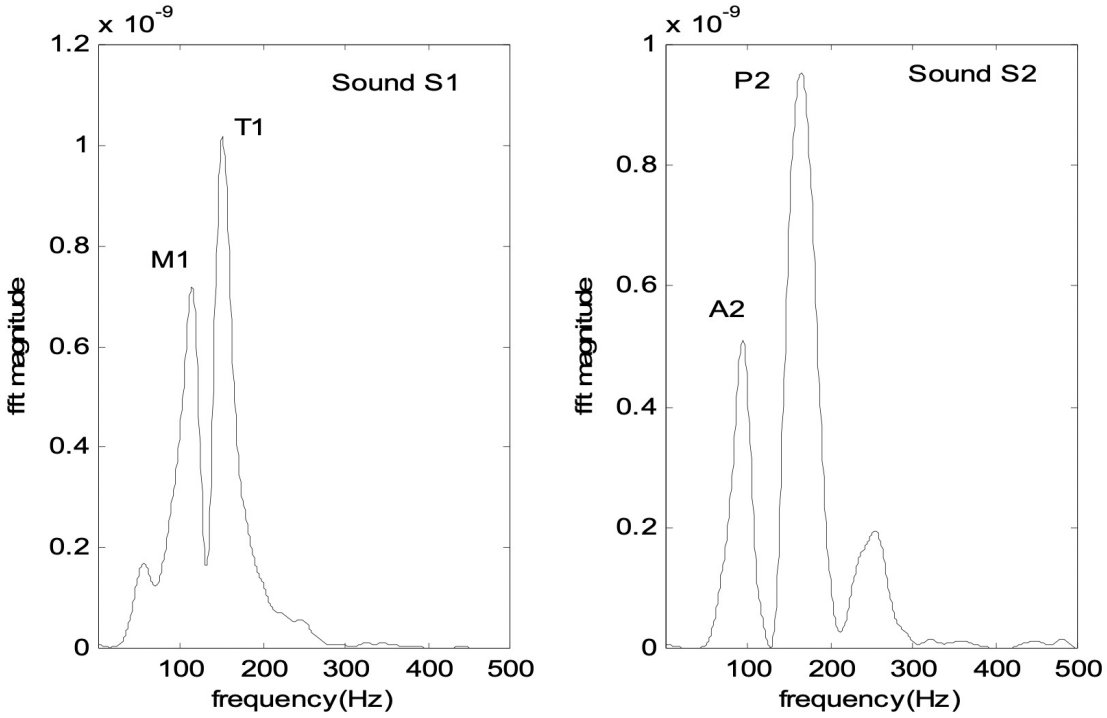
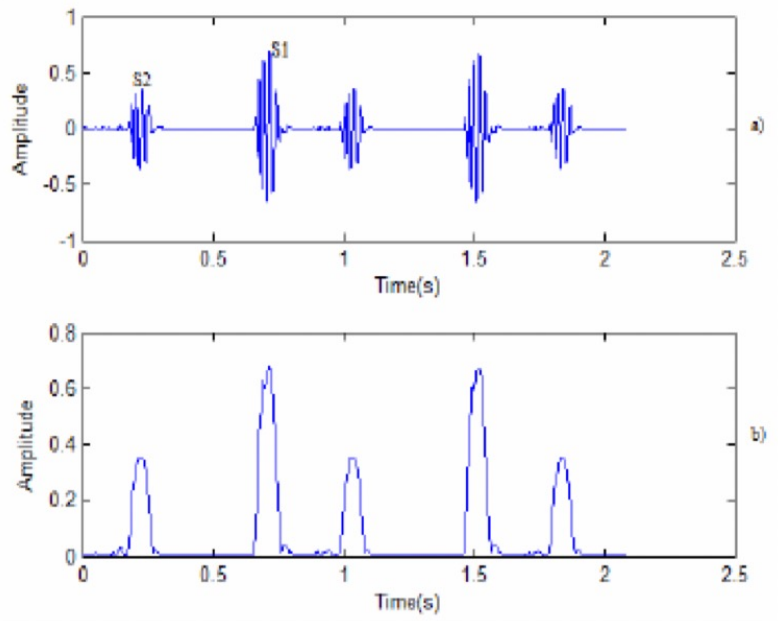


Figure from Debbal, S & bereksi reguig, Fethi. (2008). Frequency analysis of the heartbeat sounds. IJBSCHS. 13. 85-90.

Shannon Energy based Envelope Calculation

$$\text{Shannon Energy (t)} = -signal^2(\text{t}) * \log(signal^2(t))$$

$$E_{avg} = -\frac{1}{N}\sum_{t=1}^{N} \text{Shannon Energy(t)}$$



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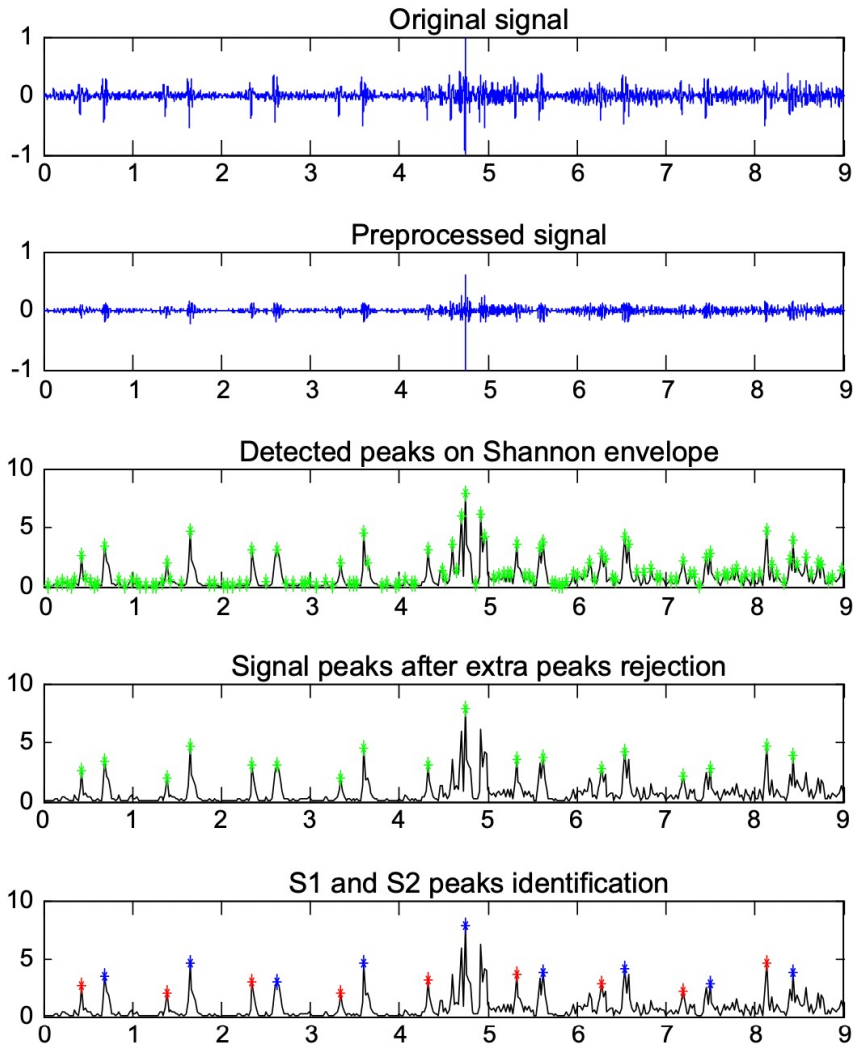
P. Sharma, S. Saha, S. Kumari (2018); Study and Design of a Shannon-Energy-Envelope based Phonocardiogram Peak Spacing Analysis for Estimating Arrhythmic Heart-Beat; Int J Sci Res Publ 4(9)

Shannon Energy based Peak Detection

- Rejection of extra peak is dataset dependent and based on peaks per time interval and their distance.



Chakir, Fatima et al. “Phonocardiogram signals processing approach for PASCAL Classifying Heart Sounds Challenge.” Signal, Image and Video Processing 12 (2018): 1149-1155.

Features…

[and KNN classifier]

Descriptor	Significance
T1	The interval between S1 and S2 peaks
T2	The interval between S2 and S1 peaks
F1	The sum of the amplitude variations between two successive samples of the signal during the period between S1 and S2 peaks divided by the length T1
F2	The sum of the amplitude variations between two successive samples of the signal during the period between S2 and S1 peaks divided by the length T2
Pw	The total original signal power
Es1	The standard deviation between S1 and S2 peaks
Es2	The standard deviation between S2 and S1 peaks
R	Takes the value 1 if there is an additional peak S1 or S2 out of rhythm; otherwise, it is equal to 0
L	Length of the signal
Zp	The zero crossing rate
Mn	The minimum amplitude of the signal
Mx	The maximum amplitude of the signal

Confusion Matrix of Classification

Table 3 Confusion matrix for Dataset A

	Normal	Murmur	Extra HS	Artifact	Total
Normal	10	1	1	2	14
Murmur	4	9	0	1	14
Extra HS	1	0	5	2	8
Artifact	2	1	0	13	16
Total	17	11	6	18	52

Table 2 Total error of the first PASCAL classifying heart sounds challenge found by our methodology and by other approaches

	Dataset A (s)	Dataset B (s)
ISEP/IPP Portugal	95.68	18.06
CS UCL	76.97	18.89
SLAC Stanford	28.2	19.11
UPD DCS Philippines	68.32	16.93
Our methodology	19.44	7.32

Deep Learning for Heart Sound Analysis: A Literature Review

A Preprint

Qinghao Zhao[1†], Shijia Geng[2†], Boya Wang[3], Yutong Sun[1], Wenchang Nie [1], Baochen Bai[1], Chao Yu[1], Feng Zhang[1], Gongzheng Tang[6,7], Deyun Zhang[2], Yuxi Zhou[4,5], Jian Liu[1*], Shenda Hong[6,7*]

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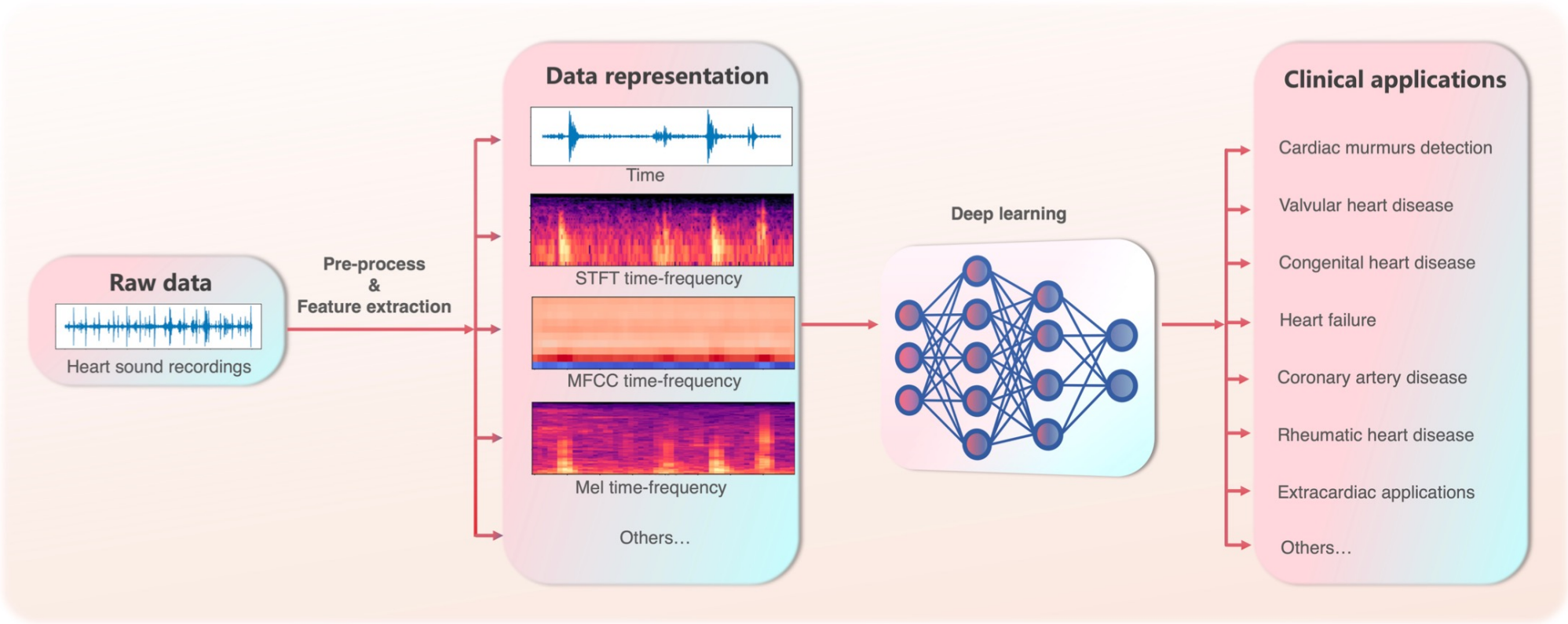

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More general audio features

Feature Group	Description
Waveform	Zero-Crossings, Extremes, DC
Signal energy	Root Mean-Square & logarithmic
Loudness	Intensity & approx. loudness
FFT spectrum	Phase, magnitude (lin, dB, dBA)
ACF, Cepstrum	Autocorrelation and Cepstrum
Mel/Bark spectr.	Bands 0-N_{mel}
Semitone spectr.	FFT based and filter based
Cepstral	Cepstral features, e.g. MFCC, PLP-CC
Pitch	F_0 via ACF and SHS methods Probability of Voicing
Voice Quality	HNR, Jitter, Shimmer
LPC	LPC coeff., reflect. coeff., residual Line spectral pairs (LSP)
Auditory	Auditory spectra and PLP coeff.
Formants	Centre frequencies and bandwidths
Spectral	Energy in N user-defined bands, multiple roll-off points, centroid, entropy, flux, and rel. pos. of max./min.
Tonal	CHROMA, CENS, CHROMA-based features

E. Bondareva, J. Han, W. Bradlow, C. Mascolo. Segmentation-free Heart Pathology Detection Using Deep Learning. In Procs of Int. Conf. of the IEEE Engineering in Medicine and Biology Society. 2021.

Deep Learning Pipeline

- Of the 6K features:
  - Principal Component Analysis used to reduce features to ~500 feature vector
- A deep learning fully connected network is used (6 layers)

	Previous works					Our method	
	[3]	[9]	[4]	[5]	[13]	SVM	DNN
PN	0.70	0.77	0.71	**0.82**	0.77	**0.82**	0.81
PM	0.30	0.37	0.33	0.59	0.76	0.70	**0.96**
PE	0.67	0.17	**1.00**	0.18	0.50	0.20	0.50
Sens	0.19	0.51	0.14	0.49	0.34	**0.54**	0.47
Spec	0.84	0.59	0.90	0.66	0.95	0.77	**0.99**

E. Bondareva, J. Han, W. Bradlow, C. Mascolo. Segmentation-free Heart Pathology Detection Using Deep Learning. In Procs of Int. Conf. of the IEEE Engineering in Medicine and Biology Society. 2021.

Deep Learning

- Often generate vectors/matrices of features as input
- Construct a DNN architecture able to solve the task

Speech analysis for health: Current state-of-the-art and the increasing impact of deep learning

Nicholas Cummins[a,*], Alice Baird[a], Björn W. Schuller[a,b]

[a] *ZD.B Chair of Embedded Intelligence for Health Care and Wellbeing, University of Augsburg, Germany*
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Keywords:
Speech

ABSTRACT

Due to the complex and intricate nature associated with their production, the acoustic-prosodic properties of a speech signal are modulated with a range of health related effects. There is an active and growing area of

Deep Learning for Cold Detection

INTERSPEECH 2017
August 20–24, 2017, Stockholm, Sweden

DNN-based Feature Extraction and Classifier Combination for Child-Directed Speech, Cold and Snoring Identification

Gábor Gosztolya[1,2], *Róbert Busa-Fekete*[3], *Tamás Grósz*[1], *László Tóth*[2]

[1]University of Szeged, Institute of Informatics, Szeged, Hungary
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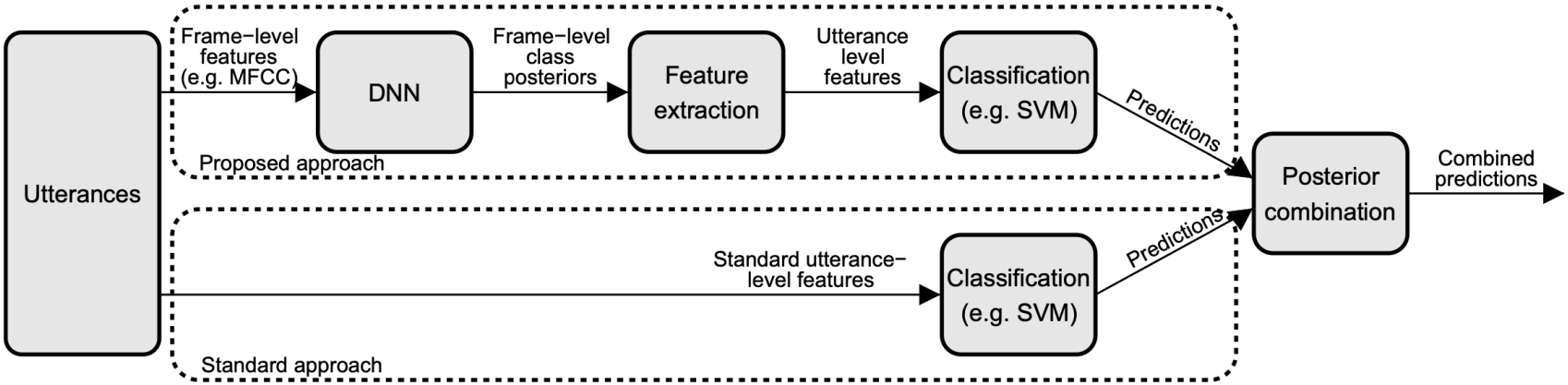
The INTERSPEECH 2017 Computational Paralinguistics Challenge: Addressee, Cold & Snoring

Björn Schuller[1,2], *Stefan Steidl*[3], *Anton Batliner*[2,3], *Elika Bergelson*[4], *Jarek Krajewski*[5], *Christoph Janott*[6], *Andrei Amatuni*[4], *Marisa Casillas*[7], *Amanda Seidl*[8], *Melanie Soderstrom*[9], *Anne S. Warlaumont*[10], *Guillermo Hidalgo*[5], *Sebastian Schnieder*[5], *Clemens Heiser*[6], *Winfried Hohenhorst*[11], *Michael Herzog*[12], *Maximilian Schmitt*[2], *Kun Qian*[6], *Yue Zhang*[1,6], *George Trigeorgis*[1], *Panagiotis Tzirakis*[1], *Stefanos Zafeiriou*[1,13]

[1]Department of Computing, Imperial College London, UK
[2]Chair of Complex & Intelligent Systems, University of Passau, Germany
[3]Pattern Recognition Lab, FAU Erlangen-Nuremberg, Germany

Architecture: Mixed Model



Results

Approach	Dev.	Test
ComParE feature set	58.3%	—
Thresholded feature set	61.1%	—
Frame-level DNN outputs (mean)	52.9%	—
Frame-level DNN outputs (product)	52.6%	—
Frame-level DNN outputs (majority)	53.1%	—
ComParE feature set (downsampled)	64.0%	—
Thresholded feature set (downsampled)	65.0%	—
ComParE + DNN-based (combined)	65.8%	72.0%

Data Augmentations

$$\text{augmentation\_signal} = \text{original\_signal} + \text{delta} * \text{random\_signal} \quad (2)$$

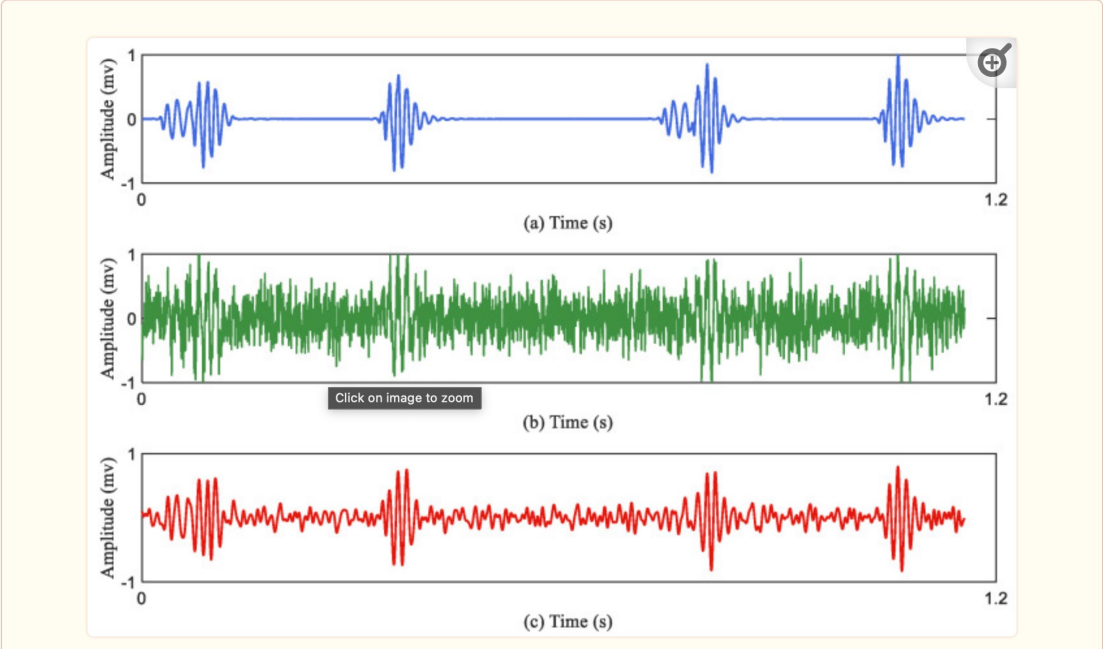


Figure from Wang M, Guo B, Hu Y, Zhao Z, Liu C, Tang H. Transfer Learning Models for Detecting Six Categories of Phonocardiogram Recordings;9(3):86.

Self Supervised and Transfer Learning

- Pretrained, self supervised and transfer learning are useful in audio analysis. Example of application of pretrained models:

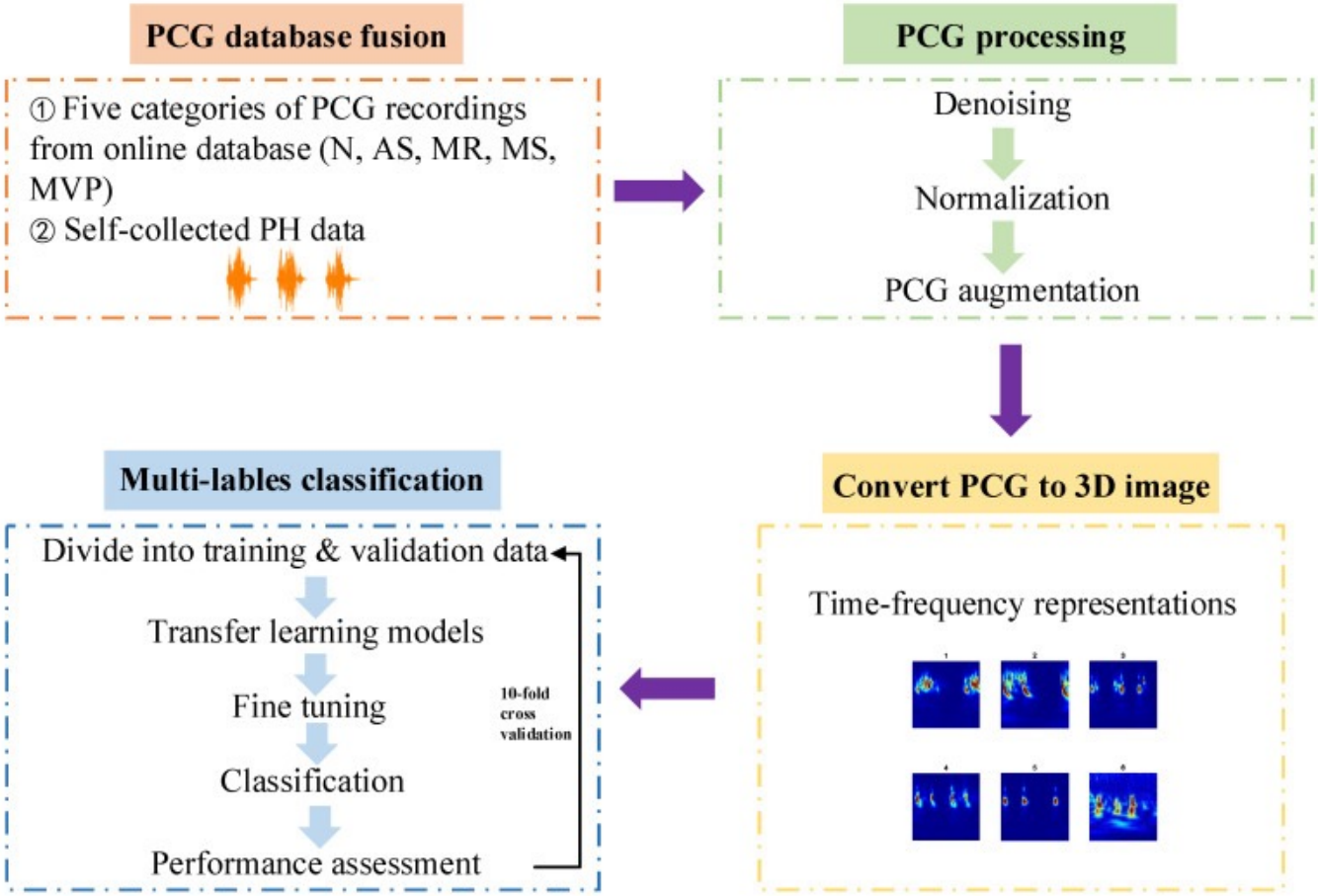


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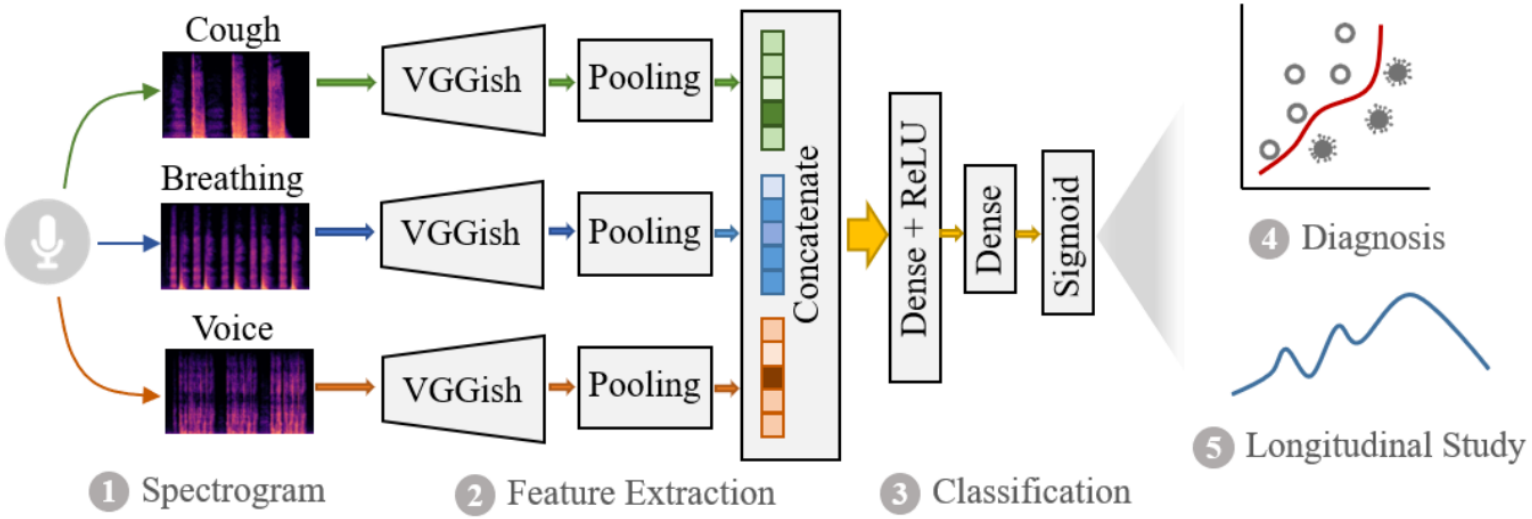
Figure from Wang M, Guo B, Hu Y, Zhao Z, Liu C, Tang H. Transfer Learning Models for Detecting Six Categories of Phonocardiogram Recordings;9(3):86.

COVID-19 Detection: pretrained audio model example



Questions