Contactless Vital-Sign Monitoring:
Benchmarking Denoising Frameworks for mmWave Radar Signals

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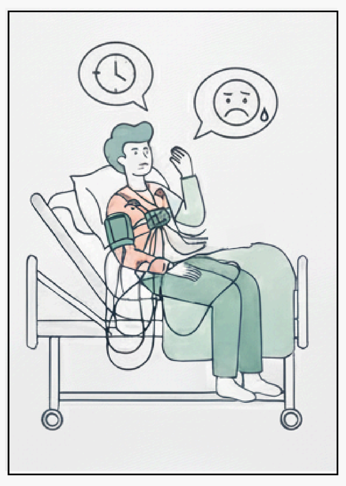
Motivation

Problem



Contact sensors
Exhausting
Uncomfortable

Suggestion

Contactless mmWave
Convenient
Comfortable

Challenge

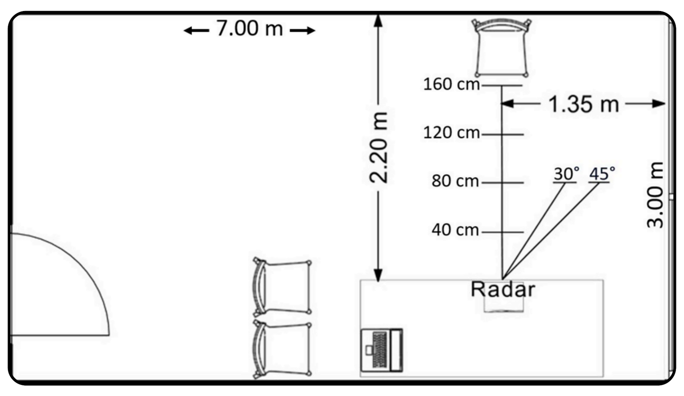
Noise Interference
Motion Artifacts
Signal Distortion

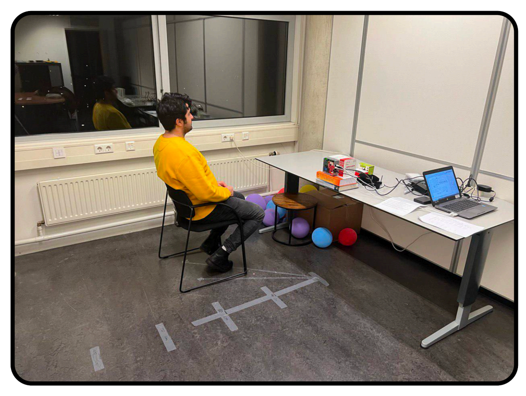
To address **noise interference** in contactless vital-sign monitoring, we developed and evaluated **three denoising frameworks**: classical signal processing, wavelet-based methods, and deep learning models, to identify the most accurate and robust approach for heart rate and breathing rate estimation.

Dataset

Attribute	Details	
Total Participants	10 (5 male, 5 female)	
Age / Weight (mean ± SD)	30.2 ± 6.32 years / 68.1 ± 14.14 kg	
Conditions	Normal Sitting (n=10) └ Asthma (n=2) └ Meditation (n=1) └ Elevated Exercise (n=4)	Participant 1~10 └ Participant 5,6 └ Participant 2 └ Participant 2,3,4,6

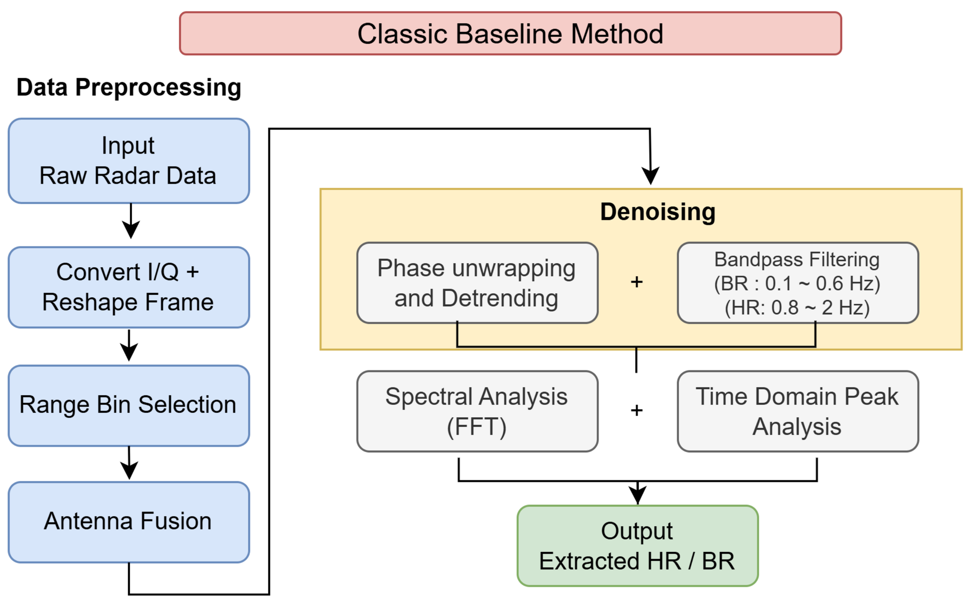
Scenario	Description	Files/Cases	Total
Distance	40 cm, 80 cm, 120 cm, 160 cm	4 files * 4 cases	**Total files** 456 files **Total Recording Time** 7h 51 mins 11s **1file = 1min*
Orientation	Front, Back, Left, Right	4 files * 4 cases	
Angle	0 deg, 30 deg, 45 deg	4 files * 3 cases	
Elevated	Elevated Exercise	4 files * 1 case	

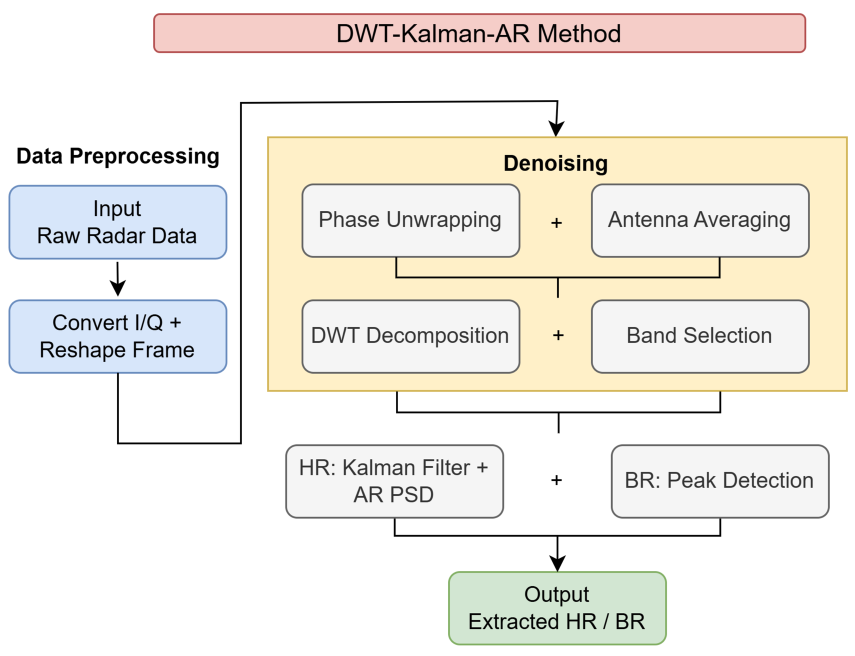


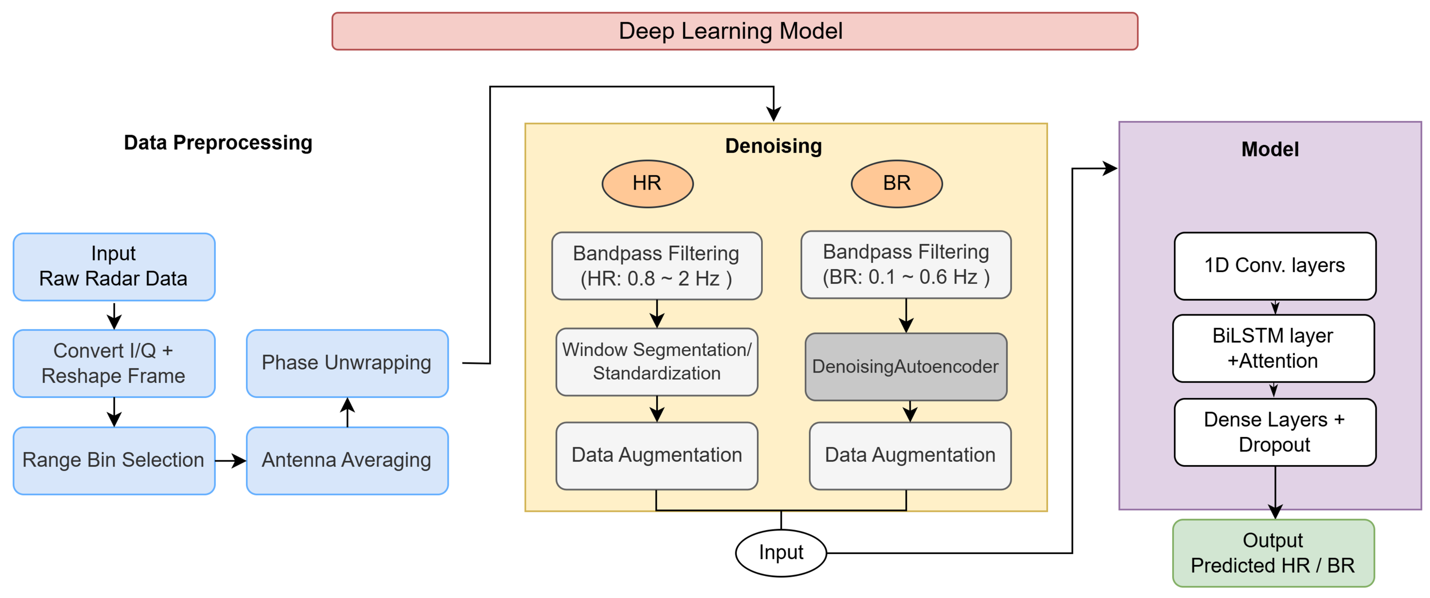


Methodology

- We implemented three complementary pipelines to extract heart rate (HR) and breathing rate (BR) from raw mmWave radar data.
  - **Classical Method:** FFT spectral analysis **+** peak detection in vital-sign bands
  - **DWT–Kalman–AR Method:** Wavelet denoising **+** Kalman filtering **+** AR spectral estimation
  - **Deep Learning Model:** 1D CNN feature extraction **+** BiLSTM temporal modeling **+** Attention-based HR/BR prediction
- Together, these pipelines let us compare how classical signal processing, wavelet-based denoising, and deep learning differ in their ability to extract clean physiological signals.
- The flowchart below details the steps for each approach from raw data to vital sign extraction.



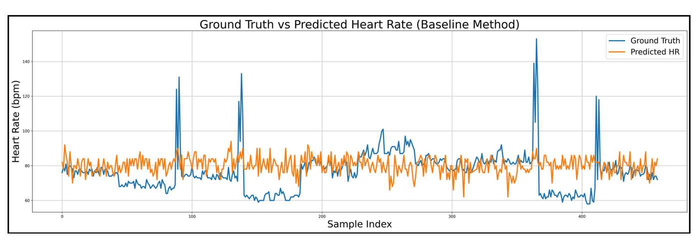




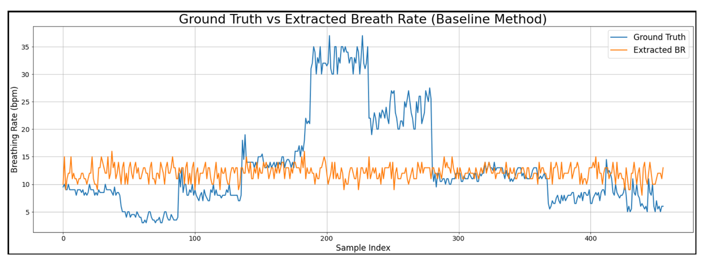
Results

Baseline Method

HR

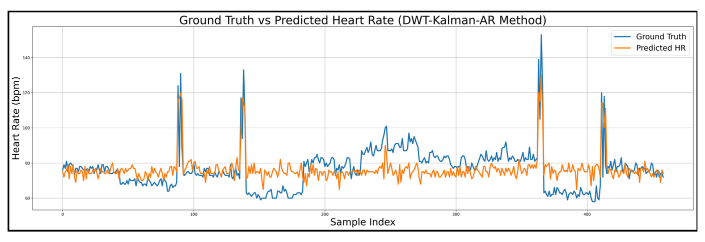


BR

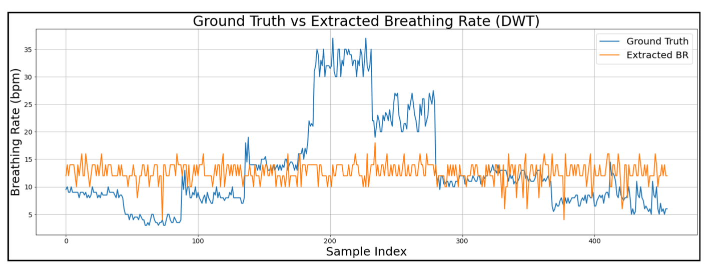


Dwt-kalman-ar Method

HR

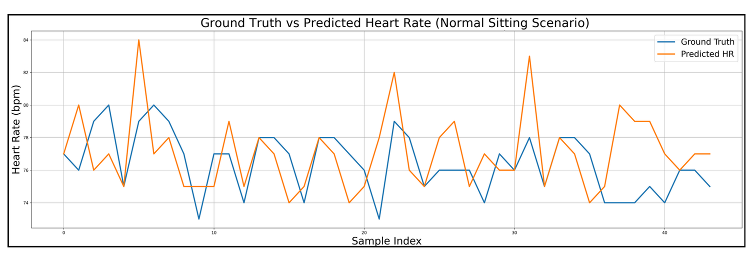


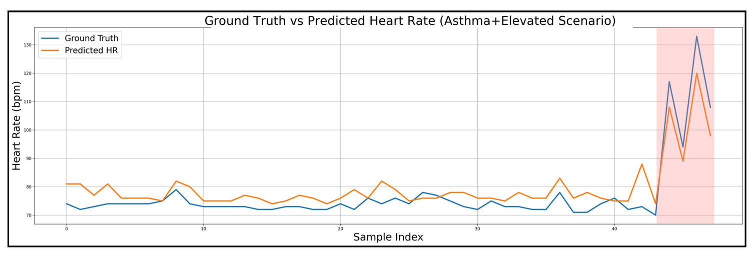
BR

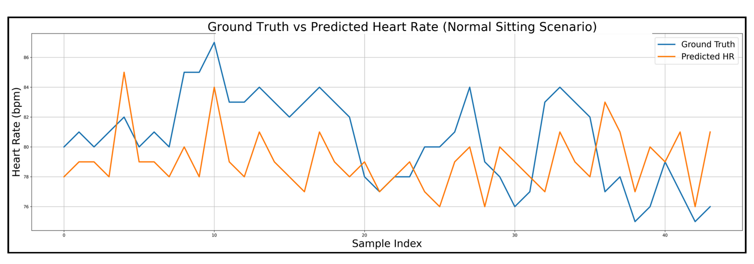


DL Model

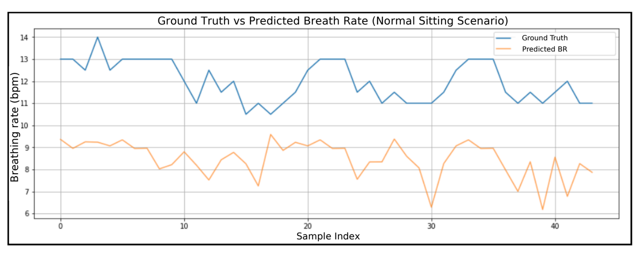
HR predictions

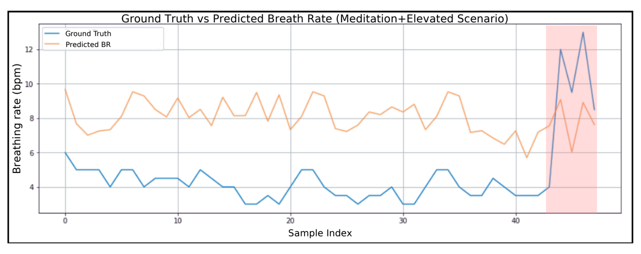


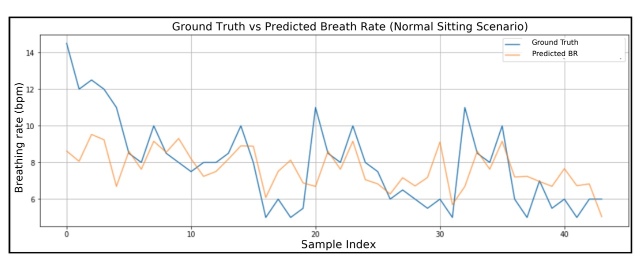




BR Predictions

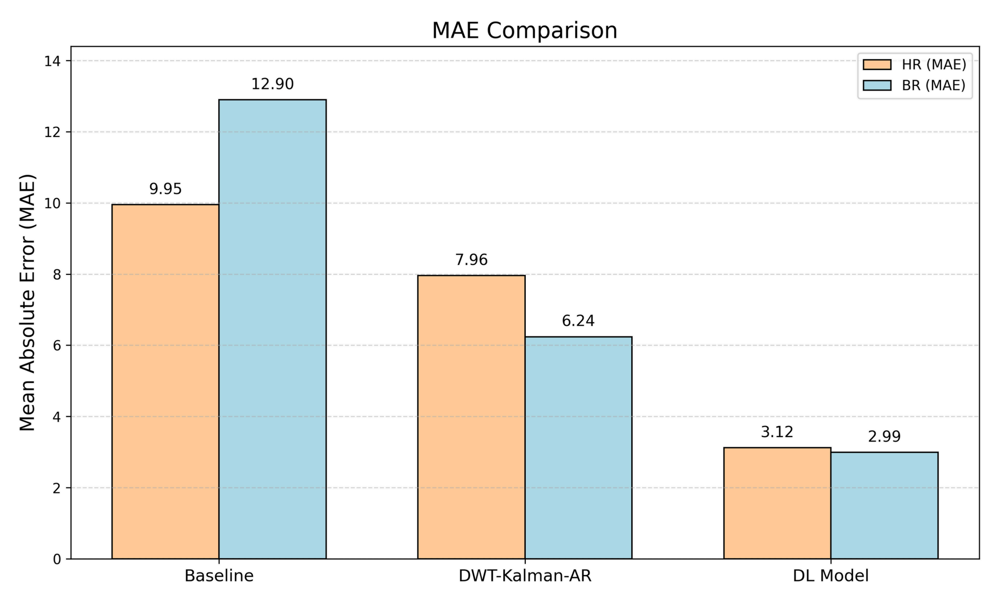






Performance Results

- **CNN-BiLSTM-Attention** significantly outperforms both classical and wavelet-based methods, reducing HR MAE from 9.95 and 7.96 to 3.12 and BR MAE from 12.9 and 6.24 to 2.99, respectively.
- This demonstrates DL model superior ability to extract clean physiological signals even under challenging noise and motion conditions.



Conclusion

- The main contribution of this project is the **mitigation of noise interference** through the comparison between **three denoising approache**s, with the deep learning model incorporating two denoising strategies.
- We **benchmarked three approaches**; classical signal processing, DWT-Kalman-AR, and a deep learning model to evaluate their ability to estimate HR and BR from noisy mmWave radar data.
- The deep learning model achieved the best performance, with **HR MAE = 3.19 bpm** and **BR MAE = 2.99 bpm**, meeting reliability standards (<4 bpm) for radar-based monitoring.
- These results show that **advanced neural models** provide the most robust, contactless, and **noise-resilient solution** for contactless vital-sign estimation.
- Future work will focus on **expanding the dataset** to include larger and more diverse physiological conditions, to **support early detection and monitoring of abnormal heart and respiratory rates** in clinical settings, contributing to patient monitoring and the prevention of potential health complications through timely intervention.