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Exploring Radio Frequency Techniques for Bone Fracture Detection: A Comprehensive Review of Low Frequency and Microwave Approaches

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Abstract

This comprehensive review paper examines bone fracture detection techniques based on time-domain low-frequency and microwave radiofrequency (RF). Early and accurate diagnosis of bone fractures remains critical in healthcare, as it can significantly improve patient outcomes. This review focuses on the potential of low-frequency and microwave RF methods, particularly their combination and application of time-domain analysis for enhanced fracture detection. We begin by providing an overview of the fundamental concepts of RF techniques and then by examining biological tissues' dielectric properties. We then compare the advantages and limitations of various bone fracture detection techniques, such as low-frequency RF methods, microwave RF methods, ultrasonography, X-ray, and CT scan. The discussion then shifts to hybrid approaches that combine low-frequency and microwave techniques, emphasising the advantages of such combinations in fracture detection. Machine learning techniques, their applications in bone fracture detection, and the role of time-domain analysis in hybrid approaches are also investigated. Finally, we examine the accuracy and reliability of simulated models for bone fracture detection. We finish with a discussion on recent advancements and future directions, such as novel sensor technologies, improved signal processing techniques, integration with medical imaging modalities, and personalised fracture detection approaches. This review aims to comprehensively understand the landscape and future potential of time-domain analysis in low-frequency and microwave RF techniques for bone fracture detection.

Keywords: Prolonged pain; Impaired function; long-term disabilities; Medical imaging modalities; X-rays, CT scans, and MRI scans; low frequencies(kHz); extremely high frequencies (GHz); Signal generators (oscillators)

Abbreviations: RF: Radiofrequency; CT: Computed tomography MWI: Microwave imaging; PET: Positron emission tomography; UWB: Ultra-wideband; RFID: Radio Frequency Identification; Internet-of-Things: Internet-of-Things; kHz: Low frequencies extremely; GHz: High frequencies; MRI: Magnetic Resonance Imaging; SAR: Specific absorption rate; MWT: Microwave Tomography; Health Insurance Portability and Accountability Act: Health Insurance Portability and Accountability Act; GDRP: General Data Protection Regulation; EIT: Electrical impedance tomography; CT: ComUHF: ultra-high frequency; PT: Puted tomography; SVM: Support Vector Machines; TA: Texture analysis; ML: Machine learning; AI: Artificial Intelligence; DNN: Deep Neural Network; NPV: Negative predictive value; CNN: Convolutional Neural Networks

Introduction

Bone fracture is a common and significant medical condition that requires accurate and timely diagnosis for effective treatment and management. Detecting fractures in a timely manner is crucial as missed or delayed diagnosis can lead to prolonged pain, impaired function, and long-term disabilities. Missed fractures are one of the most common diagnostic errors, of which up to 80% end in emergency departments, contributing to a substantial burden on healthcare systems and compromised patient outcomes [1]. Conventional techniques such as X-rays, ultrasound, and computed tomography (CT) have been widely used for fracture detection. While these methods have been valuable in clinical practice, they are accompanied by certain limitations. X-rays, for instance, are the primary imaging tool for identifying fractures. Still, they may only sometimes provide clear and definitive results, especially in complex cases or when fractures are small or occult. Additionally, the interpretation of X-ray images requires expertise, and the process can take time, leading to potential delays in diagnosis and treatment initiation [2]. The limitations of existing techniques highlight the need for advancements in bone fracture detection. Recent years have witnessed significant progress in radio frequency (RF) techniques, machine learning, and microwave imaging, offering promising avenues for more accurate, efficient, and non-invasive fracture diagnosis [3].

RF techniques, such as electrical impedance spectroscopy, have shown potential in measuring the dielectric properties of biological tissues, including bones. These properties, such as relative permittivity and conductivity, can vary in the presence of fractures, potentially providing a basis for detecting and characterising fractures. By utilising RF signals and analysing their interactions with tissues, it becomes possible to develop techniques that can enhance the accuracy and reliability of fracture detection, enabling early interventions and improved patient outcomes. Machine learning, a subset of artificial intelligence, has emerged as a powerful tool in various medical applications, including bone fracture detection. By leveraging large datasets and complex algorithms, machine learning techniques can analyse medical images, such as X-rays or CT scans, to recognise patterns and signs of fractures. Deep learning, a subset of machine learning, has shown promising results, exhibiting high diagnostic accuracy comparable to general physicians [4,5]. These advancements in machine learning offer the potential for automated and efficient fracture detection, reducing the burden on radiologists and enabling faster diagnoses.

In parallel, microwave imaging (MWI) has gained attention as a non-ionizing and cost-effective method for bone fracture detection. MWI techniques leverage the unique properties of microwave signals and their interaction with bones to identify fractures. This approach provides an alternative to traditional X-ray technologies and can be particularly useful in scenarios where X-ray use is not viable or recommended [6]

Real-world examples and statistics underscore the significance of accurate and timely fracture detection. For instance, studies have shown that missed fractures can lead to delayed treatment and long-term disability. Emergency departments' most common diagnostic error involves missed fractures, highlighting the urgent need for improved detection methods [7] Additionally, fractures in areas such as the wrist or spine can be challenging to diagnose accurately, further emphasising the importance of advancements in fracture detection techniques.

Considering the limitations of existing techniques and the potential benefits offered by RF techniques, machine learning, and microwave imaging, this review aims to explore and analyse recent advancements in bone fracture detection. We will evaluate these techniques' effectiveness, limitations, and practical applications by examining the existing literature, providing valuable insights for researchers, clinicians, and healthcare professionals. The article also delves into the significance of time-domain analysis in hybrid approaches and evaluates simulated models used for fracture detection in terms of their accuracy and reliability. Overall, this paper aims to summarise the latest developments and identify potential avenues for future research, including innovative sensor technologies, improved signal processing methodologies, integration with medical imaging modalities, and customised strategies for fracture identification (Figure 1).

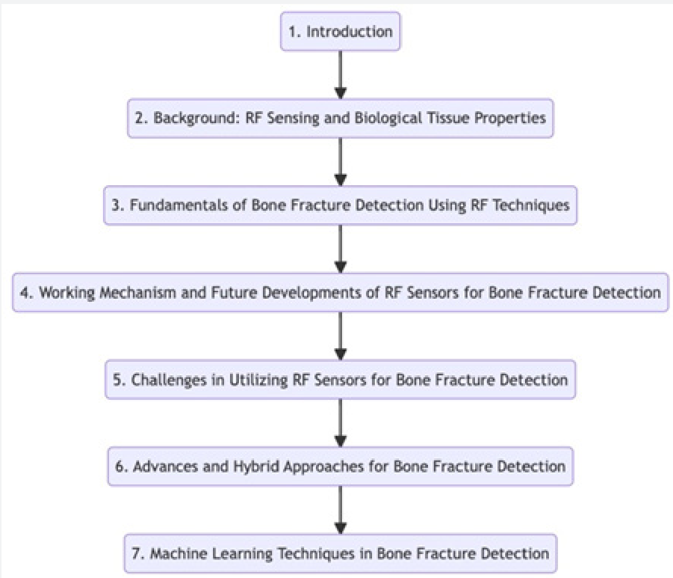

Figure 1: Structure figure of our review.

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The Objectives and Scope of the Review

This study:

i. Examines various methods for detecting bone fractures using low-frequency and microwave radio frequency (RF) techniques. It covers the fundamental principles underlying RF techniques and an overview of the dielectric properties of biological tissues. Additionally, it compares the advantages and disadvantages of these methods with other procedures like ultrasonography, X-ray, and CT scan for detecting bone fractures as shown in Table 1 & Figure 2.

ii. Investigates hybrid techniques that integrate low-frequency and microwave radio frequency (RF) methods. The focus is on the potential of time-domain analysis to improve fracture detection.

iii. This study reviews the literature highlighting the application of machine learning techniques in detecting bone fractures. The emphasis is on their incorporation within the RF methods and time-domain analysis framework.

iv. This research provides an overview of the precision and reliability of simulated models, as reported in the literature, for detecting bone fractures using the mentioned methodologies.".

v. Discusses the latest developments and potential future directions in the field. These include advancements in sensor technology, signal processing techniques, integration with medical imaging modalities, and personalised fracture detection methods.

vi. It focuses exclusively on research and methodologies utilising time-domain low-frequency and microwave RF techniques to detect bone fractures. Consequently, the primary focus of this review will be on something other than studies utilising frequency-domain analysis or other imaging modalities. However, they may be referenced for comparative purposes as illustrated in Figure 3.

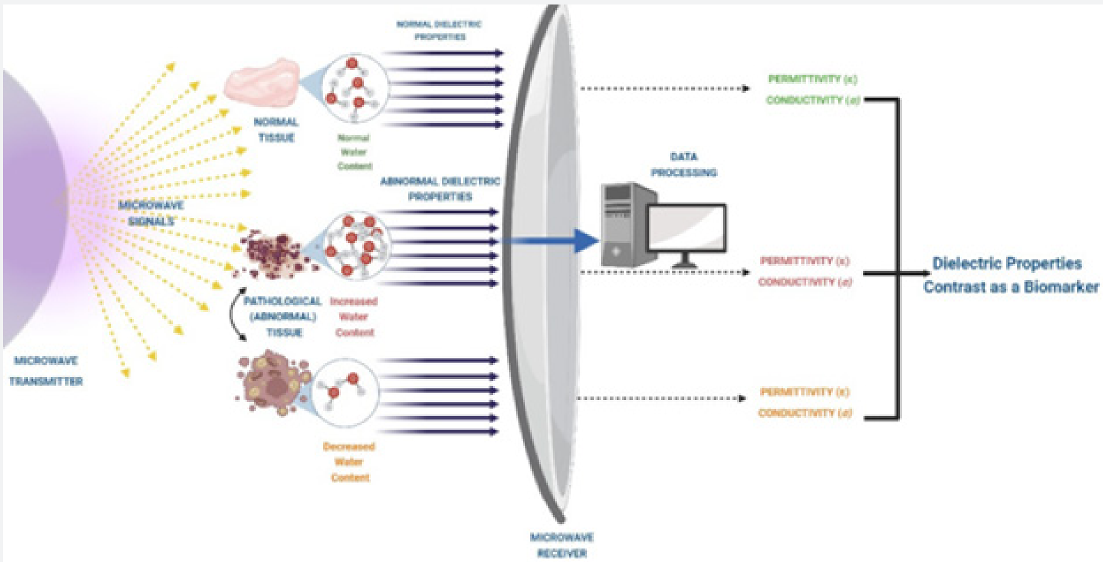

Figure 2: An image depicting the principles of Radio Frequency Application in human model [8].

Table 1: A Summary of Conventional Diagnostic Techniques.

Technique	Description	Advantages	Limitations
X-ray [12-14]	Uses electromagnetic radiation to produce images of fractures	Widely available, low cost, quick imaging	Limited sensitivity to early healing changes, ionizing radiation
Computed Tomography (CT) [13], [14],[17]	Utilizes X-ray beams to create detailed 3D images of fractures	High spatial resolution, accurate assessment of fracture alignment and callus formation	Ionizing radiation, higher cost, limited availability
Magnetic Resonance Imaging (MRI) [14]	Uses magnetic fields and radio waves to visualize fractures	Excellent soft tissue contrast, no ionizing radiation	Long acquisition times, higher cost, contraindications for certain metallic implants
Positron Emission Tomography (PET) [18]	Measures metabolic activity using radiotracers	Early detection of bone metabolism changes, quantitative analysis	Limited spatial resolution, radiation exposure

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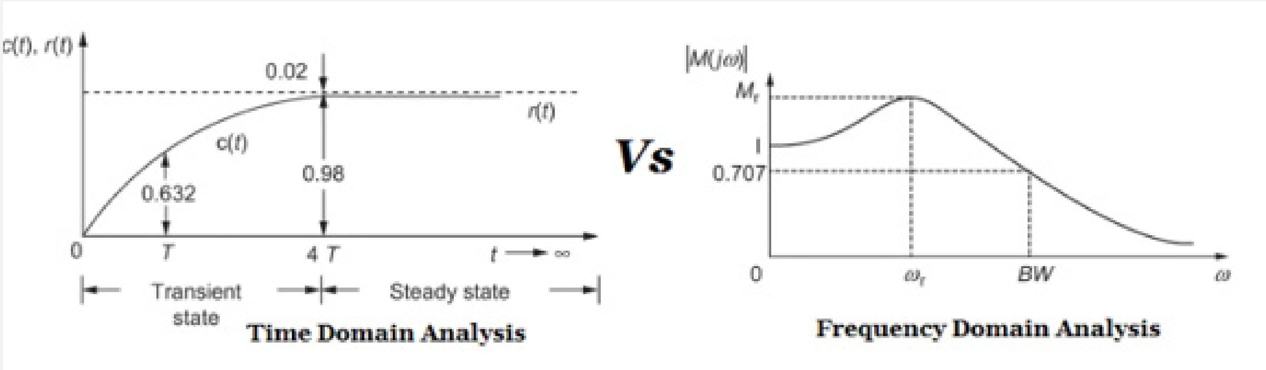

Figure 3: Comparative Overview of Time and Frequency Domain Analysis in Radio Frequency Application [9].

Background and Motivation

Bone fractures, resulting from trauma, overuse, or underlying medical conditions that weaken the bones, are commonplace injuries that require timely and accurate detection for appropriate treatment and effective healing. Traditionally, the detection of bone fractures primarily relies on imaging techniques such as X-rays, CT scans, and MRI scans. X-rays are often the first line of diagnosis due to their wide availability, speed, and cost-effectiveness. However, they have notable limitations. For instance, X-rays may struggle to detect certain types of fractures, such as hairline or stress fractures, as these may not be discernible in the X-ray images [10]. CT scans, on the other hand, provide more detailed images of the bone structure and can detect fractures that might be invisible on an X-ray. Despite these advantages, CT scans have their own set of drawbacks. They expose the patient to ionising radiation and are typically more expensive than X-rays, which make them feasible for only some patients [11]. MRI scans are a viable alternative as they do not involve ionising radiation and can provide intricate images of soft tissue and bone. This makes them particularly useful for detecting bone bruises or other injuries accompanying a fracture. However, MRI scans are generally more expensive than X-rays and CT scans, limiting their availability to only certain medical facilities [12,13]. Given these challenges, there is a clear impetus for developing more accessible, cost-effective, and less invasive methods for bone fracture detection. Integrating technologies such as RF sensing into clinical practice offers a promising solution, potentially enhancing the accuracy of diagnosis, improving patient experience, and contributing to more effective treatment strategies.

Bone Fracture Detection Techniques

In recent years, technological advancements have introduced non-invasive approaches for monitoring the process of bone fracture healing as the novel methodology to replace the conventional techniques in use. Traditional methods such as radiography, ultrasound, computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET) have been widely used for the diagnosis of bone fractures [14]. However, the merits and demerits associated with each technique can be identified through the comparative evaluation of the techniques, providing insight into the choice of method for specified jobs.

Limitations of Traditional Monitoring Methods (X-rays, CT scans, and MRI)

X-ray and computed tomography (CT) scans are conventional modalities for surveillant bone fractures. Although these techniques are extensively employed and can provide valuable insights, they have certain constraints. For example, according to [15], a constraint of X-ray imaging is its potentially reduced efficacy in areas where multiple structures overlap. In addition, it has been noted that certain anomalies affecting the left and right collar bone, heart, and lung may appear less visible on an X-ray of these areas compared to an X-ray of the forearm [16]. Computed tomography (CT) scans are a valuable diagnostic tool for detecting bone fractures; however, they possess certain limitations; one of these limitations is that no prescribed threshold exists for the quantity of CT scans a patient can undergo [17]. Furthermore, Factors such as the dimensions of the X-ray detector and the sample size can influence the resolution of 3D scans in computed tomography [17].

The examples above are just a few of the limitations inherent in the constraints of conventional techniques employed to monitor bone fractures. The existence of additional limitations is contingent upon the circumstances of each case. Other constraints of conventional monitoring techniques, such as X-rays and CT scans, encompass the potential for radiation exposure and financial expenses [18]. Research has found that exposure to ionising radiation from X-rays and CT scans can increase the risk of cancer development in patients [19]. Although the potential

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harm from a solitary X-ray or CT scan is minimal, the likelihood of adverse effects may escalate with repeated exposure [20]. An additional constraint associated with these methodologies pertains to their financial implications. Computed tomography (CT) scans can incur significant costs and may not be universally covered by insurance policies [21]. The accessibility of these tests may pose a challenge for certain patients requiring them Table 1.

The Need for a Non-Invasive, Cost-Effective, and Accessible Monitoring Method

There is a pressing need for imaging methods that are non-invasive, cost-effective, and widely accessible within the healthcare industry. Current mainstream medical imaging techniques, such as X-rays, CT scans, and MRI scans, have several drawbacks that present challenges to both healthcare providers and patients. These costly procedures may expose patients to ionising radiation, which poses health risks. Furthermore, they may not be readily available in all healthcare settings, particularly remote or underserved areas, exacerbating healthcare disparities [22]. The advent of new technologies that can surmount these challenges holds immense potential for improving patient care. RF sensing technology, for instance, presents a non-invasive approach to fracture detection, causing no discomfort to the patient. It is potentially lower cost than traditional imaging modalities and could make it more accessible, alleviating the financial burden on patients and healthcare systems. Furthermore, with developments towards more portable or wearable RF sensors, this technology could be used in a wide range of healthcare settings - from large hospitals to remote clinics and even in home-based care. This widespread accessibility could democratise health monitoring, providing valuable diagnostic information irrespective of location or socioeconomic status. The integration of such non-invasive, cost-effective, and universally accessible technology into healthcare workflows has the potential to greatly enhance the quality of patient care, facilitate early and accurate diagnosis, and reduce strain on healthcare providers and systems.

RF Sensing as an Alternative Method

A novel method for detecting fractures involves using Radio Frequency (RF) sensors. These sensors can accurately detect and measure changes in electromagnetic fields, making them suitable for various applications, including monitoring bone fracture healing. RF sensors can effectively identify bone fractures by employing an RF antenna, showing great potential for future use. Research indicates that fracture recognition can be achieved by analysing using reactive impedance surfaces [23]. This suggests that RF sensors could circumvent the constraints of traditional imaging techniques, offering a non-invasive and potentially more precise mode for fracture detection. However, applying RF sensing to fracture identification and monitoring is an emerging field with several challenges. These include sensor design and placement issues, signal processing and analysis, and ensuring desirable sensitivity and specificity levels within the complex human anatomy context. RF sensors work by discerning alterations in the dielectric properties of biological tissues caused by radio frequency waves. Factors such as bone fractures can induce these changes. When a fracture occurs, dielectric property alterations in the surrounding tissues mainly result from fluid accumulation, like blood. These changes affect the material's permittivity and conductivity, subsequently altering the behaviour of the radio frequency waves traversing the tissue [24]. RF sensors are engineered to sense these propagation changes, yielding valuable data about the physical alterations within the tissue. This data can provide detailed insights into a bone fracture's existence, size, and severity. Notably, the specific operating mechanisms of RF sensors can vary based on their design and application. Some may focus on changes in the transmitted signal, whereas others might rely on reflected or scattered signals for detection. By employing these mechanisms, RF sensors can offer a non-invasive, potentially real-time tool for detecting and monitoring bone fractures. This opens significant possibilities for improving patient care in orthopaedic and trauma scenarios.

How RF Sensors Overcome Traditional Limitations

RF sensors employ ultra-wideband (UWB) technology and Radio Frequency Identification (RFID) methodologies to overcome the limitations of traditional monitoring methods. UWB technology, operating over short distances, enables precise indoor positioning and real-time device movement and motion tracking. It outperforms conventional methods with fewer than 50 centimetres of accuracy under optimal conditions [25]. Similarly, RFID sensor tags are crucial for the future of Internet-of-Things (IoT) applications. They are contactless, wireless, lightweight, capable of non-line-of-Need to be clarified mission, and flexible [26]. From a design perspective, RF sensors are relatively diminutive in size. They do not require supplementary components like magnetic circuits, coils, or magnets and can fit onto a small silicon wafer [27]. They show their strongest response at specific optical frequencies, but broadband sensors can measure a wide spectrum of frequencies [28].

Applying RF sensors in medical settings, particularly in detecting bone fractures, has emerged as a viable and promising approach. While alternative imaging methodologies exist, RF sensors offer a non-intrusive and potentially more accurate method to identify bone fractures [29]. They have also shown potential in monitoring fracture healing, providing more accurate and sensitive information than traditional methods such as X-rays, CT scans, DEXA scans, and ultrasounds. These conventional methods have limitations. For instance, X-rays are only effective at later stages of repair and correlate poorly with bone strength. Despite their improved diagnostic capabilities, CT and DEXA scans have limited clinical use due to their cost and high radiation dose [30]. Meanwhile, physical examinations by physicians, though commonly relied upon, can result in imprecise assessments.

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In contrast, MRI provides superior soft tissue contrast without radiation, frequently used for imaging various organ systems, including the musculoskeletal system [30]. While MRI can deliver valuable information for diagnostics, 3D modelling, and treatment planning across multiple anatomical regions, RF sensors can objectively measure fracture healing. This can help guide clinical decision-making for patients, although their use is more specific and less versatile than MRI [31].

RF sensors offer significant advantages in bone fracture detection compared to alternative imaging techniques, including X-rays, MRI, and CT scans, as summarised in Table 1. This underscores the potential of RF sensing technology in reshaping healthcare diagnostics and patient treatment approaches Table 2.

Table 2: The benefits of RF sensing for bone fracture detection compared to other prevalent imaging techniques.

Benefits	RF Sensing	X-ray	CT Scan	MRI
Uses non-ionising radiation	Yes	No	No	Yes
Enhanced portability	Yes	No	No	No
Cost-effectiveness	High	Low	Low	Low
Real-time monitoring of fracture healing	Potential	No	No	No
Sensitivity to dielectric property changes	High	Low	Low	Moderate
Integration with wearable devices/smart implants	Potential	No	No	No

Background: RF Sensing and Biological Tissue Properties

Fundamentals and Medical Applications of RF Sensing

Radio Frequency (RF) sensing leverages the radio frequency spectrum to detect and analyse environmental changes. This innovative technology intersects various domains, including medicine and healthcare, where it offers unparalleled advantages. Here, we provide a comprehensive guide to the rudiments of RF sensing and illuminate its pivotal role in the medical field.

RF Sensing Basics: At its core, RF sensing relies on the principle that radio frequency signals interact dynamically with their surroundings. By meticulously examining reflected or modulated RF signals, environmental changes are detected. Consequently, these variations offer invaluable insights into the subjects' or objects' characteristics and conditions proximal to the RF sensor.

A strict frequency range doesn't bind RF sensing. It can be deployed over a spectrum ranging from low frequencies (kHz) to extremely high frequencies (GHz). The choice of operating frequency is influenced by the specific application and the target's characteristics being sensed. A distinguishing feature of RF sensing is its non-contact nature, allowing for non-invasive measurements. This attribute is notably attractive in the medical field, where contact-based sensing may need to be more practical and comfortable for patients [32]. RF signals can permeate various materials, including clothing and body tissues, obtaining information through obstacles. The signals reflected offer a wealth of information about the sensed object's structure and composition. Complex signal processing algorithms and data analysis techniques underpin RF sensing. These approaches distil meaningful information from the captured RF signals. Integrating machine learning and artificial intelligence techniques significantly enhances the sensitivity and accuracy of the sensing system.

Medical Implications of RF Sensing: One of the promising applications of RF sensing in the medical field is non-invasive wound monitoring. RF sensing can analyse RF signals reflected from the wound area, detecting changes in the healing processes, such as inflammation and oedema. This aids in prompt intervention and assessment [33].

Vital sign monitoring has also been a benefactor in RF sensing. Noncontact RF sensors can monitor heart, respiration, and blood pressure. Patients can be continuously monitored without physical contact by measuring minute changes in the reflected signals due to bodily movements [34]. In sleep medicine, RF sensing has shown potential in sleep pattern monitoring and sleep apnea detection. The technology can identify changes in breathing patterns and movements by analysing RF signals reflected from a sleeping individual, thus assisting in diagnosing and treating sleep-related disorders [35]. RF sensing is harnessed for surgeon's gesture recognition in the operating theatre. Detecting hand movements and gestures, RF sensors can manage medical equipment like robotic surgical instruments, obviating the need for direct touch or physical contact [36]. Temperature monitoring, particularly skin temperature, can be conducted non-invasively using RF sensing. Any changes in skin temperature are reflected in the variations in the RF signals, providing real-time updates on the patient's health [37]. Additionally, RF sensing has shown promise in detecting and monitoring bone fractures. By analysing the characteristics of the RF signals reflected from the bone, fractures can be identified, and the healing process can be monitored over time. This provides clinicians with a contactless and non-invasive method to track recovery, leading to personalised treatment plans and improved patient outcomes [38].

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Dielectric Properties and RF Signal Behaviour in Biological Tissues

Understanding the behaviour of RF signals within biological systems necessitates knowledge of the frequency-dependent dielectric properties of biological tissues [38]. These properties significantly impact the behaviour of RF signals, as human tissues have varying dielectric characteristics at different frequencies. The dielectric properties of a material can either reflect or penetrate RF signals and significantly affect the electromagnetic characteristics of a substance. This phenomenon is known as dielectric dispersion, a well-studied occurrence that significantly alters the dielectric properties within a specific frequency range [39,40]. Understanding this interaction between electromagnetic fields and biological tissues is very important, particularly in medical imaging and telecommunications. Several variables, such as frequency, temperature, density, water content, salt content, and the physical state of a substance, can influence the dielectric characteristics of a substance [41].

In biological tissues, dielectric dispersion can affect an RF signal's attenuation and phase velocity as it propagates through a medium. The dielectric properties of biological tissues, including their relative permittivity (ε') and conductivity (σ), are significant indicators of a substance's propensity for polarisation under an external electric field and its aptitude for conducting electrical current [42]. Relative permittivity (ε') and conductivity (σ) are integral dielectric properties of biological tissues that considerably affect the behaviour of RF signals when interacting with these tissues [43]. They are essential in determining how easily a material can become polarised by an applied electric field and how well it can conduct an electric current. Moreover, these properties significantly impact medical imaging modalities, such as Magnetic Resonance Imaging (MRI), utilising RF signals to interact with biological tissues. An accurate understanding of tissue dielectric properties is crucial for improving specific absorption rate (SAR) estimates and reducing undesired tissue heating [44]. It is also key to the design of new electromagnetic-based imaging and therapeutic technologies. Detecting changes in bone tissue composition is significantly assisted by determining these essential dielectric properties: relative permittivity (ε') and conductivity (σ). Techniques like electrical impedance spectroscopy can measure these properties related to bone tissue, such as conductivity and structure. The properties can vary substantially across various biological tissues due to dielectric dispersion, and this variance can be quite substantial over a frequency range [45].

A significant database maintained by the IT'IS Foundation provides dielectric properties of biological tissues, including values for permittivity and electrical conductivity for over 100 human tissues at frequencies of 10 Hz to 100 GHz [46]. These properties are invaluable in biological and medical applications, notably in investigations involving tissue imaging, therapeutic interventions, and electromagnetic field interactions. The distinctive features of their respective permittivity (ε) and conductivity (σ) determine the response of biological tissues when exposed to an electric field. However, these tissue properties vary according to the operating frequency [47]. Table 2 illustrates the dielectric properties of the possible tissues encountered when studying a fracture in the human thigh based on the Gabriel dispersion relationship (Table 3).

Table 3: Dielectric properties of tissues and their optimal frequencies.

Biological Tissue	500 MHz		1000 MHz		2000 MHz		3000 MHz	
	Permittivity	Conductivity S/m)	Permittivity	Conductivity S/m)	Permittivity	Conductivity S/m)	Permittivity	Conductivity (S/m)
Blood	6.33E+01	1.38E+00	6.11E+01	1.58E+00	5.90E+01	2.19E+00	5.74E+01	3.05E+00
Blood vessel wall	4.62E+01	5.86E-01	4.46E+01	7.29E-01	4.31E+01	1.17E+00	4.19E+01	1.81E+00
Cartilage	4.46E+01	6.21E-01	4.23E+01	8.29E-01	3.98E+01	1.42E+00	3.76E+01	2.21E+00
Cancellous bone	2.19E+01	2.54E-01	2.06E+01	3.64E-01	1.91E+01	6.52E-01	1.79E+01	1.01E+00
Cortical bone	1.29E+01	1.00E-01	1.24E+01	1.56E-01	1.17E+01	3.10E-01	1.11E+01	5.06E-01
Red bone marrow	1.17E+01	1.90E-01	1.12E+01	2.39E-01	1.06E+01	3.81E-01	1.00E+01	5.62E-01
Yellow bone marrow	5.62E+00	3.17E-02	5.49E+00	4.33E-02	5.35E+00	7.67E-02	5.24E+00	1.21E-01
muscle	5.64E+01	8.22E-01	5.48E+01	9.78E-01	5.33E+01	1.45E+00	5.21E+01	2.14E+00
Skin	4.49E+01	7.28E-01	4.09E+01	9.00E-01	3.86E+01	1.27E+00	3.75E+01	1.74E+00
Fat	1.15E+01	8.54E-02	1.13E+01	1.16E-01	1.10E+01	2.12E-01	1.07E+01	3.44E-01
Air	1.00E+00	0.00E+00	1.00E+00	0.00E+00	1.00E+00	0.00E+00	1.00E+00	0.00E+00

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Connective tissue	4.68E+01	5.85E-01	4.56E+01	7.60E-01	4.39E+01	1.34E+00	4.21E+01	2.17E+00
Nerves	3.44E+01	4.73E-01	3.23E+01	6.00E-01	3.06E+01	9.14E-01	2.96E+01	1.33E+00

Source: IT'IS Foundation (2022). Dielectric Properties» IT'IS Foundation. [online] itis. Swiss. Available at: https://itis.swiss/virtual-population/tissue-properties/database/dielectric-properties/

Fundamentals of Bone Fracture Detection Using RF Sensor Techniques

Low-Frequency RF Techniques

In RF technology, applied frequencies below 300 MHz are categorised as the low-frequency range. This frequency range is adopted in medical devices, communication systems, and research. The technique is needed to generate, transmit, and receive radio waves within the low-frequency range. Generally, the technique employs signal generators (oscillators) to generate the radio waves by producing electrical signals at the required frequency using techniques like LC circuits, direct digital synthesis, and crystal oscillation. Different types of antenna designs become suitable for the application requirement depending on the parameters such as range, polarization, and directionality [48]. In most cases, loop antennas, dipole antennas, and monopole antennas are the preferable options for converting electrical signals to magnetic waves capable of propagating through the surrounding medium, such as a conductive material and even the air, under a low-frequency range. These antennas can receive low-frequency RF signals via the incoming electromagnetic waves through smooth processes involving filtering, demodulation, and decoding techniques based on the application requirements. For instance, received RF signals obtained from communication systems are demodulated to retrieve the actual information in a voice or data form [49].

Microwave RF Techniques

Microwave radio frequency (RF) techniques, operating from 300 MHz to 300 GHz, are increasingly finding applications in healthcare, especially in detecting bone fractures [50]. These techniques employ microwave signal generators such as cavity resonators, solid-state devices, or crystal oscillators to produce stable and precise microwave frequencies. Once generated, these signals are amplified to optimal power levels for transmission. Microwave RF techniques are integral to various fields, including radar systems, satellite communication, telecommunications, and microwave heating. Of interest in recent times is the use of Microwave Imaging (MWI) as a revolutionary method for detecting bone fractures. MWI offers distinct advantages, including non-ionization, portability, and cost-effectiveness, which makes it an attractive alternative to traditional X-ray technologies [51]. Ground-breaking research by Santos, Fernandes, and Costa in 2022 introduced an innovative method for bone scanning inspired by synthetic aperture radar technologies. Using a singular Vivaldi antenna, the team was able to conduct linear scans of bones, successfully detecting bone transverse fractures as small as 1 mm in width and 13 mm deep [51,52]. Despite the success of the findings, the authors failed to consider the effects of surrounding tissues of the bone such as the muscles, fats, skin, etc which have different dielectric properties. This makes the clinical acceptance of their findings challenging.

Additionally, Microwave Tomography (MWT) advancements have seen significant growth, especially in bone health monitoring [53]. The pronounced dielectric contrast between healthy and diseased human trabecular bones makes MWT a promising modality for bone imaging. Efforts in this domain have yielded impressive results, such as wearable MWT systems capable of localising the tibia and fibula bones in images [54], and the use of MWT to detect bone density variations [55]. Recent strides in image enhancement in MWT also present promising developments. For instance, using ultrasound gel as a medically approved matching medium can broaden the scope for practical applications [56]. Numerical studies have further validated the potential of MWT in monitoring bone density in human lower limbs, opening avenues for diagnosing osteoporosis and tracking the disease's progression [57]. Lastly, developing compact, wearable microwave tomography systems marks a significant advancement in MWI technology. These compact systems can capture high-resolution 3D images of the lower leg, differentiating between bone and soft tissues. Such devices could find potential application in ambulatory settings and long-term health monitoring, especially for patients suffering from osteoporosis or those at risk [58]. While the advancements in MWI signal a notable shift towards more non-invasive and cost-effective health diagnostics, further research and clinical trials are necessary to fully ascertain its efficacy and accuracy, especially in orthopaedic diagnostics [59] (Table 4).

Challenges in Utilizing RF Sensors for Bone Fracture Detection

Technical Challenges in RF Sensing for Bone Fracture Detection

Signal Interference and Attenuation: The effectiveness of Radio Frequency (RF) sensing in detecting bone fractures hinges on the accurate interpretation of signals. This process can be notably affected by environmental elements such as noise, interference, and signal attenuation. Furthermore, the dielectric properties of tissues surrounding the bone can exhibit variations that may influence the RF signal. Consequently, these variations could impact the precision of fracture detection measurements [60].

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Table 4: simple comparison outlining the key features of the studies.

Reference	Year	Key Innovation	Practical Application
[51]	2022	Utilized synthetic aperture radar technologies for bone scanning	Detecting transverse fractures as small as 1 mm wide and 13 mm deep
[52]	2022	Introduction of a fully automated scanner with two antipodal Vivaldi antennas	Creating a 3D image of the tibia and fibula
[53]	2016	Further evaluation of MWI in detecting thin bone fractures	Detecting transversal bone fractures as thin as 0.35 mm
[54]	2020	Use of MWT for bone health monitoring	Differentiating results for bones affected by osteoporosis and osteoarthritis
[55]	2011	Investigation into wearable MWT systems	Localizing the tibia and fibula bones in the images
[56]	2021	Use of MWT to detect bone density variations	Localizing bones in thin and medium fat scenarios
[57]	2022	Addressed image enhancement in MWT	Enhancing image reconstruction
[58]	2020	Preliminary numerical study on MWT in monitoring bone density	Demonstrating variations in bone's relative permittivity, linked to BMD
[59]	2018	Development of a compact, wearable MWT system	High-resolution 3D imaging of lower leg, differentiating between bone and soft tissues

Therefore, it is paramount to understand and mitigate the effects of environmental interference and signal attenuation. Addressing these challenges through the development of robust signal processing and error correction algorithms, for instance, is crucial for ensuring the successful application of RF sensing in detecting bone fractures. Only by achieving high signal fidelity and accuracy can we ensure that this technology reliably aids in the diagnostic process and ultimately enhances patient care.

Sensor Calibration and Placement: The precision of RF sensors and their appropriate placement are critical factors affecting the effective detection of bone fractures. Sensor calibration is a meticulous procedure involving the transfer of a calibration factor or efficiency from a standard to the sensor, ensuring accurate measurements of RF and microwave power. This process is vital to maintain the consistency and reliability of the data captured by the sensors.

Likewise, the positioning of the RF sensor is of paramount importance. The sensor's location with the bone fracture can significantly influence the amplitude and fidelity of the received signal. If appropriately positioned, the resulting data may lead to accuracy in fracture detection, impacting the effectiveness of diagnosis and subsequent treatment plans [61].

The Complexity of Interpretation: Interpreting the data derived from RF sensors for detecting bone fractures represents a multifaceted challenge. This task requires an in-depth understanding of RF signal processing and the interaction of RF signals with various biological tissues. Additionally, the increasingly complex and crowded electromagnetic environment can further compound these challenges, adding layers of difficulty to data interpretation [62].

These complexities are particularly prominent when the data comes from intricate devices such as network analysers, which may contain substantial noise and interference, making extracting high-quality, usable data a demanding task. Advanced computational methodologies, such as deep learning, can be utilised to address these complexities. These techniques leverage the computational power of modern hardware and sophisticated algorithms to parse complex data, identify patterns, and extract actionable information. Deep learning methodologies have shown considerable promise in signal detection and classification tasks. They can enhance the precision of fracture detection by reducing false positives and negatives, even in the presence of complex and noisy data.

Moreover, deep learning methodologies can help to transform raw, noisy data into valuable, actionable insights. These insights can significantly enhance the efficacy of RF sensing technology in detecting bone fractures, leading to more accurate diagnostics and more effective patient care [63]. Furthermore, as these methodologies evolve, they will offer even more refined tools for interpreting the data from RF sensors, promising future advancements in bone fracture detection and monitoring. This underlines the importance of ongoing research and development in RF sensing technology and the advanced computational techniques used to interpret these sensors' data.

Data Quality: Ensuring data quality is one of the significant challenges when utilising RF signals for bone fracture detection. The data obtained from RF sensors, mainly sourced from complex devices such as network analysers, can be significantly impacted by various factors. These include environmental interference, signal noise, signal attenuation, and variability in signals associated with different types of bone fractures. These issues may complicate the data interpretation and extraction process of high-quality, actionable information, ultimately affecting the reliability of the machine learning models used for fracture detection [64].

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Addressing these issues necessitates the incorporation of advanced strategies for signal processing. Noise filtering techniques can be employed to reduce the impact of environmental interference and signal noise. Signal amplification can enhance the strength of relevant signals, improving the overall signal-to-noise ratio. Data cleaning techniques can further ensure that only relevant, high-quality data is used for training machine learning models, thereby improving the models' performance and reliability [65]. Moreover, it is also crucial to develop robust quality assurance mechanisms to continuously monitor and validate the data's integrity. This can involve employing outlier detection techniques to identify and address anomalies in the data and implementing rigorous testing protocols to validate the accuracy and consistency of the data. Furthermore, the large volumes of data generated by these RF sensors can pose challenges in terms of storage, retrieval, and processing. This is particularly significant given that healthcare institutions are already grappling with large volumes of data. As such, it is necessary to consider effective and efficient data management strategies, which may involve the use of cloud computing solutions or advanced data compression techniques [66].

Moreover, it is also crucial to develop robust quality assurance mechanisms to continuously monitor and validate the data's integrity. This can involve employing outlier detection techniques to identify and address anomalies in the data and implementing rigorous testing protocols to validate the accuracy and consistency of the data. In combination, these strategies can significantly improve the quality of data derived from RF sensors, leading to more reliable and accurate machine-learning models for bone fracture detection. This underlines the importance of investing in advanced signal processing and data management techniques when integrating RF sensing technology into clinical workflows for fracture detection and monitoring [67].

Variability in Biological Response: The individual variability in biological responses presents another challenge for RF sensors. Not all human bones exhibit the same response to RF signals. Factors such as age, sex, health status, and genetic makeup can significantly influence these responses, making it harder to standardize the sensor readings and interpretations. Researchers need to develop sophisticated machine learning models that can accommodate these variances and still accurately predict bone fractures. They must also collect a diverse range of data to ensure these models are trained on a wide spectrum of responses [68].

Technology Limitations: RF sensors have limitations while offering ground-breaking capabilities in detecting bone fractures. These limitations can influence their effectiveness and range of applicability in the clinical context. For example, RF sensors may struggle to accurately detect certain types of fractures, such as hairline or stress fractures, or those located in anatomically complex regions [69].

Furthermore, the performance of RF sensors is not uniform across all patients and can be impacted by many patient-specific factors. These include age, which can affect bone density and tissue properties; bone density itself, which can influence how RF signals interact with the bone; and underlying medical conditions, which can alter the physical properties of bones and surrounding tissues, thereby influencing the RF signal characteristics. The patient's body composition and the presence of implants or other medical devices could also affect the RF signals, adding another layer of complexity to the data interpretation and potentially affecting the accuracy of fracture detection [70]. These limitations necessitate careful consideration when planning and implementing the clinical application of RF sensing technology. It's essential to have a comprehensive understanding of these limitations to inform clinicians, guide patient selection, and manage expectations regarding the performance of this technology. Ongoing research and development efforts are critical to deepen our understanding of these limitations and devise strategies to overcome them. Enhancements in signal processing techniques, data interpretation algorithms, and machine learning models could mitigate some of these limitations [71]. Optimising the performance of RF sensors will require a multifaceted approach, considering both technological advancements and the unique characteristics of individual patients. Through continued research and innovation, we can strive to enhance the accuracy, reliability, and inclusivity of RF-based fracture detection, ultimately contributing to improved patient outcomes and advancing the field of bone health diagnostics.

Broader Implementation Challenges

Integration with Clinical Workflow: Incorporating RF sensing technology into the existing clinical workflow presents numerous challenges that demand thorough planning and management. One of the primary considerations is ensuring that healthcare providers are proficiently trained in using the technology and interpreting its results. This education and training aspect is critical to maximise the potential benefits of the technology and reduce the possibility of user-related errors [72].

In addition, modifications to current clinical procedures may be necessary to ensure a smooth integration process. These changes might involve altering certain routines, processes, or systems to accommodate the new technology. Optimal utilisation of RF sensors necessitates a workflow design that aligns with the technology's functional requirements while maintaining or enhancing the efficiency of clinical operations.

Interdisciplinary collaboration plays a crucial role in addressing these challenges. The combined efforts of healthcare providers, technologists, and administrators can guide the successful implementation process, addressing any technological, operational, or organisational barriers that may arise [73]. The goal is to integrate RF sensing technology seamlessly into the

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clinical workflow, providing value in enhanced bone fracture detection and monitoring while causing minimal disruption to existing practices. This balance is critical to ensuring that technology becomes a valuable and effective tool in delivering healthcare services.

Validation and Regulatory Approval: One of the significant challenges in the broader integration of RF sensing technology into clinical settings is the uncompromising approach required towards testing, validation, and regulatory approval. The process of obtaining approval can be long and arduous, involving extensive testing and rigorous evaluation to demonstrate the device's safety, efficacy, and reliability, particularly when used for detecting bone fractures. This stringent review takes place under controlled and varied conditions, ensuring the technology functions accurately and consistently as intended [74].

Moreover, this evaluation extends to the potential risks associated with the technology's usage, and measures are taken to identify and mitigate them [75]. As a medical device, an RF sensor must comply with specific safety and performance standards before gaining approval for clinical use. This laborious process, while ensuring the technology's integrity and quality, can pose a significant barrier to the rapid adoption of this technology in the healthcare system. Once the regulatory approval is achieved, it signifies that the technology has met the specific predefined standards and guidelines set by recognised health authorities. This approval is not just a testament to the integrity and quality of the technology, but also ensures that the RF sensing technology is safe for patient use, performs effectively, and adheres to ethical standards such as privacy, confidentiality, and equal access. Despite the challenges, adherence to these comprehensive procedures is paramount. They are essential to promote trust among healthcare professionals and patients and to ensure that technology contributes positively to patient outcomes and the overall healthcare system. Therefore, while the path to regulatory approval can indeed be challenging and time-consuming, it is a necessary hurdle to ensure the responsible deployment of RF sensing technology in clinical practice.

Privacy and Data Security: The widespread implementation of RF sensing technology in clinical settings necessitates rigorous testing, validation, and regulatory approval. An extensive evaluation process is imperative to affirm its safety, effectiveness, and reliability, specifically in detecting bone fractures. Ensuring the technology's compliance with regulatory standards and guidelines is a fundamental requirement that serves to maintain the technology's integrity and quality.

In addition to these crucial aspects, addressing privacy and security concerns is paramount. Applying RF sensing technology in clinical settings must be performed with stringent data protection measures to safeguard patients' personal and medical information. Secure data transmission and storage protocols should be in place to prevent unauthorised access and potential breaches [76]. Moreover, privacy regulations, such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States or the General Data Protection Regulation (GDPR) in the European Union, should guide the implementation and use of this technology. Adherence to these regulations will help ensure that patient data is handled responsibly and confidentially. These comprehensive measures, from technical performance to data security, foster trust in this technology among healthcare professionals and patients. This confidence is vital for RF sensing technology's safe, efficient, and ethical application in a clinical environment.

Ethical Considerations: Integrating RF sensing technology in healthcare necessitates a comprehensive evaluation of ethical implications, including equal access and potential unintended consequences. It is paramount to ensure the equitable distribution of this technology's benefits, addressing potential disparities in access across diverse populations. Such an approach is vital for maintaining social justice in healthcare, where the advantages of innovative technologies should not be limited to specific socioeconomic or geographic segments.

Beyond ensuring access, it's critical to identify and mitigate potential unintended consequences of this technology's deployment. For instance, overreliance on technology could inadvertently lead to diminished human interaction, altering the patient-care provider dynamic. Similarly, potential biases inherent in the decision-making algorithms of these systems could lead to disparities in diagnosis or treatment outcomes [77]. Establishing ethical frameworks and guidelines to govern the application of RF sensing technology in fracture detection is of utmost importance. These guidelines should encompass informed consent, privacy, data security, accountability, and transparency. By upholding these standards, the responsible and ethical use of RF sensing technology can be ensured, fostering trust among healthcare professionals and patients and facilitating its successful integration into clinical practice.

Financial Considerations: Another significant challenge involves the financial aspects related to the implementation of RF sensing technology in clinical settings. The cost of acquiring and maintaining these systems may be a barrier for many healthcare providers, particularly in low and middle-income regions. Also, there are costs associated with training healthcare providers on using this technology and interpreting its results. Therefore, strategies for cost reduction and efficient resource allocation need to be considered, such as developing more cost-effective RF sensors and providing online training programs for healthcare providers [78].

Future Prospects and Strategies for Overcoming Challenges

Despite the mentioned challenges, the prospects of RF sensing technology for bone fracture detection are immense.

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With continuous advancements in technology and growing understanding of the human bone anatomy, it is expected that RF sensors will play a significant role in revolutionising fracture detection [79].

Addressing technical challenges will largely depend on technological advancements and research breakthroughs. For instance, developing more sophisticated signal processing algorithms can help to minimise the impact of signal interference and attenuation, improving the accuracy and reliability of RF sensors. Also, the integration of machine learning and artificial intelligence techniques can enhance the data interpretation process, enabling more precise fracture detection, even amidst complex and noisy data [80].

The implementation challenges can be addressed through careful planning and management. One key aspect will be educating healthcare providers about the technology and providing them with the necessary training. Ensuring compatibility with existing healthcare systems and practices can also ease the integration of RF sensors into the clinical workflow. Moreover, developing cost-effective RF sensors can make the technology more accessible and ease financial constraints [81].

In terms of regulatory approval, manufacturers of RF sensors will need to work closely with regulatory bodies to ensure that the technology meets the required standards. This process should begin at the early stages of product development to streamline the approval process and ensure regulatory compliance. Privacy and data security challenges can be addressed through the application of robust data protection measures. These may include secure data transmission protocols, encrypted data storage, and training of healthcare providers on data protection policies and practices. Furthermore, ensuring compliance with privacy regulations will be key to protecting patient data and maintaining trust [82]. Addressing these challenges will not be easy and will require a concerted effort from all stakeholders involved, including researchers, healthcare providers, technology developers, and regulatory bodies. However, the potential benefits of RF sensing technology in detecting bone fractures make it a worthwhile endeavour. By overcoming these challenges, we can pave the way for this technology to become an integral part of clinical practice, significantly improving patient outcomes and advancing the field of bone health diagnostics [83].

Advancement in Innovative Approaches for Bone Fracture Detection

Hybrid Techniques

Complementary information may be obtained when combining different imaging modalities to detect bone fractures. The combination of low-frequency and microwave methods is one such hybrid strategy. Electrical impedance tomography (EIT) and electrical conductivity measurements are low-frequency methods that offer information about the electrical characteristics of tissues. Because of bone structure and mineralisation changes, fractured bones have different electrical characteristics than healthy bones. It is feasible to diagnose fractures and analyse the healing process by measuring the electrical conductivity of the bone.

Microwave methods, on the other hand, such as microwave radiometry or microwave tomography, use electromagnetic waves in the microwave frequency range [84]. These methods may offer information regarding tissue dielectric characteristics, such as changes in water content, which can be symptomatic of bone fractures. A complete examination of bone fractures may be performed by combining low-frequency and microwave approaches. Low-frequency measurements may reveal structural changes in the bone, but microwave measurements can provide information on water content and other dielectric characteristics. Combining these strategies can potentially increase the accuracy and dependability of fracture diagnosis and monitoring [84]. A hybrid technique proposed by [85] utilised image processing and machine learning-based method in classifying fracture detection using images from x-ray. The research demonstrated a commendable integration of machine learning algorithms and image processing techniques for the facilitation of fracture detection based on the severity and type of the fracture. Although this technique has the potential for a wider clinical applicability due to the reliance on existing x-ray data, no thorough investigation of the model interpretability and clinical validation process was made. Also, there was no proposed stepwise approach to real life clinical scenarios with regards to the performance of the technique.

Another research conducted by [86] on the topic "A study on the sensitivity of microwave imaging for detecting small-width bone fractures". The study's value rests in its narrow emphasis on small-width fractures and quantitative evaluation of microwave imaging sensitivity. The study provides insights into the technique's potential by methodically altering fracture widths and examining the generated photographs. However, the complexity of phantom models raises concerns about their ability to replicate genuine clinical circumstances. The lack of real-world validation using actual bone specimens is a restriction that may have an impact on the study's usefulness.

Signal Processing and Feature Extraction

Signal processing and feature extraction techniques are vital in analysing data received from various imaging modalities in hybrid methods for identifying bone fractures. These strategies assist in extracting useful information and features from the recorded signals, making fracture diagnosis and evaluation easier.

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In hybrid methods, signal processing techniques are used to pre-process the obtained data to eliminate noise, increase the signal quality, and improve the overall picture quality [87]. Following this process, the data used for the upcoming analysis will be clean and reliable. Feature extraction methods derive helpful information after pre-processing the signals or pictures. These characteristics may be quantitative data or unique patterns that are indicative of bone fractures or the healing process [88]. In fracture identification, some of the characteristics often employed include fracture line direction, bone mineral density, callus development, and local alterations in the properties of the tissue.

In recent times, the use of machine learning techniques to analyse the retrieved characteristics and construct models for fracture diagnosis have gained the attention of researchers. It is believed that these models gain the ability to categorise incoming data as either healthy or broken based on the patterns and correlations that they learn from the training data. It is possible to accomplish precise and automated fracture diagnosis via signal processing and feature extraction methods in hybrid systems [89,90]. A study demonstrated that combining machine learning techniques with signal processing and feature extraction methods enabled the creation of accurate and automated fracture diagnosis models. These models could categorize incoming data as healthy or fractured based on learned patterns and correlations, facilitating precise fracture identification.

Time-Domain Analysis in Hybrid Approaches

Analysing signals in the time domain is called time-domain analysis. This analysis investigates changes in the signal's amplitude and phase over time. In hybrid methods for detecting bone fractures, time-domain analysis is often used to extract useful information linked to the healing process compared to the use of the frequency domain technique. This is because unlike frequency domain analysis, analysis in the time domain makes it is feasible to trace the development of fracture healing by observing the temporal changes in the observed signals or pictures. For instance, in techniques based on ultrasound, the time-domain analysis may indicate the development of the fracture callus, which includes its genesis, growth, and remodelling. It is possible to evaluate the effectiveness of bone healing and its rate by examining the temporal patterns. The study demonstrated that time-domain analysis in hybrid imaging modalities allowed for the tracking and evaluation of the temporal changes in fracture healing, providing valuable insights into the development of the fracture callus, its growth, and remodelling. This approach proved to be more effective than frequency domain analysis in observing dynamic changes during the healing process [91].

Time-domain analysis may also be used in other imaging modalities, such as magnetic resonance imaging (MRI) or computed tomography (CT), to analyse dynamic changes in tissue characteristics, vascularisation, or inflammation surrounding the fracture site. These temporal differences provide helpful insights into the wound-healing process and have the potential to contribute to the diagnosis and ongoing monitoring of bone fractures. In conclusion, hybrid methods for detecting bone fractures often require the utilisation of various imaging modalities, signal processing, feature extraction strategies, and time-domain analysis. These techniques use the beneficial aspects of each method to give a thorough analysis of fractures, improve diagnostic accuracy, and more effectively monitor the healing process. A study compared time-domain analysis with frequency domain techniques in hybrid imaging systems for bone fracture diagnosis. The outcomes demonstrated that time-domain analysis provided a more comprehensive evaluation of fractures, allowing for assessing bone healing effectiveness and rate through temporal patterns [92].

UHF Antenna-Based Detection Techniques

A recent development in the field employs ultra-high frequency (UHF) antennas and s-parameters for the non-invasive detection of bone fractures [93]. The concept involves using the UHF antenna to scan a bone phantom modelled after a human femur with a fracture. The difference in reflected and transmitted signals is then used to identify the presence and location of the fracture. This innovative approach offers low-power reflection and high-power transmission coefficients, signalling the presence of a fracture. In simulations, this technique has demonstrated the ability to detect fractures at varying locations on the bone phantom, with the s-parameters displaying differences according to the fracture's position. This could indicate the technique's potential for detecting fractures in different parts of the bone, thus enhancing the method's versatility. However, using this technique in real-world scenarios requires further investigation, as the research has only encompassed simulations.

Dual-Polarized Microwave Sensor for Fracture Detection

A recent human bone fracture detection development involves a novel, compact sensor system that employs a patch antenna, reactive impedance surfaces, and a dielectric plano-concave lens [94]. This innovative system, about 30% smaller than traditional designs, is tailored to the human body to enhance impedance matching and optimise sensor performance. The methodology employed for this system includes designing and optimising sensor components using CST Microwave Studio software, fabrication via PCB technology and 3D printing, and performance validation on a semi-solid phantom. The sensor operates at a centre frequency of 2.45 GHz with a bandwidth of 12.5%, and this sensor system demonstrates impressive sensitivity and accuracy in detecting and imaging narrow cracks in bone tissue and determining their location and orientation. The system's effectiveness surpasses traditional methods such as X-ray or ultrasound. However, despite its innovative design and impressive capabilities, the system's

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implementation in real-world scenarios is yet to be explored. Future work can focus on enhancing the accuracy and robustness of the sensor system, testing on more realistic phantoms or animal models, and exploring applications in other biomedical fields, such as tumour detection or osteoporosis screening.

Application of Artificial Intelligence in Bone Fracture Detection

The challenge of accurately diagnosing fractures in emergency departments is significant, with missed fractures being the most common diagnostic error. This failure can result in delayed treatment and long-term disability [95]. This task becomes further complicated due to the variability in fracture appearances based on factors such as the affected bone, regional anatomy, and radiographic projection [96]. However, the evolution of machine learning and deep learning techniques has heralded a new era in fracture detection, significantly improving speed, efficiency, and error rates in diagnostics.

Machine Learning in Bone Fracture Detection

Machine learning is making considerable progress in healthcare, particularly in the early detection of bone fractures. Bone fractures can lead to significant morbidity if not diagnosed and treated promptly. Sophisticated machine learning algorithms, such as Support Vector Machines (SVM) and Neural Networks, can analyse imaging data from CT scans or X-rays to recognise patterns and signs indicative of fractures. Machine learning also synergises with advances in radio frequency (RF) technology, yielding non-invasive methods for fracture detection. These methods leverage the unique changes in RF signals that occur due to alterations in bone structure, opening a new avenue for early fracture detection. A study has demonstrated that deep learning is a dependable method for diagnosing fractures, with a high diagnostic accuracy comparable to that of general physicians [95]. The study aimed to investigate the accuracy and reliability of deep learning in detecting orthopaedic fractures. The pooled sensitivity and specificity for the whole group (17 trials, 5,434 images) were 0.87 and 0.91, respectively. The AUC was 0.95. Eight trials (1,574 images) were included in the long-bone group, which contained seven studies. The pooled sensitivity was 0.96, and the specificity was 0.94. The AUC was 0.99.

Another study [97], proposed a novel machine learning-based technique to detect bone fractures by analysing bone contours. Several machine-learning algorithms, including Naïve Bayes, Decision Tree, Nearest Neighbours, Random Forest, and SVM, were employed on a dataset of 270 x-ray images. The accuracy measures varied, with SVM exhibiting the highest accuracy [98]. Accuracy measures for the various algorithms employed in the study range from 0.64 to 0.92, with values obtained for Naïve Bayes, Decision Tree, Nearest Neighbours, Random Forest, and SVM. Statistically, the accuracy for SVM was found to be the highest in this research. This method overcomes the shortcoming of the method used in another study, which works on texture analysis only that investigates the effectiveness of bone texture analysis (TA) and machine learning (ML) in identifying patients at risk for vertebrae fractures from CT scans. The results showed that this method was significantly more accurate than traditional methods in identifying at-risk patients. However, it struggled to identify individual at-risk vertebrae accurately. Human assessment could have been more accurate overall. The study found that bone texture analysis combined with machine learning allows identifying patients at risk for vertebral body insufficiency fractures on standard CT scans with high accuracy and improves fracture risk prediction compared to mere Hounsfield unit measurements on CT scans. This analysis can potentially identify vertebrae at risk for insufficiency fracture and may thus increase the diagnostic value of standard CT scans.

Deep Learning and Neural Networks

While earlier deep-learning systems for fracture detection were limited, focusing on single bones or specific anatomical regions, recent advancements have considerably broadened this scope, making them powerful tools for addressing fracture detection in medical imaging [99]. In October 2020, npj Digital Medicine published a study titled “Assessment of a deep-learning system for fracture detection in musculoskeletal radiographs”. The study aimed to create a deep-learning system that could assist clinicians in detecting fractures in musculoskeletal imaging. The system was trained on data manually annotated by senior orthopaedic surgeons and radiologists. The results showed that the system was able to accurately detect fractures in adult musculoskeletal radiographs, which is a challenging problem and the largest source of diagnostic errors in emergency departments. This technique could help reduce missed fractures, which are the most common diagnostic error in emergency departments and can lead to delays in treatment and long-term disabilities. The overall AUC of the deep-learning system was 0.974, with a sensitivity of 95.2% and a specificity of 81.3%. The positive predictive value was 47.4%, and the negative predictive value. The study also shows that missed fractures are the most common diagnostic error in emergency departments and can lead to treatment delays and long-term disability.

Artificial Intelligence (AI) comprises a range of technologies, including Deep Learning, which uses artificial neuron layers to improve machines’ ability to understand and interpret complex data [100]. One such application was the development of a Deep Neural Network (DNN) for detecting fractured bones in X-ray images. They developed a system that uses a deep neural network (DNN) to detect fractured bones in X-ray images. Manual diagnosis of bone fractures takes a lot of time and has a high chance of errors. Hence, an automated system is required to diagnose fractured bones accurately. The proposed system uses a deep neural network model to differentiate between healthy and fractured bones. However, when working with small datasets, the

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model tends to overfit, so data augmentation techniques are used to increase the size of the dataset. The accuracy of the proposed model for classifying healthy and fractured bones is 92.44% using 5-fold cross-validation. Additionally, the accuracy of the model on 10% and 20% of the test data is more than 95% and 93%, respectively. The proposed model performs much better than previous models [101]. In recent times, Deep Learning has made significant progress in perception tasks. In orthopaedics and traumatology, deep Learning has been used to identify fractures in radiographs. Researchers have designed a deep neural network model that can classify fractured and healthy bones with an accuracy of 92.44% using 5-fold cross-validation. To increase the size of the data set, they employed data augmentation techniques. The model's accuracy is more than 95% and 93% for 10% and 20% of the test data, respectively [102]. However, studies on using Deep Learning to detect and classify fractures on computed tomography (CT) scans still need to be completed.

Another study [102]., evaluated whether a Food and Drug Administration-cleared deep learning system that identifies fractures in adult musculoskeletal radiographs would improve diagnostic accuracy for fracture detection across different types of clinicians. The study found that clinicians were more accurate at diagnosing fractures when aided by the deep learning system, particularly those clinicians with limited training in musculoskeletal image interpretation. Reducing the number of missed fractures may allow for improved patient care and increased patient mobility. The study shows that a deep-learning system can accurately identify fractures throughout the adult musculoskeletal system. The overall AUC of the deep-learning system was 0.974 (95% CI: 0.971–0.977), sensitivity was 95.2% (95% CI: 94.2–96.0%), specificity was 81.3% (95% CI: 80.7–81.9%), positive predictive value (PPV) was 47.4% (95% CI: 46.0–48.9%), and negative predictive value (NPV) of 99.0% (95% CI: 98.8–99.1%).

A recent study proposes a two-stage region-based convolutional neural network for thighbone fracture detection. The pre-trained model is implemented on the dataset reported in the previous study, which includes 3842 thighbone X-ray radiographs. The experimental results show that the Average Precision of the proposed detection framework reaches 88.9% in thighbone fracture detection. This result proves the effectiveness of our framework and its superiority over other state-of-the-art methods [103]. A recently conducted survey [104]., delves into the diagnosis of bone fractures, aiming to help researchers develop models that can automatically detect such fractures in human bones. The survey's authors discuss several image-processing techniques that can be used for fracture detection, including conventional and deep learning-based methods. They also compare the various techniques available and highlight the challenges researchers face in this field. To enhance fracture detection, the authors suggest using automated models such as Convolutional Neural Networks (CNN) that are pre-trained on diverse bone X-ray images. To combat the issue of observer bias in creating labelled datasets, they propose using a "gold standard" dataset that receives input from multiple expert radiologists. Additionally, they suggest addressing overfitting by cropping regions of interest from images and using different network architectures. The authors conclude that automated fracture classification models have the potential to improve radiographic interpretations and advocate for the creation of more comprehensive labelled datasets and efficient models that can detect various fractures across different anatomical regions.

In another study, Deepa Joshi, Thipendra P. Singh, and Anil Kumar Joshi developed a deep neural network to detect, localise and divide the wrist region into segments to identify fractures around the wrist joint in radiographs [105]. Their study aims to assist investigators in developing models that automatically detect fractures in human bones. The authors discuss the data preparation stage and present various image-processing techniques for fracture detection. Then, they analyse conventional and deep learning-based techniques for diagnosing bone fractures. They make a comparative analysis of existing techniques. The proposed model achieved an average precision of 92.278 on 50° and 79.003 on a strict scale of 75° for fracture detection. Similarly, the average precision of 77.445 on 50° and 52.156 on a strict scale of 75° was reported for fracture segmentation [105]. Several examples of using deep learning techniques, such as Convolutional Neural Networks (CNN), for automated fracture detection and localisation on radiographs. For instance, a deep learning object detection network detected and localised radius and ulna fractures on wrist radiographs with high sensitivity at a per-fracture (frontal 91.2%, lateral 96.3%), the per-image sensitivity, specificity, and AUC were 95.7%, 82.5%, and 0.918, respectively, for the frontal view and 96.7%, 86.4%, and 0.933, for the lateral view, even with a relatively modest training dataset size of 7356 radiographic studies [106] (Table 5 & Table 6).

Advancements in RF Sensing Technology for Fracture Detection: A Future Perspective

Emerging computational techniques like artificial intelligence (AI), machine learning, and deep learning could revolutionise RF sensors' usage in bone fracture detection. By analysing radio frequency signals emitted from bones and identifying patterns or anomalies, these techniques could significantly improve fracture detection precision and sensitivity. Real-time monitoring could further enhance this area, enabling prompt tracking of the healing process and timely detection of complications. Such capabilities would improve clinical decision-making and patient management, resulting in better outcomes. Predictive algorithms could facilitate anticipatory analysis, providing insights into future fracture risks and enabling preventive measures, especially beneficial for conditions like osteoporosis, where fracture risk is considerably elevated [107]. Moreover, integrating RF sensor data with comprehensive patient information—like medical history,

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demographics, and data from other imaging modalities—can enrich the overall understanding of a patient's health status. This integrated view can aid in crafting more personalised treatment plans, thereby increasing the effectiveness of interventions and hastening recovery times.

Table 5: Comparison of Deep Learning Systems for Fracture Detection.

System	Study Number	Sensitivity	Specificity	AUC	Positive Predictive Value	Negative Predictive Value
Deep Learning	[84]	0.91 (whole group), 0.94 (long-bone group)	0.95 (whole group), 0.99 (long-bone group)	0.87 (whole group), 0.96 (long-bone group)	Not provided	Not provided
Deep-learning System	[100]	95.20%	81.30%	0.974	47.40%	99.00%
Deep Learning Object Detection Network	[106]	95.7% (frontal view), 96.7% (lateral view)	Not provided	0.918 (frontal view), 0.933 (lateral view)	Not provided	Not provided

Table 6: Deep Learning Methods for Fracture Detection and Localisation.

Method	Study Number	Average Precision	Application
Convolutional Neural Networks (CNN)	[103]	88.90%	Thighbone fracture detection
Deep Neural Network	[105]	92.278 (for fracture detection), 77.445 (for fracture segmentation)	Detection, localisation, and segmentation of fractures around the wrist joint

In line with technological advancements, future RF sensors could be more compact, portable, and cost-effective, enhancing accessibility in diverse healthcare settings. These developments could dramatically refine bone fracture diagnosis, monitoring, and management, signalling a new era in orthopaedic care. Inventive sensor technologies could significantly enhance fracture diagnosis. Flexible and wearable sensors, for instance, which adapt to the body's contours and allow continuous healing process monitoring, can be integrated into clothing or bandages, enabling real-time data collection without disturbing everyday activities. Miniaturised sensors embedded in implantable devices can facilitate direct healing process monitoring [108]. Advanced signal processing techniques can enhance bone fracture diagnosis, utilising machine learning and AI for pattern detection and fracture-related signal categorisation. These algorithms, trained on expansive datasets, can discern between normal and fractured bone patterns, increasing fracture detection accuracy. Researchers can explore complex feature extraction techniques, examining signal frequency content, energy distribution, or statistical properties to gain deeper insights into fracture characteristics. Combining sensor data with conventional imaging methods such as X-rays, MRIs, or ultrasound can yield comprehensive bone fracture analysis. Integrating sensor data and MRI scans, for example, provides a more accurate depiction of the fracture location, granting a greater understanding of the fracture's severity, alignment, and healing progress.

Individualised approaches for fracture detection can adjust to unique patient characteristics such as age, bone density, and medical history, leading to more accurate identification and tailored treatments. Patient-specific biomechanical models considering the patient's anatomy, bone characteristics, and loading conditions can provide more accurate fracture predictions and diagnoses [109]. Detecting bone fractures could also be improved by investigating multi-modal systems combining several sensing techniques, such as RF, ultrasound, or optical imaging. Non-linear analytic approaches like chaos theory or fractal analysis could identify minor changes in fracture-related signals that standard linear methods may not capture. Modern data fusion and fusion algorithms can integrate information from different sensors or imaging modalities, facilitating an all-encompassing analysis of bone fractures. Significant strides in bone fracture detection research require collaborative efforts between researchers, clinicians, and industry partners. Establishing partnerships could translate research results into practical clinical solutions and foster the development of commercial devices convenient for regular clinical practice. Standardised methods and benchmarks should be implemented to assess and compare various fracture detection systems, ensuring research and clinical application consistency and reproducibility.

Further research to advance RF-based bone fracture detection could explore enhanced RF techniques. Frequency-domain analysis can offer detailed insights into fracture features and healing process progression. Techniques such as impedance spectroscopy or time-reversal imaging could improve RF-based fracture detection's precision and sensitivity. Extensive clinical research could evaluate the efficacy and reliability of RF-based

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approaches for monitoring fracture healing and therapy outcomes. Collaboration with radiologists and orthopaedic surgeons is crucial to ensure RF-based fracture diagnostic systems' clinical relevance and practical usability. Partnerships with industry stakeholders could assist in the development of cost-effective, portable devices convenient for regular clinical use. Comparisons between RF-based fracture detection approaches, other imaging modalities, and clinical standards are necessary, providing a solid base to evaluate their precision and efficacy. By focusing on these future directions and suggestions, researchers could facilitate breakthroughs in bone fracture detection, improving patient outcomes by providing accurate, timely diagnoses and monitoring.

Conclusion

In conclusion, this comprehensive review has examined the latest bone fracture detection methods advancements, specifically focusing on time-domain low-frequency and microwave radio frequency (RF) techniques. These innovative technologies have shown promise in improving diagnostic accuracy, efficiency, and safety, potentially enhancing patient outcomes. Our detailed analysis of RF techniques highlights their ability to precisely measure the dielectric properties of biological tissues, which could provide critical insights for detecting fractures. This represents a significant leap over traditional detection methods. Additionally, the integration of machine learning and artificial intelligence has proven crucial in identifying complex patterns and anomalies, enabling faster and more accurate fracture diagnosis, thus reducing the pressure on healthcare systems.

Microwave imaging techniques offer a more affordable and safer alternative to traditional methods, as they do not use ionising radiation, thereby benefiting healthcare facilities where X-ray usage could be more practical and encouraged. We also spotlighted the advantages of innovative hybrid techniques that merge low-frequency and microwave approaches, with the incorporation of time-domain analysis presenting an exciting opportunity to magnify diagnostic accuracy further. While we have navigated the challenges of utilising RF sensors for bone fracture detection, further research is encouraged to overcome these challenges and optimise the performance of these techniques. This review underscores the immense potential of new sensor technologies, improved signal processing techniques, integration with current medical imaging methods, and personalised fracture detection approaches. As we refine these techniques and broaden our understanding of their practical applications, we will likely see enhanced patient outcomes, eased burdens on healthcare systems, and improve overall healthcare delivery.

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