Wireless-Based Human Vital Signs Monitoring Technology and Its Applications

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Abstract. In recent years, the rapid development of wireless sensing technology has given birth to a lot of cutting-edge development achievements, which indicates that wireless signal has great potential in human vital signs monitoring. This paper reviews the current state-of-the-art methods and literature on the use of wireless sensing for vital sign monitoring. This work aims to fill a gap in this aspect of research and provide researchers in related fields with reference and inspiration, systematically summarize the principles and signal processing methods of various wireless signals including WiFi, mmWave and hybrid signals, and discuss the gap between typical approaches and actual industrial production. The research also reveals that the applicable domains of three wireless signals differ significantly, which provides valuable insights for product industrialization, and further confirms the feasibility of combining wireless sensing technology with deep learning based on the SenseFi dataset, highlighting a promising future development of wireless sensing.

Keywords: Wireless sensing monitoring; vital signs monitoring; Wi-Fi sensing; mmWave sensing; deep learning.

1. Introduction

According to the data from the CDC, in 2023, the mortality rate due to accidental falls among elderly people aged 65 and above reached 69.9 per 100,000 population [1]. Additionally, sudden infant death syndrome is also one of the leading causes of death among newborns in the United States [2]. These data emphasize that real-time vital signs monitoring plays a critical role in special populations' health and well-being.

Table 1. Comparative Analysis of Respiratory Monitoring Methods

Method	Type	Application	Limitation	
PSG (Polysomnography)	Contact	Hospital Respiratory/Sleep Analysis	Highly Invasive	
ECG (Electrocardiogram)	Contact	Heart Rate Monitoring	High Interference, Uncomfortable	
Pressure Sensor Pad	Contact	Respiratory Monitoring	Low Sensitivity, Mattress Effect	
Accelerometer	Contact	Respiratory/Activity Sensing	High Noise, Requires Attachment	
Camera Monitoring	Contact	Respiratory Rhythm, Facial Pulse	Light/Privacy Constraints	

However, as shown in Table 1, there are many limitations of traditional monitoring devices in real-world applications. For example, contact sensors can cause discomfort and are generally expensive; acoustic sensors are prone to interference; optical sensors may raise privacy concerns. In contrast, wireless sensing devices have unique advantages such as non-contact, high precision, and privacy protection. Thanks to the upgrade of artificial intelligence, wireless sensing has become a hot topic for researchers in the field of health monitoring in the 2020s.

The specific objective of this study was to systematically compare existing wireless sensing technology solutions, thoroughly explore their technological potential in diverse application scenarios and verify optimization paths through experiments to provide ideas for industrial production. This paper also leads to a forward-looking reflection on the development prospects of wireless sensing-based vital signs monitoring.

The findings should make an important contribution to cutting-edge applications of wireless sensing.

2. Overview of Wireless Sensing Technology

2.1. Classification and characteristics of mainstream wireless signals

Mainstream wireless sensing technologies can be broadly classified into three types based on carrier signal (see Table 2). First, Wi-Fi signals operate in the 2.4-5GHz frequency band, using CSI containing magnitude and phase information to sense human activity and capture subtle environment changes. Due to the reusability of existing routers, methods based on Wi-Fi signals have extremely low deployment costs. Second, millimeter wave radar operates in the 30-300GHz high frequency band and detects minute displacements through the Doppler effect. Although methods based on mmWave signals offer centimeter-level ranging accuracy and millimeter-level displacement detection capabilities, they have a higher cost. Third, Fusion signals combine the advantages of multiple signal sources, improving monitoring reliability through information complementarity. Fusion signal-based methods greatly increase system complexity, considered cutting-edge technology.

Table 2. Comparative Analysis of Wireless Sensing Technologies

Signal Type / Comparison Dimension	Wi-Fi Signal	mmWave Signal	Fusion Signal	
Spatial Resolution	Medium (tens of cm level)	Very high (cm to mm level)	High (depends on radar component)	
Vital Sign Recognition	High (breathing < 1 bpm, heart rate accuracy up to 95%)	High (heartbeat/HRV reaches 85-95%)	Very high (fusion enhancement)	
Penetration Capability	Good, can penetrate fabrics/blankets	Excellent, can penetrate walls/furniture	Excellent (depends on radar component)	
Multi-target Detection	Limited (requires signal decoupling & spatial filtering)	Good (MIMO array + multi-angle)	Excellent (WiFi assists identity, radar distinguishes targets)	
Privacy Protection	Strong (no images, contactless)	Strong (no visual information)	Moderate (depends on image integration)	
Deployment Difficulty & Cost	Very low (COTS devices)	High (professional hardware, complex calibration)	High (involves multi-sensor synchronization & integration)	
Real-time Performance	High (latency < 200ms)	High (fast mmWave response)	Medium (requires fusion processing & decoding)	
Computational Complexity	Medium (CSI features + traditional algorithms/DL)	High (signal modeling + multi-dimensional analysis)	Very high (multi-channel/multi-modal sync & processing)	
Adaptability & Robustness	Poor (affected by multi-path & reflection interference)	Strong (anti-occlusion, posture-independent)	Strong (high signal redundancy, strong fusion compensation)	
Representative Systems	[3-5]	[6]	[6-8]	

2.2. Comparison of Existing Methods

This study performed a qualitative comparative analysis of the typical wireless sensing monitoring technologies, categorized into the three groups mentioned above, based on authoritative papers collected. The comparison will cover seven dimensions, aiming to evaluate the strengths and drawbacks of each method in practical production.

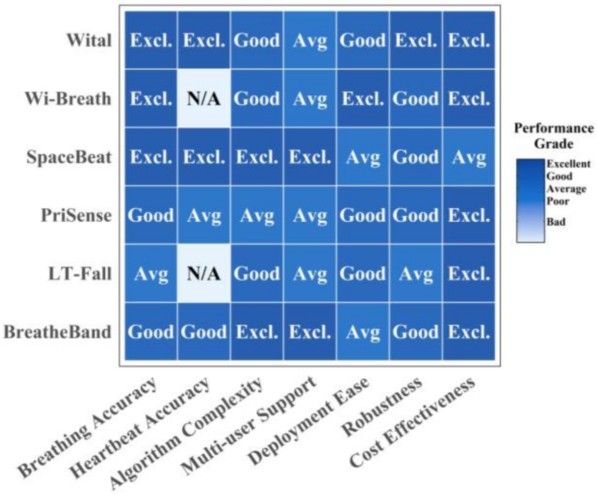

Fig. 1 Comparative Analysis of Methods Based on Wi-Fi Technology [3] [4] [5] [9] [10] [11]

As shown in Fig. 1, different methods can have different focuses in terms of breathing detection accuracy, heartbeat detection accuracy, and multi-person support, among others. Wi-Breath and PriSense perform well in breathing detection [4,10]. BreathBand has made breakthrough in heartbeat detection [5].

Fig. 2 Comparative Analysis of Methods Based on mm Wave Technology [6] [7] [12]

mm Wave technologies generally outperform Wi-Fi in terms of detection accuracy. VitalHide and TDM-MIMO can support multi-person detection simultaneously [7,12], showcasing the potential applications in medical and military fields (see Fig.2).

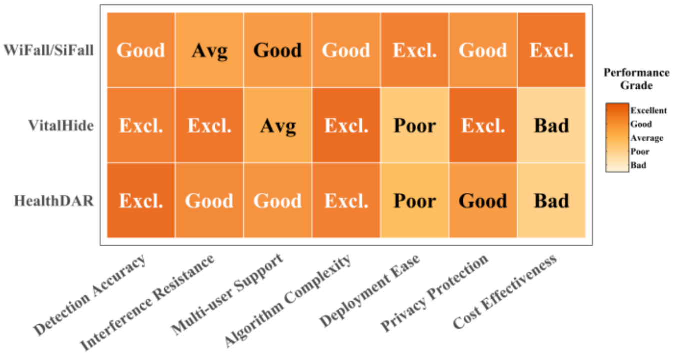

Fig. 3 Comparative Analysis of Methods Based on Fusion Technology [6] [7] [13]

As Fig. 3 presents, SiFall has relatively balanced indicators, suitable for muti-task environments with limited resources.

2.3. Introduction of Technological Background and Key Concepts

The introduction of key concepts will also focus on the three categories mentioned above. The Wi-Fi-based method focuses on CSI extraction. Vital sign information is extracted by analyzing the amplitude and phase variation characteristics of CSI, which can be represented as

$$\begin{gathered}\Delta\left|H\left(f_k\right)\right|=\left|H_{new}\left(f_k\right)\right|-\left|H_{old}\left(f_k\right)\right|,\\ \Delta\varphi_k=\varphi_{new}\left(f_k\right)-\varphi_{old}\left(f_k\right).\end{gathered} \tag{1}$$

cooperating with OFDM (Orthogonal Frequency Division Multiplexing) and Ricean K factor model. The signal processing workflow covers key steps such as SVM filtering, amplitude and phase difference calculation, and spectrum analysis. Methods based on mm Wave utilize the Doppler frequency shift principle to detect target movement, which can be expressed as

$$\Delta f=\frac{2vf_0}{c}. \tag{2}$$

where Δf , v , f_0 and c represent the Doppler frequency shift, relative velocity of objects, radar signal transmission rate and speed of light. High-precision monitoring is achieved by using FMCW (Frequency-Modulated Continuous Wave) radar to transmit continuous waves and receive reflected signals, which are then processed through time delay approximation, Kalman filtering, and SAR imaging. Meanwhile, methods based on fusion signals integrate multi-source information employing a weighted average formula represented as

$$\hat{y}=\sum_{i=1}^{N}\omega_i x_i. \tag{3}$$

where $\hat{y}$ denotes combined signal, ω_i and x_i represent the weight and output of the i-th signal source, and N is the number of the signal sources. Traditional methods primarily utilize techniques such as MLE parameter optimization and covariance matrix fusion to fully leverage the advantages of individual sensors. However, modern cutting-edge methods increasingly employ deep learning algorisms to integrate multimodal information intelligently.

2.4. Summary of Wireless Sensing Technology Application Scenarios

Wi-Fi, with its low cost, popularity, and ease of deployment, is suitable for smart furniture and elderly care at home. Millimeter-wave technology, with higher cost in exchange for high-precision monitoring, is ideal for medical and military applications. Fusion one, through multi-source data complementarity and deep learning of multi-modal signals, enables the collaborative monitoring of behaviors and multiple vital signs, representing the future developing trend.

3. Specific Applications of Wireless Sensing in Vital Sign Monitoring

3.1. Respiratory Rate Monitoring

Breathing causes human chest to rise and fall by approximately 1-12mm, producing noticeable signal changes. The Wi-Fi system detects breathing through CSI phase changes, which are represented by

$$BR=\frac{\Delta\left|H\left(f_k\right)\right|}{TW}. \tag{4}$$

where BR and TW represent breath rate and time window, and $\Delta\left|H\left(f_k\right)\right|$ is the amplitude difference of CSI. The main technical challenge lies in how to effectively eliminate other motion interference and multipath effects.

3.2. Heartbeat Rate Monitoring

The displacement caused by heartbeat is only 0.1-0.5mm, which is so weak that it can be easily masked by breathing motion. Therefore, it is not only need to extract the signal, however, more significantly, to perform filtering. The basic formula of Wi-Fi-based heartbeat rate monitoring can be represented as

$$HR = \frac{\Delta\varphi_k}{TW}. \tag{5}$$

where HR and TW represent heartbeat rate and time window, and $\Delta\varphi_k$ is the phase difference of CSI. The formula of mmWave-based heartbeat rate monitoring can be slightly different from the Wi-Fi one, represented as

$$HR = \frac{\Delta f}{HB}. \tag{6}$$

where HB represents the period of heartbeat, and Δf is the Doppler frequency shift. Both types of signals require Kalman filter to remove noise interference

$$\begin{aligned} \hat{x}_k &= \hat{x}_{k|k-1} + K_k\left(z_k - \hat{x}_{k|k-1}\right), \\ x_k &= \mathbf{F}\hat{x}_{k-1} + \mathbf{B}\mu_k + \omega_k, \\ z_k &= \mathbf{H}\hat{x}_k + \nu_k. \end{aligned} \tag{7}$$

where $\mathbf{F}$, $\mathbf{B}$ and $\mathbf{H}$ represent state transition matrix, control matrix and measurement matrix, z_k, K_k, $\hat{x}_{k|k-1}$ and $\hat{x}_k$ are current measurement value, Kalman gain, prior state and state prediction, μ_k, ω_k and ν_k are control input, process noise and measurement noise. The Kalman filter is a "predict-upgrade" iterative process that provides fine noise filtering capabilities.

3.3. Multi-signal comprehensive monitoring

Simultaneous monitoring of multiple vital signs including respiration, heart rate, and body movement requires solving the problem of signal separation and recoupling. In order to distinguish between chest expansion caused by breathing and other movements, a segmentation method based on movement regularity was adopted

$$SE = \frac{\sum_{i=1}^{N}\left|r_i - \hat{r}_i\right|}{N}. \tag{8}$$

where SE represents segmentation error, r_i is real physiological data and $\hat{r}_i$ is segmented physiological data. Fusion signals enable complementary multimodal information, providing a comprehensive assessment of health. For example, heart rate and respiratory rate monitoring can be used together to assist in dynamic human monitoring to determine and alert when an elderly person has fallen.

3.4. Multi-person monitoring

Nursing homes, hospital wards, and other applications require simultaneous monitoring of multi-personal information. Multi-person monitoring typically uses spatial contrast learning methods to distinguish between multiple feature signals

$$CL = \frac{1}{N}\sum_{i}\sum_{j}\max\left(0, m - \left\| f\left(x_i\right) - f\left(x_j\right)\right\|_2\right). \tag{9}$$

where CL represents contrastive loss, $f\left(x\right)$ is feature function extracted through deep learning, m is a hyperparameter, and x_i as well as x_j are signals of two different people. In carrier monitoring based primarily on Wi-Fi CSI, multipath effects can also be used to identify multiple signals

$$CSI_{total} = \sum_{i=1}^{N} CSI_i. \tag{10}$$

where CSI_i represents the CSI signal of the i-th person. However, the results obtained by using these formulas to separate and categorize multi-person signals are often unsatisfactory, which is precisely the current research frontier.

4. Approach to addressing challenges: SenseFi replication and optimization attempts

4.1. SensiFi System Architecture

SenseFi adopts a modular design consisting of four stages (see Fig. 4). Firstly, Tx transmits a Wi-Fi signal and Rx receives it. Secondly, data extraction via the CSI Tool to obtain CSI data, including amplitude and phase of signals, at the pre-processing stage. Thirdly, data processing includes such tasks as normalization, noise filtering and feature extraction. Finally, a recognition output is produced.

This study replicated two strategies combining supervised learning and unsupervised learning with transfer learning, namely self-supervised learning. Each strategy underwent 44 training rounds containing a free combination of 11 models and 4 datasets. Moreover, the results were analyzed in terms of both the model and the dataset.

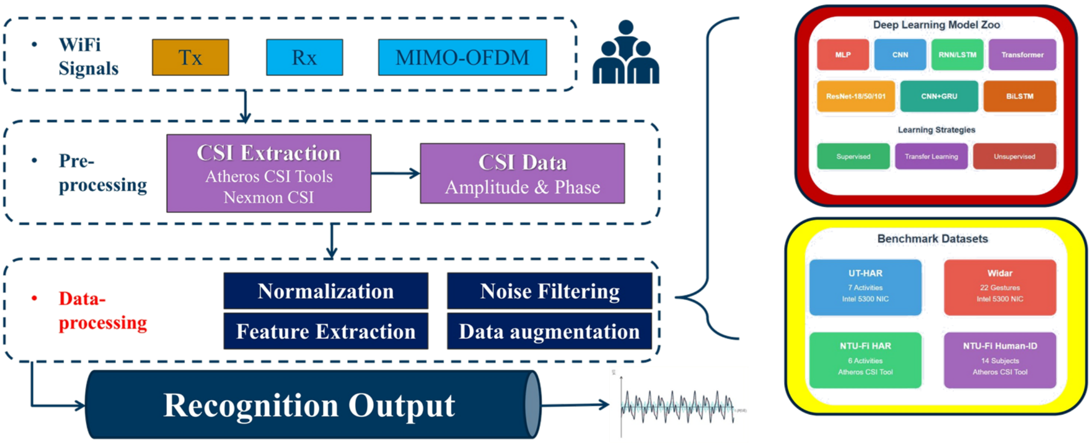

Fig. 4 System Block Diagram of SenseFi [14]

4.2. Deep Learning Data Comparison Analysis

4.2.1 Supervised Learning Training Evaluation

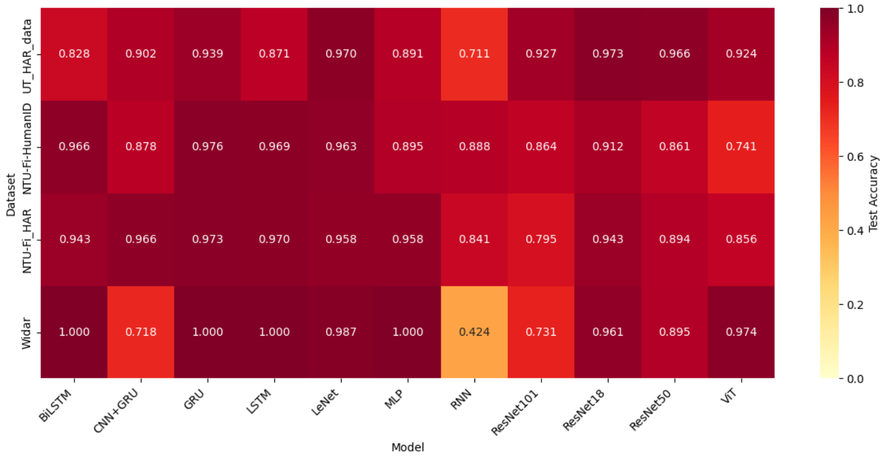

Fig. 5 Model Performance Across Datasets Heatmap of Supervised Learning

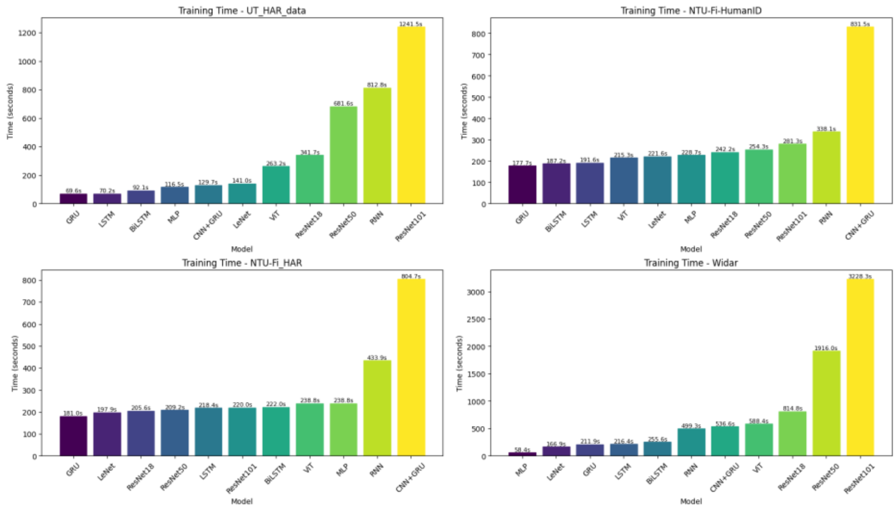

Fig. 6 Training Time Across Datasets of Supervised Learning

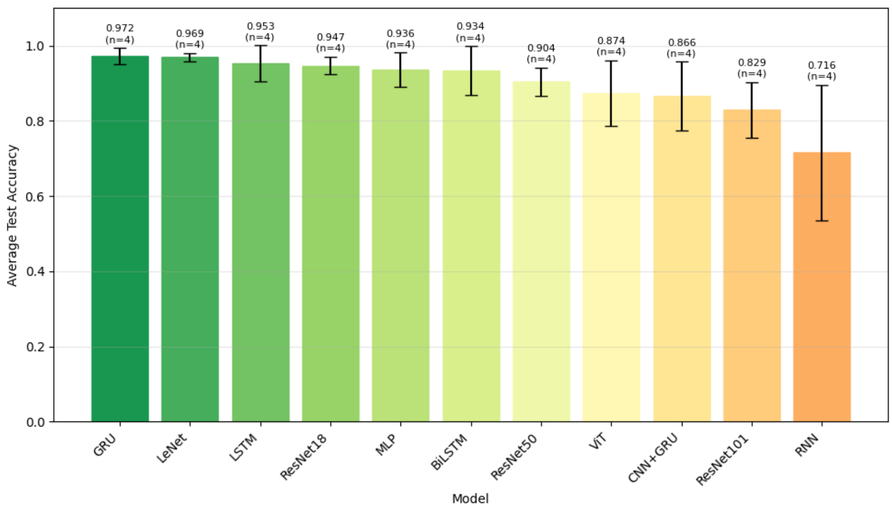

Fig. 7 Model Performance Ranking of Supervised Learning

As demonstrated in Fig. 5, Fig. 6 and Fig. 7, at the dataset level, Widar (a gesture dataset) demonstrated an accuracy rate as high as 94.7%, nevertheless, the training time cost was relatively high. At the model level, GRU achieved an accuracy of 92.3% with an average training time of only about 15 minutes per epoch, making it the best performer overall. Although LeNet had an accuracy rate of 91.5%, which was slightly lower than GRU, its model size was small enough for embedded deployment.

4.2.2 Self-supervised Learning Training Evaluation

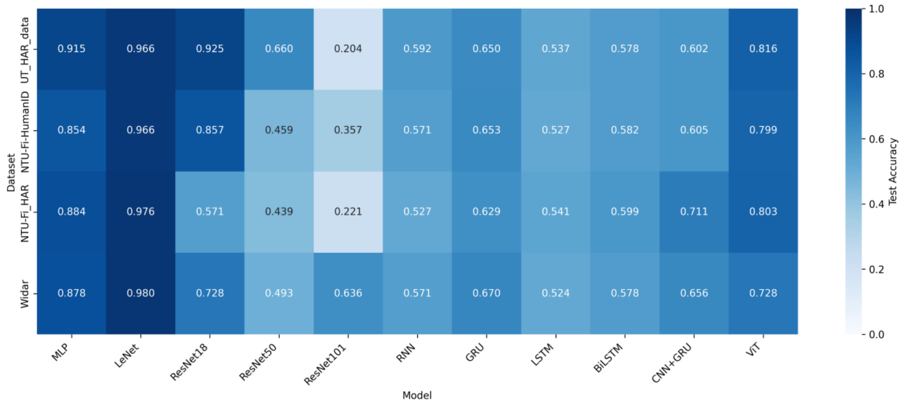

Fig. 8 Model Performance Across Datasets Heatmap of Self-supervised Learning

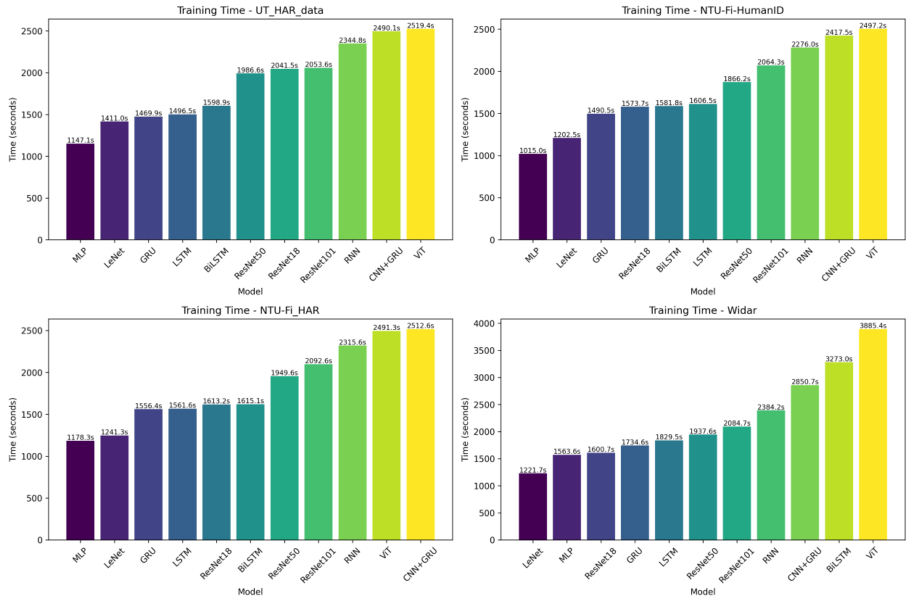

Fig. 9 Training Time Across Datasets of Self-supervised Learning

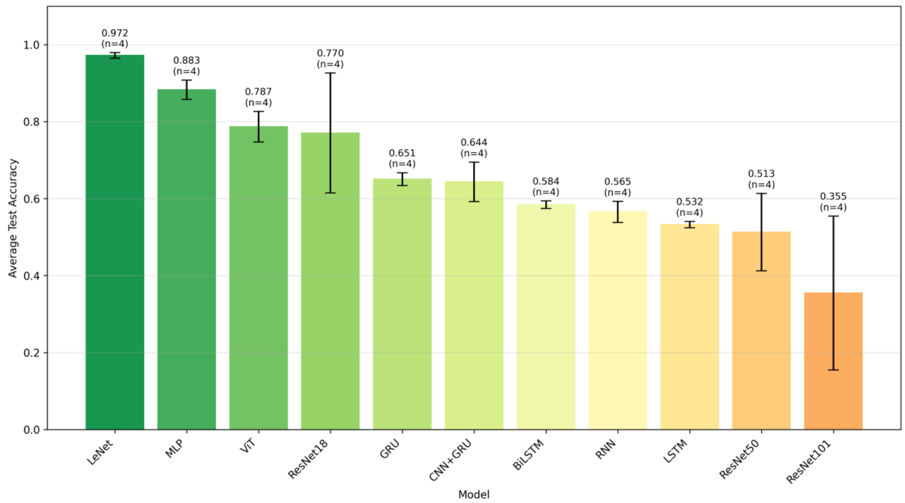

Fig. 10 Model Performance Ranking of Self-supervised Learning

As illustrated in Fig. 8, Fig. 9 and Fig. 10, at dataset level, Widar took the longest to train; nonetheless, all models performed consistently on it. In contrast, the ResNet series showed significant performance fluctuations across different datasets, indicating that dataset characteristics have a critical influence on model selection. At model level, LeNet led with an average accuracy rate of 97.2% and a training time of only about 1,400 seconds, giving the best overall performance. Thanks to its small model size, MLP showed high cost-effectiveness with an average accuracy rate of 88.3% and the shortest training time.

Based on the experimental results above, both supervised and self-supervised strategies exhibit high accuracy but are time-consuming when processing Widar. At the same time, they all show stability when handling various CSI datasets; however, the self-supervised one tends to perform much more inefficiently. It is worth noting that deep networks may not be significantly better than shallow ones.

5. Conclusion

In conclusion, this paper has argued that the application positioning and technical characteristics of three mainstream wireless sensing technologies in the field of vital signs monitoring through systematic literature research and technical comparative analysis. The analysis revealed the trade-offs between three wireless sensing solutions in terms of cost-effectiveness, detection accuracy, and ease of deployment, providing clear technical selection references for the industrial application of wireless sensing vital signs monitoring technology.

Nevertheless, practical application still faces many challenges including low signal response, signal aliasing difficulties in multi-signal monitoring, and difficulties in target identification and tracking in multi-person scenarios. The validation of deep learning algorithms based on the SenseFi dataset shows that lightweight DL models can achieve a good balance between accuracy and training efficiency through reasonable model selection and parameter tuning, properly addressing the challenges.

A limitation of this study includes scarcity of experimental hardware and time, incomplete literature coverage and unobjective comparative evaluation criteria.

Looking ahead, wireless vital signs monitoring systems will evolve toward AI-enabled intellifence, utilizing deep learning-driven signal processing cores to select signal source, filter noise and extract features. Subsequent studies could continuously explore how to further integrate multimodal perception with large-scale artificial intelligence models.

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