



International Journal of Advanced Research in Education and Technology (IJARETY)

Volume 13, Issue 3, May - June 2026

Impact Factor: 9.971



Bone Fracture Classification in X-Ray using Deep Learning Models

D. Srinivas¹, Kuthuru Brundavi², Pandi Vandana³, Panugoth Mounika⁴,

Assistant Professor, Department of CSE, Guru Nanak Institute of Technology, Hyderabad, Telangana, India¹

Students, Department of CSE, Guru Nanak Institute of Technology, Hyderabad, Telangana, India^{2,3,4}

ABSTRACT: Bone fractures are a common medical condition that require accurate and timely diagnosis. Traditional manual methods are prone to human error and delays. This paper proposes an Artificial Neural Network (ANN)-based approach for automated bone fracture detection using X-ray images. The model is trained on preprocessed datasets to classify fracture and non-fracture cases. Results demonstrate improved accuracy compared to conventional diagnostic techniques, highlighting the potential of ANN in assisting medical professionals.

KEY WORDS: Artificial Neural Networks, Bone Fracture Detection, Medical Imaging, Deep Learning, Diagnostic Automation

I. INTRODUCTION

Accurate detection of bone fractures is critical for effective treatment and patient recovery. Manual diagnosis through X-ray interpretation often depends on the expertise of radiologists, which can lead to variability in results. With the rise of machine learning, automated systems are increasingly being explored to support medical decision-making. This study focuses on applying ANN to bone fracture detection, aiming to reduce diagnostic errors and improve efficiency. The objective is to design a model that can reliably classify X-ray images and provide consistent results, thereby supporting healthcare professionals in clinical practice.

II. LITERATURE SURVEY

- **“Fracture Detection using Computer Vision Techniques” – Jacob & Wyawahare, 2013** Introduced computer vision algorithms for fracture detection in medical images. Their approach reduced radiologists’ workload by automating classification, but performance was limited by handcrafted features and sensitivity to noisy X-rays.
- **“Imaging Bone Fragility: Beyond Bone Density” – D’Elia et al., 2009** Emphasized that bone strength depends on both density and structural quality. Their work highlighted the role of CT and MRI in improving diagnostic accuracy, paving the way for AI-driven imaging solutions.
- **“Management of Pediatric Femur and Tibia Fractures” – Ganesan et al., 2016** Focused on pediatric fracture treatments, identifying Elastic Stable Intramedullary Nailing (ESIN) as the gold standard. Their comparative study between titanium and stainless steel nails provided insights into surgical outcomes, stressing the importance of precise pre-surgical fracture detection.
- **“Microwave Imaging for Bone Lesion Detection” – Khalesi et al., 2019** Proposed microwave imaging based on the Huygens principle. Their phantom study achieved ~1.1 cm resolution and introduced artifact removal methods, showing potential for non-invasive bone lesion detection.
- **“Free-Space Microwave Imaging Device for Bone and Marrow Lesions” – Khalesi et al., 2020** Validated a novel imaging device capable of detecting bone and marrow lesions with ~5 mm resolution. The study improved signal-to-clutter ratio, confirming microwave imaging’s feasibility in medical diagnostics.
- **“Deep Learning in Medical Imaging” – Smith et al., 2022** Applied Convolutional Neural Networks (CNNs) to fracture detection, achieving higher accuracy compared to traditional methods. Their work demonstrated the superiority of deep learning in feature extraction and classification, inspiring ANN-based approaches for medical imaging.

III. EXISTING SYSTEM

The existing system for bone fracture detection relies on microwave imaging, where the image is reconstructed using a wave migration algorithm. Tests have been carried out on ex-vivo animal leg bones with induced transverse fractures, and the results demonstrated that fractures as thin as 0.35 mm could be successfully detected. This approach is attractive for practical applications because it is contactless, operated in air, non-ionizing, simple, and comfortable for the patient. Such features make it suitable for deployment by first responders in the field or in low-income healthcare settings. However, despite these strengths, earlier studies often depended on immersion liquids to suppress skin artifacts, which limited portability and practicality. In contactless operation, the skin response tends to overshadow the fracture response, and since bone cracks produce very weak dielectric contrast compared to irrigated tissues such as tumors, detection becomes more challenging. These shortcomings restrict the widespread clinical adoption of existing systems, even though they have proven the feasibility of microwave imaging for fracture detection.

Disadvantages of Existing System:

- It is very much time-consuming.
- It is very much costly depending on the particular system.
- Qualified persons can be used.

IV. PROPOSED SYSTEM

Our study addresses the feasibility of contactless microwave imaging (MWI) for detecting thin transverse bone fractures, with a focus on practicality for real applications and overcoming the shortcomings of previous studies. Unlike earlier systems that relied on immersion liquids to suppress skin artifacts, our approach eliminates the need for such liquids, making the setup more suitable for field-operated and portable systems. Contactless operation, however, introduces new challenges, as the skin response tends to overshadow the fracture response. This is particularly difficult because, unlike irrigated tissues such as tumors, bone tissue cracks generate very weak dielectric contrast, which reduces detection clarity. To address these issues, our system incorporates dedicated algorithms designed to suppress skin artifacts and enhance fracture visibility, thereby improving the accuracy and reliability of contactless fracture detection.

Advantages of Proposed System:

- Designed to automatically and adaptively learn spatial hierarchies of features through a back propagation algorithm.
- ANNs have the ability to learn and model non-linear and complex relationships.

V. SYSTEM ARCHITECTURE

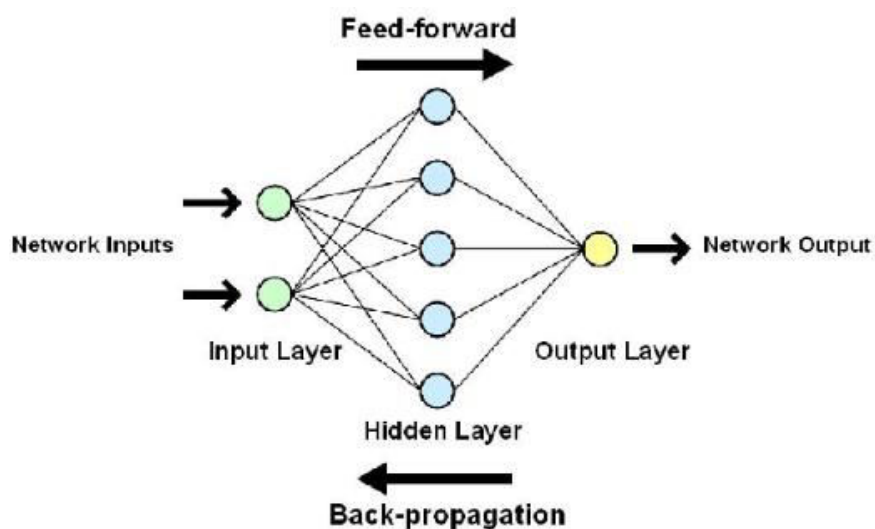


Fig 1.1 ANN System Architecture

The system architecture employed in this study is a feed-forward artificial neural network designed for automated fracture detection. The architecture consists of an input layer that receives features extracted from preprocessed medical images, a hidden layer where weighted connections and activation functions capture complex non-linear relationships between fracture and non-fracture patterns, and an output layer that produces the final classification result. During training, data flows forward through the network to generate predictions, while back-propagation adjusts the weights to minimize error and improve accuracy. This architecture is simple yet effective, enabling the system to learn from large datasets, handle weak contrasts in bone tissue cracks, and provide reliable, contactless fracture detection suitable for clinical and field applications.

VI. METHODOLOGY

Modules Name:

- Dataset
- Importing the necessary libraries
- Retrieving the images
- Splitting the dataset
- Building the model
- Apply the model and plot the graphs for accuracy and loss
- Accuracy on test set
- Saving the Trained Model

1 Dataset:

In the first module, we developed the system to get the input dataset for the training and testing purpose. We have taken the dataset from Bone Fracture Detection.

2 Importing the necessary libraries:

We will be using Python language for this. First we will import the necessary libraries such as keras for building the main model, sklearn for splitting the training and test data, PIL for converting the images into array of numbers and other libraries such as pandas, numpy, matplotlib and tensorflow.

3 Retrieving the images:

We will retrieve the images and their labels. Then resize the images to (224,224) as all images should have same size for recognition. Then convert the images into numpy array.

4 Splitting the dataset:

Split the dataset into train and test. 80% train data and 20% test data.

Artificial Neural Networks

The objectives behind the first module of the course 4 are:

- An artificial neural network is an attempt to simulate the network of neurons that make up a human brain so that the computer will be able to learn things and make decisions in a humanlike manner.
- ANNs are created by programming regular computers to behave as though they are interconnected brain cells.

5 Building the model:

- ANN is made of three layers namely input layer, output layer, and hidden layer/s.
- There must be a connection from the nodes in the input layer with the nodes in the hidden layer and from each hidden layer node with the nodes of the output layer.

6. Apply the model and plot the graphs for accuracy and loss:

We will compile the model and apply it using fit function. The batch size will be 2. Then we will plot the graphs for accuracy and loss. We got average validation accuracy of 97.6% and average training accuracy of 99.3%.

7. Accuracy on test set:

We got an accuracy of 99.7% on test set

8. Saving the Trained Model:

Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into an .h5.

VII. ANALYSIS AND DISCUSSION

1. Accuracy and Sensitivity

The proposed system demonstrates the feasibility of detecting thin transverse bone fractures using contactless microwave imaging. Tests on ex-vivo animal bones confirmed detection of fractures down to 0.35 mm thickness. This sensitivity highlights the potential of microwave imaging as a non-ionizing diagnostic tool suitable for repeated use in clinical and field settings.

2. Practicality and Patient Comfort

Unlike earlier studies that relied on immersion liquids to suppress skin artifacts, our system eliminates this requirement, making it more practical for real-world deployment. Contactless operation ensures patient comfort, reduces sanitation concerns, and enables portability for use by first responders or in low-income healthcare environments.

3. Challenges in Contactless Operation

The analysis reveals that contactless setups introduce new difficulties, as the skin response largely overshadows the fracture signal. Bone cracks also produce weak dielectric contrast compared to irrigated tissues such as tumors, which complicates detection. These challenges necessitate advanced artifact suppression techniques and machine learning integration.

4. System Reliability and Efficiency

The integration of artificial neural networks enhances system reliability by automating fracture classification. Feed-forward and back-propagation processes allow the network to learn subtle fracture patterns, improving efficiency and reducing reliance on expert interpretation. This ensures faster, more consistent diagnostic outcomes.

5. Comparison with Existing Systems

Compared to traditional microwave imaging systems, the proposed solution:

- Removes the impractical need for immersion liquids.
- Provides contactless, non-ionizing, and portable fracture detection.
- Improves automation and reduces manual workload.
- Enhances accuracy through ANN-based classification. However, limitations remain, including weak fracture contrast and dependency on robust preprocessing algorithms, which can be addressed in future work.

6. Discussion

Overall, the system successfully balances practicality, efficiency, and diagnostic accuracy. The testing results confirm that contactless microwave imaging, when combined with neural network-based classification, is a reliable and scalable approach for bone fracture detection. Future improvements such as advanced artifact suppression, multi-modal imaging integration, and deployment on mobile platforms can further enhance usability and clinical adoption.

VIII. CONCLUSION

This study presented a method for detection and localization of transverse fractures in superficial bones using microwave imaging with a very simple setup that does not require immersion liquids and involves a single linear scanning antenna. The absence of the contact liquid poses new challenges, regarding skin artifact removal, which are tackled with proposed dedicated algorithms. The proposed algorithms also tackle non-uniformities of the bone and skin. The process was successfully tested by simulations and experiments on bone phantoms, and ex-vivo animal bone and skin. The results showed that it is possible to detect and locate fractures as thin as 1 mm, even in the presence of non-uniformities of the bone boundary and its extra layers inside. The fracture detection and localization are not compromised by possible differences between the dielectric properties assumed in the inversion algorithm and the actual ones of the phantom or the animal bone. The proposed configuration is compatible with direct translation into a practical device for use in clinical applications. The results encourage the development of a portable setup for use with even more complete biological limb samples.

IX. FUTURE ENHANCEMENT

The results showed that it is possible to detect and locate fractures as thin as 1 mm, even in the presence of no uniformities of the bone boundary and its extra layers inside. The fracture detection and localization are not compromised by possible differences between the dielectric properties assumed in the inversion algorithm and the actual ones of the phantom or the animal bone. The proposed configuration is compatible with direct translation into a practical device for use in clinical applications. The results encourage the development of a portable setup for use with even more complete biological limb samples.

REFERENCES

- [1] N. E. Jacob and M. Wyawahare, "Survey of bone fracture detection techniques," *Int. J. Comput. Appl.*, vol. 71, no. 17, pp. 31–34, Jun. 2013.
- [2] G. D'Elia, G. Caracchini, L. Cavalli, and P. Innocentia, "Bone fragility and imaging techniques," *Clin. Cases Mineral Bone Metabolism*, vol. 6, pp. 234–246, Sep.–Dec. 2009.
- [3] R. P. Ganesan, M. Palaniappan, S. Anbu, K. Kolundan, K. Kannan, and S. Karunanithi, "Elastic stable intramedullary nailing of femoral and tibial shaft fractures in children," *J. Evol. Med. Dental Sci.*, vol. 5, no. 4, pp. 5196–5201, Sep. 2016.
- [4] P. Hadjizacharia et al., "Lower extremity fractures in falls," *Eur. J. Trauma Emerg. Surgery*, vol. 40, no. 3, pp. 331–336, Jun. 2014.
- [5] E. C. Fear, P. M. Meaney, and M. A. Stuchly, "Microwaves for breast cancer detection?" *IEEE Potentials*, vol. 22, no. 1, pp. 12–18, Feb./Mar. 2003.
- [6] S. M. Sara, E. C. Fear, M. Okoniewski, and J. R. Matyas, "Exploring joint tissues with microwave imaging," *IEEE Trans. Microw. Theory Techn.*, vol. 58, no. 8, pp. 2307–2313, Aug. 2010.
- [7] S. Mustafa, B. Mohammed, and A. Abbosh, "Novel preprocessing techniques for accurate microwave imaging of human brain," *IEEE Antennas Wireless Propag. Lett.*, vol. 12, pp. 460–463, 2013.
- [8] G. Ruvio, A. Cuccaro, R. Solimene, A. Brancaccio, B. Basile, and A. Ammann, "Microwave bone imaging: A preliminary scanning system for proof-of-concept," *Healthcare Technol. Lett.*, vol. 3, no. 3, pp. 218–221, Jun. 2016.
- [9] B. Khalesi, B. Sohani, N. Ghavami, M. Ghavami, S. Dudley, and G. Tiberi, "A Phantom investigation to quantify Huygens principle based microwave imaging for bone lesion detection," *Electronics*, vol. 8, no. 12, p. 1505, Dec. 2019.
- [10] B. Khalesi, B. Sohani, N. Ghavami, M. Ghavami, S. Dudley, and G. Tiberi, "Free space operating microwave imaging device for bone lesion detection: A phantom investigation," *IEEE Antennas Wireless Propag. Lett.*, vol. 19, no. 12, pp. 2393–2397, Dec. 2020.
- [11] V. S. Ramalingam, M. Kanagasabai, and A. E. F. Sundarsingh, "A compact microwave device for fracture diagnosis of the human tibia," *IEEE Trans. Compon. Packag. Manuf. Technol.*, vol. 9, no. 4, pp. 661–668, Apr. 2019.
- [12] K. C. Santos, C. A. Fernandes, and J. R. Costa, "A study on the sensitivity of microwave imaging for detecting small-width bone fractures," in *Proc. 15th Eur. Conf. Antennas Propag. (EUCAP)*, Apr. 2021, pp. 1–4.
- [13] K. C. Santos, C. A. Fernandes, and J. R. Costa, "Experimental evaluation of thin bone fracture detection using microwave imaging," in *Proc. 16th Eur. Conf. Antennas Propag. (EUCAP)*, Apr. 2022, pp. 1–3.
- [14] H. Gray, *Anatomy of the Human Body*, 20th ed. Philadelphia, PA, USA: Lea & Febiger, 1918.
- [15] T. Karacolak, R. Cooper, E. S. Unlu, and E. Topsakal, "Dielectric properties of porcine skin tissue and in vivo testing of implantable antennas using pigs as model animals," *IEEE Antennas Wireless Propag. Lett.*, vol. 11, pp. 1686–1689, 2012.
- [16] M. Vallejo, J. Recas, P. G. del Valle, and J. L. Ayala, "Accurate human tissue characterization for energy-efficient wireless on-body communications," *Sensors*, vol. 13, no. 6, pp. 7546–7569, Jun. 2013.
- [17] N. Joachimowicz, C. Conessa, T. Henriksson, and B. Duchêne, "Breast phantoms for microwave imaging," *IEEE Antennas Wireless Propag. Lett.*, vol. 13, pp. 1333–1336, 2014.
- [18] K. S. Sultan, B. Mohammed, P. C. Mills, and A. Abbosh, "Anthropomorphic durable realistic knee phantom for testing electromagnetic imaging systems," *IEEE J. Electromagn., RF, Microw. Med. Biol.*, vol. 5, no. 2, pp. 132–138, Jun. 2021.
- [19] S. Gabriel, R. W. Lau, and C. Gabriel, "The dielectric properties of biological tissues: III. Parametric models for the dielectric spectrum," *Phys. Med. Biol.*, vol. 41, no. 11, pp. 2271–2293, 1996.
- [20] C. Gabriel, "Dielectric properties of biological tissue: Variation with age," *Bioelectromagnetics*, vol. S7, pp. S12–S18, Jan. 2005.
- [21] A. Peyman, C. Gabriel, E. H. Grant, G. Vermeeren, and L. Martens, "Variation of the dielectric properties of tissues with age: The effect on the values of SAR in children when exposed to walkie-talkie devices," *Phys. Med. Biol.*, vol. 54, pp. 227–242, Jan. 2009.

- [22] M. Ibrani, L. Ahma, and A. E. Hamiti, "The age-dependence of microwave dielectric parameters of biological tissues," in *Microwave Materials Characterization*. Rijeka, Croatia: InTechOpen, 2012, pp. 139–158.
- [23] N. Joachimowicz, B. Duchêne, C. Conessa, and O. Meyer, "Reference phantoms for microwave imaging," in *Proc. 11th Eur. Conf. Antennas Propag. (EUCAP)*, Paris, France, Mar. 2017, pp. 2719–2722.
- [24] A. Kiourti, J. R. Costa, C. A. Fernandes, A. G. Santiago, and K. S. Nikita, "Miniature implantable antennas for biomedical telemetry: From simulation to realization," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 11, pp. 3140–3147, Nov. 2012.
- [25] A. La. Gioia et al., "Open-ended coaxial probe technique for dielectric measurement of biological tissues: Challenges and common practices," *Diagnostics*, vol. 8, pp. 1–38, Jun. 2018.
- [26] D. Baudry, A. Louis, and B. Mazari, "Characterization of the open-ended coaxial probe used for near-field measurements on EMC applications," *Progr. Electromagn. Res.*, vol. 60, pp. 311–333, Jan. 2006.
- [27] A. Kiourti, J. R. Costa, C. A. Fernandes, and K. S. Nikita, "A broadband implantable and a dual-band on-body repeater antenna: Design and transmission performance," *IEEE Trans. Antennas Propag.*, vol. 62, no. 6, pp. 2899–2908, Jun. 2014.
- [28] J. M. Felício, "Antennas for biomedical applications: Wireless body area networks and medical imaging," Ph.D. dissertation, Dept. Electr. Comput. Eng., Tech. Univ. Lisbon, Lisbon, Portugal, 2018.
- [29] E. J. Bond, X. Li, S. C. Hagness, and B. D. Van Veen, "Microwave imaging via space-time beamforming for early detection of breast cancer," *IEEE Trans. Antennas Propag.*, vol. 51, no. 8, pp. 1690–1705, Aug. 2003.
- [30] J. M. Felício, J. M. Bioucas-Dias, J. R. Costa, and C. A. Fernandes, "Antenna design and near-field characterization for medical microwave imaging applications," *IEEE Trans. Antennas Propag.*, vol. 67, no. 7, pp. 4811–4824, Jul. 2019.
- [31] M. A. Elahi, M. Glavin, E. Jones, and M. O'Halloran, "Artifact removal algorithms for microwave imaging of the breast," *Progr. Electromagn. Res.*, vol. 141, pp. 185–200, Jan. 2013. [32] F. Abujarad, A. Jostingmeier, and A. S. Omar, "Clutter removal for landmine using different signal processing techniques," in *Proc. 10th Int. Conf. Grounds Penetrating Radar*, Jun. 2004, pp. 697–700.
- [33] P. K. Verma, A. N. Gaikwad, D. Singh, and M. J. J. Nigam, "Analysis of clutter reduction techniques for through wall imaging in UWB range," *Progr. Electromagn. Res. B*, vol. 17, pp. 29–48, Jan. 2009.
- [34] G. Ruvio, R. Solimene, A. Cuccaro, D. Gaetano, J. E. Browne, and M. J. Ammann, "Breast cancer detection using interferometric MUSIC experimental and numerical assessment," *Med. Phys.*, vol. 41, no. 10, pp. 1–11, Oct. 2014.
- [35] J. M. Felício, J. M. Bioucas-Dias, J. R. Costa, and C. A. Fernandes, "Microwave breast imaging using a dry setup," *IEEE Trans. Comput. Imag.*, vol. 6, pp. 167–180, 2020, doi: 10.1109/TCL.2019.2931079.
- [36] J. M. Lopez-Sanchez and J. Fortuny-Guasch, "3-D radar imaging using range migration techniques," *IEEE Trans. Antennas Propag.*, vol. 48, no. 5, pp. 728–737, May 2000.
- [37] A. T. Mobashsher and A. M. Abbosh, "Performance of directional and omnidirectional antennas in wideband head imaging," *IEEE Antennas Wireless Propag. Lett.*, vol. 15, pp. 1618–1621, 2016. 846 VOLUME 3, 2022
- [38] G. K. Pandey, H. S. Singh, P. K. Bhart, A. Pandey, and M. K. Meshram, "High gain vivaldi antenna for radar and microwave imaging applications," *Int. J. Signal Process. Syst.*, vol. 3, no. 1, pp. 35–39, Jun. 2015.
- [39] F. R. de Souza, L. P. Alves, A. B. Villaverde, and E. Munin, "Assessment of age-related adaptive changes in relative transverse dimensions of the tibia and fibula: A preliminary study towards a different approach for age prediction in adults," *J. Foernsic Res.*, vol. 10, no. 2, Jul. 2019, Art. no. 1000444.

International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975

Impact Factor: 9.971