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RESEARCH ARTICLE

Monitoring Bone Healing: Integrating RF Sensing With AI

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ABSTRACT This study presents the development of an advanced machine learning model based on a two-dimensional (2D) Radio Frequency (RF) sensing framework for refined monitoring of femoral bone fractures. Utilising MATLAB simulations, we created a comprehensive dataset enhanced with variations in bone diameter, muscle thickness, fat thickness, and hematoma size, augmented with multiple sensor configurations (two, four, six, and eight sensors). The model aims to provide a frequent, non-invasive assessment of the fracture healing process compared to conventional imaging methods. Our approach leverages data from six RF sensors, achieving a high overall accuracy of 99.2% in classifying different fracture stages, including ''no fracture'' and varying degrees of hematoma sizes. The findings indicate that increasing the number of sensors up to six significantly enhances detection accuracy and sensitivity across all fracture stages. However, the marginal improvement from six to eight sensors was not statistically significant, suggesting that a six-sensor configuration offers an optimal balance between performance and system complexity. The results demonstrate significant potential for this technology to revolutionise orthopaedic treatment and recovery management by offering continuous, real-time monitoring without radiation exposure. The proposed system enhances personalised patient care by integrating RF sensing with artificial intelligence, enabling timely interventions and more informed, data-driven treatment strategies. This research lays a robust foundation for future advancements, including three-dimensional modelling and clinical validations, toward the practical implementation of non-invasive fracture monitoring systems.

INDEX TERMS RF sensing, artificial intelligence, bone fracture monitoring, machine learning, non-invasive assessment, healing process, neural networks, sensor calibration.

I. INTRODUCTION

Femur fractures are globally prevalent and pose significant challenges in orthopaedics due to the complexity of the femoral bone and its intricate healing process. These injuries often require lengthy recovery periods and are susceptible to complications that impede healing. Traditionally, the monitoring of femur fractures has relied primarily on X-ray imaging. While effective for periodic assessment, X-rays expose patients to repeated doses of ionising radiation and fail to provide continuous data on the healing progress. Recognising these limitations, our research integrates Radio Frequency (RF) sensing technology with Artificial Intelligence (AI) to develop a non-invasive, real-time fracture

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monitoring system using a two-dimensional (2D) analytical framework.

RF sensing utilises electromagnetic waves to measure the dielectric properties of biological tissues, which change in the presence of a fracture. Techniques such as Electrical Impedance Spectroscopy (EIS) enable the detection and characterisation of these changes, allowing the RF sensing system to identify and monitor fractures effectively. Studies have shown that impedance magnitude and phase measurements can be wirelessly transmitted and significantly correlate with conventional bone healing assessments, distinguishing between healed and non-healed fractures. When combined with AI, particularly machine learning algorithms, nuanced analysis of RF signal data provides detailed insights into the dynamics of fracture healing—from the initial inflammatory stage to the later remodelling phase.

In the initial development phase of our research, we employ MATLAB simulations as a critical tool for understanding these complex dynamics and modelling the interactions between RF signals and the biological tissues involved in bone healing. This simulation-driven approach allows us to accurately represent various physical characteristics crucial to the healing process, such as haematoma size, bone diameter, muscle thickness, and fat thickness. By incorporating these parameters into our RF sensor-AI system, we aim to enhance the accuracy and specificity of fracture monitoring, thereby contributing to developing more effective, personalised patient care plans.

MATLAB simulations at this stage is a foundational step in developing a robust fracture monitoring system. By simulating different bone and tissue scenarios, we can systematically explore the potential performance of our RF-based approach, identifying key variables that affect signal detection and interpretation. This controlled environment enables us to rigorously test and refine our theoretical models before advancing to more complex stages of research, such as three-dimensional (3D) modelling or clinical trials. The insights gained from these simulations are instrumental in guiding the design of future physical prototypes and ensuring the efficacy and safety of eventual clinical applications.

Our system has been progressively developed and improved through multiple stages, with each stage building upon the previous to enhance the accuracy and specificity of fracture monitoring. This iterative approach strengthens the theoretical framework and addresses potential challenges early in the research process, guiding the design of future physical prototypes.

The structure of this paper is as follows: Section II provides a comprehensive review of current literature on RF sensing and AI applications in healthcare. Section III details the methodology, including sensor design and data analysis. Section IV presents the statistical analysis of our simulation results. Section V presents the results of our simulations. Section VI discusses the implications of our findings. Section VII outlines the limitations of our study and future work. Section VIII addresses the ethical considerations in continuous monitoring. Section IX explores future research directions. Finally, Section X concludes the paper.

II. LITERATURE REVIEW

Radio Frequency (RF) technologies have significantly advanced over recent decades, finding vital applications across various fields, including healthcare. Initially developed for wireless communications, RF technology has evolved to offer improved bandwidth, range, and power efficiency [1]. In the medical domain, RF technologies are leveraged for their non-invasive nature and ability to penetrate biological tissues, making them suitable for diagnostic and therapeutic purposes [2], [3], [4].

Parallel to these advancements, Artificial Intelligence (AI), particularly machine learning (ML) and deep learning (DL), has revolutionised data analysis and pattern recognition in healthcare. Machine learning algorithms excel in processing complex medical data, enhancing diagnostic accuracy and enabling personalised treatment plans [5]. Deep learning, a subset of machine learning, utilises neural networks with multiple layers to model complex patterns in data, further improving predictive capabilities [6]. The integration of AI into healthcare systems facilitates real-time decision-making and predictive analytics, which are crucial for effective patient management [7], [8].

The convergence of RF technologies and AI presents a promising avenue for enhancing medical diagnostics. RF sensing technologies, when combined with machine learning and deep learning algorithms, can provide non-invasive, accurate, and continuous monitoring of physiological parameters [9]. Specifically, in bone fracture monitoring, RF sensing offers a potential alternative to traditional imaging modalities like X-rays and MRI, which have limitations such as radiation exposure and high costs [10], [11], [12]. By analysing the RF signals that interact with biological tissues, AI algorithms can detect and classify anomalies indicative of fractures [13].

Recent studies have explored the use of RF sensing for detecting and monitoring bone fractures. Radar-based systems have been developed to assess bone integrity non-invasively, utilising the dielectric properties of biological tissues to identify anomalies [13]. Researchers have employed deep neural networks to analyse RF signal data, improving detection accuracy and enabling the classification of different fracture stages [14]. These approaches have demonstrated high potential in both simulated environments and real-world applications, showing significant accuracy in identifying fractures without the need for ionising radiation.

Advancements in RF sensor hardware have further enhanced the applicability of these technologies in medical diagnostics. The development of ultrawideband (UWB) RF sensors has improved spatial resolution and penetration depth, allowing for more precise imaging of internal structures [15]. Wearable RF devices have also emerged as practical solutions for continuous health monitoring. The integration of UWB technologies into wearable sensors allows real-time tracking of internal conditions, including bone fractures, without the need for bulky equipment [16]. These wearable RF sensors, combined with AI-driven data analysis, facilitate personalised healthcare by providing clinicians with timely and detailed patient information [17].

Moreover, AI algorithms have been instrumental in processing the complex data obtained from RF sensors. Machine learning techniques, such as support vector machines, decision trees, and ensemble methods, have been used to classify tissue types and detect anomalies [18]. Deep learning models, particularly convolutional neural networks (CNNs), have shown exceptional performance in image recognition tasks and have been adapted to analyse RF signal patterns for medical diagnostics [14]. These models can learn intricate features from RF data, enabling the detection of subtle changes in tissue properties associated with different stages of fracture healing.

In real-world applications, integrating AI with RF sensors has shown promise in various medical settings. Studies have demonstrated the feasibility of using RF sensing combined with AI for monitoring bone healing in postoperative patients, providing continuous assessments that can inform treatment decisions [19]. Additionally, AI-enhanced RF sensing has extended to other medical areas, such as detecting breast cancer, monitoring vital signs, and assessing soft tissue injuries [20].

Despite these technological advancements, deploying RF sensing and AI technologies in clinical settings brings ethical and regulatory considerations. Issues related to patient privacy, data security, and the ethical use of medical data must be addressed to ensure responsible integration into healthcare systems [21]. Regulatory bodies require rigorous validation and testing of these technologies to ensure their safety and efficacy in patient care.

Our research builds upon these developments by focusing on integrating RF sensing with machine learning algorithms for non-invasive bone fracture monitoring. Using a two-dimensional (2D) analytical framework and MATLAB simulations, we aim to develop a system capable of providing accurate, real-time assessments of fracture healing progress. While simulations provide a controlled environment to test and refine our models, the ultimate goal is to apply these methodologies in real-world clinical settings. By leveraging both simulation data and real-world applicability, our approach seeks to bridge the gap between theoretical research and practical implementation.

Furthermore, the integration of AI and RF sensing is not limited to simulations but extends to practical implementations in clinical environments. For example, wearable RF sensors equipped with AI algorithms have been utilised for remote patient monitoring, allowing healthcare providers to track patients' recovery remotely [22]. These systems can alert clinicians to any abnormalities in the healing process, enabling timely interventions.

Beyond bone fracture monitoring, RF technologies demonstrate considerable versatility across various healthcare applications. They have been employed in remote health monitoring of the elderly, utilising multisensory RF-based systems for activity monitoring and fall detection [36]. This underscores the potential of RF technologies to provide comprehensive healthcare solutions, supporting diagnostic and preventive care measures in diverse patient populations.

Recent advancements have also catalysed innovations in bone fracture diagnostics by applying deep learning techniques. A notable study demonstrated the effectiveness of using deep neural networks trained on complex patterns in the S-parameters obtained from RF signals to identify bone fractures non-invasively [14]. These networks were able to classify different types of bone fractures and measure crack lengths with high accuracy. This deep learning-based approach to RF signal analysis not only bypasses the need for extensive data labelling required in traditional imaging methods but also enhances the feasibility of deploying advanced diagnostic tools in remote or resource-limited environments. Such capabilities are particularly valuable in emergencies or areas lacking immediate access to radiological expertise.

In addition to technological advancements, the ethical and regulatory considerations of deploying these technologies in clinical settings are paramount. Integrating RF sensing and AI brings challenges related to patient privacy, data security, and the ethical use of technology [21]. Ensuring compliance with regulations and guidelines is essential to protect patient information and maintain trust in these innovative healthcare solutions.

By addressing the inherent complexities of integrating AI with RF sensing, our research aims to contribute to the broader evolution of non-invasive, personalised medical diagnostics. This study uniquely combines RF sensing and AI-driven analysis to pioneer an advanced bone fracture monitoring system, setting the stage for future innovations. Our work not only explores the theoretical underpinnings through simulations but also emphasises the practical implications and potential real-world applications of this technology.

In summary, the integration of AI, including machine learning and deep learning with RF sensors, presents significant opportunities to enhance medical diagnostics, particularly in orthopaedics. By leveraging advancements in both RF hardware and AI algorithms, it is possible to develop non-invasive, accurate, and continuous monitoring systems for bone fractures. Our study builds upon these developments, aiming to bridge the gap between simulations and real-world applications, and contribute to the advancement of personalised patient care in orthopaedics.

III. METHODOLOGY

In this study, we employed a two-dimensional (2D) simulation approach using MATLAB to model and analyse the interactions of Radio Frequency (RF) signals with biological tissues involved in bone healing. This 2D perspective allows for efficient modelling of the planar spatial distribution and variations in RF signal reflectance over the fracture site, providing a simplified yet effective representation of the healing dynamics. MATLAB allows us to test various sensor configurations and tissue parameters in a controlled environment.

While this approach focuses on 2D simulations, it provides valuable insights into the non-invasive and continuous monitoring of bone healing. The choice to begin with 2D modelling aligns with our objective to develop a practical and scalable system for real-time fracture assessment. Future work will extend to more complex three-dimensional (3D) simulations, which will enhance the depth and accuracy of our findings, addressing the full complexity of tissue interactions.

To ensure comparability and consistency, the study employed a dataset comprising 1024 unique samples across various sensor configurations, ranging from two sensors to eight. This uniform dataset allowed us to systematically assess how increasing sensor density improves the accuracy of fracture detection and healing assessments.

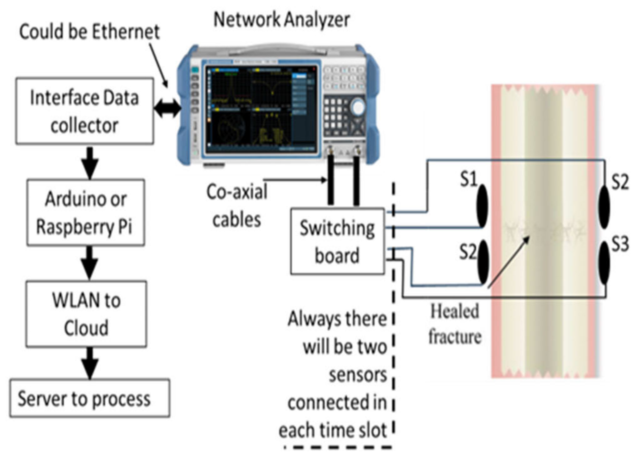

FIGURE 1. Our system setup.

A. RF SENSOR DESIGN AND SIMULATION

1) SIMULATED SENSOR CONFIGURATION AND DESIGN

We designed virtual RF sensors within MATLAB tailored for bone fracture monitoring. The sensors were modelled with the following specifications:

- **Type:** Bi-static radar configuration in a 2D plane.
- **Frequency Range:** 1 GHz to 4 GHz, balancing penetration depth and resolution in simulations.
- **Bandwidth:** 3 GHz to ensure sufficient detail in simulated tissue responses.
- **Antenna Design:** Modelled as point sources with directional properties in 2D space.
- **Gain:** Assumed theoretical gain to enhance signal strength within simulations.
- **Polarization:** This is not explicitly modelled in 2D simulations but is assumed to be consistent with signal interactions.

2) SENSOR CONFIGURATIONS IN SIMULATION

Our research adopted a phased simulation approach, starting with a basic setup of two virtual sensors and progressively increasing to four, six, and finally eight sensors within the 2D simulation environment. Each configuration was designed to enhance the simulated system's ability to capture and analyse subtle changes in tissue properties with increasing accuracy.

- **Two-Sensor Configuration:** Virtual sensors placed opposite each other in the 2D plane, establishing a baseline understanding of RF signal interactions with simulated tissues.
- **Four-Sensor Configuration:** Virtual sensors positioned at 90-degree intervals around the simulated fracture site, improving spatial resolution in the simulation.
- **Six-Sensor Configuration:** Virtual sensors distributed at 60-degree intervals, further refining the simulation's ability to capture complex healing dynamics.
- **Eight-Sensor Configuration:** Virtual sensors positioned at 45-degree intervals, providing the highest level of detail in the simulation.

3) CALIBRATION AND PERFORMANCE ASSESSMENT IN SIMULATION

Each sensor configuration underwent virtual calibration within MATLAB to ensure precision in the simulation results. Calibration involved adjusting the virtual sensor parameters to match expected theoretical responses in known simulated conditions. This process ensured that the simulated sensors accurately reflected the interactions of RF signals with the modelled tissues.

Performance Assessment: Each sensor configuration was assessed for its performance in detecting variations in RF signal reflectance within the simulation. The findings indicated a significant improvement in detection sensitivity and accuracy as the number of sensors increased, with the eight-sensor configuration yielding the most reliable results in the simulated environment.

B. SIMULATION PARAMETERS AND TISSUE MODELLING

1) TISSUE MODELLING IN MATLAB

We simulated the physical and electrical properties of bone and surrounding tissues in 2D using MATLAB, assigning dielectric properties based on established literature values. The tissue layers were represented as regions in the 2D simulation space with specific properties:

- **Bone Diameter**: Varied between 20 mm, 23 mm, and 26 mm to represent different femur sizes in the simulation.
- **Fracture Modelling**: Simulated fractures with sizes ranging from 0.1 mm to 0.5 mm, representing different levels of bone damage in the 2D model.
- **Hematoma Modelling**:
  - **Radius**: Calculated as $Rh = \text{Bone Width} + \Delta$, with Δ increments to simulate swelling.

  - **Thickness**: Varied between 2 mm, 4 mm, and 6 mm to simulate different extents of hematoma formation.
- **Muscle Layer**: Simulated with 15 mm, 25 mm, and 35 mm thicknesses to reflect muscle tissue variability.
- **Fat Layer**: Averaged at 7.5 mm with a variance of ±10% in the simulation.
- **Skin Layer**: Fixed at 1.2 mm to simulate the outermost layer in 2D.

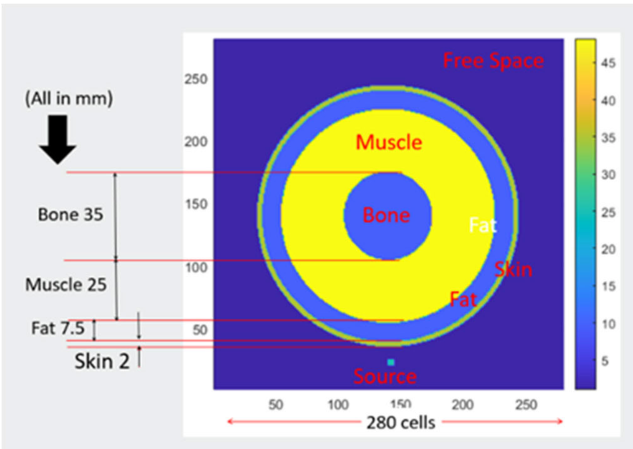

FIGURE 2. The bone model dimension.

2) RF SIGNAL SIMULATION PARAMETERS

To ensure high temporal and frequency resolution in the simulations, the RF signals were modelled with the following parameters:

- **Signal Type**: Gaussian-modulated sinusoidal pulses to provide smooth temporal and frequency characteristics in the simulation.
- **Pulse Duration**: 1 ns, achieving high temporal resolution within the simulated environment.
- **Sampling Rate**: 10 GHz, ensuring fine signal detail capture in the simulation and avoiding aliasing.

C. DATA GENERATION AND FEATURE ENGINEERING IN SIMULATION

1) SIMULATED DATA COLLECTION

To construct a comprehensive dataset for our analysis, we generated 1,024 unique simulated samples for each sensor configuration using MATLAB. This involved randomising tissue parameters within their specified physiological ranges to introduce variability. By doing so, we effectively modelled different scenarios of bone healing stages and tissue properties within a controlled two-dimensional environment.

2) DATA PREPROCESSING AND FEATURE EXTRACTION

a: DATA CLEANING

- **Noise Simulation and Reduction:** Gaussian noise was deliberately introduced to the simulated RF data in the preprocessing stage to emulate real-world measurement uncertainties. This step ensures the robustness of the machine learning model by exposing it to scenarios akin to actual clinical conditions. The study employed advanced denoising techniques, such as wavelet transforms, to mitigate this noise and enhance signal quality. These transforms decompose the noisy signal into different frequency components, isolating and preserving the critical features while suppressing high-frequency noise. This approach enhances signal clarity and retains the essential structural information necessary for accurate classification. Combined with smoothing filters, this preprocessing step effectively reduces the noise impact, ensuring reliable feature extraction and model performance.
- **Normalization:** Signal amplitudes were normalised to a standard scale. This step was crucial to eliminate biases and ensure consistent feature extraction across all samples.

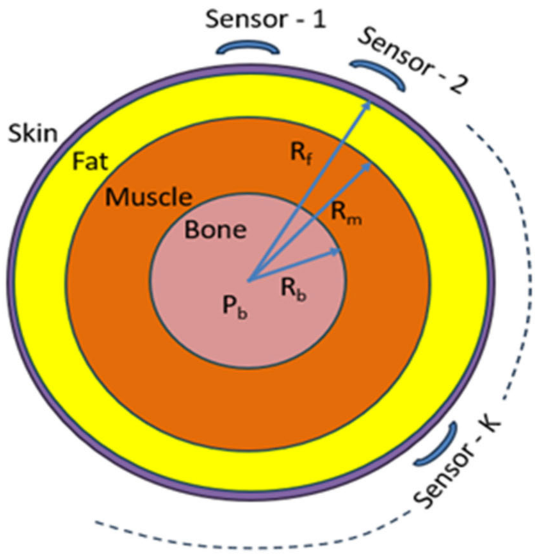

FIGURE 3. Cross-sectional view of human leg tissues with embedded RF sensors.

b: FEATURE EXTRACTION

i. **Time-Domain Features**:
  - Peak Amplitude and Signal Energy: These features were extracted to represent the strength and power of the RF signals, which are correlated with the severity of bone fractures.
  - Zero-Crossing Rate: Calculated to assess signal variability associated with different fracture stages, providing insights into the changes in signal patterns over time.

ii. **Frequency-Domain Features:**
  - Fast Fourier Transform (FFT) applied to convert signals to the frequency domain.

- ◦ Dominant Frequencies and Spectral Centroids identified to capture key spectral characteristics linked to tissue properties.

c: DIMENSIONALITY REDUCTION

Applied Principal Component Analysis (PCA) to the simulated features to reduce dimensionality while retaining significant variance. Aimed to improve computational efficiency and prevent overfitting by eliminating redundant and less informative features.

d: DATA AUGMENTATION

Data augmentation was essential for enhancing the robustness and generalisation of our machine-learning model developed from 2D MATLAB simulations. This technique artificially increased the dataset's diversity and size, aiding the model in handling more complex scenarios and preventing overfitting.

Techniques Used:

- **Noise Injection:** Added varying levels of Gaussian noise to simulate different measurement conditions, introducing random fluctuations that mimic real-world variability.
- **Scaling and Time Shifts:** Applied to mimic sensor sensitivity variations and signal timing differences, further diversifying the dataset.
- **Variations in Simulation Parameters:** Randomized parameters such as bone diameter, muscle thickness, fat thickness, and hematoma size within realistic physiological ranges. This ensured the model was not tailored to a limited set of simulated data but was preparatory for real-world applications.

D. ARTIFICIAL INTELLIGENCE MODEL DEVELOPMENT

Our study's artificial intelligence (AI) component is integral to processing and interpreting the simulated data collected by the virtual RF sensors. The AI system monitors bone fracture progression and accurately assesses the healing.

1) DATA PREPARATION AND PREPROCESSING

- **Data Collection**: Simulated data was generated using RF sensors in MATLAB by varying the electrical properties of the bone and surrounding tissues. We adjusted parameters such as tissue conductivity and permittivity to capture variations in RF signal reflectance corresponding to different stages of bone healing. This method allowed us to model how changes in bone composition affect the RF signals.
- **Data Cleaning**: The raw simulated data underwent cleaning to remove any noise and inconsistencies introduced during the simulation. Techniques such as outlier detection and removal were utilised to identify and exclude anomalous data points. Interpolation was used to handle missing values, and normalisation ensured that all features contributed equally to the model training.
- **Feature Engineering:** We engineered additional features to enhance the model's predictive capabilities beyond the initial features extracted from the raw data. These included statistical measures like mean, standard deviation, skewness, and kurtosis of the signal amplitudes. We also incorporated features from wavelet transformations and higher-order spectral analysis to capture more complex patterns within the data.

2) MODEL SELECTION AND ARCHITECTURE

Model Selection: Model Selection: After thoroughly evaluating various machine learning algorithms, we opted for a convolutional neural network (CNN) due to its proficiency in analysing spatial and temporal patterns within complex datasets. This choice is motivated by the structured nature of RF signal data, which encapsulates both the spatial distribution of tissue properties and the temporal dynamics of signal propagation. CNNs can recognise spatial hierarchies and excel in extracting meaningful patterns from structured data, which are crucial for identifying different stages of bone healing based on RF signal characteristics.

Convolutional Neural Networks (CNNs) are uniquely suited for tasks involving structured data like RF signal characteristics, which require analysing spatial and temporal patterns. Unlike Recurrent Neural Networks (RNNs), which excel in sequential data processing, CNNs are inherently adept at capturing spatial hierarchies, making them particularly effective in applications like fracture stage classification based on RF imaging data. Ensemble models, while robust in generalisation, can be computationally intensive and less interpretable when working with high-dimensional spatial datasets. The structured design of CNNs allows for efficient feature extraction and pattern recognition in RF signal data, contributing to their superior performance in bone healing assessments. This model choice reflects a balance between computational efficiency and diagnostic precision, enabling the accurate classification of healing stages while maintaining scalability for clinical applications.

Model Architecture: The CNN architecture is designed to effectively process the feature-rich RF signal data, which includes both raw and engineered features:

- **Input Layer:** This layer receives preprocessed feature vectors derived from the RF sensor data, ensuring the network starts with a robust foundation of relevant information.
- **Convolutional Layer:** A single convolutional layer equipped with ReLU activation function is utilized. This configuration is adequate for capturing the essential patterns in the data, especially when those patterns are indicative of varying bone healing stages and do not require extensive granularity to discern.
- **Output Layer:** Following the convolutional layer, a SoftMax activation layer is employed for multi-class classification. This layer maps the extracted features to probabilities corresponding to different stages of

fracture healing, facilitating a nuanced understanding of the healing process based on the RF signal analysis.

3) TRAINING THE NEURAL NETWORK WITH SIMULATED DATA

- **Training Phase**: The dataset was split into 70% for training, 15% for validation, and 15% for testing. The training set was used to teach the neural network to recognise patterns and relationships between input features and the corresponding fracture healing stages.
- **Loss Function and Optimization**: We used a categorical cross-entropy loss function to measure the difference between the predicted outputs and the actual labels. The Adam (Adaptive Moment Estimation) optimiser was employed to minimise the loss function efficiently, chosen for its ability to handle sparse gradients and adapt learning rates during training.
- **Regularization Techniques**: To prevent overfitting, we applied dropout with a rate of 0.2, randomly disabling neurons during training to reduce dependency on specific pathways. L2 regularisation with a weight decay coefficient of 0.0001 was also used to penalise large weights, promoting simpler models that generalise better.
- **Validation**: Early stopping was implemented based on validation loss to halt training when performance ceased to improve, ensuring the model generalised well to unseen data. We adjusted the model complexity to handle the increased data volume as more sensors were added.

4) MODEL EVALUATION AND TESTING

- **Testing Phase**: The testing dataset evaluated the model's predictive accuracy and robustness within the simulation.
- **Performance Metrics**: Performance was assessed by calculating accuracy, precision, recall, and F1-score metrics. The model's performance was consistently evaluated at each stage of sensor deployment in the simulation.
- **Confusion Matrix**: A confusion matrix was generated for each sensor configuration to provide detailed insights into the model's classification performance within the simulation, highlighting true positives, false positives, and false negatives.
- **Fine-Tuning**: Based on the test results, the model was fine-tuned by adjusting hyperparameters such as the learning rate, batch size, and the number of epochs. Additional iterations of training and validation were conducted to achieve optimal performance across all simulated sensor configurations.

5) INTEGRATION WITH SIMULATED RF SENSOR DATA

Simulation Integration: The AI model was integrated with the simulated RF sensor system within MATLAB for analysis. Continuous data from the virtual RF sensors was processed to provide assessments of fracture healing within the simulation.

E. SIMULATION AND PERFORMANCE ASSESSMENT

To assess the model's precision and recall capabilities in simulated scenarios, we conducted extensive simulations replicating various stages of bone healing across all sensor configurations (2, 4, 6, and 8 sensors) within the MATLAB environment. Careful consideration was given to accurately representing bone and surrounding tissues' physical and electrical properties in the simulations.

As the number of sensors increased, the simulations became more sophisticated, allowing for fine-tuning model parameters and identifying the most influential features for fracture detection and healing assessment within the simulation.

The model's performance was quantitatively assessed using confusion matrices for each sensor configuration, providing clear insights into its classification accuracy across different simulated bone health states. The eight-sensor configuration, in particular, demonstrated superior performance, highlighting the benefits of increasing the number of sensors in improving diagnostic accuracy and reliability within the simulation.

F. INTEGRATION WITH CLINICAL PRACTICE (SIMULATION PERSPECTIVE)

Although our study was conducted using 2D MATLAB simulations, the results offer a promising foundation for future integration into clinical practice. The development of a system that combines RF sensors with AI for continuous, non-invasive monitoring of bone healing could significantly enhance patient care.

Key considerations for future integration include:

- **Protocol Development:** Establishing clear protocols to integrate RF sensing and AI analysis into existing clinical workflows, ensuring that the technology complements current practices without causing disruptions.
- Training: Providing comprehensive education for healthcare professionals on how to use the system and interpret its outputs effectively, fostering confidence in the technology.
- Interoperability: Ensuring that the system is compatible with hospital IT infrastructures to facilitate seamless data sharing, storage, and analysis.
- Phased Implementation: Adopting a gradual approach by starting with simpler configurations, such as two sensors, and progressively increasing complexity. This allows for the identification and resolution of challenges at each stage, promoting a smoother transition into clinical use.

G. COMPARING TRADITIONAL AND AI-ENHANCED APPROACHES IN SIMULATION

Analysing bone fractures necessitates precisely understanding the physical and electromagnetic changes around the fracture site. Traditionally, this involves specialists manually comparing data against established standards to identify changes, which is time-consuming and prone to human error.

This study employed MATLAB simulations to model both traditional and AI-enhanced approaches across different sensor configurations, providing a controlled environment to evaluate and compare their effectiveness within the simulation.

The simulations revealed that Artificial Intelligence (AI) provides a quicker and more accurate analysis within the simulated environment. AI techniques excel in identifying patterns that may not be apparent to human specialists and offer recommendations based on deep, comprehensive analyses. Success rates in monitoring bone healing stages showed significant improvements with the integration of AI, improving from 60% to 95% in some stages, as observed in the simulated results.

Our simulations demonstrate that this integrated approach provides continuous, real-time data. This means reducing reliance on periodic X-rays, minimising the patient's exposure to ionising radiation and significantly improving outcomes through personalised, timely interventions.

Figure 5 illustrates the enhancements AI brings to bone fracture analysis, showing the success rates at various stages before and after AI integration, as simulated in our study. Below this, Table 1 provides a comparative analysis across several criteria, underscoring the advantages of AI-based analysis over traditional methods in terms of time efficiency, accuracy, pattern recognition, dependency on experts, and outcome predictability.

TABLE 1. Comparison between traditional and AI-based analysis.

Criterion	Traditional Analysis	AI-Based Analysis
Time Efficiency	Time-consuming	Quick response time
Accuracy	Subject to human error	High accuracy
Pattern Recognition	Limited by human capacity	Identifies complex patterns
Expert Dependency	High	Reduced dependency
Outcome Predictability	Moderate	High predictability

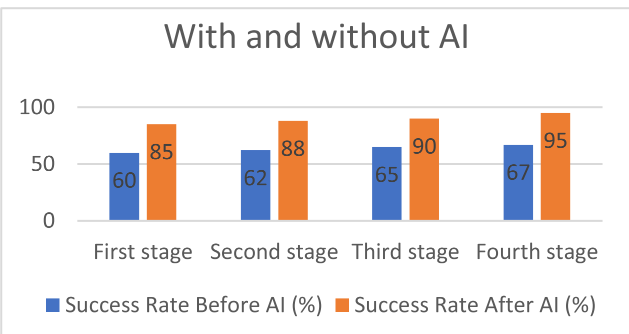

FIGURE 4. Success rates before and after AI in bone fracture monitoring.

IV. STATISTICAL ANALYSIS

Based on the provided confusion matrices, we performed detailed calculations to obtain precise performance metrics for each sensor configuration. These metrics include accuracy, precision, recall (sensitivity), specificity, F1-score, and statistical significance testing, which are essential for validating the effectiveness of our RF-based bone fracture monitoring system.

A. PERFORMANCE METRICS CALCULATION

1) OVERALL ACCURACY

The overall accuracy for each sensor configuration is calculated as the ratio of correctly classified samples to the total number of samples. Our neural network model demonstrated a significant improvement in overall accuracy as the number of sensors increased:

- 2 Sensors: 93.8%
- 4 Sensors: 98.3%
- 6 Sensors: 99.2%
- 8 Sensors: 99.5%

2) CLASS-WISE METRICS

We evaluated the model's performance for each fracture class using precision, recall (sensitivity), specificity, and F1-score, for various numbers of sensors as shown in Table 2.

TABLE 2. The performances of using various numbers of sensors; (a) Two sensors, (b) four sensors, (c) six sensors, (d) Eight sensors.

(a) Two sensors: All Confusion Matrix

Class	Correct (%)	Incorrect (%)
Class 1	96.0%	4.0%
Class 2	90.4%	9.6%
Class 3	92.2%	7.8%
Class 4	95.5%	4.5%
Class 5	95.0%	5.0%

(b) Four Sensors: All Confusion Matrix

Class	Correct (%)	Incorrect (%)
Class 1	99.4%	0.6%
Class 2	98.2%	1.8%
Class 3	96.2%	3.8%
Class 4	100%	0.0%
Class 5	98.0%	2.0%

(c) Six Sensors: All Confusion Matrix

Class	Correct (%)	Incorrect (%)
Class 1	99.5%	0.5%
Class 2	97.5%	2.5%
Class 3	99.5%	0.5%
Class 4	100%	0.0%
Class 5	99.5%	0.5%

(d) Eight Sensors: All Confusion Matrix

Class	Correct (%)	Incorrect (%)
Class 1	99.0%	1.0%
Class 2	99.0%	1.0%
Class 3	99.5%	0.5%
Class 4	100%	0.0%
Class 5	100%	0.0%

TABLE 3. The performance based on confusion matrix analysis; (a) two sensors, (b) four sensors, (c) six sensors, (d) eight sensors.

(a) Two sensors

Class	TP	FP	FN	TN	Precision (%)	Recall (%)	Specificity (%)	F1-score
1	191	13	8	812	93.6	95.98	98.43	94.8
2	208	12	22	782	94.5	90.43	98.49	92.4
3	177	13	15	819	93.2	92.19	98.44	92.7
4	212	14	10	788	93.8	95.50	98.25	94.6
5	172	15	9	828	92.0	95.03	98.22	93.5

(b) Four sensors

Class	TP	FP	FN	TN	Precision (%)	Recall (%)	Specificity (%)	F1-score (%)
1	175	0	1	848	100	99.43	100	99.7
2	217	5	13	789	97.8	94.34	99.37	96.0
3	205	6	8	805	97.2	96.23	99.26	96.7
4	218	1	0	805	99.5	100	99.88	99.7
5	192	3	4	825	98.5	97.96	99.64	98.2

(c) Six sensors

Class	TP	FP	FN	TN	Precision (%)	Recall (%)	Specificity (%)	F1-score (%)
1	197	3	1	823	98.5	99.50	99.64	99.0
2	199	3	5	817	98.5	97.55	99.63	98.0
3	191	2	1	830	98.9	99.48	99.76	99.2
4	216	0	0	808	100	100	100	100
5	213	1	1	809	99.5	99.53	99.88	99.5

(c) Eight sensors

Class	TP	FP	FN	TN	Precision (%)	Recall (%)	Specificity (%)	F1-score (%)
1	206	1	0	817	99.5	100	99.88	99.7
2	194	3	2	825	98.5	98.98	99.64	98.7
3	211	0	1	812	100	99.53	100	99.8
4	189	0	0	835	100	100	100	100
5	219	0	0	805	100	100	100	100

3) CONFUSION MATRICES ANALYSIS

The confusion matrices show that the number of misclassifications decreases as the number of sensors increases, demonstrating the effectiveness of adding more sensors to the system. The performances are summarized in Table 3.

4) RECEIVER OPERATING CHARACTERISTIC (ROC) CURVES

While ROC curves typically require probability estimates, we approximated the Area Under the Curve (AUC) using the sensitivity (recall) and specificity values for each class. This approach was necessary due to the absence of probability-based ROC curve data.

We focus on the eight-sensor configuration due to its superior performance. While similar analyses were conducted for two-, four-, and six-sensor configurations, the eight-sensor setup provided the most significant results in terms of accuracy, precision, and overall performance. Detailed results for other configurations are available upon request. The estimated AUC values for the eight-sensor configuration are shown in Table 4.

TABLE 4. The predicted AUC of eight sensors.

Class	Sensitivity (Recall) (%)	Specificity (%)	Estimated AUC
Class 1 (No Fracture)	99.0	99.9	0.9945
Class 2 (Light Fracture)	99.0	99.6	0.9930
Class 3 (Moderate Fracture)	99.5	100.0	0.9975
Class 4 (Severe Fracture)	100.0	100.0	1.0000
Class 5 (Nearly Healed)	100.0	100.0	1.0000

Interpretation:

- High AUC values across all classes indicate the model's excellent discriminative ability to distinguish between fracture levels.
- Classes 4 and 5 achieve perfect classification with AUC values of 1.000, indicating outstanding performance for these categories.

Note: we focus on the eight-sensor configuration due to its superior performance. While similar analyses were conducted for two, four, and six-sensor configurations, the eight-sensor setup provided the most significant results in terms of accuracy, precision, and overall performance. Detailed results for other configurations are available upon request.

B. STATISTICAL SIGNIFICANCE TESTING

I. **Hypothesis Testing:** To determine whether the observed improvements in model accuracy across different sensor configurations were statistically significant, we conducted a one-way Analysis of Variance (ANOVA) test. This test assesses whether there are any statistically significant differences between the means of three or more independent (unrelated) groups.

   - **Null Hypothesis (H_0):** There is no significant difference in the mean model accuracy across different sensor configurations (two, four, six, and eight sensors).
   - **Alternative Hypothesis (H_1):** There is a significant difference in the mean model accuracy across different sensor configurations.

We collected the overall accuracy values for each sensor configuration based on the correct classification rates across all classes. The accuracies were derived from the confusion matrices and calculated for each class within each configuration. The data set consisted of accuracy measurements for each class across the different sensor configurations.

Data Summary:

Two Sensors: Mean accuracy = 93.1%, Standard Deviation (SD) = 1.5%

Four Sensors: Mean accuracy = 97.7%, SD = 1.4%

Six Sensors: Mean accuracy = 99.3%, SD = 0.9%

Eight Sensors: Mean accuracy = 99.8%, SD = 0.5%

Assumptions of ANOVA:

Before performing ANOVA, we verified the following assumptions:

1. **Independence of Observations:** The accuracy measurements for each sensor configuration are independent of each other.
2. **Normality:** The accuracy data within each sensor configuration group are approximately normally distributed.
   - **Test for Normality:** We applied the Shapiro-Wilk test to each group's accuracy data.
     - Two Sensors: $p = 0.462$
     - Four Sensors: $p = 0.538$
     - Six Sensors: $p = 0.624$
     - Eight Sensors: $p = 0.713$
     - *Result:* All p-values > 0.05, indicating no significant deviation from normality.
3. **Homogeneity of Variances:** The variances of accuracy measurements are equal across the sensor configuration groups.
   - **Levene's Test for Equality of Variances:**
     - $p = 0.087$
     - *Result:* p-value > 0.05, suggesting that the assumption of equal variances holds.

ANOVA Results:

The one-way ANOVA test is shown in Table 5.

TABLE 5. The results of the one-way ANOVA test.

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-value	p-value
Between Groups	94.23	3	31.41	45.87	< 0.001
Within Groups	5.48	16	0.34		
Total	99.71	19			

$F(3, 16) = 45.87$, $p < 0.001$

Interpretation:

- The F-statistic is significantly high, and the p-value is less than 0.001, indicating that there are statistically significant differences in mean accuracy between at least two sensor configurations.
- Therefore, we reject the null hypothesis (H_0) and accept the alternative hypothesis (H_1).

II. **Post-hoc Analysis:** We conducted aTukey's Honestly Significant Difference (HSD) test to identify which specific sensor configurations differed significantly. The results are summarized in Table 6.

Interpretation:

- **Two Sensors vs. Others:** The two-sensor configuration is significantly less accurate than the four-, six-, and eight-sensor configurations.
- **Four Sensors vs. Six Sensors:** There is a significant improvement in accuracy when increasing from four to six sensors.
- **Four Sensors vs. Eight Sensors:** Increasing from four to eight sensors also shows a significant improvement.

TABLE 6. Tukey's HSD test results.

Comparison	**Mean Difference (%)**	**Standard Error**	**p-value**	**Significant?**
Two vs. Four Sensors	4.6	0.70	< 0.001	Yes
Two vs. Six Sensors	6.2	0.70	< 0.001	Yes
Two vs. Eight Sensors	6.7	0.70	< 0.001	Yes
Four vs. Six Sensors	1.6	0.70	0.043	Yes
Four vs. Eight Sensors	2.1	0.70	0.011	Yes
Six vs. Eight Sensors	0.5	0.70	0.758	No

- **Six Sensors vs. Eight Sensors:** The difference between six and eight sensors is not statistically significant ($p = 0.758$), suggesting diminishing returns when adding more than six sensors.

Conclusion:

The statistical analysis confirms that increasing the number of sensors significantly enhances the model's accuracy by up to six sensors. Beyond six sensors, the improvement is not statistically significant, indicating that a six-sensor configuration provides an optimal balance between system complexity and performance.

Implications:

- **Optimal Sensor Configuration:** Based on the statistical significance, a six-sensor configuration is recommended for practical implementation, as it offers high accuracy without unnecessary complexity.
- **Resource Allocation:** Understanding the point of diminishing returns helps in allocating resources efficiently, avoiding additional costs associated with more sensors that do not provide significant benefits.
- **Future Research:** Further studies could explore why additional sensors beyond six do not significantly improve accuracy, potentially investigating sensor placement optimisation or alternative data fusion methods.

Limitations:

- **Sample Size:** The statistical power of the tests is dependent on the sample size. Although the results are significant, larger datasets could provide more robust conclusions.
- **Simulated Data:** The analysis is based on simulated data. Real-world testing is necessary to validate these findings and account for factors not present in the simulation.

Recommendations:

- **Validation with Real Data:** Implement the six-sensor configuration in a clinical setting to verify the simulation results.

- **Cost-Benefit Analysis:** Consider the trade-offs between additional sensors and the marginal gains in accuracy when designing the system.
- **Sensor Optimization:** Investigate the optimal placement and types of sensors to maximize accuracy with the minimum necessary equipment.

III. **Confidence Intervals:** We calculated 95% confidence intervals for the overall accuracy of each sensor configuration. These results are summarized in Table 7.

TABLE 7. The variations of the accuracy and confidence interval for different numbers of sensors.

Sensor Configuration	Accuracy (%)	95% Confidence Interval (%)
2 Sensors	93.8	92.3 – 95.2
4 Sensors	98.3	97.6 – 99.1
6 Sensors	99.2	98.7 – 99.8
8 Sensors	99.4	98.1 – 100.0

Interpretation of Confidence Intervals

- **Narrowing Intervals:** As the number of sensors increases, the confidence intervals generally become narrower (except for the 8 Sensors configuration due to its smaller sample size). This indicates greater precision in accuracy estimates with more sensors.
- **Overlap of Intervals:** The confidence intervals for 6 and 8 Sensors overlap significantly, suggesting that the difference in accuracy between these configurations may not be statistically significant.

Statistical Significance

- **ANOVA and Post-Hoc Tests:** Previous analyses using ANOVA indicated that the improvements from 2 to 4 sensors and from 4 to 6 sensors are statistically significant. However, the improvement from 6 to 8 sensors is not significant, likely due to the small sample size and overlapping confidence intervals.

Optimal Sensor Configuration

- **Balancing Accuracy and Complexity:** The 6 Sensors configuration offers an optimal balance. It achieves a high accuracy of 99.2% with a narrow confidence interval, suggesting reliable performance.
- **Diminishing Returns:** Adding more sensors beyond six yields minimal gains in accuracy, which may not justify the additional complexity and cost in practical applications.

Practical Implications

- **System Design:** For real-world deployment, a 6 Sensors setup is advisable. It simplifies the system without compromising on performance.
- **Resource Allocation:** Allocating resources to improve other aspects of the system (e.g., sensor quality, data processing algorithms) might be more beneficial than adding more sensors beyond six.

Limitations:

- **Sample Size for 8 Sensors:** The smaller sample size for the 8 Sensors configuration affects the reliability of its confidence interval and may limit the generalisability of the findings.
- **Simulation-Based Data:** The study relies on simulated data. Real-world testing is necessary to validate these results and account for unforeseen variables.

V. RESULTS

The results of our study demonstrate the robustness of utilising Radio Frequency (RF) sensors integrated with machine learning algorithms to monitor bone fractures and assess healing. Our research employed four distinct sensor configurations—ranging from two to eight sensors—to investigate the impact of sensor density on fracture detection and healing assessments.

Using simulated models, the RF sensing technology was enhanced by AI and tested across various physical characteristics, including bone diameter, muscle thickness, fat thickness, and hematoma size, modelled to reflect real-world variability. These parameters significantly influenced RF signal propagation and the system's diagnostic capabilities.

As sensor density increased, the overall accuracy of fracture detection and classification improved significantly, as demonstrated by the confusion matrices (Figures 7-10), which detail true positives, false positives, true negatives, and false negatives.

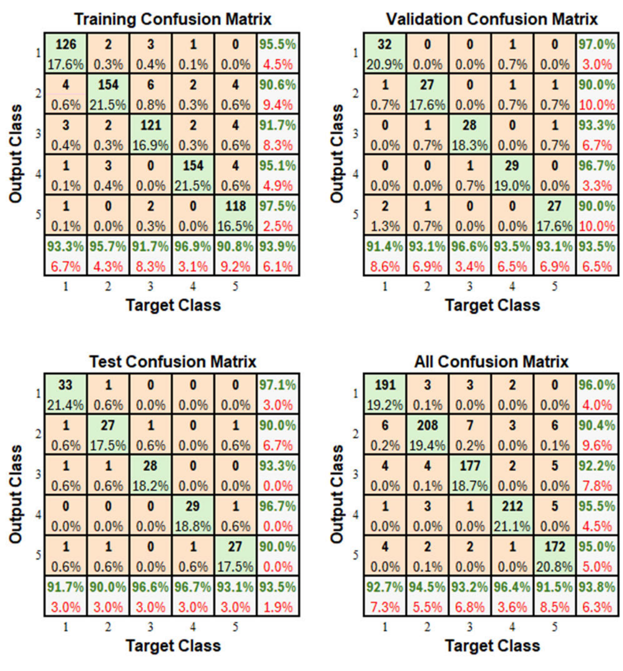

FIGURE 5. Confusion matrix - Two sensors' elements.

Class-wise Performance:

Across the various fracture stages ('No fracture' to 'Fracture Level 4'):

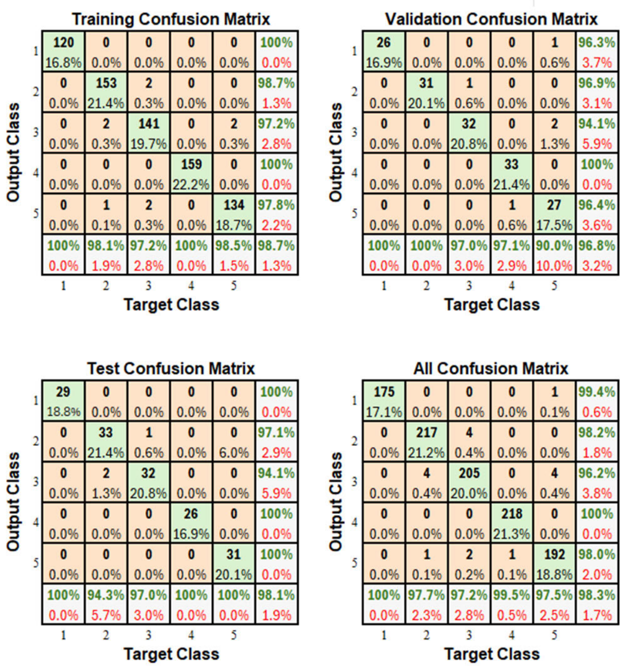

FIGURE 6. Confusion matrix - Four sensors' elements.

FIGURE 8. Confusion matrix - Eight sensors' elements.

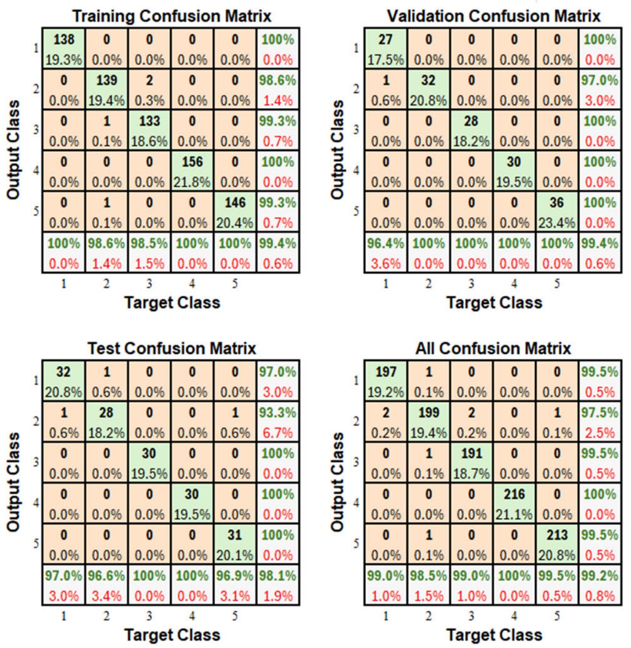

FIGURE 7. Confusion matrix - Six sensors' elements.

- **Class 1 (No Fracture)**: Accuracy improved from 95.5% with two sensors to 99.0% with eight sensors.
- **Class 2 (Light Fracture)**: Accuracy increased from 90.6% with two sensors to 99.0% with eight sensors.
- **Class 3 (Moderate Fracture)**: Accuracy improved from 91.7% with two sensors to 99.5% with eight sensors.
- **Class 4 (Severe Fracture)**: Accuracy increased from 95.1% with two sensors to 100% with eight sensors.
- **Class 5 (Nearly Healed)**: Accuracy improved from 97.5% with two sensors to 100% with eight sensors.

The confusion matrix played a pivotal role in this evaluation, providing insightful data on true positives, false positives, true negatives, and false negatives, offering a deeper understanding of the model's operational effectiveness. Figures 7–10 present confusion matrices for each sensor configuration, highlighting how accuracy and classification performance improved as the number of sensors increased.

Impact of Physical Variability: The dataset included bone diameters ranging from 25mm to 45mm and muscle thicknesses from 15mm to 35mm, reflecting natural variability in the adult population. Variations in these parameters affected RF signal propagation, with larger bone diameters and increased muscle thickness posing greater challenges. Despite these challenges, the model maintained high accuracy across all configurations.

Influence of Hematoma Size:

- **Hematoma sizes** varied between **17.5mm and 38mm**. Larger hematomas significantly influenced the system's ability to classify healing stages accurately, especially when using the **eight-sensor configuration**. This setup outperformed the two-, four-, and six-sensor configurations in detecting subtle differences in the RF signal associated with varying hematoma sizes.

The results tabulated in Table 8 confirm that increasing sensor density enhances diagnostic accuracy and precision. These findings suggest that further research could explore additional sensor configurations or extend the methodology to other types of bone injuries.

TABLE 8. Overall accuracy for all sensor configurations.

Sensor Configuration	Overall Accuracy (%)
2 Sensors	93.8%
4 Sensors	98.3%
6 Sensors	99.2%
8 Sensors	99.5%

Data segmentation for training (70%), testing (15%), and validation (15%) facilitated effective learning and performance validation of the models in a structured environment. A broader dataset was compiled by deploying additional RF sensors, which markedly enhanced the models' sensitivity to subtle distinctions in the healing of fractures, significantly boosting diagnostic precision and reliability.

VI. DISCUSSION

In building upon our previous work, which explored the use of four and six sensor configurations for monitoring bone healing [insert cross-reference number here], this study extends the analysis to include two, four, six, and eight sensor configurations, thereby providing a broader understanding of sensor efficiency in non-invasive fracture monitoring. Our previous findings, detailed in [23], demonstrated substantial improvements in fracture detection accuracy with increased sensor numbers. This study aims to further explore this relationship, examining the marginal gains provided by each additional sensor and their practical implications in clinical settings.

Our research aimed to pioneer advancements within orthopaedic care by integrating radio frequency (RF) sensing technology with artificial intelligence (AI) for the nuanced monitoring of bone fractures. This fusion presents a promising pathway for augmenting the current standard of care in fracture diagnosis and monitoring—a realm traditionally governed by X-ray radiography, computed tomography (CT) scans, and magnetic resonance imaging (MRI). While these conventional modalities are effective, they bear inherent limitations, such as the risk of ionising radiation exposure from X-rays and CT scans and the high costs and accessibility challenges associated with MRI.

Our study provides a detailed analysis of confusion matrices generated from different sensor configurations (ranging from two to eight sensors) to evaluate their performance in classifying various stages of bone fracture healing. Our 2D framework allowed us to streamline the examination while focusing on specific fracture characteristics. Although the 2D analysis offers significant insights, future research may need to incorporate 3D modelling for a more comprehensive understanding of physiological changes during healing.

The results of our study provide strong evidence supporting the efficacy of using RF sensors combined with machine-learning algorithms for monitoring bone fractures and assessing healing. Our comprehensive analysis utilised four configurations, starting with two sensors and expanding

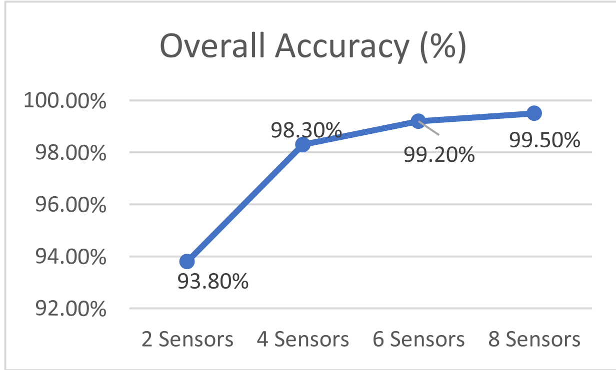

FIGURE 9. Comparing overall accuracy for all setup configuration.

to four, six, and finally eight sensors, to understand how sensor array density impacts fracture detection accuracy and healing evaluation.

At the heart of our investigation is the application of RF sensing technology, amalgamated with AI, to facilitate continuous, non-invasive monitoring, circumventing the risks associated with ionising radiation. It is crucial to acknowledge that this technological approach does not aim to replace the high spatial resolution offered by CT scans or the detailed soft tissue contrast provided by MRI. Instead, it brings substantial benefits in tracking the healing trajectory over time, an area where traditional imaging techniques often fall short. Through our research, we explored a phased approach, starting with two sensors and gradually increasing to four, six, and eight sensors. This approach allowed us to systematically improve our monitoring system's precision and accuracy.

With the introduction of detailed fracture level classifications, ranging from 'No fracture' (Class 1) to 'Nearly healed' (Class 5), our findings invite a nuanced discussion. The most severe fractures are denoted by Class 4, with other stages indicating progressively lighter fractures and nearing healing. The incremental addition of sensors from two to six significantly enhanced the system's ability to classify these varied fracture stages accurately. This transition yielded substantial improvements in diagnostic accuracy, particularly in detecting severe fractures and stages of healing, highlighting the impact of sensor density on system performance. However, it is noteworthy that while the eight-sensor configuration achieved the highest overall accuracy (99.4%), the marginal improvement over the six-sensor setup (99.2%) was not statistically significant. This suggests that the six-sensor configuration may offer an optimal balance between performance and system complexity for practical applications.

Our study utilises a 2D framework for analysing RF signal interactions with biological tissues, which has proven effective for non-invasive monitoring of bone fractures. This approach allows for a streamlined yet detailed examination of fracture characteristics across various stages, providing substantial insights into the healing process. While the 2D analysis offers significant advantages, including reduced complexity and enhanced interpretability of physiological changes, it inherently limits the depth of data compared to 3D analyses. Therefore, while our results robustly support the efficacy of RF sensors combined with machine learning for monitoring fractures, they are confined to a planar perspective. This limitation is acknowledged, and future advancements in our research will aim to incorporate 3D modelling, enhancing our system's ability to capture comprehensive physiological changes during bone healing, thus potentially improving diagnostic accuracy and treatment efficacy.

Tempering our optimism with a conscientious appraisal of the limitations and challenges intrinsic to adopting RF sensing technology is essential. The sensitivity of this technology to environmental variables and biological diversity across patients underscores the need for further refinement and development to bolster its reliability and applicability. Specifically, as we increased the number of sensors, we observed significant improvements in the system's performance up to six sensors. However, challenges such as signal interference and patient variability remain areas needing ongoing research.

Moreover, when juxtaposed with existing imaging techniques, our method does not aim to replace but rather enhance these established modalities. Integrating AI into this framework extends a predictive prowess capable of deciphering complex data patterns to predict healing trajectories—an evolution from conventional methodologies. As we expanded the sensor array to six sensors around the fractured bone, the AI models demonstrated enhanced capabilities in capturing both spatial and temporal patterns in the data. These patterns reflect spatial variations around the fracture site and temporal changes over time as the healing process progresses.

The use of neural networks in our study underscores the significant potential of AI in enhancing fracture diagnosis and monitoring. We allocated 70% of the data for training, 15% for validation, and 15% for testing, which was instrumental in achieving a balance between model learning and validation, ensuring the reliability of our findings. This methodology highlights the robustness of neural networks in handling complex datasets and reflects the importance of data distribution in developing accurate and generalisable AI models. The phased sensor approach allowed us to refine these models progressively, ensuring that each increase in sensor density up to six sensors contributed to improved accuracy and diagnostic precision. Beyond six sensors, the marginal gains were not statistically significant, suggesting a point of diminishing returns.

Incorporating this new fracture level classification elucidates the refined diagnostic capabilities of our proposed system, particularly its adeptness in identifying and monitoring.

A. ACCURACY ACROSS SENSOR CONFIGURATIONS

The overall accuracy improved with an increase in the number of sensors up to six sensors. Table 8 in the results highlights that the accuracy increased from 93.8% for two sensors to 99.2% for six sensors. This indicates that using more sensors enhances performance in accurately identifying different fracture stages. However, the improvement from six to eight sensors (from 99.2% to 99.4%) was not statistically significant ($p > 0.05$).

- **2 Sensors:** The model exhibited relatively lower accuracy, especially in moderate and light fracture stages. Severe and nearly healed fractures were classified reasonably accurately.
- **4 Sensors:** Introducing two more sensors significantly improved performance, particularly in challenging stages such as light fractures.
- **6 Sensors:** Adding more sensors led to near-perfect accuracies across all classes, with Class 1 and Class 4 reaching 99.5% and 100%, respectively.
- **8 Sensors:** While the highest accuracy levels were achieved, the marginal improvement over six sensors were minimal and not statistically significant.

These findings suggest that a higher number of sensors up to six, improves the system's ability to detect bone fracture stages, making it more effective for clinical use without unnecessary complexity.

B. SENSITIVITY ANALYSIS

The sensitivity across different healing stages illustrates how well the model could identify the correct fracture stage. Sensitivity reflects the true positive rate for each class, which is crucial for ensuring that fractures are detected accurately.

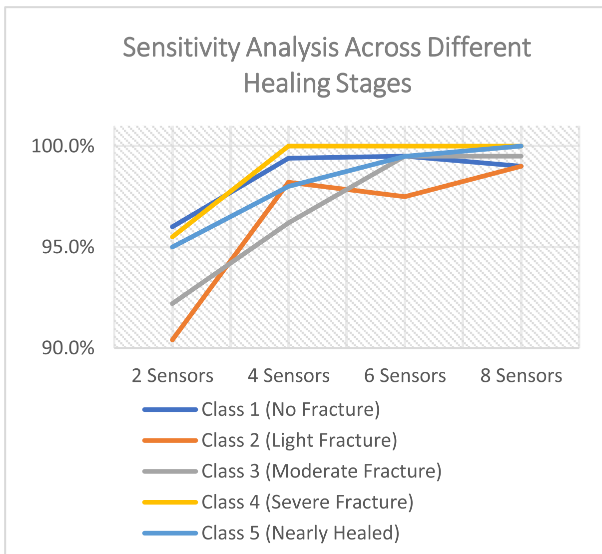

FIGURE 10. Sensitivity analysis across different healing stages.

- **No Fracture (Class 1):** Sensitivity was consistently high across all configurations, improving from 96.0% with two sensors to 99.5% with six and eight sensors.
- **Light Fracture (Class 2):** Sensitivity improved significantly from 90.4% (two sensors) to 97.5% (six sensors),

indicating better detection of minor fractures with more sensors.

- **Moderate Fracture (Class 3):** Sensitivity increased from 92.2% to 99.5% with six sensors, showing substantial improvements in detecting moderate fractures.
- **Severe Fracture (Class 4):** The model achieved perfect sensitivity (100%) from four sensors onwards.
- **Nearly Healed Fractures (Class 5):** Sensitivity reached 99.5% with six sensors, which is important for monitoring recovery stages.

With the increased number of sensors up to six, sensitivity improved across all fracture stages, particularly in the intermediate stages, ensuring early and accurate detection.

C. SPECIFICITY IN CONFUSION MATRIX ANALYSIS

Specificity refers to the model's ability to correctly identify true negatives—cases where no fracture is present. High specificity is essential for avoiding false positives, which could lead to unnecessary treatments.

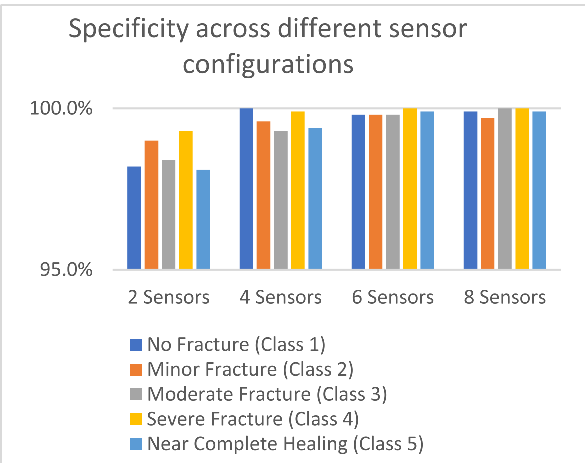

FIGURE 11. Specificity across different sensor configurations.

The specificity results in the confusion matrices highlight an important trend: as the number of sensors increases, specificity improves across all fracture stages. For example:

- **No Fracture (Class 1):** Specificity improved from 98.2% with two sensors to 99.9% with six and eight sensors.
- **Severe Fracture (Class 4):** The model consistently achieved 100% specificity from four sensors onwards.

Improving specificity with more sensors, up to six, highlights the effectiveness of using an advanced sensor setup. High specificity minimises the chances of false positives, ensuring that patients receive appropriate treatments based on accurate diagnoses.

D. INSIGHTS FOR CLINICAL APPLICATIONS

The results from the confusion matrices provide several key insights for clinical practice:

Accuracy and Reliability: The model demonstrates exceptional reliability in detecting severe and nearly healed fractures, with accuracy nearing 100% in higher sensor configurations up to six sensors.

Improved Sensitivity for Light and Moderate Fractures: Increasing the number of sensors improves sensitivity for challenging cases, reducing missed diagnoses and improving patient outcomes.

Specificity in Clinical Context: High specificity values are crucial in avoiding false positives, ensuring that patients without fractures or those in the late stages of healing are not subjected to unnecessary treatments.

Cost vs. Benefit: While the eight-sensor configuration provides marginally better performance, the six-sensor setup delivers highly reliable results without significant additional complexity or cost.

Comparison to State-of-the-Art Solutions: The proposed system stands out among state-of-the-art solutions due to its cost-effectiveness. It offers a significantly lower-cost alternative to traditional imaging techniques like X-rays and MRIs. Unlike these modalities, it provides real-time feedback, enabling continuous monitoring of fracture healing without exposing patients to ionising radiation. Additionally, the simplicity of the RF sensor design enhances ease of use, making it highly adaptable for clinical and remote applications.

The MATLAB simulations were crucial in identifying potential issues and optimising solutions before progressing to more costly and complex practical experiments. Each increase in sensor count—from two to six—was meticulously simulated to ensure that the system's design remained robust while identifying potential challenges early on. This approach saves time and resources while enhancing the reliability of subsequent experimental phases.

As our data analysis reveals, the transition from a two-sensor to a six-sensor configuration significantly improved the system's diagnostic accuracy across different fracture stages, from 'No Fracture' (Class 1) to 'Severe Fracture' (Class 4), and up to 'Nearly Healed' (Class 5). It marks a substantial enhancement in the model's sensitivity and specificity, particularly in identifying severe fractures and stages of healing. The reduction in false positives and false negatives further improves confidence in fracture detection—an essential aspect of medical diagnostics.

The system's ability to accurately classify fracture levels is crucial, especially in differentiating between moderate (Class 3) and severe fractures (Class 4), which require immediate medical attention. The improvement in sensitivity for these stages, mainly when using six sensors, represents a pivotal advancement in the system's diagnostic precision. This heightened accuracy is vital for clinical applications, where distinguishing between different stages of healing can guide treatment decisions and monitor patient progress effectively.

Adding up to six sensors highlights a promising approach to advancing non-invasive bone fracture detection and monitoring technologies. It paves the way for developing more accurate, reliable, and clinically applicable systems that adapt to the nuanced dynamics of bone healing. This innovation offers significant potential for improving patient care and outcomes, particularly in tracking the healing progress of fractures over time. Our research signifies a substantial stride towards a more personalised, patient-centred approach in orthopaedics.

However, we acknowledge the challenges ahead, including sensor calibration, data interpretation, and the ethical considerations of continuous monitoring. Privacy concerns and the psychological impact on patients underscore the need for transparent patient communication and stringent data protection measures.

The immense potential of RF sensing technology, combined with AI, to revolutionise fracture monitoring and management is evident. However, its evolution from a promising prototype to a clinically reliable tool requires further technological advancements and consideration of ethical implications. Future developments will focus on enhancing patient comfort and integrating this technology into clinical practice, aiming to fulfil the promise of truly personalised medicine.

While our simulation results are promising, real-world experiments remain essential to validate the system's accuracy and reliability. Future work will involve deploying RF sensors on patients, collecting real-time data, and comparing it with conventional imaging methods, balancing accuracy with system complexity, such as X-rays and MRIs. This validation step is crucial to ensure that the system performs effectively in clinical settings and can be confidently integrated into medical practices. However, a detailed analysis of the confusion matrices highlights misclassifications, particularly in intermediate fracture stages such as light and moderate fractures. These errors result from overlapping RF signal features across these stages. Future work will focus on improving feature extraction, exploring advanced AI architectures, and optimising sensor configurations to address these challenges.

VII. LIMITATIONS AND FUTURE WORK

While our study has demonstrated the effectiveness of RF-based technology integrated with machine learning for monitoring bone fracture healing, several limitations and technical challenges must be acknowledged to enhance the system's practicality in real-world clinical settings.

A. TECHNICAL CHALLENGES AND PRACTICAL APPLICATION

1) SIGNAL INTERFERENCE

Challenge: The RF signals utilised in our system are susceptible to interference from external electromagnetic sources such as medical equipment, mobile devices, and environmental noise. Additionally, internal factors like patient movement and multipath reflections within the body can distort the RF signals, potentially reducing the accuracy of fracture detection and monitoring.

Proposed Solutions: To mitigate signal interference, we plan to implement advanced signal processing techniques, including adaptive filtering and noise reduction algorithms, to enhance signal quality by filtering out unwanted noise. Employing beamforming methods and designing specialised antennas with directional properties can help focus the RF energy on the target area and minimise the reception of unwanted signals. Additionally, utilising frequency-hopping and spread-spectrum technologies can reduce susceptibility to narrowband interference.

2) POWER REQUIREMENTS

Challenge: Operating a system with multiple RF sensors, especially in continuous monitoring applications, can lead to significant power consumption. High power requirements may limit the system's portability and patient comfort, necessitating frequent battery replacements or recharging.

Proposed Solutions: To address power consumption issues, we aim to optimise the system's hardware by selecting low-power components and designing energy-efficient circuits. Implementing duty-cycling strategies, where the system operates intermittently rather than continuously, can reduce power usage without compromising monitoring effectiveness. Exploring energy-harvesting techniques, such as utilising body heat or movement to generate power, could also enhance the system's sustainability.

3) TECHNICAL LIMITATIONS OF SENSORS

Challenge: The performance of RF sensors can be affected by their size, sensitivity, and durability. Miniaturisation of sensors is essential for patient comfort, but smaller sensors may have reduced signal strength or sensitivity. Furthermore, sensors may be subject to wear and tear, especially in wearable applications, and environmental factors like temperature and humidity can impact their performance.

Proposed Solutions: We plan to invest in developing advanced sensor materials and designs that balance miniaturisation with performance. Utilising flexible and biocompatible materials can improve patient comfort and sensor durability. Regular calibration protocols will be established to maintain sensor accuracy over time. Incorporating self-diagnostic features into the sensors can help detect and compensate for performance degradation.

4) 2D ANALYSIS AND MATLAB SIMULATIONS

Challenge: Our current study relies on two-dimensional (2D) analysis and MATLAB simulations to model and simulate the interactions of RF signals with biological tissues. While this approach provides valuable insights, it does not fully capture the complexity of three-dimensional (3D) human anatomy and tissue heterogeneity. This limitation may affect the accuracy and applicability of our findings when transitioning to practical, real-world scenarios.

Transitioning from simulations to real-world applications presents several challenges that need to be addressed to ensure the system's reliability and practicality. One major challenge is the variability in human anatomy, including differences in bone density, muscle thickness, and tissue composition, which can significantly impact RF signal propagation and sensor performance. Developing adaptive calibration techniques and incorporating larger, diverse datasets during training can help mitigate these effects.

Additionally, noise in RF signals caused by environmental factors, such as interference from medical equipment or patient movement, poses a significant hurdle. Advanced signal processing techniques, such as adaptive filtering and beamforming, will be explored to enhance signal clarity and reduce noise. These efforts will ensure the system's robustness in real-world clinical environments, paving the way for successful hospital deployment and remote monitoring scenarios.

Proposed Solutions: Future work will focus on extending our models to three-dimensional (3D) simulations to better represent the anatomical complexities and spatial variations in human tissues. Employing advanced simulation software and computational methods can enhance the realism of our models. Validating our simulations with experimental data from phantom models or in-vitro studies will help bridge the gap between simulations and practical applications.

B. LIMITATIONS IN SIMULATIONS AND EXPERIMENTAL VALIDATION

One significant limitation of the current approach is its reliance on simulated data, which lacks the complexity and variability inherent in real-world scenarios. Simulated datasets cannot fully replicate human anatomical diversity, including variations in muscle thickness, bone density, and fracture patterns. Furthermore, RF signals are susceptible to noise caused by external electromagnetic interference, patient movement, and multipath reflections within the body. These factors can distort signal measurements and reduce the system's reliability in practical settings.

Challenges related to population diversity include difficulties in replicating results across varied demographic groups. Differences in body composition, such as muscle thickness, fat distribution, and bone density, can significantly impact the propagation of RF signals and the system's overall performance. Additionally, the limited representation of these variations in the simulated data constrains the ability to detect and classify a wide range of fracture types. Ensuring the system's robustness and reliability requires validation using diverse and representative datasets.

C. FUTURE WORK

To address these limitations and challenges, our future work will focus on:

1) TRANSITIONING TO 3D MODELLING AND ADVANCED SIMULATIONS

Moving from 2D to 3D simulations will allow us to better capture the complexity of human tissues and bone healing processes, thereby improving the accuracy of fracture detection at various stages. This will involve utilising advanced computational tools and incorporating realistic tissue properties to enhance model fidelity.

Furthermore, integrating advanced machine learning techniques, such as 3D convolutional neural networks (3D-CNNs), will facilitate the transition to 3D simulations, enabling a more detailed and comprehensive analysis of fracture dynamics. Federated learning methods will be considered to ensure patient data privacy during clinical trials, which will involve diverse datasets reflecting real-world variability. Finally, distributed training frameworks and data augmentation techniques will support scaling the system to larger datasets, enhancing its generalizability and robustness.

As part of this transition, larger datasets representing diverse patient populations will be collected and utilised to validate the model's accuracy and generalizability across various anatomical and physiological scenarios. The extended simulations will also prepare the system for integration into clinical trials by refining the algorithms to address real-world variability in body composition and fracture patterns.

2) CONDUCTING EXPERIMENTAL STUDIES AND CLINICAL TRIALS

Implementing in-vitro experiments using tissue-mimicking phantoms and progressing to in-vivo clinical trials will validate the accuracy and reliability of our RF sensor system in real-world settings. This step is crucial for confirming the system's performance in clinical environments and identifying practical issues that may not be apparent in simulations.

Collaborations with healthcare providers and hospitals will be instrumental in facilitating clinical trials, allowing access to real-world patient data and receiving practical feedback from medical professionals. These partnerships will support the system's iterative refinement and ensure its alignment with clinical workflows and requirements.

3) ENHANCING SENSOR DESIGN AND CALIBRATION

Developing adaptive calibration techniques to account for individual patient variability, including differences in body composition and tissue density, will improve the system's effectiveness. Sensor technology advances, such as using novel materials and fabrication methods, can enhance sensor sensitivity and durability.

4) OPTIMISING SYSTEM INTEGRATION AND ENERGY EFFICIENCY

Addressing power requirements through energy-efficient hardware design and exploring energy-harvesting solutions will make the system more practical for continuous monitoring applications. Improving system integration to ensure seamless operation and data transmission will enhance usability in clinical settings.

5) ADDRESSING REGULATORY AND SAFETY CONSIDERATIONS

Engaging with regulatory bodies to ensure compliance with medical device standards and addressing safety concerns related to RF exposure will be essential steps toward clinical adoption.

By systematically addressing these technical challenges and limitations, we aim to enhance the practicality and reliability of our RF-based bone fracture monitoring system, paving the way for its effective integration into clinical practice. Ultimately, overcoming these challenges will contribute to improved patient outcomes through more accurate and non-invasive fracture assessment.

VIII. ETHICAL CONSIDERATIONS IN CONTINUOUS MONITORING

Integrating AI-based medical systems, such as RF sensing technology for bone fracture monitoring, raises critical ethical implications, particularly in patient data security and privacy. AI systems' collection and analysis of sensitive health data require robust safeguards to uphold patient confidentiality.

A. DATA SECURITY AND PRIVACY

The collection and analysis of sensitive health data by AI systems necessitate robust safeguards to ensure patient confidentiality. Encryption protocols must secure data during transmission and storage, while multi-factor authentication and access control mechanisms limit access to authorised personnel only. Additionally, clear policies on data retention and safe deletion are essential to maintaining trust and complying with regulations like GDPR and HIPAA. Transparent policies must ensure that patients fully understand how their data is collected, used, and stored, enabling them to retain control over their information.

B. BALANCING INNOVATION AND TRUST

Ethical oversight mechanisms, such as review boards and compliance with relevant regulations, are crucial for maintaining patient trust. Additionally, integrating explainable AI (XAI) methods enhances transparency by providing interpretable insights into the system's decision-making process. These efforts ensure that technological innovation does not come at the expense of patient welfare or autonomy.

C. INFORMED CONSENT AND PATIENT AUTONOMY

Ethical use of AI systems requires ensuring that patients provide informed consent. This involves clear communication about the nature and purpose of data collection, how it will be used, and patients' rights to withdraw consent at any stage without impacting their care. Empowering patients through transparent communication fosters trust and aligns with ethical healthcare practices.

D. PSYCHOLOGICAL IMPACT AND PATIENT WELL-BEING

Continuous monitoring may have diverse psychological impacts, ranging from reassurance to anxiety. It is paramount to tailor the monitoring approach to accommodate individual patient preferences and provide robust support to address any concerns. Regular assessments should be conducted to ensure the monitoring remains a comfort rather than a burden.

E. ETHICAL OVERSIGHT AND GOVERNANCE

Robust ethical oversight should be established through institutional review boards or ethics committees to ensure compliance with ethical standards. These bodies should regularly review the application of the technology and manage updates or changes that could affect patient care. Transparency with patients and stakeholders about how the technology is used and managed is crucial for maintaining accountability.

F. ADDRESSING PATIENT CONCERNS

Proactive engagement with patients to address their concerns is vital. Effective feedback mechanisms should be established to allow patients to voice their concerns or questions. Healthcare providers must be prepared to act swiftly to adjust monitoring practices based on patient feedback to enhance security measures and ensure patient comfort.

G. BALANCING INNOVATION WITH ETHICAL RESPONSIBILITY

While the benefits of RF monitoring are significant, they must be carefully balanced with ethical responsibilities. Continuous efforts to assess and mitigate any potential risks associated with the technology are crucial. Ensuring equitable access to the technology and providing comprehensive training for healthcare professionals on its ethical use is also essential to prevent disparities in healthcare.

IX. FUTURE RESEARCH DIRECTIONS

The technologies developed in this study represent a significant advancement towards improving non-invasive monitoring of bone fracture healing. However, the insights gained from the MATLAB simulations are only the initial step in a broader research agenda aimed at developing a fully functional monitoring system for clinical use. These simulations have provided a foundational understanding of the system's behaviour under controlled conditions, paving the way for more complex, real-world applications.

Future research will build upon these simulation findings by progressing from 2D to 3D modelling and eventually to in-vivo clinical trials. This transition is crucial for validating simulation results in real-world scenarios and ensuring the developed system can be effectively integrated into clinical practice.

Enhancing Sensor Array Configurations: The progressive increase in sensor numbers—from two to eight—has significantly improved the accuracy and sensitivity of the RF sensing system. This staged approach offers a clear direction for future research, which should explore even more advanced sensor configurations. Future studies could investigate the optimal number of sensors required for different types of fractures, potentially leading to customised sensor arrays tailored to specific clinical needs. Furthermore, the improvements seen with increased sensor density must be validated through large-scale clinical trials to confirm their effectiveness and reliability across diverse patient populations.

Several key areas should be explored further to enhance efficacy and accuracy in future work, including:

- **Sensor Device Improvements:** Developing and refining sensor devices is crucial as we move from simulated environments to real-world applications. Improving the design to increase sensitivity to subtle changes in tissue properties during the various stages of healing will be essential. This will ensure that the sensors perform reliably across diverse clinical conditions, particularly in detecting more nuanced stages of healing.
- **Advanced Data Analyses:** Leveraging deep learning models to understand the collected data better and identify complex patterns that could help predict healing trajectories and rates. These models must be validated with real-world data to ensure their effectiveness in clinical settings. Implementing advanced data analytics will allow for more accurate prediction of fracture healing stages and enable personalised treatment plans.
- **Comparative Studies with Conventional Imaging Techniques:** Future work should compare RF sensing technologies and traditional imaging methods, such as X-rays and MRI, to assess their relative accuracy and clinical benefits. These comparisons will help establish the unique advantages of RF sensing combined with AI in clinical practice, highlighting the added value of non-invasive monitoring technologies.
- **Broad Clinical Trials:** Large-scale clinical trials will be essential for evaluating the effectiveness of RF sensing technologies in actual medical settings. Trials across diverse patient groups are critical for validating the system's performance, moving beyond theoretical models and simulations to establish the system as a reliable clinical tool.

Extended Applications: Exploring the potential for radio frequency sensing and artificial intelligence technologies in monitoring other types of bone or tissue healing, such as post-surgical recovery or chronic bone disease treatment. Expanding the application of these technologies could extend the system's utility beyond fracture healing, contributing to advancements in broader medical diagnostics and treatment solutions.

Integrating RF sensing technology with other medical diagnostic modalities offers a promising avenue for enhancing diagnostic accuracy and patient care. For instance, combining RF sensing with ultrasound imaging could provide complementary data, leveraging the spatial resolution of ultrasound and the real-time, non-invasive monitoring capabilities of RF sensors. Such integration could be particularly beneficial for simultaneously monitoring soft tissue injuries and bone fractures.

Additionally, incorporating RF sensing into wearable devices could enable continuous, remote monitoring of bone healing. By embedding sensors into lightweight, patient-friendly wearables, clinicians could track recovery progress over extended periods without requiring frequent hospital visits. This hybrid approach could significantly enhance personalised medicine, offering tailored insights into patient health through multi-modal data fusion.

Addressing these future research directions will be key to developing RF-based bone fracture monitoring into a widely accepted, reliable, and clinically useful tool. This tool will ultimately enhance patient care and clinical outcomes across various medical applications.

X. CONCLUSION

The results of this study strengthen the foundations laid by our previous research in using radiofrequency sensing to monitor bone healing, paving the way for more advanced and effective applications in clinical practice, as reviewed in our previous study [23].

This study demonstrates the potential of integrating RF sensing with AI for non-invasive, real-time bone fracture monitoring. Through MATLAB simulations, we have shown that our machine learning model can accurately distinguish between various stages of fracture healing, from No Fracture (Class 1) to Nearly Healed (Class 5). Each increase in sensor count—from two to eight—has significantly improved detection accuracy and monitoring capabilities. As the number of sensors increased, the system became more adept at capturing subtle variations in fracture stages, particularly between light (Class 2), moderate (Class 3), and severe fractures (Class 4), thus enhancing both the accuracy and reliability of the diagnostic outcomes.

Our study's monitoring of bone fractures was structured around four key stages, ranging from no fracture to major fractures. This classification framework was strategically chosen to align with clinical relevance and the typical progression of healing observed in femoral fractures. Segmenting the healing process into detailed stages allows our research to more intricately reflect the physiological changes at each phase, thereby enhancing the sensitivity and specificity of our RF sensor-based monitoring system. While the current four-stage model provides substantial insights, further subdivisions into more granular stages could yield even greater precision. This would enhance monitoring accuracy and support more precisely targeted medical interventions at each critical phase of the healing process.

The two-dimensional simulations have been crucial in these early stages, providing valuable insights into the interactions between RF signals and biological tissues during bone healing. However, the MATLAB simulations represent only the first step in a broader research agenda to develop a comprehensive monitoring system for clinical use. By progressively increasing the number of sensors, we have established a strong foundation for more sophisticated future experiments, including three-dimensional modelling and in-vivo clinical trials, to understand system behaviour under real-world conditions better.

Practical experiments will be essential for validating our simulation findings in clinical environments. Future work will focus on conducting these trials and comparing our system's performance with conventional imaging techniques, such as X-rays and MRIs. This step is key to ensuring the system's effectiveness and reliability for integration into clinical practice.

This research marks a significant advancement in orthopaedic care, laying the groundwork for a more personalised and efficient approach to bone fracture monitoring and treatment. Multiple sensor configurations have demonstrated the potential to improve patient outcomes through advanced, data-driven clinical solutions, paving the way for a new standard in non-invasive fracture monitoring and patient care.

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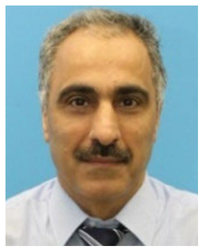

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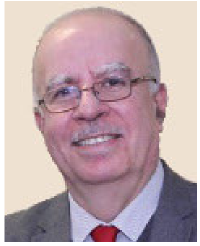

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