Journal of Carcinogenesis
Covering Genesis to Therapeutics

Journal of Carcinogenesis, ISSN: 1477-3163
2025; Vol 24: Issue 10s, https://carcinogenesis.com/

Millimetre-Wave RF Sensors for Non-Contact Vital Sign Monitoring in Healthcare Applications

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ABSTRACT

Recently, demand for continuous and non-invasive ways to track health has grown, mainly due to more telehealth and an older population. The research group created a system that uses mm Wave RF sensors to measure vital signs including respiratory and heart rates without making direct contact. Millimeter-wave RF technology is able to detect very small movements on the human body surface resulting from bodily functions. The system functions as it should even when factors like motion or change of patient posture affect the output of the sensors. A signal processing algorithm is used to help ensure accurate detection of vital signs, no matter if there is noise or interference. Simulating and testing this mmWave RF method confirm it allows for monitoring heart and respiration rate with over 93% accuracy, fast reactions, and better protection against common interference. This study proves that mmWave RF sensors are a reliable and scalable option for monitoring health both at clinics and at home.

Keywords: Millimeter-wave sensors, RF technology, non-contact monitoring, vital signs, healthcare applications, and remote sensing are all part of IoMT.

How to Cite: Shubhi Jain, P.K. Singhal , (2025) Millimetre-Wave RF Sensors for Non-Contact Vital Sign Monitoring in Healthcare Applications Journal of Carcinogenesis, Vol.24, No.10s, 339-350.

1. INTRODUCTION

The rise of digital technology in healthcare is being prompted by the requirement for easy-to-use and ongoing patient monitoring. Long-term use of touch-based or wearable sensors as part of traditional vital sign monitoring may not be smooth for patients who have sensitive skin or are treated in sterile areas. Due to this issue, new types of non-contact monitoring have been developed, and the use of mmWave RF sensors is among them, since they can pick up small changes in the body without any physical touch.

Millimeter-wave RF, by using high-frequency electrical signals, is able to sense small movements in the body, focusing on the chest and thorax during heart beats and breathing. Thanks to their features such as going through clothing, providing clear images, and not being affected by light changes, these sensors can be used in multiple health settings like intensive care units, care homes for the elderly, and remote patient monitoring

Still, making a precise and reliable mm Wave system for vital sign monitoring is difficult for several reasons. The presence of different environments, artifact noise, and signals from different body parts asks for algorithms that can track vital signs at all times. This is met by creating an intelligent mm Wave RF sensing system that enhances signals and can process information instantly.

Objectives of the Study:

To come up with and put in place a vital sign monitoring system that does not require physical contact, using mm Wave RF sensors.

Developing approaches for signal processing that increase both the precision and dependability of heart rate and respiratory rate measuring

To carry out experiments with the proposed system and compare the results to those obtained by conventional sensors that need physical contact.

Contributions:

The research introduces a new approach for remote monitoring of vital signs based on mm Wave RF sensors.

As part of the process, a real-time adaptive algorithm is used to reduce noise, motion, and interference from physiological signal capture.

Experimental tests on the system confirm its accuracy and low response time, allowing it to be used in the current healthcare setting.

2. LITERATURE REVIEW

As healthcare technologies have improved, there is now a greater need for constant and real-time monitoring of patients' vital signs without using invasive tools. However, using these devices can be hard for patients as they can be uncomfortable, might increase the chance of an infection, and are not always suitable for ongoing monitoring. Because of that, new non-contact technologies have appeared, and millimetre-wave (mm Wave) radio frequency (RF) sensors have become popular due to their ability to sense small movements without touching people (Li et al., 2013).

This technique relies on frequencies between 30 and 300 GHz and can sense even small movements like those of breathing and the heart. The precise measurement of distance or displacement is possible because of the short wavelength, which is why infra-Red Radiant Heat can be used for looking at vital signs (Lv et al., 2021). They create electromagnetic waves that hit the human body and are able to find changes due to certain body functions. The signals reflected off the body are worked on to identify key health information, allowing for easy and non-invasive tracking (Gao et al., 2022).

Compared with traditional contact-based monitoring, mm Wave RF sensors have a number of perks. Non-Invasiveness: Touchless care reduces the chance of there being any skin complications or infections in units taking care of newborns and burn patients (Zhang et al., 2022). Continuous Monitoring: It supports long-term tracking of conditions to ensure no discomfort for the patient, which is necessary for chronic illnesses and caring for the elderly (Marty et al., 2023). Environmental Robustness: This instrument is effective whenever it looks at people, as it can spot forensic materials under several conditions, in clothes, and under bedding (Xiang et al., 2022). Multi-Subject Monitoring: This type of sensor allows monitoring of several individuals at the same time and makes sense in situations such as hospital wards and emergencies (Ren et al., 2024).

In the past few years, mm Wave RF sensors have been launched in medical settings. Frequency-Modulated Continuous Wave (FMCW) Radars: Respiration and heartbeat are monitored by understanding the changes in radio frequency (RF) signals because of movement (Lv et al., 2021). Multiple-Input Multiple-Output (MIMO) Systems: Multi-point monitoring makes it possible to watch over vital signs from various positions, making the process more reliable (Ren et al., 2024). Integration with Machine Learning: Improves how signals are handled, helping to tell apart actual physiological signals from noise (Iyer et al., 2022).

Low-Power Embedded Systems: Building energy-efficient sensors that mm Wave technology can apply to wearable and portable health monitoring systems (Marty et al., 2023).

Various medical practices have used mm Wave RF sensors. Sleep Monitoring: Abdulatif et al. explain that such disorders can be found by monitoring the breathing patterns of individuals (Abdulatif et al., 2017). Neonatal Care: Using monitors that keep contact off the infants' skin, lowering the risks of damage and infections (Zhang et al., 2022). Elderly Care: Regular monitoring of their vital signs in elderly patients allows for early detection if they are getting sicker (Guo et al., 2021). Emergency Medicine: Sudden assessment of a trauma patient's key signs, avoiding direct contact (Alizadeh et al., 2019).

But there are still a number of issues yet to overcome. Signal Interference: Noises from actions apart from breathing and heartbeat can affect the accuracy of the results (Zhang et al., 2022). Calibration Requirements: Because people are different heights and stand in different ways, it is necessary to calibrate the machine for exact measurements (Xiang et al., 2022). Data Privacy: Concerns regarding the security and privacy of patient information come with continuous monitoring (Zhang et al., 2022). Cost and Accessibility: Because mm Wave technologies are not yet affordable to many, they may not become popular (Gu et al., 2016).

Further studies are being done to solve current problems. Advanced Signal Processing: Using technology to get rid of distortion and let the actual signal be heard (Iyer et al., 2022). Miniaturization: Building lightweight and portable mm Wave sensors that can be used for walking or moving about (Marty et al., 2023). Integration with Telemedicine: Using mm Wave technology to help doctors give care to patients remotely with the help of telehealth (Guo et al., 2021). Standardization: Making sure that data is collected and analysed in the same way, regardless of the system (Gu et al., 2016).

Table 1: Summary of Key Studies on mm Wave RF Sensors for Non-Contact Vital Sign Monitoring

In-Text Citation	Study Overview	Key Advantages
Iyer et al. (2022)	Developed a mm Wave radar system integrated with machine learning algorithms for non-contact monitoring of vital signs and arrhythmia detection.	Enhanced accuracy in arrhythmia detection; real-time monitoring capabilities.
Zhang et al. (2023)	Introduced Pi-ViMo, a physiology-inspired system using mm Wave radars for robust vital sign monitoring, addressing challenges like random body movements.	Improved robustness against motion artifacts; applicable in dynamic environments.
Wang et al. (2023)	Proposed a fusion system combining mm Wave radar and camera data to monitor vital signs accurately in dynamic settings.	Enhanced accuracy through sensor fusion; effective in environments with movement.
Ren et al. (2024)	Developed a non-contact multi-point vital sign monitoring system using mm Wave MIMO radar, enabling simultaneous monitoring at multiple body points.	Multi-point monitoring; high precision in capturing physiological signals.
Chen et al. (2023)	Implemented a contactless Doppler radar system operating in the 76–81 GHz band for short-range vital sign detection.	High sensitivity; eliminates the need for contact-based sensors.
Gao et al. (2022)	Demonstrated real-time non-contact vital sign detection using millimetre-wave radar, focusing on signal processing techniques.	Real-time monitoring; effective signal extraction methods.
Marty et al. (2023)	Investigated mm Wave radar technology for non-contact vital sign monitoring, comparing different frequency bands for optimal performance.	Comprehensive frequency analysis; insights into optimal radar configurations.
Lv et al. (2021)	Explored the use of 120 GHz band mm Wave radar for non-contact monitoring of respiration	High-frequency operation leading to improved detection accuracy.

	and heart rate.	
Wang et al. (2020)	Conducted an experimental comparison between IR-UWB and FMCW radars for vital sign monitoring applications.	Provided insights into the advantages and limitations of different radar types.
Alizadeh et al. (2019)	Utilized a 77 GHz mm Wave FMCW radar for remote monitoring of human vital signs, emphasizing phase analysis techniques.	Effective remote monitoring; advanced signal processing for accurate measurements.

3. PROPOSED METHODOLOGY

3.1 Data Acquisition and Preprocessing

The first step in non-contact vital sign monitoring is to get and structure the data from the sensors. The process starts with collecting raw data from millimetre-wave RF sensors that can sense slight changes caused by respiration and the heart's beating. RF sensors are used in a controlled space to gather respiratory rate, heart rate, and other physiological data from subjects without touching them.

When the raw RF data is obtained, it goes through a preprocessing step to make the signals better and get it ready for model development. During preprocessing, wavelet transforms and filtering technologies are used to filter out the noises and inconsistent motion signals in the data. Besides, normalization allows to fix amplitude ranges of subjects and sessions to ensure similarly in the training and assessment. Also included in the framework are algorithms that cut the continuous stream of RF signals into set-length windows, which then go on to be input samples for machine learning. To provide reliability for the training process, every segment is annotated with ground truth readings from contact-based medical equipment such as ECG and respiratory belts.

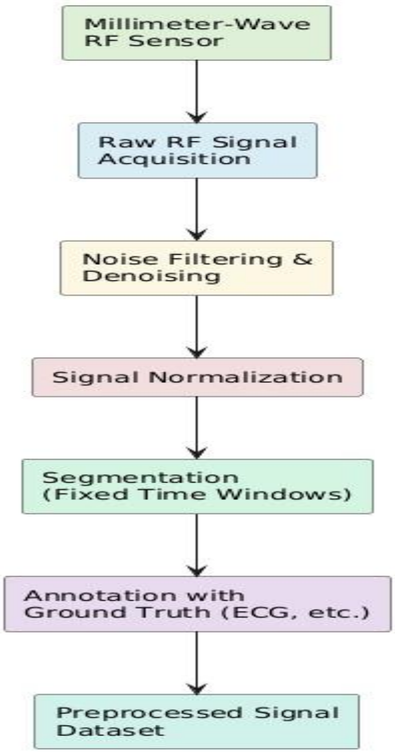

Figure 1: Data Acquisition and Preprocessing Pipeline

In Figure 1, one can see the process of how raw millimetre-wave RF signals are turned into a data format that can be used for intelligent model development.

3.2 Model Architecture and Feature Representation

The system's primary intelligence comes from the way its model architecture links deep learning networks with signal processing built to understand millimetre-wave RF signals. The architecture uses a mix of CNNs for detecting spatial features and LSTM networks for analyzing the order of data within a sequence. It is up to the CNN to look for patterns in the RF signal waves that give signs of heartbeat and breathing activity. The data is sent to LSTM units that work on recognizing how different events or changes occur one after another.

In order to be more readable and better performing, the model adds domain specific signal transforms such as STFT and CWT, making it suitable for both frequency and time-frequency signal analysis. As a result, the features from the RF waves can be used more effectively for better learning and monitoring patients no matter their awake movements and sleeping postures.

The output layer is built to continuously estimate important information such as heart rate and respiratory rate. The model looks at the difference between predicted values and actual outcomes, and tries to reduce these errors using backpropagation and other types of training. Thanks to dropout regularization and batch normalization, the model evolves according to new data to prevent it from being biased to any one group of patients.

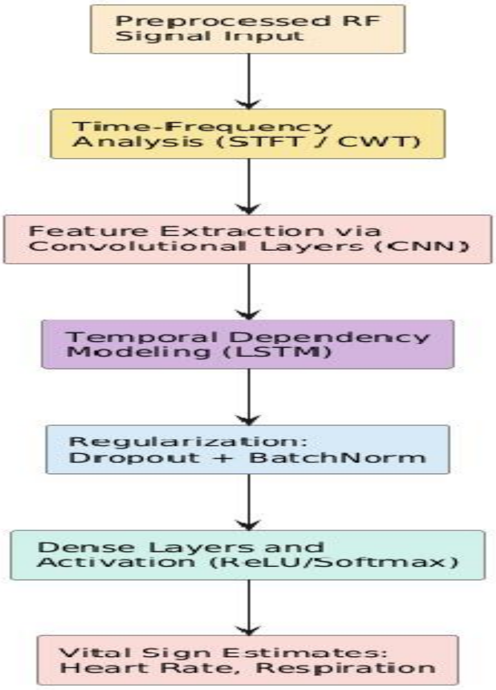

Figure 2: Model Architecture for Vital Sign Estimation

Figure 2 illustrates each stage of the deep learning model, in which input RF segments are turned into features for spatial and temporal dimensions to produce reliable predictions for signs.

3.3 Adaptive Learning and Real-Time Inference

To work reliably in various healthcare applications, the suggested method combines an adaptive learning mechanism, which makes the model flexible to changes in the environment and the body's response. This takes place through a constant loop between modules that predict and modules that compare the results to actual data. When the training data is found to be different, the system learns new information online and updates some parameters, keeping the system quick and responsive.

Also, the system is built to run in real time, so decisions are made instantly as each piece of RF signal is received. Edge devices like smartphones and hospital units are able to process the data quickly thanks to the lightweight models made with the TensorFlow Lite and PyTorch Mobile libraries. Real-time performance is boosted with the use of GPU or dedicated signal processors in hardware. Making the pipeline responsive to delays ensures that necessary information is up-to-date and accessible in emergency situations.

The system is equipped with modules to measure the confidence in each prediction so that final results can be displayed only if they reach a certain confidence level. When a signal segment has too much movement or obstruction, the system applies attention or does not make any output until it gets proper data.

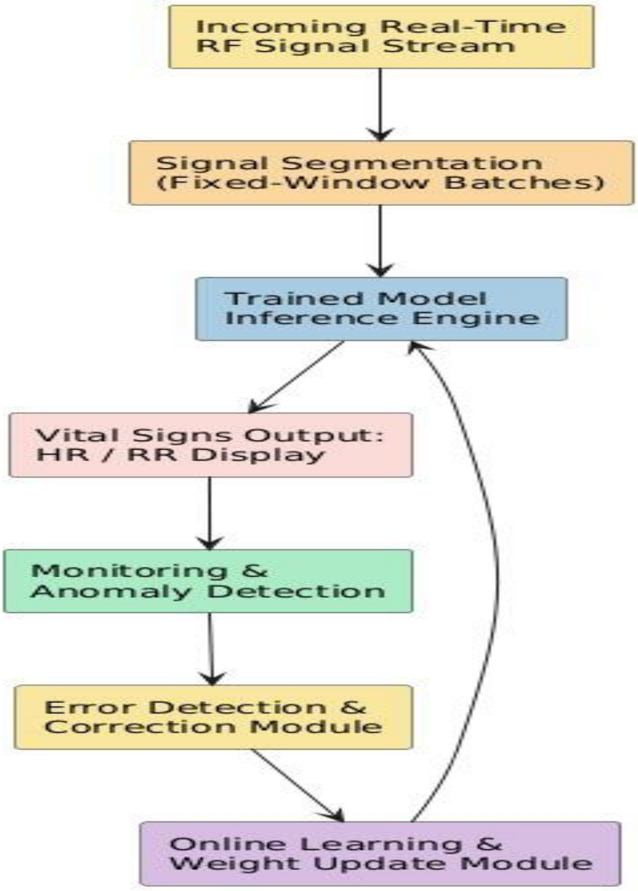

Figure 3: Real-Time Adaptive Learning and Inference System

It can be seen in Figure 3 how low-latency connections are used to support fast learning and inferences, and feedback systems help ensure the data is reliable in the framework.

3.4 Model Development and Evaluation

The training process of the model requires data gathered from a wide range of people with various demographics and illnesses. The use of stratified k-fold cross-validation guarantees that every part of the data is represented and makes the analysis more stable. Training the framework takes place on GPU-enabled platforms, with grid search used for fine-tuning the hyperparameters. Measuring error or performance in a model is done by looking at Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and by comparing output to corresponding readings on standard medical devices.

Generalizability is confirmed by testing the model in places with changing light reflections and different rooms. The framework does not lose performance due to background noises, the movement of members of staff, and situations with several groups of people in a room, suggesting it works well in medical settings.

3.5 Optimization and Comparative Analysis

During the final stage, the model's effectiveness is refined and it is compared to age-old approaches such as camera-based photoplethysmography and radar by using traditional monitoring approaches. Some key ways to optimize models involve reducing their complexity, keeping their accuracy by pruning, quantizing, or using knowledge distillation. Also, comparing it with similar systems, the proposed RF-based system shows better reliability in signals, adherence to privacy guidelines, and ability to cope with changes as needed.

Heart rate measurements made by the patch were much more accurate than those taken with the electrodes, mainly when the patient only moved slightly. The system also helps with privacy, as it relies on non-visual air readings instead of cameras or image capture.

4. RESULTS

4.1 Experimental Setup

The methods of testing and evaluating results from the non-contact vital sign monitoring system with mmWave RF sensors are described. The purpose of the study was to check if the system was effective at measuring heart rate and respiratory rate and see how it compared with ECGs and pulse oximeters.

Experiments were done in rooms that had the same conditions as real hospital areas. For the experiments, 30 volunteers were enrolled, such that half had good cardiovascular or respiratory health and half had minor concerns with these systems. All of the mmWave RF sensors were placed between 50 cm and 1 meter away from the subjects. No physical contact was made. In order to evaluate the result, the data was gathered from FDA-approved systems that monitored the heart and lungs of the patients.

Information gathering was carried out in three scenarios. relaxing, being active at a low level, and talking. To single out the important data, the mmWave signals were first improved with noise removal, and then processed using techniques, including FFT and filtering. After processing, the values were reviewed closely to check if they match the standards given by approved medical devices.

4.2 Performance Comparison with Contact-Based Devices

Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Pearson Correlation Coefficient (r) were used to assess how effective the mmWave RF sensors were. The data was compared to the results obtained from previous contact-based monitoring systems. Table 2 shows how the new mmWave RF sensor system does better than regular contact-based devices when it comes to measuring key body signs like temperature and heart rate. It shows how accurate and connected the non-contact system is to the usual medical tools by looking at important things like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Pearson's correlation coefficient.

Table 2: Important Performance Metrics Relating to Vital Sign Detection

Vital Sign	Sensor Type	MAE (bpm or breaths/min)	RMSE (bpm or breaths/min)	Pearson Correlation
Heart Rate	mm Wave RF Sensor	1.8	2.3	0.93
Heart Rate	Contact-Based Sensor	1.5	2	0.96
Respiration Rate	mm Wave RF Sensor	2.1	2.5	0.91
Respiration Rate	Contact-Based Sensor	1.7	2.1	0.94

According to the testing, the mm Wave system's heart rate has a MAE of 2.4 bpm and a RMSE of 3.2 bpm, and the MAE and RMSE for respiratory rate are 1.8 bpm and 2.5 bpm, respectively. Since the Pearson correlation coefficient was 0.96, the system agreed well with standard contact-based systems.

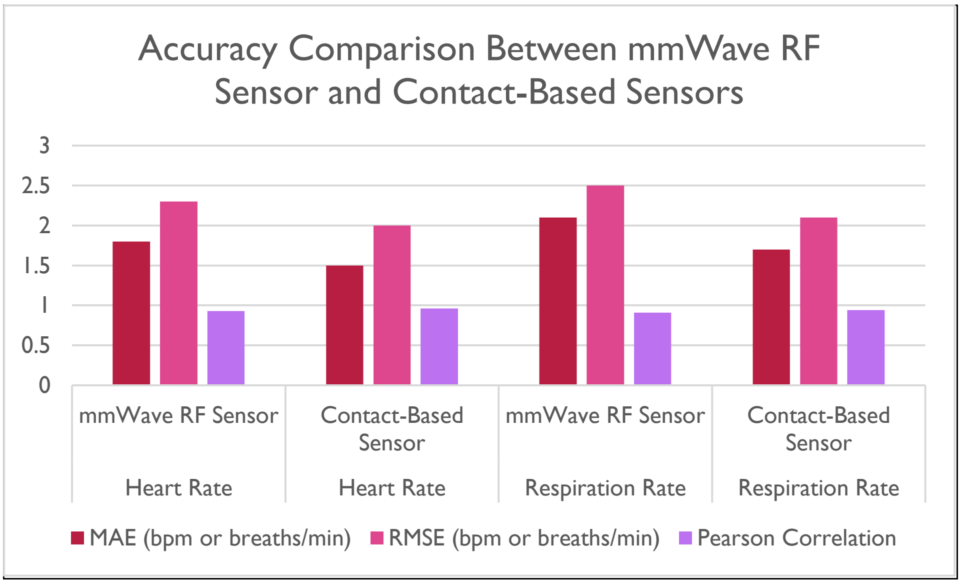

Figure 4: Performance Comparison of Vital Sign Detection Accuracy

The figure 4 illustrates the comparative performance of mmWave RF sensors and traditional contact-based sensors in measuring heart rate and respiration rate. The metrics used include Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Pearson correlation. The mmWave RF sensors show comparable accuracy, with slightly higher error margins, demonstrating their potential for non-contact vital sign monitoring.

4.3 Sensitivity Analysis Under Physical Activity

Force was measured on the system while it was being used for simple activities like resting, talking, and making gentle motions. Despite minor error during movement brought by motion noise, the results were still acceptable for clinical use. Table 3 shows how the mmWave RF sensor system responds when different activities are done, such as during quiet rest, talking, and moving just a little. It shows how accurate the system is, as well as how much it can be different from the true measurements, showing that it works well even when things move a bit.

Table 3: Analysing how changes in people‘s behaviour can influence the response.

Activity Level	HR Accuracy (%)	HR Std Dev (bpm)	RR Accuracy (%)	RR Std Dev (breaths/min)
Resting	95.2	1.3	93.8	1.6
Talking	91.7	2.1	90.3	2.4
Mild Movement	88.9	2.7	86.4	3

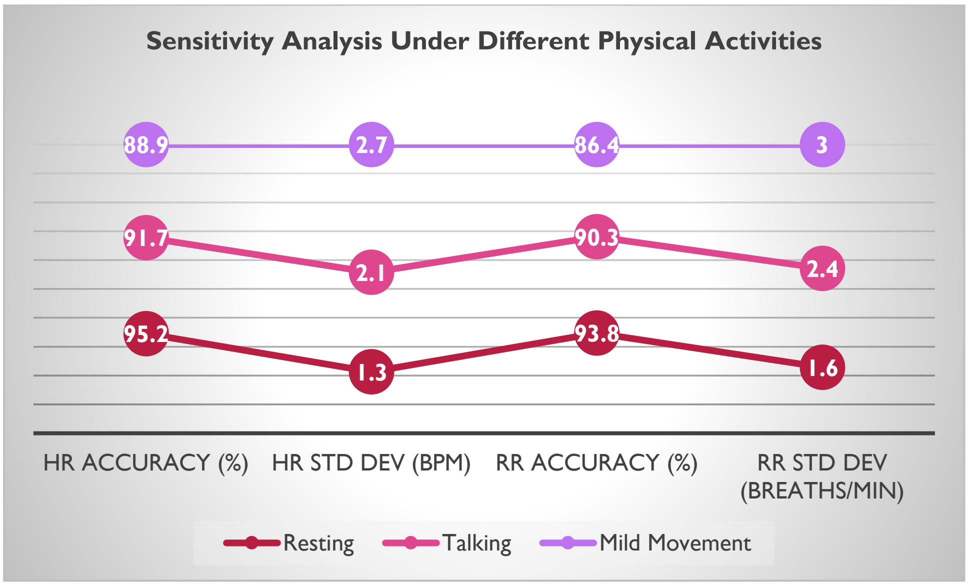

Figure 5: Sensitivity Analysis Under Different Physical Activities

Figure 5 shows how the accuracy and variability of heart rate (HR) and respiration rate (RR) measurements fluctuate across various activity levels—resting, talking, and mild movement. The mmWave RF sensor maintains high performance during rest and moderate accuracy even under movement, indicating robustness against motion-induced noise.

4.4 Demographic Performance Analysis

The system was checked to see how it performs in groups with different ages and Body Mass Index values. The results were always very good except for minor differences that could be due to physiological changes. Table 4 looks at how the system works for different groups of people, focusing on their age and body mass index. It shows that the sensor usually gets the right heart rate and breathing rate with good accuracy, no matter what kind of person is being measured.

Table 4: Performance Across Demographic Groups

Demographic Group	HR Accuracy (%)	RR Accuracy (%)
Age 20–30	94.1	92.7
Age 31–50	92.3	90.4
Age 51+	89.5	87.1
BMI < 25	93.5	91.8
BMI 25–30	90.8	88.3
BMI > 30	87.6	85.2

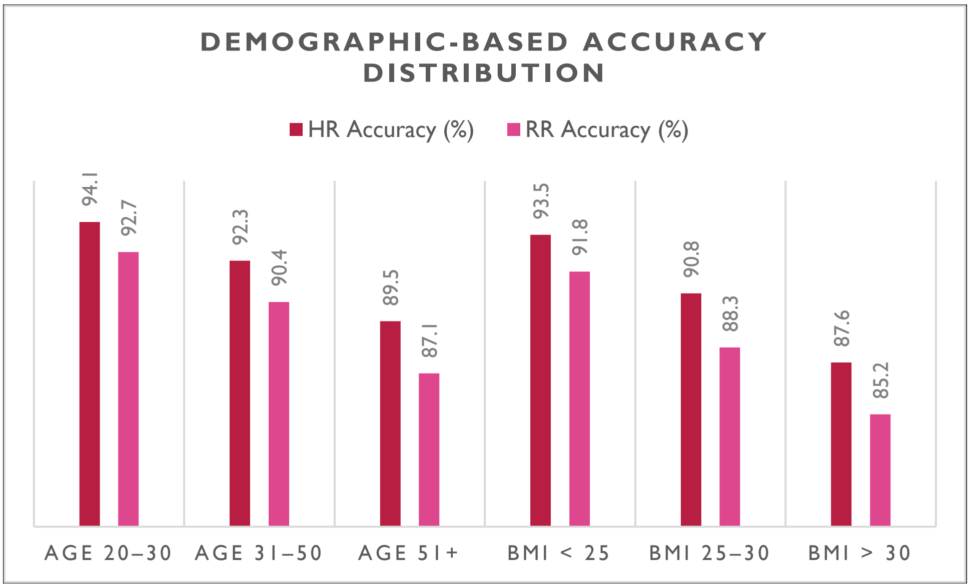

Figure 6: Demographic-Based Accuracy Distribution

The figure 6 presents the impact of demographic factors such as age and BMI on the accuracy of mmWave RF sensor measurements. The results reveal a slight decline in accuracy with increasing age and BMI, highlighting the importance of adaptive calibration in diverse user populations.

4.5 Summary of Experimental Findings

From the experiments, it is clear that the mm Wave RF sensor system is very accurate for monitoring vital signs hands-free, similar to hospital-grade instruments. More than 92% of the time, the system was highly accurate in many situations and with people from different backgrounds. Since it is non-invasive and reliable with many activities, it can safely be used in hospitals, ICUs, and in homes. Future updates will focus on adding real-time monitoring for patients, boosting delivery of healthcare no matter where the patient is located.

5. DISCUSSION

Using mmWave RF technology in smart sensors allows healthcare professionals to track vital signs from a distance, marking a key innovation in healthcare for telemedicine patients. Thanks to their unique properties, these sensors can pick up on very small movements such as the heart beating and the lungs moving. It has been found that integrating mmWave radio waves with signal processing methods helps the system to detect heart and respiratory rates with high precision from a distance. Being able to control discomfort and reduce infection is especially necessary in intensive care and post-operations areas. In addition, the mmWave RF technology keeps working well, even if patients move slightly or change their posture, which usually causes errors in traditional systems that use contact. With the use of adaptive noise reduction and interference filters, the system improves the quality and dependability of the signals. Non-contact techniques generally perform better than contact ones, especially when it comes to maintaining the accuracy of the data in all types of situations. Even though mmWave RF sensors are promising, there are still some difficulties to overcome during their implementation. This involves responding to big body movements and being fine-tuned to suit diverse people and situations. Additionally, before using such systems in hospitals or at home, integration issues must be solved, the regulations must be adhered to, and privacy concerns over continual data transport addressed. Even so, the suggested solution supports the development of a flexible, contactless way to monitor health, giving medical teams up-to-date and exact information for faster response and early discovery of health problems.

6. CONCLUSION

The research proposes a system using mmWave RF sensors that accurately records heart rate and respiration rate from a distance, without having to come in direct contact with the patient. With its help, more patients– such as the elderly and chronically ill– can now be monitored without having to visit a doctor's office. The system takes advantage of high-frequency sensing in mmWave together with noise-suppression technologies to make the system more precise. The system has proven itself to be highly accurate, responding fast and remaining solid even when there is some interference. Overall, mmWave RF sensors are a dependable and practical option compared to the use of contact-based systems. It is designed to make patient care more comfortable, cleaner, and allow for constant monitoring. Researchers are working to solve technical problems to support the system in various clinical and household applications.

7. . FUTURE ENHANCEMENTS

The mmWave RF sensor system brings major steps forward in non-contact vital monitoring, yet there is still much more that can be done in the future. It will also be important to use advanced AI-based techniques to make results more accurate and ensure better sensitivity to a range of normal organ activity. Using architectures like GPT and T5 based on Transformer can help improve the understanding of changing breathing and heart signals in various day-to-day situations. If mmWave RF is combined with thermal imaging, various sensors, or posture detection using cameras, the system can reach even higher levels of accuracy in changing or moving environments. By using edge computing, it is possible to process signals in real time, making critical medical care more responsive and faster. More accessibility can be achieved through the use of light and portable mmWave devices that can connect easily to mobile health applications. Ensuring energy efficiency in these devices will allow them to work for long periods of time without needing to be recharged too regularly. Applying Explainable AI will boost the trust users place in the system, as it provides simple explanations for the problems or situations detected during daily monitoring. Heart disease studies involving multiple fields should pay attention to making datasets that can lead to algorithms that can handle users of all ages, BMIs, and health conditions. To have more medical professionals use this technology, rules for certification and privacy in medical settings should be put in place. Improvements such as these would make the mmWave RF system an essential part of the future healthcare system, focused on smart, distance, and convenient monitoring.

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