Integration of MmWave Radar Smart Sensing and Deep Learning in Non-Invasive Healthcare Systems: A Survey

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Abstract

The integration of mmWave radar, smart sensing, and deep learning technologies into non-invasive healthcare systems presents transformative potential for remote patient monitoring. This survey examines the application of these advanced technologies, highlighting their ability to overcome traditional healthcare challenges such as patient compliance, privacy concerns, and environmental limitations. mmWave radar offers precise, non-contact monitoring capabilities, while smart sensing technologies enhance data collection through IoT-enabled systems and wearable sensors. Deep learning techniques further improve the analysis of complex physiological data, enabling real-time and efficient processing. Despite these advancements, challenges related to radar resolution, data security, and computational requirements persist. Future research directions focus on enhancing sensor performance, developing standardized protocols, and optimizing deep learning models for broader healthcare applications. The integration of these technologies promises significant improvements in patient monitoring and healthcare delivery, paving the way for innovative, non-invasive solutions that enhance patient outcomes.

1 Introduction

1.1 Healthcare Challenges and Significance of Non-Invasive Monitoring

The healthcare sector faces numerous challenges that necessitate the development of non-invasive monitoring technologies. Traditional monitoring methods, often requiring direct patient contact, are hindered by issues such as patient compliance and geographical barriers, which impede continuous health assessments [1]. This is particularly critical for vulnerable populations, including the elderly and post-operative patients, who require consistent monitoring. The limitations of current methods in tracking and classifying behaviors, especially among cognitively impaired individuals in hospital settings, further emphasize the need for non-invasive solutions [1].

Accurately capturing physiological signals is complicated by data scarcity and bias, highlighting the demand for advanced non-invasive technologies [2]. Current human sensing methods, largely dependent on cameras and wearable sensors, face significant challenges, including privacy concerns and user compliance issues. This necessitates innovative approaches that can accurately identify individuals using physiological signals without being affected by environmental conditions or privacy issues.

The integration of AI in remote patient monitoring systems introduces challenges related to model explainability and patient data privacy [3]. Ensuring model stability and interpretability, alongside addressing data sparsity and label noise, are critical challenges in healthcare that require robust non-invasive monitoring solutions [4].

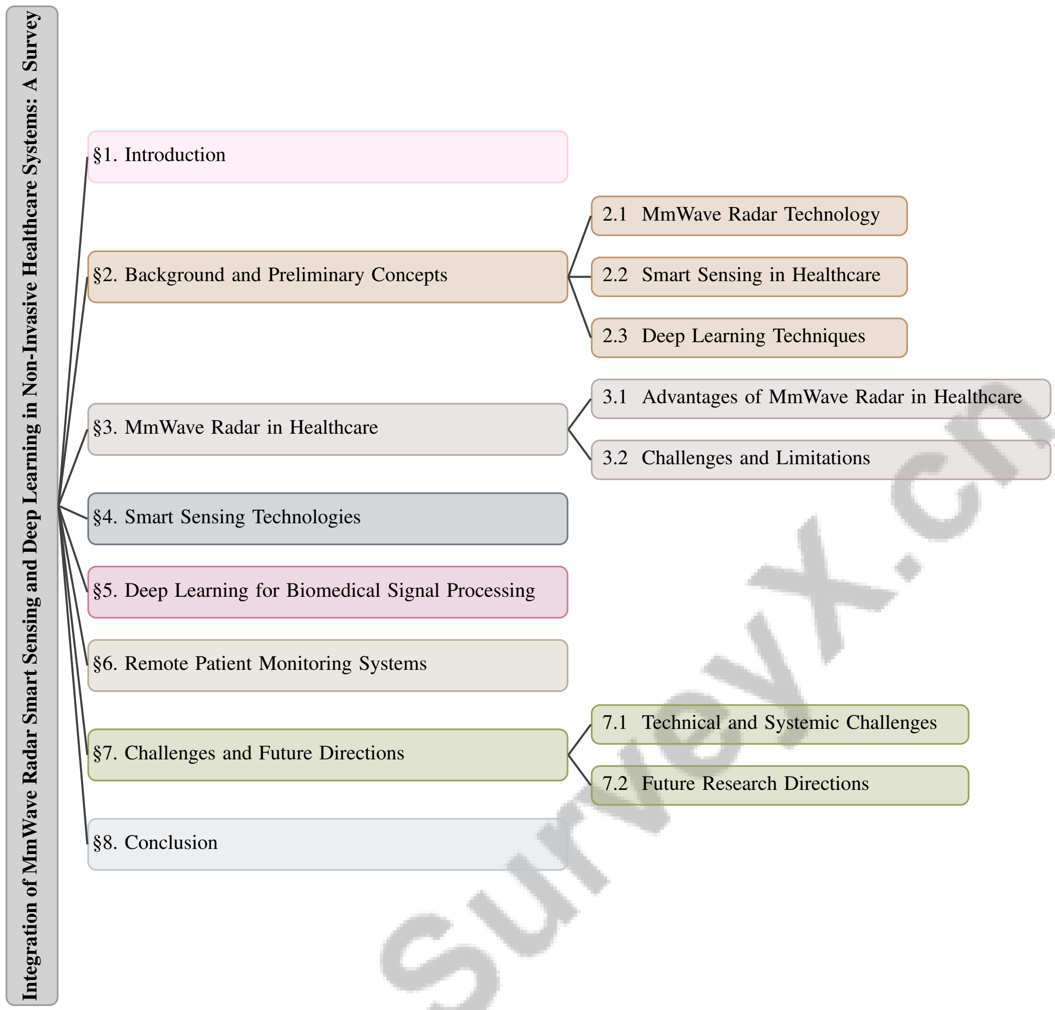


Figure 1: chapter structure

Measuring vital signs, such as heart rate and breathing states, through non-invasive methods like bioradar is complicated by the small amplitude of chest wall micromotions caused by cardiorespiratory activity [3]. The aging population further underscores the necessity for daily elderly care through sensing technologies, reinforcing the potential of non-invasive monitoring to enhance patient outcomes and healthcare delivery [5]. Additionally, the need for non-invasive solutions is particularly pronounced in elderly fall detection and prevention, where traditional vision-based systems encounter privacy issues and data collection challenges [6].

Addressing these challenges is essential for advancing non-invasive monitoring technologies, which can lead to improved patient outcomes and more efficient healthcare delivery. The integration of communication and sensing capabilities in emerging technologies offers promising solutions but also presents new technical and systemic hurdles that must be addressed to realize effective non-invasive monitoring [7]. The increasing demand for personalized healthcare solutions, which enhance patient outcomes and health management, further necessitates innovations in non-invasive monitoring [8]. The real-time diagnosis of heart diseases using IoT devices further highlights the critical need for non-invasive monitoring and efficient data processing [9].

1.2 Structure of the Survey

This survey conducts an in-depth analysis of the integration of millimeter-wave (mmWave) radar, advanced smart sensing technologies, and deep learning algorithms within non-invasive healthcare systems, focusing on applications in real-time patient behavior detection, human activity recognition, and challenges such as privacy concerns and environmental dependencies [1, 10, 11, 12, 13]. The introduction emphasizes the significance of non-invasive monitoring and remote patient care, followed by a discussion of healthcare challenges necessitating these advanced solutions.

Section 2 provides background and preliminary concepts, outlining core technologies: mmWave radar, smart sensing, and deep learning, and their roles in enhancing non-invasive monitoring and remote patient care.

Section 3 explores the application of mmWave radar technology in healthcare, highlighting its benefits such as non-contact monitoring that enhances patient comfort and reduces infection risks, along with its precision in detecting vital signs. It also addresses technical challenges, including the need for low-power systems for accurate heart-rate tracking and complexities due to high frequencies and component integration. Evaluations of mmWave radar systems operating at 24 GHz, 60 GHz, and 120 GHz reveal significant performance differences, with the 120 GHz system demonstrating superior accuracy and lower noise levels in identifying heartbeat and breathing activity [14, 15].

Section 4 discusses various smart sensing technologies, emphasizing their role in enhancing data collection and patient monitoring, particularly when integrated with mmWave radar for comprehensive monitoring solutions.

In Section 5, the role of deep learning in processing biomedical signals is examined, showcasing its potential to improve the accuracy and efficiency of analyzing physiological data collected through smart sensing technologies. This section also details various deep learning architectures and models that facilitate real-time processing.

Section 6 describes the architecture and components of remote patient monitoring systems, illustrating the integration of mmWave radar, smart sensing, and deep learning to provide comprehensive patient care, alongside advanced technologies that support remote monitoring.

Section 7 examines current obstacles in integrating Internet of Things (IoT) and machine learning (ML) technologies into healthcare systems, highlighting data management complexities and the need for effective decision-making tools. It outlines potential avenues for future research and technological innovations aimed at overcoming these challenges, including advancements in wearable devices, remote patient monitoring systems, and AI-driven analytics, which could enhance personalized healthcare and improve service delivery. This comprehensive analysis serves as a valuable resource for researchers, healthcare professionals, and policymakers navigating the evolving landscape of smart healthcare [16, 17, 18, 19, 8].

Section 8 concludes the survey by highlighting critical advancements in non-invasive healthcare systems, particularly the integration of mmWave radar technology, smart sensing capabilities, and deep learning algorithms. These innovations collectively enhance patient monitoring by enabling real-time detection of multiple patients' behaviors, improving safety through timely alerts for emergencies such as falls or seizures, and addressing the limitations of traditional observation methods. The findings underscore the transformative potential of these technologies in healthcare monitoring, especially for vulnerable populations, by providing automated, efficient, and privacy-respecting solutions [1, 10, 13, 12].The following sections are organized as shown in Figure 1.

2 Background and Preliminary Concepts

2.1 MmWave Radar Technology

Millimeter-wave (mmWave) radar technology, particularly at frequencies like 77 GHz, is integral to non-invasive healthcare applications [5]. Its ability to provide detailed environmental insights through RF signal processing makes it ideal for fall detection and vital sign monitoring, surpassing traditional methods [6]. The use of frequency-modulated continuous wave (FMCW) radar enhances motion detection and environmental monitoring, proving advantageous for tasks such as gait recognition and breath rate classification, even in low-light or occluded conditions [20, 5].

Integrating mmWave radar with other sensing modalities addresses challenges like low angular resolution and noise interference, crucial for applications such as human pose estimation. The development of datasets for mmWave radar activity recognition aids in bridging macro and micro-scale activity recognition, enhancing scene understanding and human activity analysis [6].

2.2 Smart Sensing in Healthcare

Smart sensing technologies are revolutionizing healthcare by enabling continuous non-invasive monitoring. IoT-enabled ambient sensors and large language models (LLMs) exemplify this by improving remote monitoring of elderly individuals, facilitating timely interventions and personalized care [7]. Wearable sensors, integral to smart sensing, enable seamless physiological data collection and transmission, as demonstrated by the Wearable Ubiquitous Healthcare System (WUHS) [18]. These sensors, encompassing various modalities, benefit from short-range wireless systems like Bluetooth and NFC [21].

Innovations such as the iGLU 2.0 device, utilizing near-infrared spectroscopy and machine learning for non-invasive glucose measurement, highlight smart sensing's role in chronic disease management [22]. WiFi Channel State Information (CSI) Doppler Sensing offers a non-invasive alternative for capturing human movement [23]. Advanced computational techniques, including Colliding Bodies Optimization (CBO) with Recurrent Neural Networks (RNN), further enhance human activity recognition [24].

Smart footwear sensors exemplify the diverse applications of smart sensing, offering performance tracking and disorder detection [19]. Multimodal and multi-sensor fusion methods, such as the Fusion Transformer, improve activity recognition by integrating various image-based features [25]. Dynamic sensor selection methods optimize energy usage and classification performance, ensuring effective healthcare monitoring [26].

Recent advancements in smart sensing, particularly in wearable devices and smart footwear, significantly improve healthcare monitoring by enabling real-time tracking of vital metrics, facilitating early diagnosis, and enhancing treatment effectiveness [21, 19, 16].

2.3 Deep Learning Techniques

Deep learning techniques have transformed biomedical signal processing, improving the analysis of complex physiological data. Hybrid analog-digital deep neural network (HDNN) architectures enhance signal processing capabilities through novel analog structures [27]. Convolutional Neural Networks (CNNs) are effective in real-time patient behavior classification and myocardial infarction detection, enhancing diagnostic precision [1, 28].

The AutoHR method, utilizing neural architecture search approaches, demonstrates deep learning's potential in non-invasive healthcare by improving heart rate monitoring accuracy [29]. Deep learning also excels in identity recognition using Magnetocardiography (MCG) signals [30]. The MM-Fi dataset facilitates advancements in pose estimation and action recognition, highlighting the synergy between deep learning and multimodal data [31].

Innovative methods like GaitSADA employ domain adaptation with semi-supervised learning to enhance gait analysis [32]. The FUSE framework combines multi-frame representation with meta-learning, improving joint coordinate estimation from mmWave data [33]. In healthcare, the HealthFog framework utilizes ensemble deep learning in fog computing environments to enhance heart disease diagnosis [9].

Deep learning techniques significantly enhance physiological data analysis, leveraging hierarchical feature representations to improve the identification and classification of complex patterns in medical images and signals. This approach enhances diagnostic capabilities across various medical applications and opens new avenues for improving patient care through integration in consumer health technologies and wearable devices [34, 35, 36].

In recent years, the application of millimeter-wave (mmWave) radar technology in healthcare has garnered significant attention due to its potential to revolutionize patient monitoring and treatment. As illustrated in Figure **??**, this figure elucidates the advantages and challenges associated with mmWave radar technology. It highlights not only the precision and non-contact monitoring capabilities that this technology offers but also its benefits in providing real-time assistance to healthcare professionals. However, the figure also addresses the challenges that accompany this innovative technology, including issues related to signal quality, data sparsity, and computational constraints. By examining these factors, we can better understand the implications of mmWave radar technology in enhancing healthcare delivery while acknowledging the hurdles that must be overcome for its successful implementation.

Figure 2: This figure illustrates the advantages and challenges of mmWave radar technology in healthcare, highlighting its precision, non-contact monitoring capabilities, and real-time assistance benefits, alongside challenges related to signal quality, data sparsity, and computational constraints.

3 MmWave Radar in Healthcare

3.1 Advantages of MmWave Radar in Healthcare

Millimeter-wave (mmWave) radar technology offers significant benefits for healthcare, primarily through enhanced precision and non-contact monitoring. Notably, mmWave systems provide high localization accuracy crucial for patient monitoring, as demonstrated by mm-Pose, which achieves average localization errors of 3.2 cm in depth, 2.7 cm in elevation, and 7.5 cm in azimuth [37]. Techniques like FUSE further advance human pose estimation from sparse mmWave data, adapting efficiently with minimal training data [33].

The robustness of mmWave radar in diverse environmental conditions is another advantage, maintaining consistent performance across various human sensing applications [31]. This is particularly important in applications such as fall detection, where systems like FADE achieve up to 95% accuracy, highlighting their effectiveness in real-world scenarios and potential for integration into smart homes [5]. Additionally, Baek et al.'s denoising algorithm enhances hand gesture recognition accuracy to over 90%, even in noisy environments [11].

Beyond precision, mmWave radar's non-contact monitoring capability allows for the simultaneous observation of multiple patients without the need for wearable devices. This is exemplified by systems that function independently of lighting conditions, making them suitable for various healthcare applications [38]. The SDI method showcases non-contact monitoring benefits by enabling precise, non-destructive measurement of complex permittivity with compact radar systems [20].

Real-time assistance, while ensuring user privacy through non-intrusive monitoring, is another key advantage, as seen in IoT-enabled ambient systems [7]. Innovative methods like GaitSADA improve gait recognition accuracy, addressing domain shifts and achieving accuracy enhancements of 15.41% to 26.32

Furthermore, the BERT method accelerates measurement speeds with competitive accuracy, enhancing mmWave radar systems' efficiency in healthcare applications [3]. The HealthFog framework demonstrates high accuracy in heart disease diagnosis with low latency, suitable for real-time applications [9].

As illustrated in Figure **??**, these features enable accurate localization, effective fall and gesture detection, and simultaneous observation of multiple patients without the need for wearable devices, thereby enhancing patient care and healthcare delivery. Collectively, these advantages position mmWave radar as a versatile solution for non-invasive monitoring, significantly improving patient care and healthcare delivery.

Figure 3: This figure illustrates the primary advantages of mmWave radar in healthcare, highlighting its enhanced precision, robustness in diverse environments, and non-contact monitoring capabilities. These features enable accurate localization, effective fall and gesture detection, and simultaneous observation of multiple patients without the need for wearable devices, enhancing patient care and healthcare delivery.

3.2 Challenges and Limitations

The deployment of millimeter-wave (mmWave) radar technology in healthcare encounters several challenges and limitations that need addressing to fully leverage its potential. A primary issue is the reliance on radar signal quality, crucial for accurately detecting multiple individuals simultaneously. This challenge is exacerbated in environments where signal quality is compromised by clutter or ghost targets, affecting systems like FADE. Variability in noise intensity and distribution, due to sensor manufacturing differences and environmental conditions, complicates precise signal processing [11].

The sparsity of mmWave point cloud data poses another significant challenge. Compared to video or lidar, mmWave data is less informative, hindering machine learning algorithms that require rich datasets for training and generalization [33]. The randomness in radar point cloud data complicates the collection and labeling of fall data, a critical step for traditional supervised learning approaches in healthcare applications [6].

In computational terms, while effective, the BERT method employs a heuristic and coarse-grained scheme for error compensation, which may not achieve the precision required for bioradar applications [3]. Additionally, reliance on older hardware, such as outdated Raspberry Pi versions, can hinder real-time inference capabilities necessary for timely healthcare interventions [7]. The HealthFog framework, despite its potential, may require significant computational resources for training deep learning models, limiting deployment in resource-constrained environments [9].

Domain shift presents another challenge, where discrepancies between training and testing data distributions can degrade performance, particularly in applications requiring adaptation to new motions or environmental conditions not represented in training data. Variability in readings due to external factors affecting techniques like NIR spectroscopy further complicates validation across diverse populations, necessitating extensive testing and calibration [22].

Challenges related to precision in distance increments and the calibration process also hinder mmWave radar technology's practical implementation in healthcare [20]. Moreover, implementing complementary wearable technologies faces obstacles like ensuring data privacy and security and managing the vast amounts of generated data [8].

Addressing these challenges is essential for enhancing the robustness and generalizability of mmWave radar systems in healthcare applications, particularly for improving human activity recognition, facilitating real-time monitoring, and ensuring privacy while supporting the elderly living independently [39, 10, 40, 12]. Continued research and development are vital to overcoming these limitations and realizing mmWave radar technology's full potential for accurate and reliable non-invasive monitoring solutions.

4 Smart Sensing Technologies

4.1 Integration of Multifunctional Sensors

The integration of multifunctional sensors enhances data acquisition and patient monitoring in healthcare systems. The milliTRACE-IR system exemplifies this by combining mmWave radar with thermal cameras for non-invasive temperature and movement monitoring, crucial for precise health assessments while addressing privacy concerns [41]. Similarly, the OpenRadar toolkit facilitates rapid prototyping and AI integration with mmWave radar, enabling the development of customized healthcare applications through a modular framework [42]. This adaptability is essential for creating robust systems tailored to diverse healthcare challenges.

The MM-Fi benchmark, integrating various non-intrusive modalities including mmWave radar, provides a comprehensive dataset that advances research in human sensing and pose estimation, facilitating the development of systems capable of interpreting complex human activities non-invasively [31]. Such datasets are instrumental in advancing smart sensing technologies, leading to more precise monitoring solutions.

Furthermore, the integration of the Small Distance Increment (SDI) method with complex baseband radar modules illustrates how advanced processing techniques can enhance data collection in healthcare, allowing for precise physiological measurements and improving the accuracy of non-invasive monitoring systems [20]. Leveraging these technologies, healthcare systems can achieve greater precision and reliability, ultimately enhancing patient outcomes and healthcare delivery efficiency.

4.2 Non-Contact and Hybrid Monitoring Systems

Non-contact and hybrid monitoring systems represent significant advancements in healthcare by merging the benefits of contact and non-contact methods. These systems integrate non-contact technologies, such as mmWave radar, with traditional contact-based systems, enabling comprehensive physiological monitoring while reducing patient discomfort and compliance issues [38]. They are particularly beneficial in settings where privacy and non-intrusiveness are critical, such as elderly care and intensive care units.

Non-contact systems utilizing WiFi Channel State Information (CSI) exploit variations in wireless signals caused by human movements to monitor activities and vital signs without wearable devices, preserving patient privacy and facilitating continuous monitoring in remote or resource-limited environments [23]. Hybrid systems that combine non-contact technologies with wearable sensors enhance the robustness and accuracy of health monitoring. For example, integrating wearable sensors with IoT-enabled ambient systems allows for comprehensive data collection that encompasses environmental and physiological information [7]. This synergy provides healthcare providers with deeper insights into patient health, facilitating timely interventions and personalized care.

Advancements in computational techniques, such as neural architecture search and meta-learning frameworks, significantly enhance the processing capabilities of hybrid systems in medical imaging. These methods enable systems to adapt efficiently to new medical scenarios with minimal data, improving their ability to identify, classify, and quantify patterns in medical images [16, 36]. Such adaptability is crucial for intelligent healthcare solutions, where rapid and accurate decision-making is essential for effective patient care. These techniques improve the interpretation of complex physiological signals and human activities, increasing the reliability and effectiveness of patient monitoring solutions.

The implementation of non-contact and hybrid monitoring systems offers a promising avenue for improving patient care and outcomes. By integrating both contact and non-contact monitoring methods, these advanced healthcare systems provide a holistic approach that addresses the limitations of traditional practices. This innovative strategy enhances the efficiency and effectiveness of healthcare delivery, leveraging cutting-edge technologies such as IoT devices and artificial intelligence (AI) to collect and analyze extensive health data. Consequently, these systems facilitate real-time patient monitoring, personalized health management, and improved decision-making processes, addressing the urgent need for responsive healthcare solutions in the face of ongoing health crises [8, 16, 17].

5 Deep Learning for Biomedical Signal Processing

5.1 Deep Learning Architectures for Biomedical Signal Processing

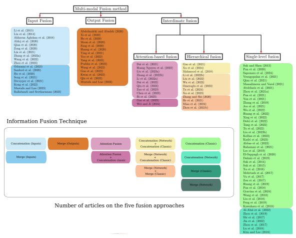
Deep learning architectures are pivotal in biomedical signal processing, offering advanced methodologies for analyzing complex physiological data. Integration with mmWave radar has notably improved 3D imaging and motion detection, surpassing traditional radar limitations. The BERT method, utilizing a recursive technique based on the Markov-Gauss model, exemplifies its application in processing vital signs [3].

Convolutional Neural Networks (CNNs) are extensively employed for interpreting radar-generated heatmaps, enabling real-time human pose estimation and tracking of over 15 skeletal joints. This capability is essential for patient monitoring, aiding early mobility identification in ICUs, gait analysis for conditions like Duchenne muscular dystrophy, and supporting rehabilitation through advanced wearable sensors and smart footwear technology [43, 19].

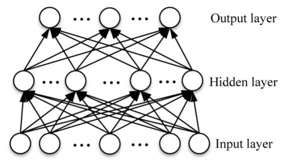
The FUSE framework illustrates deep learning's potential in enhancing data representation from mmWave point cloud data through multi-frame fusion and meta-learning, improving human pose estimation accuracy and adaptability [33]. It preprocesses radar images using U-Net and EfficientNet for denoising, enhancing input data quality [11].

Ensemble deep learning techniques, such as those in the HealthFog framework, leverage edge computing for timely health diagnostics, underscoring the integration of deep learning with edge devices to enhance real-time healthcare applications [9].

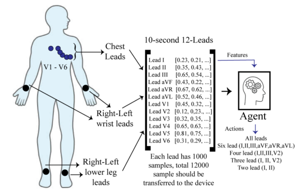
These architectures transform biomedical signal processing by autonomously learning intricate feature representations from raw data, which advances healthcare delivery by enhancing the identification, classification, and quantification of patterns in medical images. This integration streamlines data interpretation, fostering intelligent healthcare systems that effectively address emerging health challenges, as observed during the COVID-19 pandemic [16, 36, 44]. These advancements pave the way for innovative applications that improve patient care and healthcare outcomes.



(a) Multi-modal Fusion Method: A Comprehensive Overview[35]



(b) A Neural Network Architecture[36]



(c) 10-Second 12-Leads Transfer to Device[26]

Figure 4: Examples of Deep Learning Architectures for Biomedical Signal Processing

As illustrated in Figure 4, deep learning architectures offer transformative methodologies in biomedical signal processing. The first figure provides an overview of multi-modal fusion methods essential for integrating diverse data types to enhance decision-making and predictive accuracy. The second figure depicts a multilayer perceptron (MLP), crucial for modeling non-linear relationships within biomedical data. The third figure demonstrates practical applications in a 10-second, 12-lead transfer schematic, highlighting precise lead placements and extensive data collection. These examples underscore the versatility and depth of deep learning architectures in advancing biomedical signal processing, paving the way for more accurate and efficient healthcare solutions [35, 36, 26].

5.2 Real-time and Efficient Deep Learning Models

Method Name	Real-time Processing	Model Robustness	Feature Extraction
VaR-VSM[45]	Real-time	Advanced Signal Processing	Vital Sign Extraction
UTM[46]	Runtime Efficiency	Uncertainty-guided Fusion	Bayesian Feature Extractor

Table 1: Comparison of deep learning models for real-time processing, model robustness, and feature extraction in biomedical signal analysis, highlighting the capabilities of the VaR-VSM and UTM methods. The table outlines the specific techniques employed by each method to enhance performance in dynamic healthcare environments.

Real-time processing and efficiency in biomedical signal analysis are crucial for healthcare monitoring systems. Advanced deep learning models, particularly those using Convolutional Neural Networks (CNNs), show significant promise. A sub-resolution mmWave FMCW radar-based approach achieves real-time processing with a median inference time of just 2 ms, enhancing physiological data analysis efficiency [47]. This rapid processing is vital for applications requiring immediate feedback, such as continuous patient monitoring and emergency response systems. Table 1 presents a comparative analysis of advanced deep learning methods, focusing on their real-time processing capabilities, model robustness, and feature extraction techniques, which are crucial for effective biomedical signal analysis in healthcare systems.

Advanced signal processing and fusion techniques further enhance model robustness in dynamic environments. The WMC-VMD algorithm effectively separates vital sign signals from noise, ensuring accurate monitoring in challenging conditions [45]. Such techniques are essential for maintaining the reliability of non-invasive monitoring systems, particularly in high-variability settings.

The UTM framework incorporates a Bayesian feature extractor, an uncertainty-guided fusion module, and a multiscale detection network, optimizing human detection and activity recognition [46]. These components synergistically enhance model performance, enabling adaptation to varying data inputs while maintaining high accuracy.

Integrating advanced real-time deep learning models in healthcare systems significantly improves the speed and accuracy of biomedical signal processing, leading to enhanced diagnostic capabilities in medical imaging and better patient outcomes. By leveraging hierarchical feature representations derived from data rather than relying solely on handcrafted features, these models facilitate precise identification, classification, and quantification of patterns in medical images. They also support efficient management of extensive data generated by IoT devices, contributing to higher quality patient care and more effective healthcare delivery [16, 36]. By harnessing these advanced models, healthcare providers achieve timely and precise monitoring, leading to improved health outcomes and more efficient healthcare delivery.

6 Remote Patient Monitoring Systems

6.1 Advanced Technologies in Remote Patient Monitoring

The advancement of remote patient monitoring systems is propelled by technologies like mmWave radar, smart sensing, and deep learning, which enhance non-invasive monitoring capabilities. These innovations enable continuous assessment of vital signs such as heart rate and respiratory patterns through smart sensors and AI, overcoming the limitations of traditional methods. This technological shift facilitates real-time health assessments, early disease detection, and personalized care, especially for chronic conditions or patients in remote areas [21, 3, 45, 17].

IoT-enabled ambient systems exemplify these advancements by seamlessly collecting and analyzing health data, utilizing large language models (LLMs) to interpret activity sequences and provide timely health insights [7]. Wearable sensors further enhance continuous data collection, crucial for managing chronic conditions and personalized care [8].

Deep learning models are integral for processing the vast data generated by these systems. Techniques like ensemble deep learning, as seen in the HealthFog framework, optimize edge device resources to deliver accurate diagnostics with minimal latency, essential for real-time monitoring and decision-making in urgent medical scenarios [9]. Moreover, robust frameworks like the UTM model, leveraging Bayesian feature extraction and uncertainty-guided fusion, enhance detection accuracy and ensure reliable monitoring in dynamic environments [46]. The integration of these technologies into remote monitoring systems significantly improves healthcare delivery efficiency and patient outcomes through proactive and preventive care.

6.2 Integration of Core Technologies

Integrating mmWave radar, smart sensing, and deep learning into remote monitoring systems represents a significant advancement in non-invasive healthcare solutions, addressing privacy and performance challenges. The Gemini system exemplifies this integration by merging sensing and communication functions within the mmWave band, using smart beamforming and deep learning to mitigate interference and optimize performance [48].

The synergy between mmWave radar and deep learning is particularly impactful in applications like human pose estimation, enabling accurate movement detection without compromising privacy [38]. These systems leverage mmWave radar's high-resolution capabilities to capture detailed motion data, processed by advanced deep learning algorithms for valuable health insights.

Smart sensing technologies enhance remote monitoring by enabling continuous, non-intrusive data collection. Integrating IoT-enabled ambient systems with LLMs aids in interpreting complex activity sequences, providing insights into patient behavior and health status [7]. Wearable sensors complement these systems by providing physiological data, which, when integrated with environmental information, offers a holistic approach to patient monitoring [8].

Advanced deep learning architectures, including ensemble models and meta-learning frameworks, bolster these integrated systems' processing capabilities, enabling real-time analysis and decision-making. The HealthFog framework demonstrates deep learning's effective deployment within a fog computing environment, achieving accurate health diagnostics with minimal latency [9].

The integration of mmWave radar, smart sensing technologies, and deep learning algorithms in remote monitoring systems marks a groundbreaking advancement in healthcare delivery, particularly for vulnerable populations like the elderly. These systems enable real-time detection of critical events, such as falls, through sophisticated human activity recognition models capable of processing sparse point cloud data. For instance, RobHAR, a mobile robot-mounted mmWave radar system, utilizes lightweight deep neural networks for continuous monitoring, while other implementations employ deep convolutional neural networks (CNNs) to track and classify multiple patients' behaviors simultaneously. This technological synergy enhances healthcare interventions' accuracy and responsiveness, addressing significant gaps in patient supervision and ensuring timely alerts and interventions during unsupervised care [1, 10, 13, 49]. Delivering accurate, real-time, and non-invasive monitoring solutions, these systems overcome traditional methods' limitations, paving the way for improved patient care and outcomes.

7 Challenges and Future Directions

7.1 Technical and Systemic Challenges

Integrating mmWave radar, smart sensing, and deep learning into healthcare systems presents several technical and systemic challenges. A key technical issue is the lower resolution of mmWave radar compared to optical sensors, which complicates accurate skeletal key-point capture, especially in multi-person scenarios [38]. The lack of a comprehensive mmWave radar-skeletal database further limits the applicability of methods like mm-Pose [37]. Additionally, datasets from controlled environments may not translate well to real-world applications [31]. Balancing measurement accuracy and time efficiency in bioradar-based vital signs monitoring remains crucial [3]. Morphological variations in SCG signals due to respiratory conditions challenge existing analysis methods [2]. The limited reasoning capabilities of edge devices, due to traditional machine learning model constraints, restrict effective real-time processing in IoT-enabled environments [7].

Deep learning models, while powerful, often exceed the computational resources of embedded systems, complicating real-time healthcare applications [11]. The reliance on labeled data for training poses limitations, particularly in sparse conditions [33]. Unaccounted noise or sensor configurations in training datasets can adversely affect performance [11]. Systemically, scalability and ethical considerations in integrating machine learning with IoT in healthcare are significant challenges. Limited reasoning ability of edge devices complicates real-time processing, diminishing system effectiveness in dynamic environments [7]. Overfitting to training data threatens model generalization to unseen subjects, necessitating robust validation frameworks.

Accurate non-invasive serum glucose measurement remains a major challenge for diabetes management [22]. In fall detection, reliance on environment-sensitive features results in high false alarm rates, complicating monitoring [5]. Technical challenges include the need for data from individuals with similar body types, limiting broader model applicability [6]. Current methods for measuring complex permittivity often require large equipment or destructive sample preparation, highlighting systemic challenges in non-invasive technology integration [20]. Existing healthcare systems frequently struggle to meet stringent accuracy requirements while processing data rapidly enough for real-time demands [9]. Addressing these challenges is crucial for successful technology integration into healthcare systems, paving the way for accurate and reliable non-invasive monitoring solutions. Future research should enhance the robustness of methods like HDNet against occlusions and their application in real-world scenarios [4].

7.2 Future Research Directions

Future research in integrating mmWave radar, smart sensing, and deep learning technologies in non-invasive healthcare systems is poised to drive significant advancements. Enhancing radar sensor performance in complex environments and improving model generalizability across diverse body types by collecting varied training data will be critical [6]. This approach ensures robustness and adaptability in real-world healthcare applications. Developing standardized protocols for wearable devices and enhancing data security measures are crucial to ensure secure and reliable integration of smart sensing technologies into healthcare systems [8]. These initiatives address privacy concerns and facilitate the widespread adoption of wearable technologies in personalized healthcare management.

Exploring the application of the Small Distance Increment (SDI) method with other radar technologies and materials presents opportunities for advancements in non-invasive healthcare monitoring [20]. By broadening the spectrum of technologies and materials utilized, researchers can enhance the accuracy and effectiveness of non-invasive monitoring solutions, paving the way for comprehensive healthcare applications. Future work will also prioritize optimizing models for cost-effective execution and integrating direct sensor data inputs, extending frameworks like HealthFog to encompass additional healthcare domains such as diabetes and cancer [9]. These advancements will enable more efficient and targeted healthcare delivery, improving patient outcomes across a broader range of conditions.

AI-generated, for reference only.

The convergence of research in smart healthcare technologies, particularly through the integration of the Internet of Things (IoT) and machine learning (ML), is set to revolutionize non-invasive healthcare systems. This advancement aims to enhance patient outcomes and streamline healthcare delivery by leveraging intelligent wearable devices for comprehensive health monitoring, utilizing big data analytics for informed decision-making, and implementing innovative applications such as smart footwear and advanced medical image analysis. These developments promise to address critical challenges in traditional healthcare models, ultimately facilitating personalized and efficient healthcare solutions [36, 16, 18, 19, 8].

8 Conclusion

This survey delves into the integration of mmWave radar, smart sensing, and deep learning within non-invasive healthcare systems, highlighting their transformative impact on patient monitoring. The advent of wearable technologies, exemplified by systems like the WUHS, presents cost-effective healthcare solutions while maintaining patient privacy and security, although challenges in terms of reliability and user-friendliness remain. mmWave radar applications have shown significant potential in non-contact monitoring, particularly in assessing muscle activity and estimating human skeletal poses, offering advantages over conventional methods.

Smart sensing technologies, such as intelligent footwear, promise significant advancements in health monitoring and assistive technologies for individuals with disabilities, though further research is needed to address existing challenges. The survey also underscores the pivotal role of AI in remote patient monitoring applications, despite persistent issues related to explainability, privacy, and data processing.

Innovative approaches like the SCG-based breathing-state detector demonstrate deep learning's potential in non-invasive healthcare, achieving high accuracy in remote health monitoring and advancing biomedical signal processing. However, ongoing challenges in resource management, security, and data processing highlight the need for continued research to enhance smart healthcare solutions.

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