Remote heart sound collection and analysis in early diagnosis of heart disease using artificial intelligence

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University of Nebraska Medical Center

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Department of Computer Science and Engineering

University of Nebraska – Lincoln

Acknowledgements

NU System Collaboration-Initiative Team

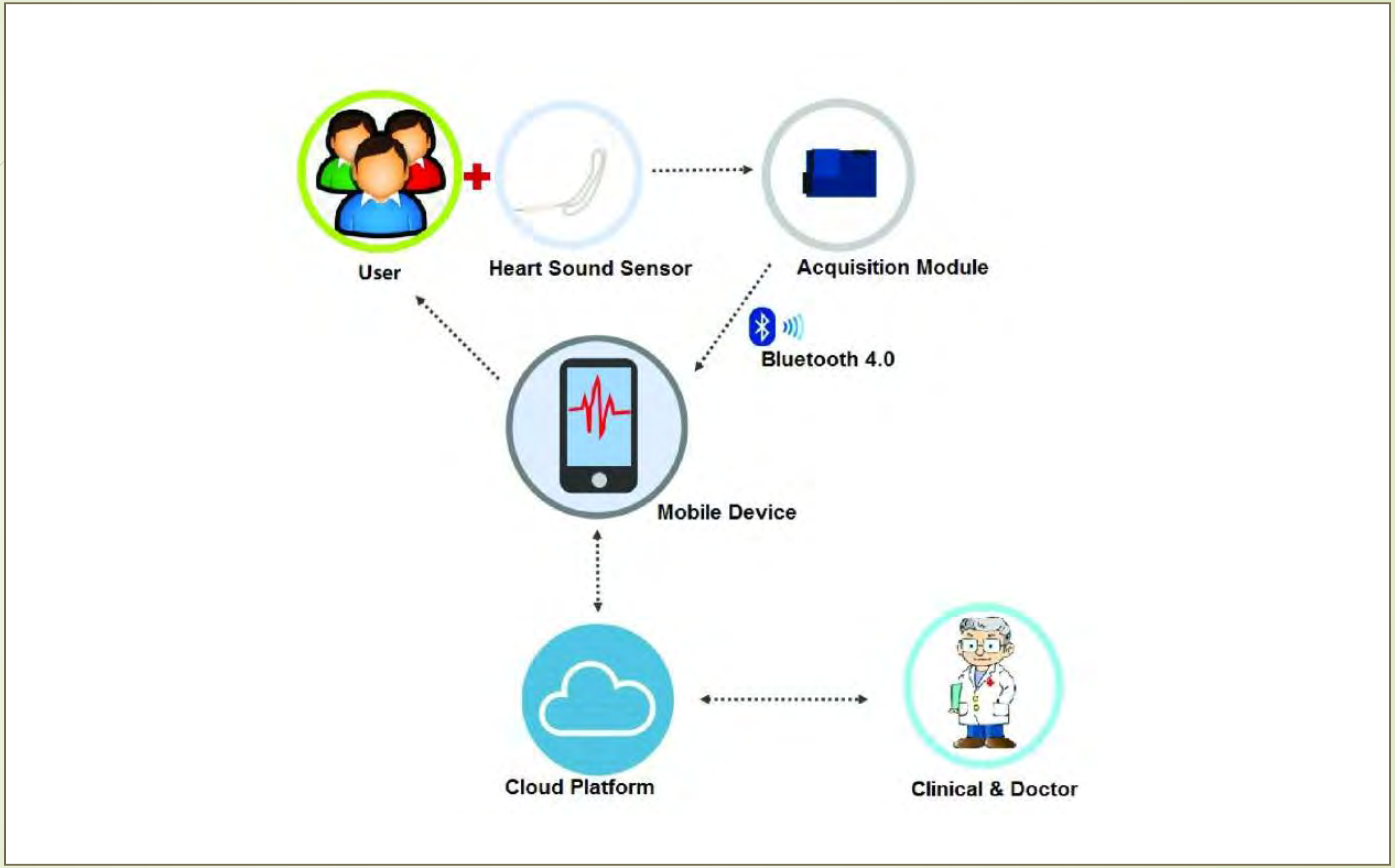
Identification of abnormal heart sounds using phonocardiograms

Accuracy of remote auscultation vs face-to-face auscultation

Detection of heart disease in a clinical setting

Identification of abnormal heart sounds

Phonocardiogram (PCG): graphic record in the form of a wave of the heart sounds obtained by a stethoscope


User
Heart Sound Sensor
Acquisition Module
Bluetooth 4.0
Mobile Device
Cloud Platform
Clinical & Doctor

Development of Wireless Heart Sound Acquisition System for Screening Heart Valvular Disorder

Samjin Choi and Zhongwei Jiang
Department of Mechanical Engineering, Yamaguchi University, Ube, 755-8611, Japan
{b3678, jiang}@yamaguchi-u.ac.jp

> Biomed Eng Online. 2011 Feb 9;10:13. doi: 10.1186/1475-925X-10-13.

A framework for automatic heart sound analysis without segmentation

Sumeth Yuenyong [1], Akinori Nishihara, Waree Kongprawechnon, Kanokvate Tungpimolrut

> Physiol Meas. 2017 Jul 31;38(8):1658-1670. doi: 10.1088/1361-6579/aa724c.

Heart sound classification from unsegmented phonocardiograms

Philip Langley [1], Alan Murray

PeerJ. 2015; 3: e1178.
Published online 2015 Aug 11. doi: 10.7717/peerj.1178
PMCID: PMC4558084
PMID: 26339555

Wireless laptop-based phonocardiograph and diagnosis

Amy T. Dao

Real-Time Smart-Digital Stethoscope System for Heart Diseases Monitoring

Muhammad E.H. Chowdhury [1,*], Amith Khandakar [1], Khawla Alzoubi [1], Samar Mansoor [1], Anas M. Tahir [1], Mamun Bin Ibne Reaz [2] and Nasser Al-Emadi [1]

Asia International Symposium on Mechatronics 2008
27-31 August 2008 Hokkaido University, Japan
TA1-1(6)

Heart Sound Measurement and Analysis System with Digital Stethoscope

Wang Haibin[1] Hu Yuliang[1] Jiang Zhongwei[2] Zhang Junqi[3] Choi Samjin[2] Sun Shuping[1]

- Does this translate to diagnosing heart disease in a real-world setting?

Sensors (Basel). 2021 Oct; 21(19): 6558.
Published online 2021 Sep 30. doi: 10.3390/s21196558

PMCID: PMC8512197
PMID: 34640876

Rheumatic Heart Disease Screening Based on Phonocardiogram

Melkamu Hunegnaw Asmare,[1,2,*] Benjamin Filtjens,[1,3] Frehiwot Woldehanna,[2] Luc Janssens,[1] and Bart Vanrumste[1]

Automated RHD screening approach using machine learning

(a) (b) (c)

Heart sound data was collected from

124 patients with RHD and

127 healthy controls (HC) (46 healthy persons+ 81 healthy control records from an open-access dataset)

Thirty-one distinct features on phonocardiogram were extracted to correctly represent RHD

A recall value of 95.8 ± 1.5%, precision of 96.2 ± 0.6% and a specificity of 96.0 ± 0.6% was achieved

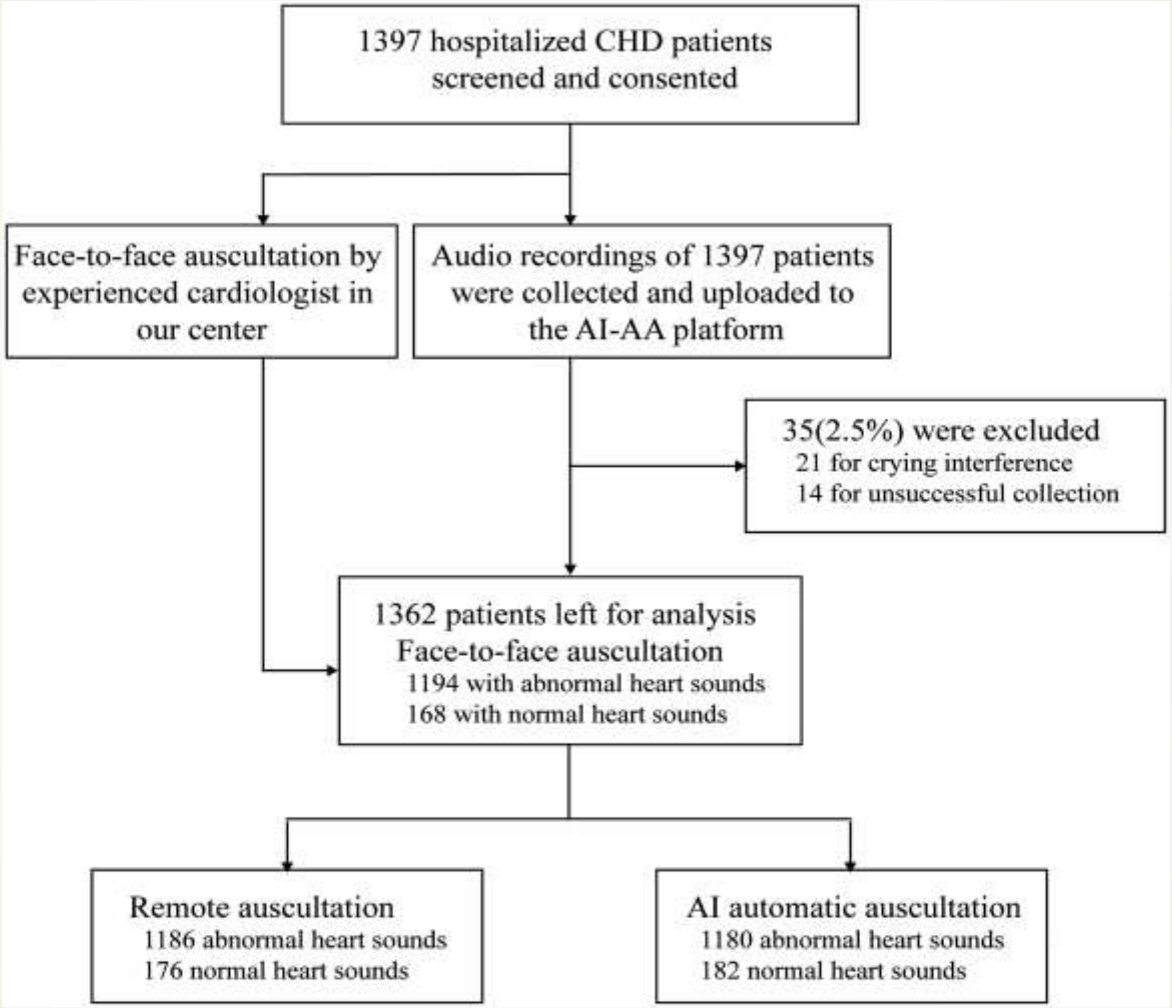
When corrected to a *prevalence rate of 5%,* a recall of 92.3 ± 0.4%, precision of 59.2 ± 3.6%, and a specificity of 94.8 ± 0.6% was noted

Artificial intelligence-assisted auscultation in detecting congenital heart disease

Jingjing Lv, Bin Dong, Hao Lei, Guocheng Shi, Hansong Wang, Fang Zhu, Chen Wen, Qian Zhang, Lijun Fu, Xiaorong Gu ... Show more
Author Notes

European Heart Journal - Digital Health, Volume 2, Issue 1, March 2021, Pages 119–124,

Figure 1 The flow chart of this study.



Eur Heart J Digit Health, Volume 2, Issue 1, March 2021, Pages 119–124, https://doi.org/10.1093/ehjdh/ztaa017

- Compared to face-to-face auscultation
  - Remote auscultation detected abnormal heart sound with
    - 98% sensitivity
    - 91% specificity
    - 97% accuracy
  - While the AI-AA demonstrated
    - 97% sensitivity
    - 89% specificity
    - 96% accuracy

- Does this translate to screening for heart disease in a rural setting?

Springer Link

Original Article | Published: 02 February 2017

Initial Field Test of a Cloud-Based Cardiac Auscultation System to Determine Murmur Etiology in Rural China

Lee Pyles, Pouya Hemmati, J Pan, Xiaoju Yu, Ke Liu, Jing Wang, Andreas Tsakistos, Bistra Zheleva, Weiguang Shao & Quan Ni

Pediatric Cardiology **38**, 656–662 (2017) | Cite this article

7993 school children underwent screening

149 had a murmur

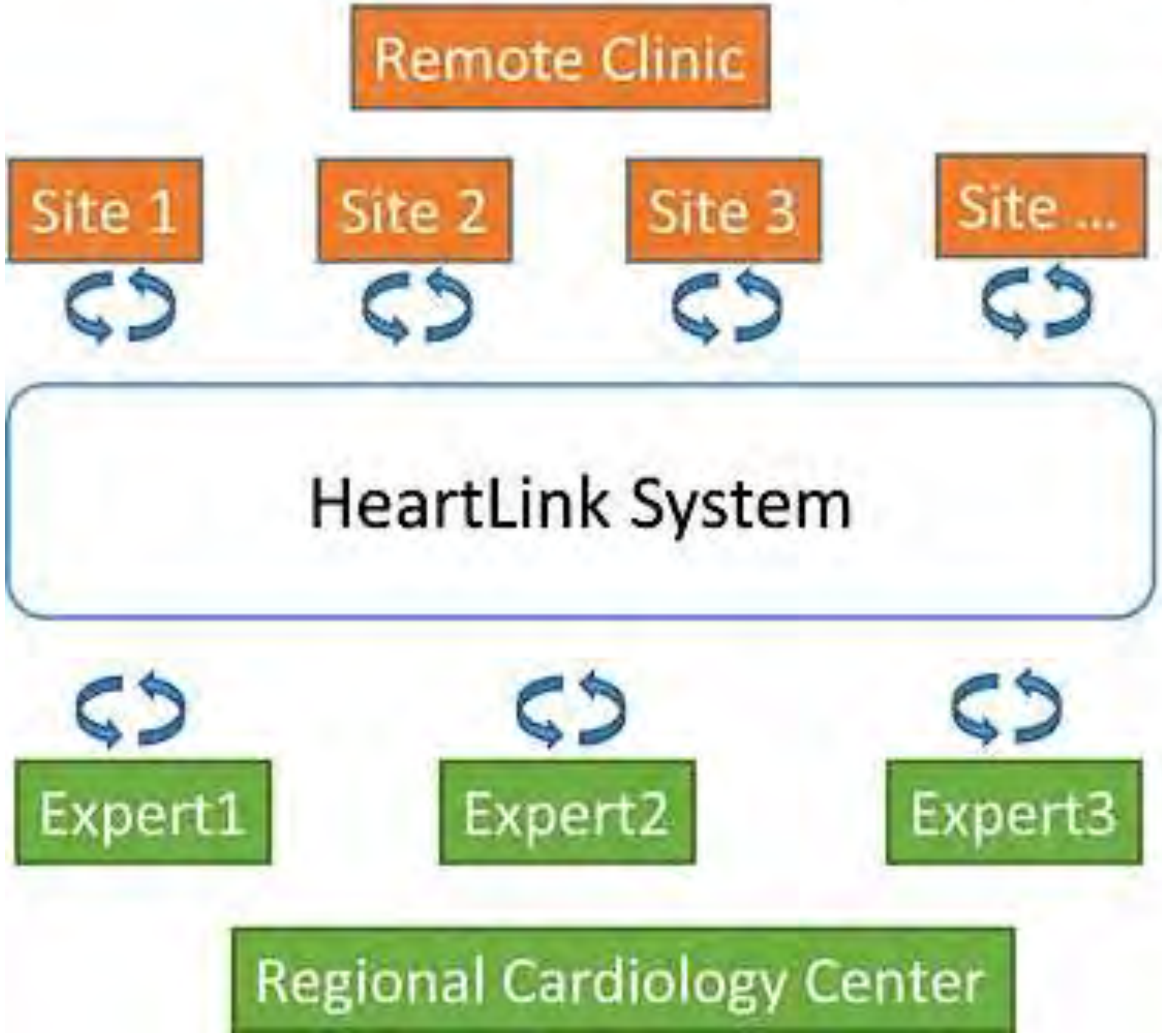
Phonocardiograms were collected using a "HeartLink tele-auscultation system"

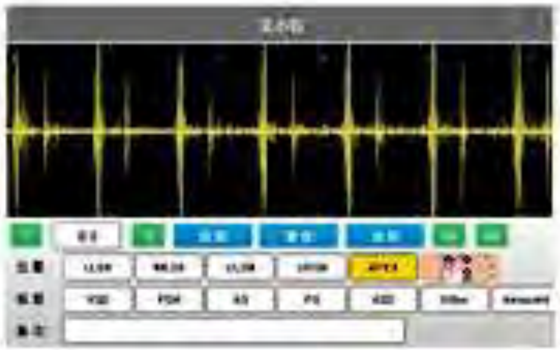
Echocardiography was performed by a cardiology resident

Digital PCGs were stored on a cloud server

Remotely reviewed by a board-certified American pediatric cardiologist

HeartLinkAuscultation System





14 out of 149 were found to have congenital heart disease

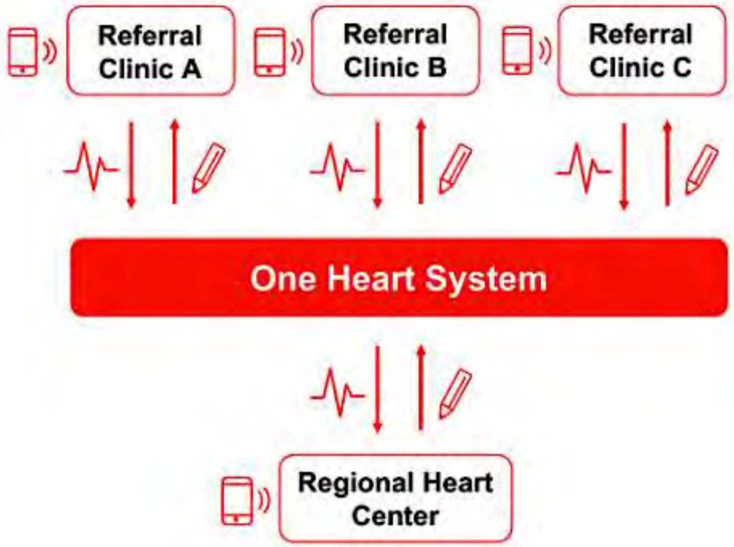
The pediatric cardiologist identified 11 of the 14 with pathological murmurs

Overall test accuracy was 91% with 78.5% sensitivity and 92.6% specificity

Mobile Screening

One Heart Health Telemedicine System

The system consists of an electronic stethoscope and the One Heart App. A health worker can acquire heart murmurs at a remote clinic, and transmit the phonocardiogram via the One Heart server for remote consultation by experts from regional cardiac centers with a network connection.



Title: Collection and Analysis of Heart Sounds to Aid Early Diagnosis of Valvular Heart disease

Purpose

Can family physicians identify abnormal heart sounds similar to cardiologists?

Can both groups use advanced stethoscopes to record these heart sounds in an interpretable manner?

Can both groups identify the recorded heart sounds as compared to a gold standard?

Study layout

30 patients and 10 physicians

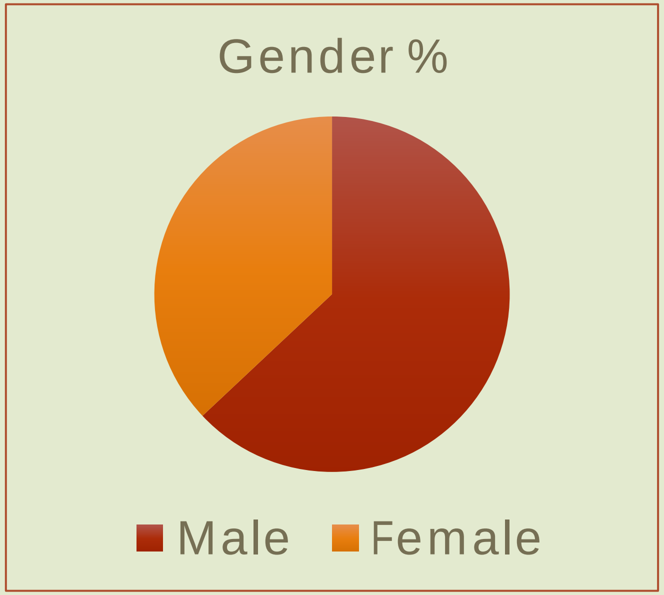
The 30 patients, aged 20-75 years, were *divided in 3 groups of 10 patients each*

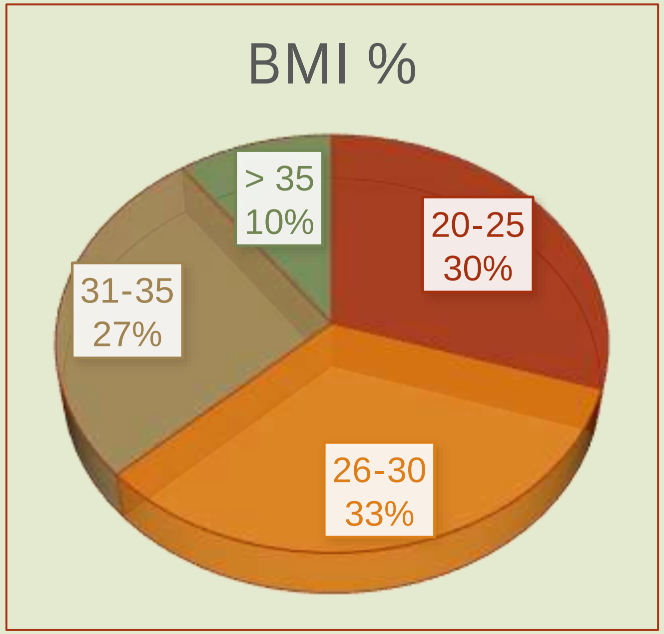
Each group represents a category - normal, valvular heart disease, other abnormal heart sounds

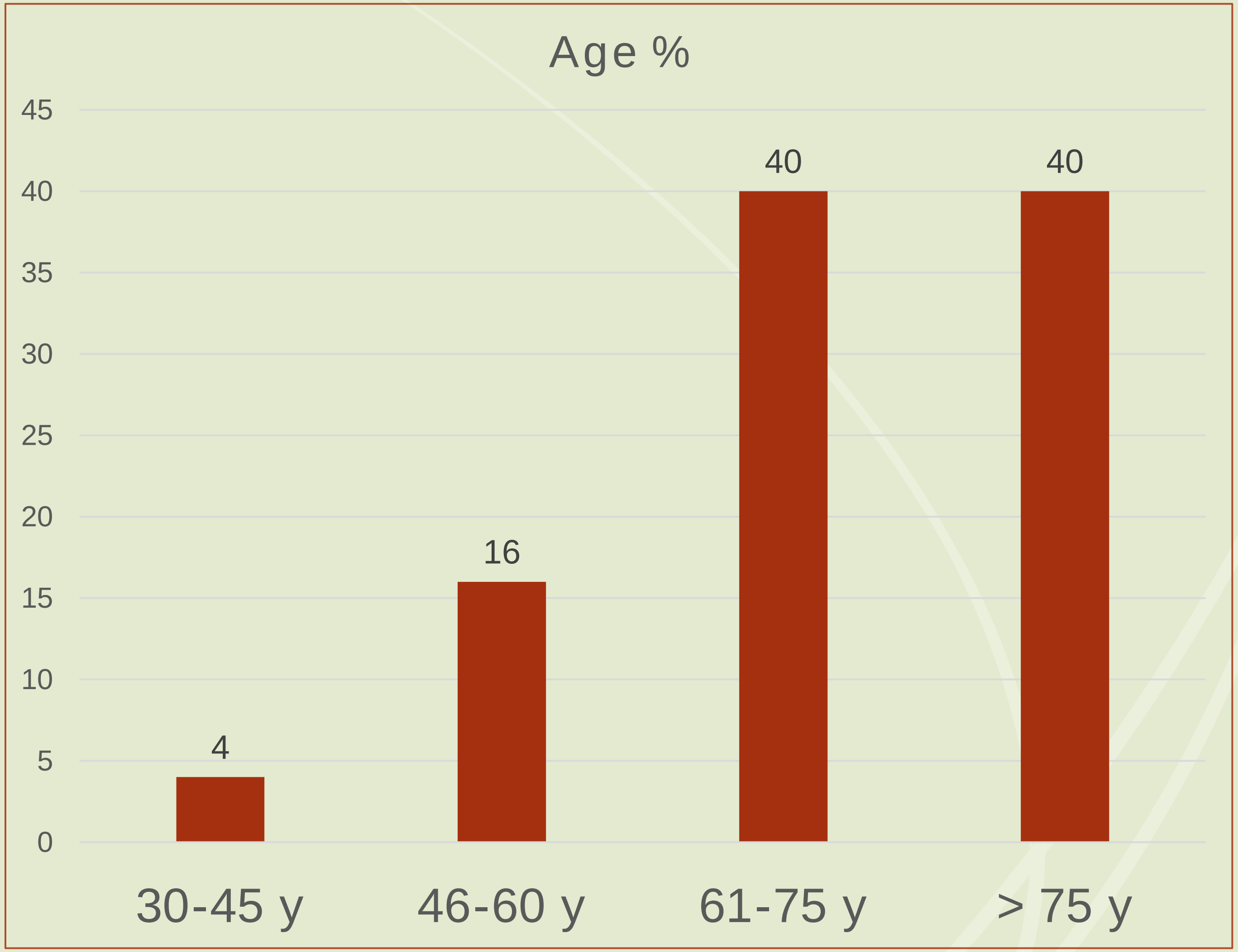
The 10 physicians are from 2 specialty groups;

- *5 belonging to Cardiology and*
- *5 belonging to Family Medicine*

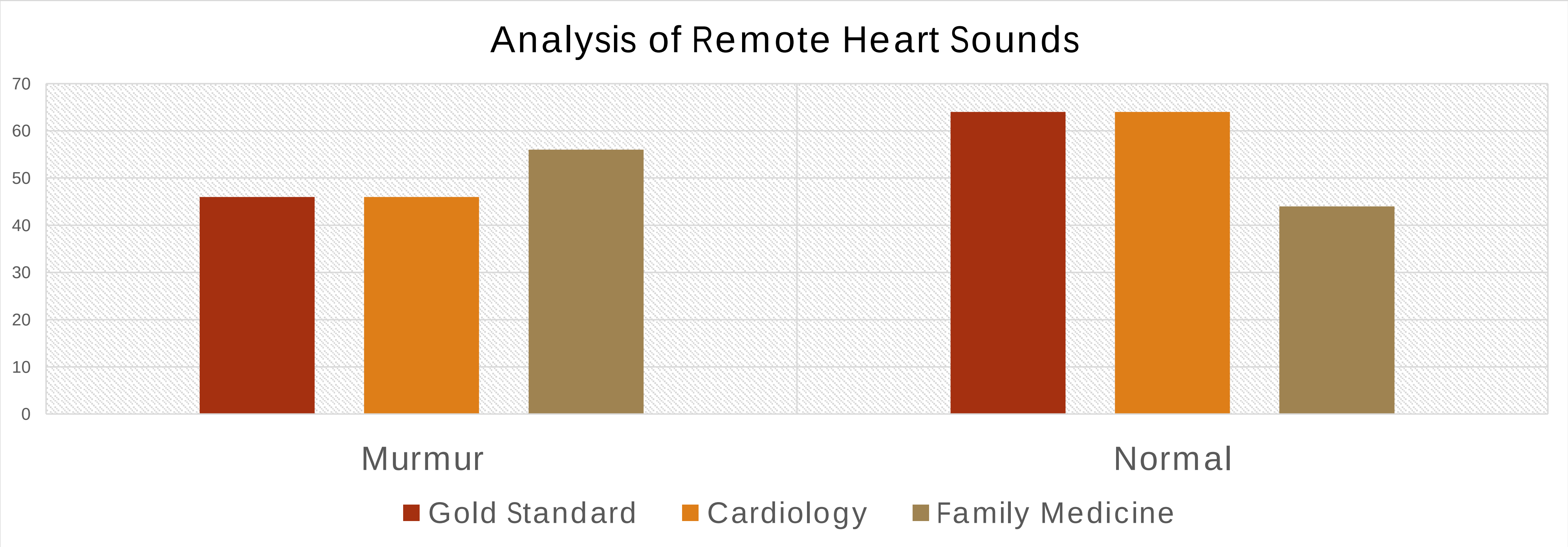
Demographics at a glance..



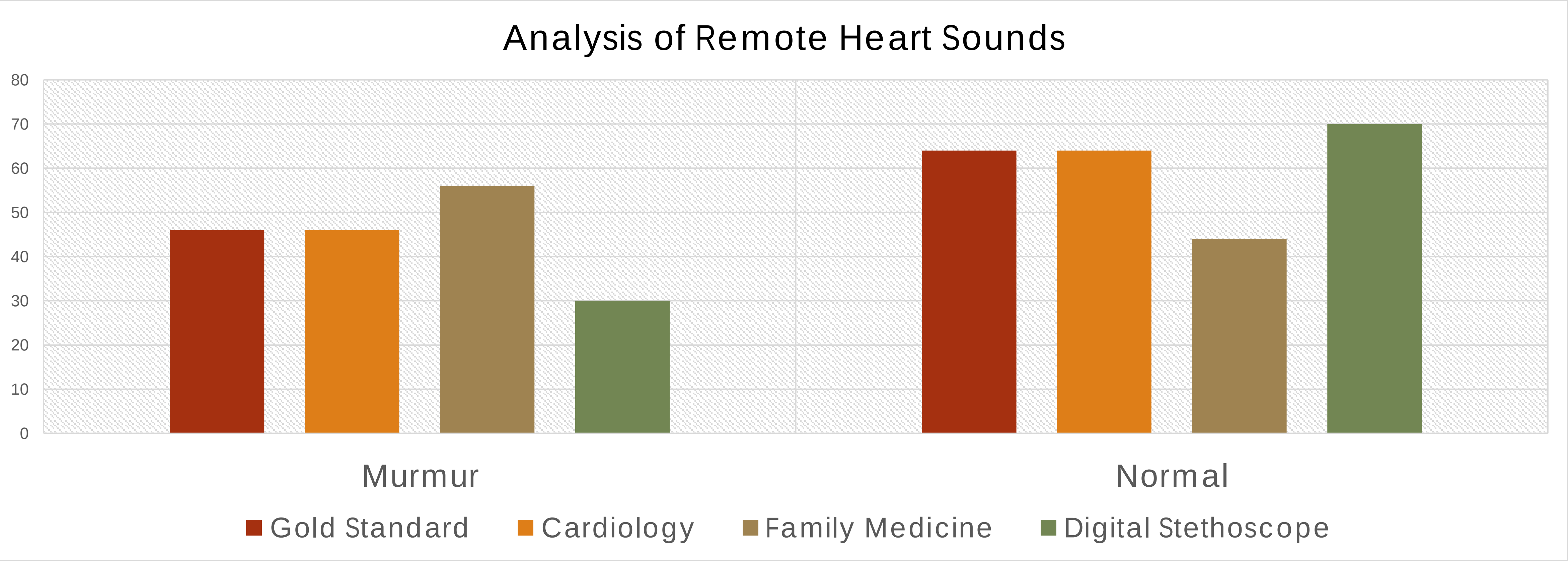




Results


Analysis of Remote Heart Sounds
70
60
50
40
30
20
10
0
Murmur
Normal
Gold Standard
Cardiology
Family Medicine

Results



Analysis of Remote Heart Sounds
80
70
60
50
40
30
20
10
0
Murmur
Normal
Gold Standard
Cardiology
Family Medicine
Digital Stethoscope

Results

Statistic	Value	95% CI
Sensitivity	21.43%	4.66% to 50.80%
Specificity	75.00%	47.62% to 92.73%
Positive Likelihood Ratio	0.86	0.23 to 3.19
Negative Likelihood Ratio	1.05	0.71 to 1.55
Disease prevalence (*)	46.67%	28.34% to 65.67%
Positive Predictive Value (*)	42.86%	16.78% to 73.62%
Negative Predictive Value (*)	52.17%	42.40% to 61.79%
Accuracy (*)	50.00%	31.30% to 68.70%

In conclusion,

Results from traditional in-person auscultation were in agreement

Analysis of remote heart sounds by both groups were similar to gold standard

Recognition of abnormal heart sounds by AI in the real-world setting needs further improvement

Heart Disease Pre-screening using AI

Shine Bedi, School of Computing, University of Nebraska-Lincoln

Introduction to Heart Sounds Classification

- Importance: Accurate classification of heart sounds is critical for the early diagnosis and treatment of cardiovascular diseases.

1. Traditional Models:
   a. Uses handcrafted features and simple algorithms (e.g., k-NN, HMM).
   b. Relies heavily on domain expertise for feature extraction.
2. Machine Learning:
   a) Combines automated feature extraction with advanced algorithms (e.g., SVM, Random Forests).
   b) Enhances performance but still requires significant preprocessing.

Introduction to Heart Sounds Classification

3. Deep Learning:
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    b. Provides high accuracy and can handle different data modalities (e.g., time series signal, spectrogram images) but requires large datasets and computational resources.

Stages of Heart Sounds Analysis

Pre-processing

- Purpose: Clean and prepare raw heart sound signals for further analysis.
- Methods: Noise reduction, normalization, filtering.

Segmentation

- Purpose: Extract specific segments of the heart cycle, such as the S1 and S2 sounds, from PCG signal for further analysis.
- Methods: Time-domain analysis, Wavelet Transform, HMM.

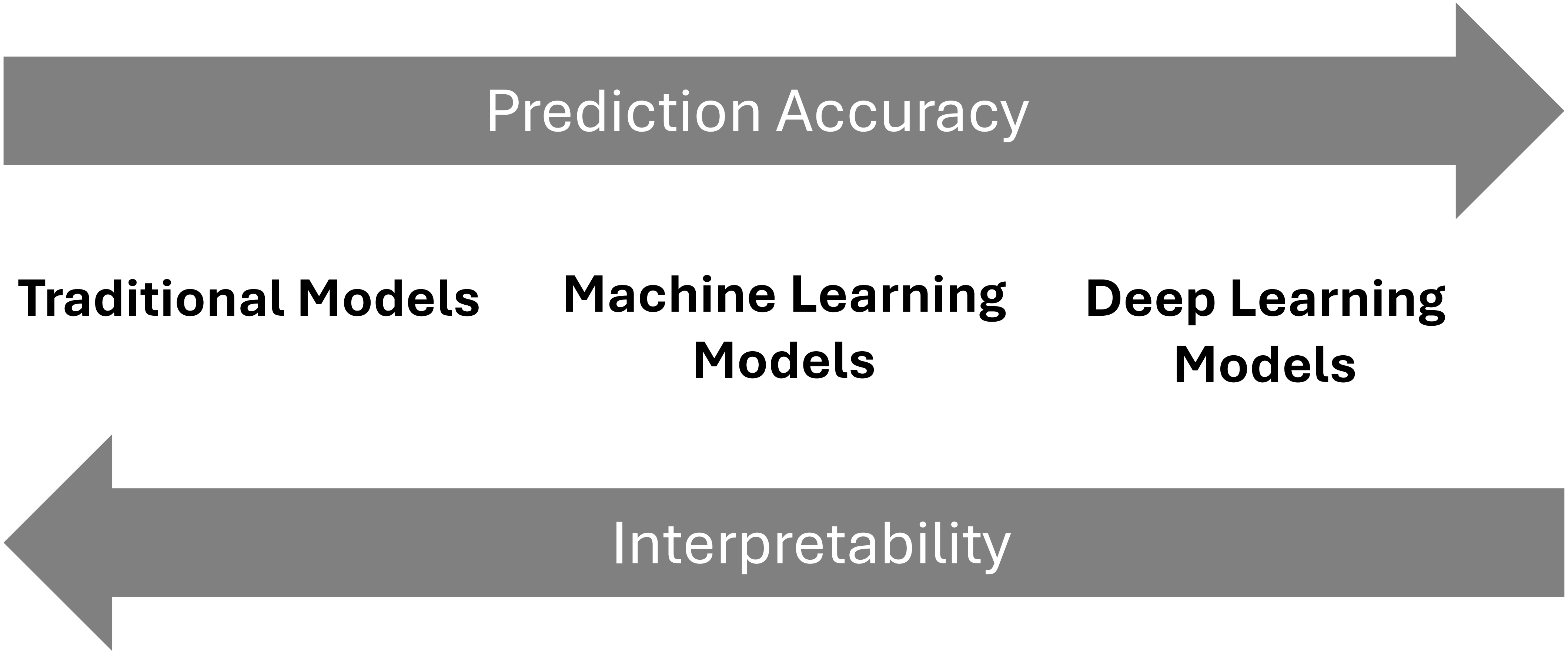
Classification

- Purpose: Categorize heart sounds into normal or pathological classes.
- Methods: Simple classifiers (e.g., k-NN), advanced machine learning models (e.g., SVM, RF), deep learning models (e.g., CNNs, RNNs).

Comparison of Approaches: Traditional vs Machine Learning vs Deep Learning

Stage	Traditional Models	Machine Learning	Deep Learning
Pre-processing	Filtering (Butterworth, Savitzky-Golay), Normalization, Adaptive Filters (Kalman)	Bandpass Filtering, Feature Scaling (Min-Max, Z-score), Normalization	Minimal Preprocessing, Data Augmentation (Noise Addition, Time Warping)
Segmentation	Envelope Extraction (Hilbert Transform, Wavelet Transform), Time-domain Analysis (Autocorrelation, Spectral Analysis)	Feature-based Segmentation (MFCC, DWT), Clustering (K-means, DBSCAN)	
Classification	Bayesian Classifiers, Decision Trees, Logistic Regression	SVM, Random Forests, Gradient Boosting	CNNs, RNNs (LSTM, GRU), Transfer Learning (Pre-trained CNNs)

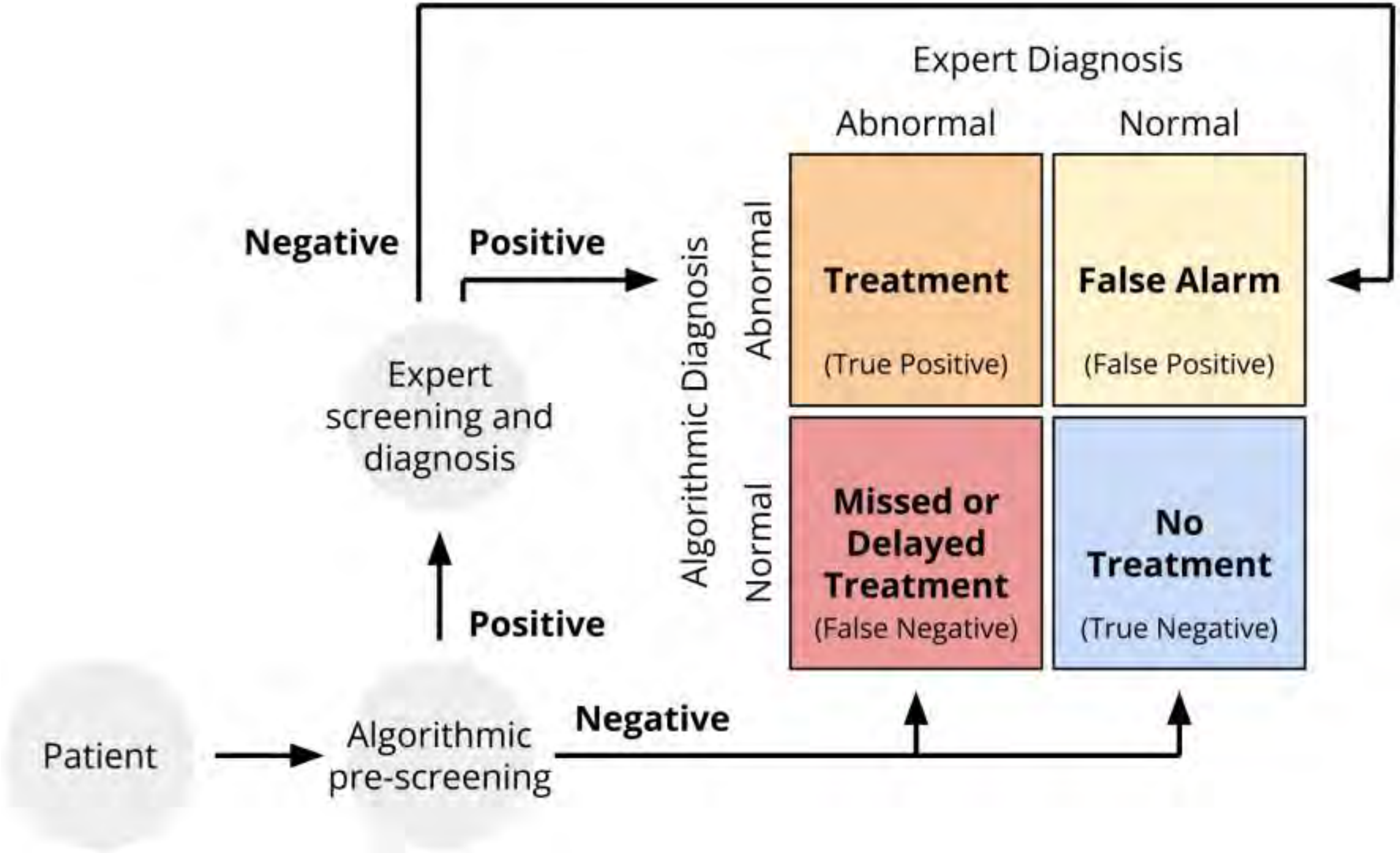
The Trade-off



Classification of Normal/Abnormal Heart Sound Recordings: the PhysioNet/Computing in Cardiology Challenge [1,7]

- Encourage development of automated approaches for detecting heart murmurs and abnormal cardiac function from PCG recordings.
- Identify whether a subject needs further expert diagnosis based on a short recording from a single precordial location.
- The normal recordings were from healthy subjects and the abnormal ones were from patients typically with heart valve defects and coronary artery disease (CAD).
- Challenge: Accurate classification of normal and abnormal heart sounds, especially when some heart sounds exhibit very poor signal quality.

Screening and diagnosis pipeline for the Challenge [7]



PhysioNet/CinC Challenge 2016-Data [1]

- Challenge provides heart sound database, aggregated from eight databases obtained by seven independent research groups around the world.
- The Challenge training set includes a total of 3,153 heart sound recordings from 764 subjects/patients.
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Top-Scoring 2016 (top), 2022 (bottom) PhysioNet/CinC Challenge Entries

Weighted Test Score	Author	Method
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0.8590	Zabihi et al. [3]	Ensemble of Neural Networks
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CNN: Convolutional Neural Network; PCA: Principal Component Analysis; KNN: K-Nearest Neighbors; RNN: Recurrent Neural Network; HSMM: Hidden Semi-Markov Models

Deep Learning Architecture Overview [2]

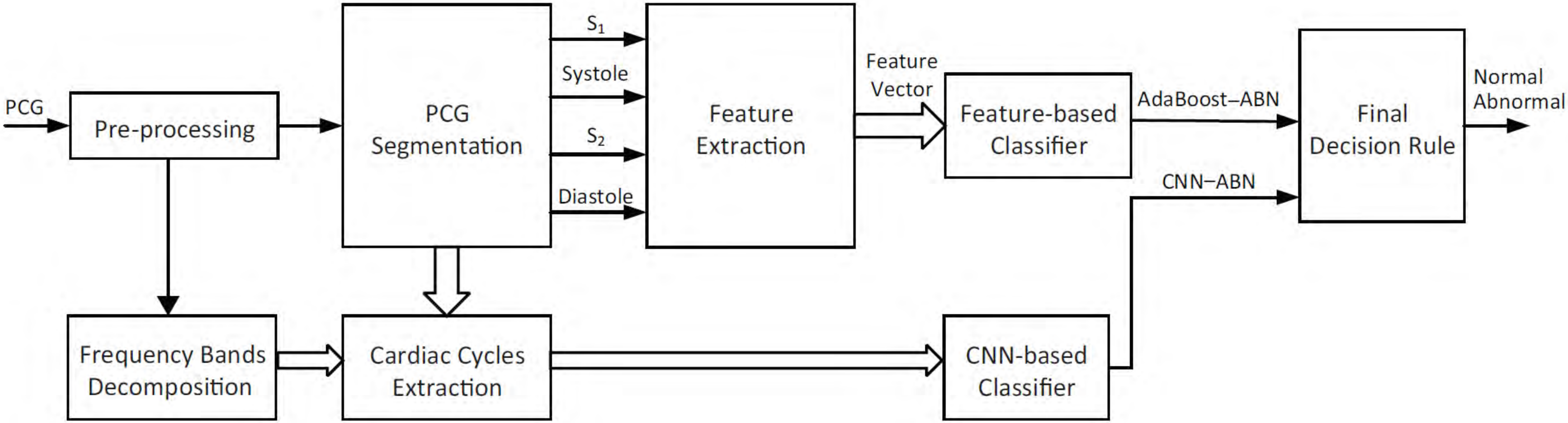

Figure 1. Block diagram of the proposed approach for classification of normal/abnormal heart sounds.

Deep Learning Architecture Overview [2]

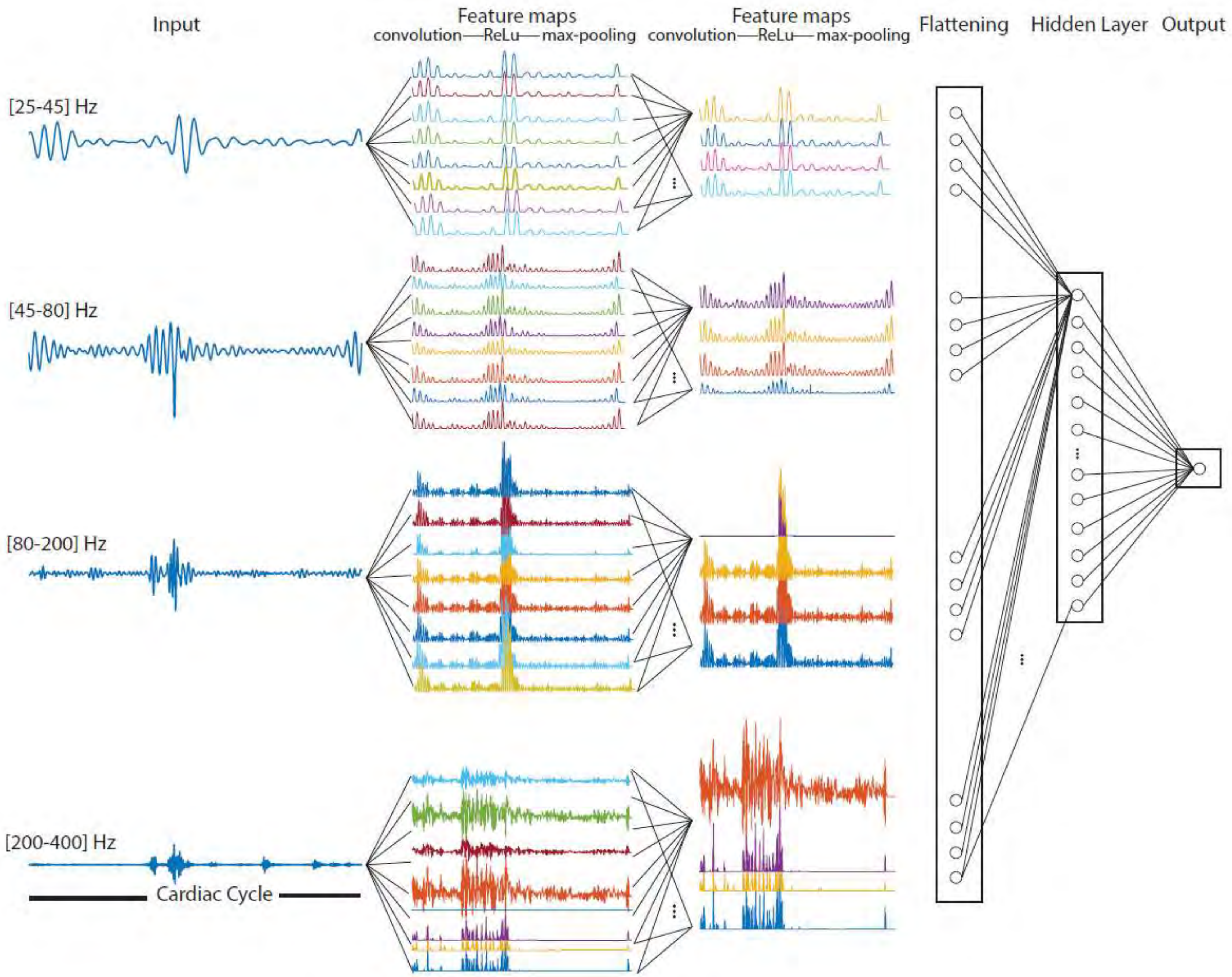

Figure 2. CNN architecture for classification of normal/abnormal heart sounds.

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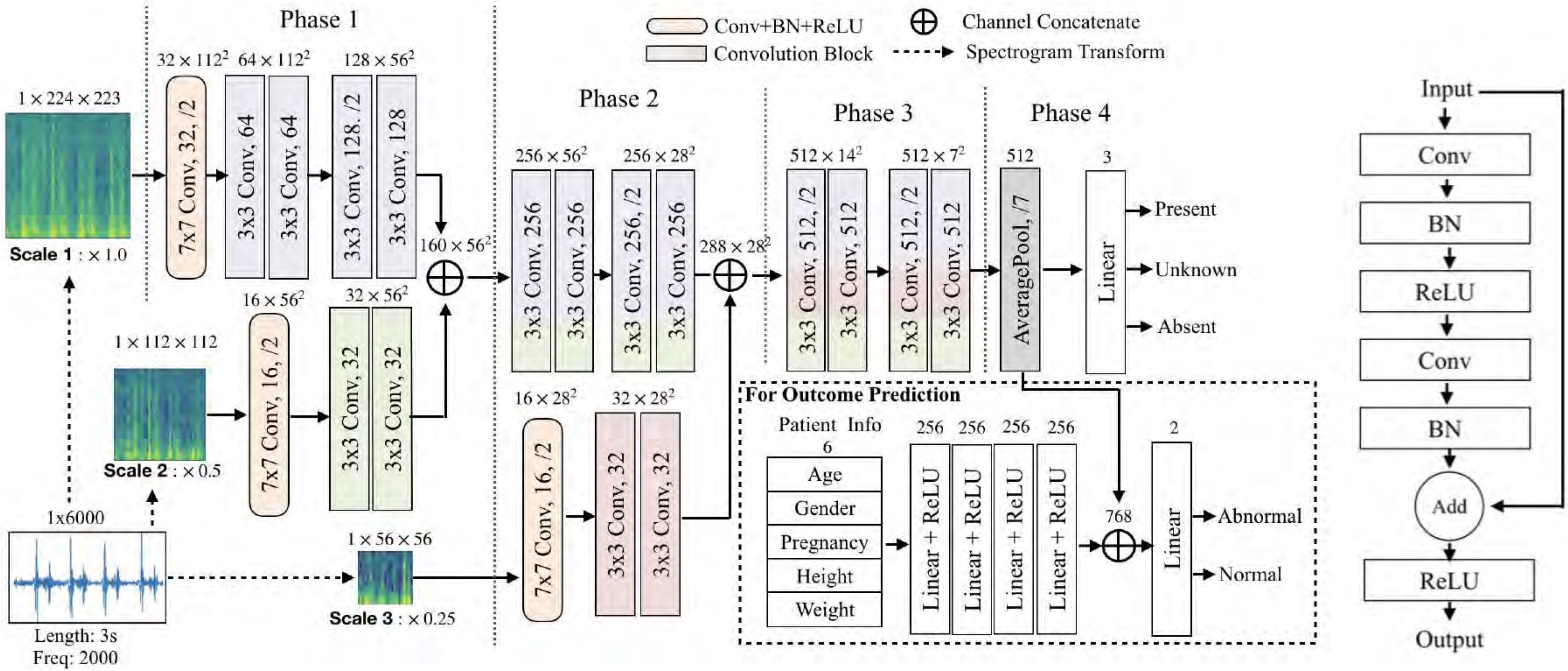

Challenges & Future Work

- **Generalization Issues**: Models struggle to generalize on samples outside competition datasets.
- **Data Scarcity**: Insufficient data to effectively train and test novel deep learning architectures.
- **Transfer Learning**: Potential for transfer learning requires further investigation.
- **Impact Studies**: Need for studies measuring the impact of algorithmic pre-screening on healthcare costs, screening capacity, and patient outcomes.

References

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8. McDonald A, Gales MJ, Agarwal A. Detection of heart murmurs in phonocardiograms with parallel hidden semi-markov models. In2022 Computing in Cardiology (CinC) 2022 Sep 4 (Vol. 498, pp. 1-4). IEEE.

References

9. Xu Y, Bao X, Lam HK, Kamavuako EN. Hierarchical multi-scale convolutional network for murmurs detection on pcg signals. In2022 Computing in Cardiology (CinC) 2022 Sep 4 (Vol. 498, pp. 1-4). IEEE.
10. Lee J, Kang T, Kim N, Han S, Won H, Gong W, Kwak IY. Deep learning based heart murmur detection using frequency-time domain features of heartbeat sounds. In2022 Computing in Cardiology (CinC) 2022 Sep 4 (Vol. 498, pp. 1-4). IEEE.

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Disclosures: None

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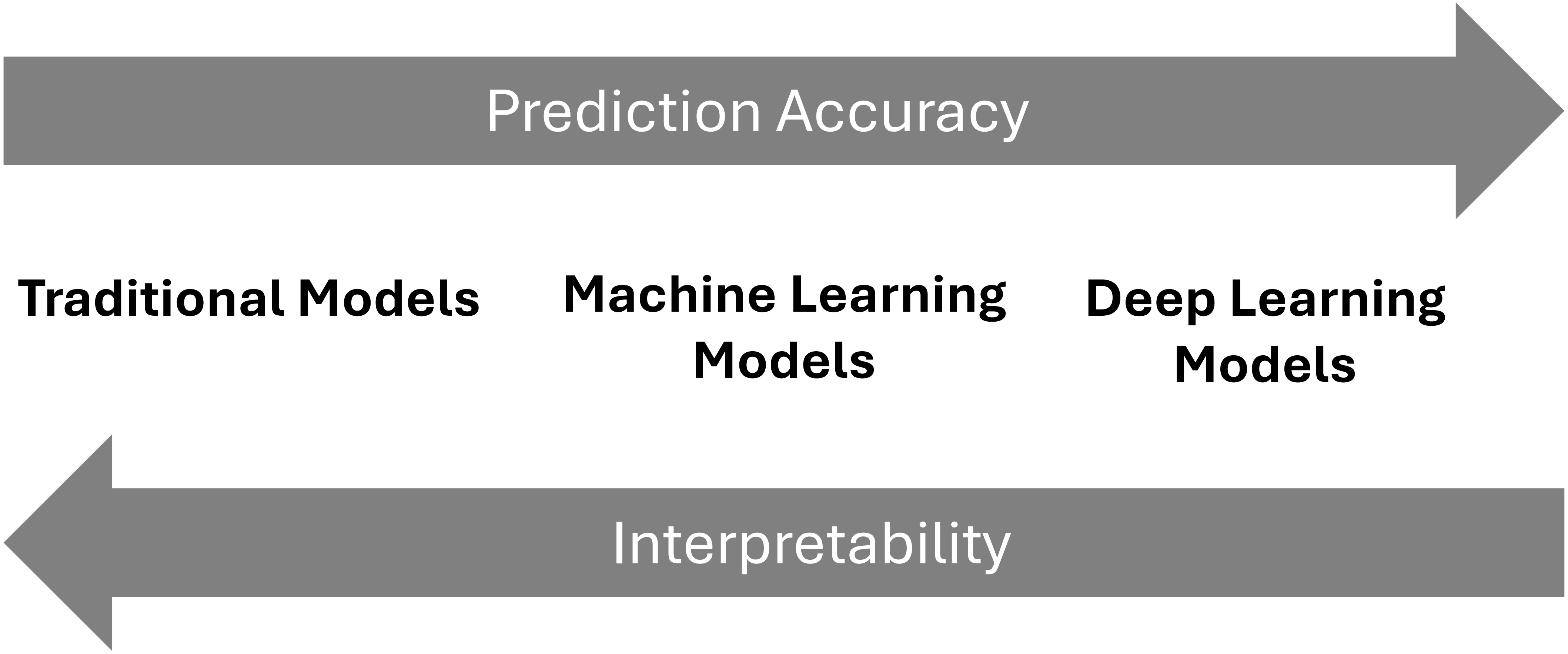

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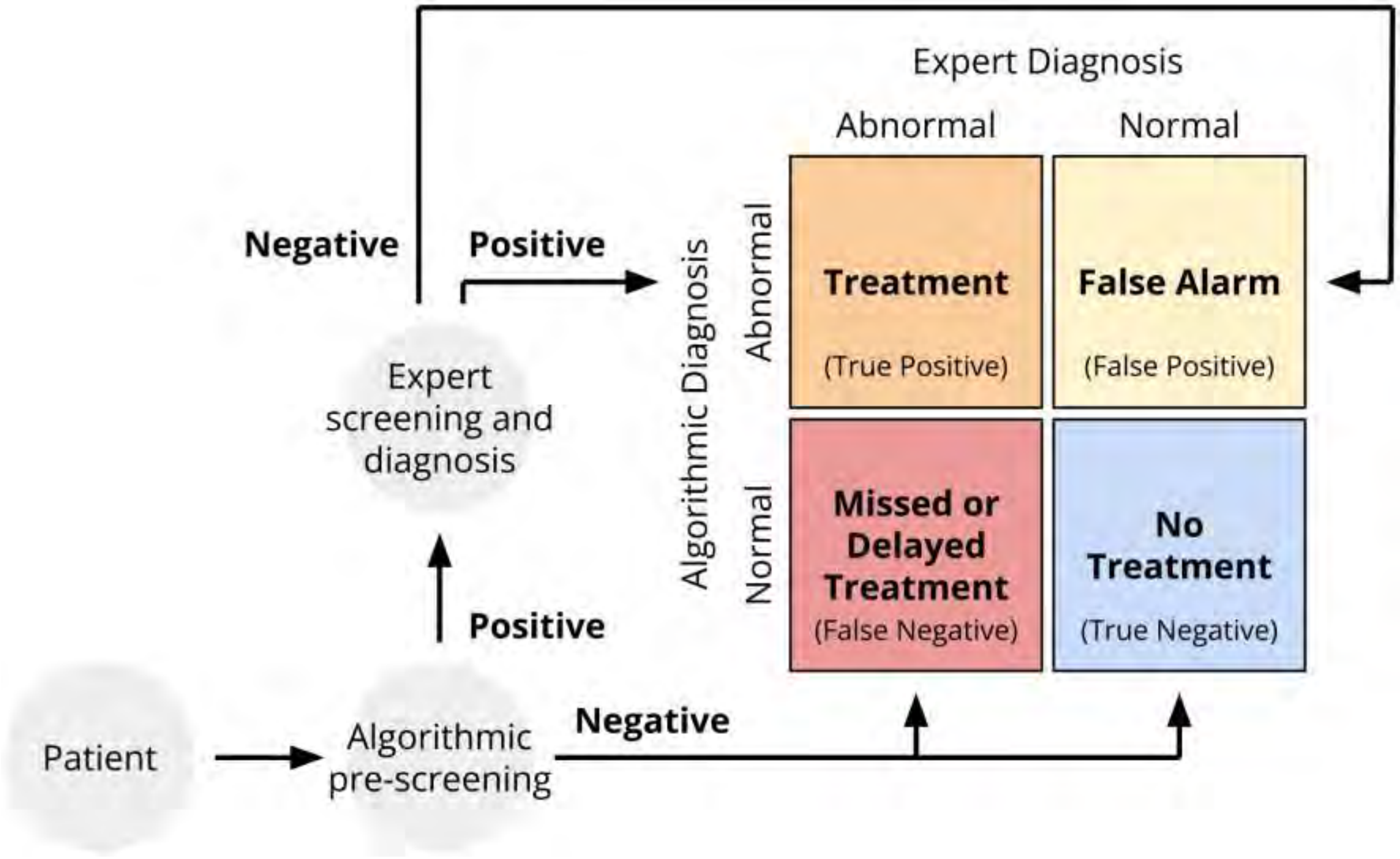

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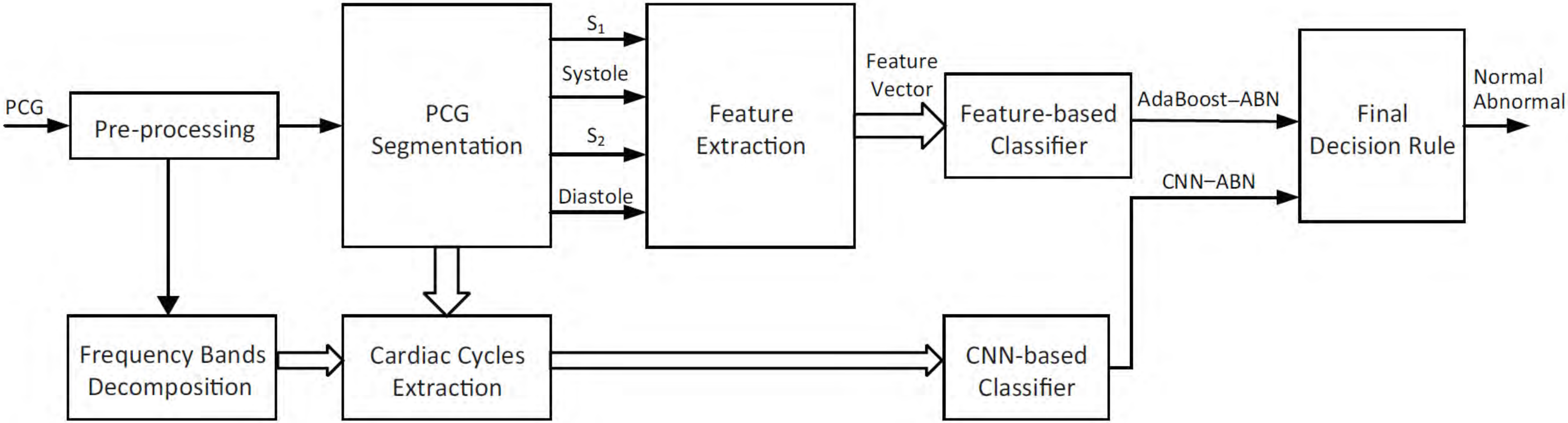

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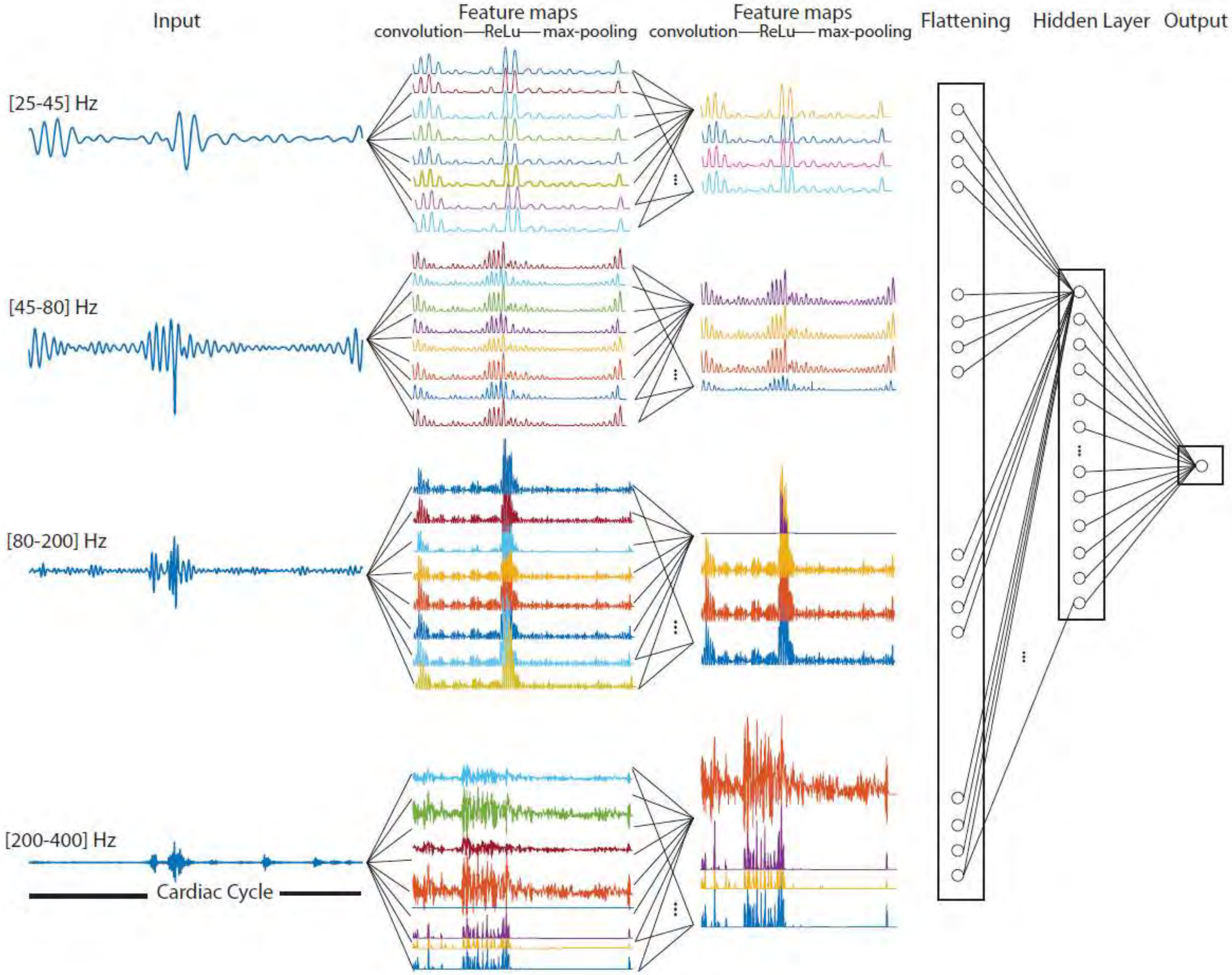

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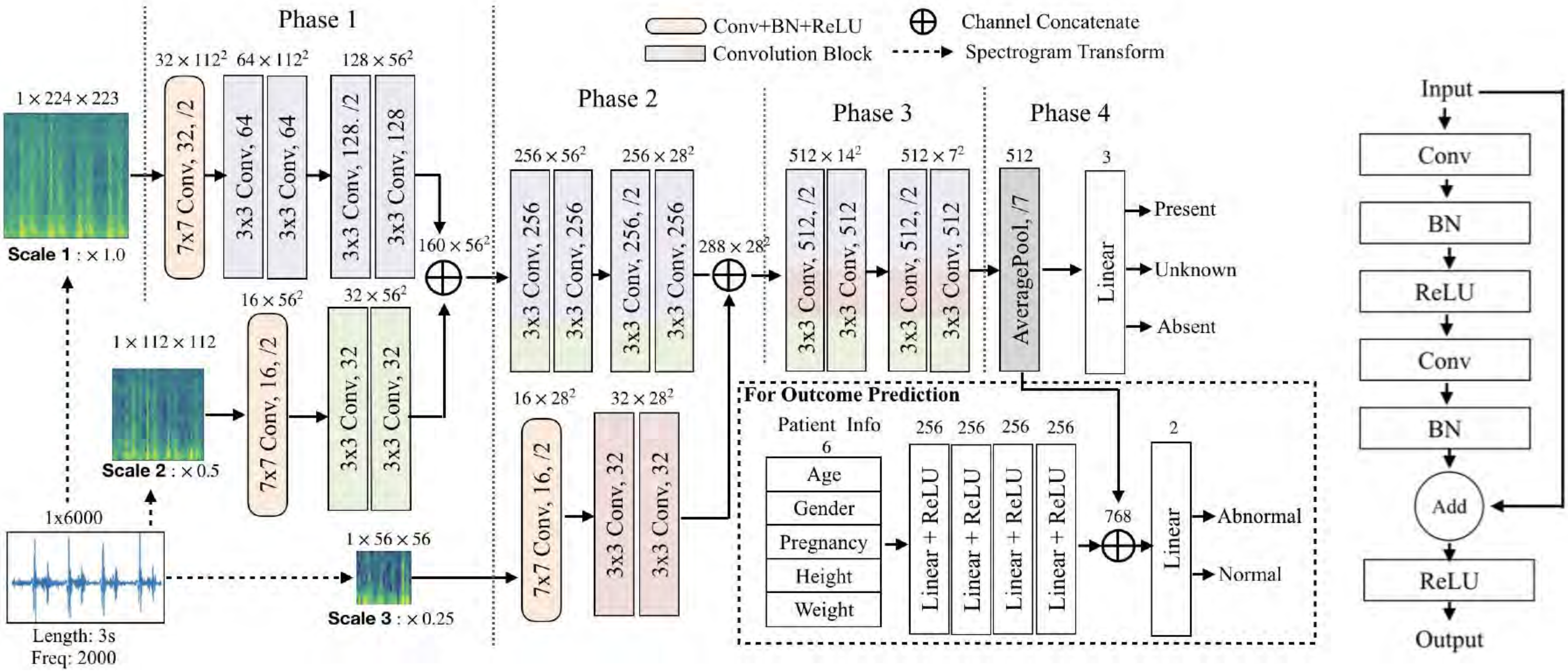

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6. Homsi MN, Medina N, Hernandez M, Quintero N, Perpiñan G, Quintana A, Warrick P. Automatic heart sound recording classification using a nested set of ensemble algorithms. In2016 Computing in Cardiology Conference (CinC) 2016 Sep 11 (pp. 817-820). IEEE.
7. Reyna MA, Kiarashi Y, Elola A, Oliveira J, Renna F, Gu A, Perez Alday EA, Sadr N, Sharma A, Kpodonu J, Mattos S. Heart murmur detection from phonocardiogram recordings: The george b. moody physionet challenge 2022. PLOS Digital Health. 2023 Sep 11;2(9):e0000324.
8. McDonald A, Gales MJ, Agarwal A. Detection of heart murmurs in phonocardiograms with parallel hidden semi-markov models. In2022 Computing in Cardiology (CinC) 2022 Sep 4 (Vol. 498, pp. 1-4). IEEE.

References

9. Xu Y, Bao X, Lam HK, Kamavuako EN. Hierarchical multi-scale convolutional network for murmurs detection on pcg signals. In2022 Computing in Cardiology (CinC) 2022 Sep 4 (Vol. 498, pp. 1-4). IEEE.
10. Lee J, Kang T, Kim N, Han S, Won H, Gong W, Kwak IY. Deep learning based heart murmur detection using frequency-time domain features of heartbeat sounds. In2022 Computing in Cardiology (CinC) 2022 Sep 4 (Vol. 498, pp. 1-4). IEEE.