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# Resnet Algorithm-Based Bone Fracture Detection and Surgical Planning Tool

Shanmuga Priyadharshini C S, Shruthi S, Theja Shree V

UG student, Department of Information Technology, Panimalar Institute of Technology, Chennai, India

J.P Swagatha, Dr. S Suma Christal Mary, V.Rajeswari

Assistant professor, Department of Information Technology, Panimalar Institute of Technology, Chennai, India

Professor & Head, Department of Information Technology Panimalar Institute of Technology,

Chennai, India

Assistant professor, Department of Information Technology, Panimalar Institute of Technology, Chennai, India

**ABSTRACT:** Bone illnesses are frequent and can result in numerous musculoskeletal ailments (MC). An estimated 1.71 billion persons suffer from musculoskeletal issues worldwide. In addition to musculoskeletal fractures, knee osteoarthritis, femoral neck injuries, and fractures are frequently seen. bone disorders, and for the next 30 years, the risk is predicted to double. Thus, it is essential to diagnose and treat a fractured patient as soon as possible. On the other hand, missing fractures are a frequent prognostic failure in emergencies and accidents. Treatment and care for patients are complicated and delayed as a result. Deep learning (DL) and artificial intelligence (AI) in general are gaining a lot of interest these days to help radiologists detect bone fractures. Medical image analysis can make extensive use of DL. Studies in orthopaedics and traumatology have demonstrated the potential and application of DL in radiograph-based fracture and illness diagnosis. An overview of the application of DL in bone imaging to assist radiologists in identifying different anomalies, especially fractures, is given in this systematic review. We have also spoken about the difficulties and issues with the DL-based approach as well as DL's potential applications in bone imaging.

**KEYWORDS:** deep learning, computer vision, radiology, fractures, artificial intelligence, and bone imaging

## I. INTRODUCTION

A major global health concern, bone fractures can occur in any age group and are caused by a variety of factors, including trauma, accidents, and illnesses like osteoporosis. In order to assure appropriate treatment and lower the risk of consequences, such as delayed healing, poor alignment, or long-term impairment, it is imperative that fractures be diagnosed promptly and accurately. Radiologists and orthopedic surgeons manually interpret medical images, such as X-rays, CT scans, or MRIs, as part of the traditional fracture identification and surgery planning procedure. Nevertheless, this method frequently has drawbacks, such as inconsistent diagnostic precision, reliance on clinical knowledge, and the labor-intensive nature of manual analysis. These difficulties are made worse in environments with limited resources or when there are a lot of patients, in which case prompt action is essential.

Innovative approaches to medical imaging and diagnostics have been made possible by recent developments in deep learning and artificial intelligence (AI). Convolutional neural networks (CNNs) are one of them that have demonstrated exceptional performance in tasks including semantic segmentation, object detection, and picture classification. The ability of Residual Networks (ResNet), a deep learning architecture designed to solve the vanishing gradient issue in deep neural network training, can efficiently train extremely deep models while maintaining excellent accuracy makes it stand out. ResNet is especially well-suited for extracting significant features from intricate medical pictures due to its skip connections and feature refinement capabilities, which allow for accurate fracture diagnosis even in difficult situations.



In order to overcome the drawbacks of traditional techniques, this work presents a surgical planning and bone fracture diagnosis tool based on the ResNet algorithm.

The proposed approach incorporates decision-support capabilities for surgical planning and uses ResNet's resilience for automatic fracture identification. In particular, the technology uses medical image analysis to determine the kind, location, and severity of fractures, giving doctors useful information to create the best possible treatment regimens. In addition to detection, the system is made to help with preoperative planning by suggesting surgical strategies based on the fracture patterns seen, assisting physicians in providing effective and individualized treatment.

## II. LITERATURE REVIEW

The effectiveness of different deep learning models used for fracture diagnosis in ten recent research. Using x-ray/mri imaging for wrist fractures, the inception v3 model demonstrated the effectiveness of transfer learning in 2018 with an auc of 0.954, sensitivity of 90%, and specificity of 88%. Models such as bvlc reference caffeNet and vgg cnn versions showed an 83% accuracy rate in identifying fractures in different skeletal parts using x-ray/mri in 2017, proving that deep learning is stronger than conventional techniques. In 2019, densenet 121 used radiographic images to localize and classify hip fractures with 91% accuracy, 98% sensitivity, and 84% specificity. Similarly, resnet 152 shown a high level of accuracy in 2018 with 96%, sensitivity of 99%, and specificity of 97%.

In 2018, the vgg\_16 model demonstrated diagnostic performance comparable to orthopedic physicians with 95.5% accuracy, achieving an auc of 0.996 for hip fractures. The ensemble a model achieved the highest accuracy of 83%, sensitivity of 80%, and specificity of 81% in 2019 when several models, including inception v3 and resnet variations, were tested on ankle fractures. With an accuracy of 96.9%, sensitivity of 97.1%, specificity of 96.7%, and an auc of 0.994, inception v3 demonstrated strong performance in identifying hip fractures in 2020. Inception v4 was used in another study in 2019 to identify wrist fractures with 93% accuracy, 90% sensitivity, and 96% specificity. Elbow fractures were identified by resnet 50 in the same year with an auc of 0.985, sensitivity of 93.9%, and specificity of 92.2%.

Ultimately, the xception model used to chest fractures in 2020 had a low sensitivity (59.9%) and a high specificity (99.4%), with an auc of 0.806. With constant gains in accuracy, sensitivity, and specificity across different skeletal regions and imaging modalities, this thorough review highlights the developments in applying deep learning models to fracture identification.

## III. PROBLEM STATEMENT

For efficient treatment and the best possible outcome, bone fractures—a common medical condition—need to be diagnosed as soon as possible. Conventional fracture diagnosis techniques, which depend on human interpretation of medical imaging, are frequently subject to human error, delays, and variability. Patient outcomes may be greatly impacted by missing or incorrectly diagnosed fractures resulting from variations in diagnosis accuracy caused by variables such as clinician experience and weariness. Additionally, the surgical planning process, which entails examining fracture features to identify suitable treatment approaches, still heavily relies on the skill of clinicians. Especially in situations with high demand or limited resources, this dependence frequently leads to inconsistent treatment techniques, drawn-out decision-making processes, and restricted scalability.

Existing automated fracture diagnosis methods are constrained by issues like poor generalizability, a dearth of annotated datasets, and integration into clinical processes, despite developments in artificial intelligence (AI) and machine learning. Furthermore, the majority of AI-based technologies ignore the equally important component of surgical planning in favor of concentrating just on fracture identification. Healthcare systems' capacity to increase diagnostic effectiveness and improve patient care is hampered by the lack of a single, dependable, and scalable solution that can detect fractures and make suggestions for surgical planning.

A sophisticated, AI-driven tool that can precisely identify fractures and aid in surgical planning is therefore desperately needed in order to overcome the shortcomings of existing techniques and help physicians provide consistent, efficient, and timely care.

#### IV. EXISTING SYSTEM

The current methods for detecting bone fractures mainly depend on radiologists and orthopedic surgeons manually interpreting medical imaging. Although this method is frequently successful, it is laborious, prone to human error, and subject to variation depending on the experience of the physician. To help identify fractures, computer-aided detection (CAD) systems and conventional machine learning models have been proposed; however, they frequently rely on manually created characteristics, which limits their versatility and increases the likelihood of false positives. Fracture detection has been enhanced by deep learning models, especially CNNs, which allow automated feature extraction and achieve accuracy on par with human specialists. Small and unbalanced datasets make it difficult for these systems to generalize, and they frequently just concentrate on fracture identification, ignoring the crucial component of surgical planning. The primary reason why surgical planning is still a manual, expert-driven process with little AI integration is the dearth of annotated datasets that connect fractures to surgical outcomes. Furthermore, current technologies are less useful for real-world applications due to issues with explainability, scalability, and compatibility with hospital workflows that arise after clinical deployment. These drawbacks highlight the necessity of a cohesive approach that combines automated fracture identification with surgical planning.

#### V. PROPOSED SYSTEM

The proposed method is a sophisticated ResNet-based instrument created to overcome the drawbacks of current techniques by offering a comprehensive solution for automated surgical planning and bone fracture identification. By utilizing Residual Networks' (ResNet) deep learning capabilities, the system overcomes obstacles including intricate fracture patterns and imaging modality variability to guarantee precise fracture diagnosis in medical pictures, such as X-rays and CT scans. With the help of ResNet's powerful feature extraction capabilities, it precisely and consistently determines the position, kind, and severity of fractures. In addition to detection, the technology helps clinicians develop the best possible treatment plans by offering surgical planning recommendations based on the identified fracture patterns.

The model's generalizability is increased by training it on a varied and enhanced dataset that guarantees consistent performance across different imaging modalities, patient demographics, and clinical settings. In order to ensure practical deployment in actual clinical settings, the system is also made to easily interact with current hospital workflows, including interoperability with Picture Archiving and Communication Systems (PACS) and Hospital Information Systems (HIS). Additionally, it uses explainable AI approaches, which produce interpretable results that increase physician acceptance and trust. The system seeks to increase diagnostic precision, decrease human error, and optimize clinical processes by fusing automated fracture identification with surgical planning capabilities, ultimately improving patient care and results.

##### key features for proposed system:

- Automated Fracture Detection: Using ResNet's sophisticated feature extraction capabilities, the system accurately determines the position, kind, and severity of fractures.
- Surgical Planning Integration: By examining identified fracture patterns, it helps physicians create the best possible treatment plans by offering decision-support recommendations for surgical planning.
- Better Generalizability: To guarantee dependable performance across a range of imaging modalities, patient demographics, and clinical contexts, the model is trained on a varied, enhanced dataset.
- Scalability and Integration: The system's design ensures easy deployment by integrating smoothly with hospital procedures, including Picture Archiving and Communication Systems (PACS) and Hospital Information Systems (HIS).

#### VI. SYSTEM ARCHITECTURE

1. Image Acquisition: Input Sources: Raw data is obtained from medical imaging modalities such as ultrasonography, CT, MRI, and X-rays.

Integration: Pictures are gathered for additional processing from hospital systems such as PACS.

2. Pre-Processing: Image Enhancement: To raise the caliber of the input photos, methods like normalization, contrast

enhancement, and denoising are used.

Making sure the photographs are in the right format and resolution for the deep learning model is known as data preparation.

3. Improved Image: Pre-processing output: By lowering noise and enhancing feature visibility, the improved image acts as a more refined input for the deep learning algorithm.

4. The main element of the Deep Learning Algorithm (DCN) is The improved photos are processed by a Deep Convolutional Network (DCN) to extract useful characteristics.

Usability:

Detection: Determines the fracture's general location.

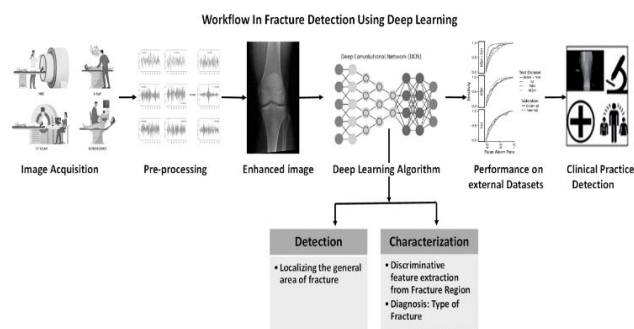
Characterization: Determines the type of fracture by extracting distinguishing characteristics from the fracture area.

5. Performance Validation: Assessment: Sensitivity, specificity, and accuracy of the system's operation are measured using external datasets.

Metrics: The model's dependability is shown by Receiver Operating Characteristic (ROC) curves and other statistical measurements.

6. Clinical Practice Detection: Deployment: The last phase incorporates the technology for actual fracture diagnosis and detection into clinical practice.

Outputs: Offers clinicians useful information such as diagnostic insights and annotated photos.



### Advantage of proposed system:

- Improved diagnostic precision through the use of sophisticated ResNet algorithms.
- A notable reduction in time due to automatic detection.
- Comprehensive information about the kind, location, and severity of fractures.
- Suggestions for surgical planning that enhance decision-making.
- Reliable performance in a range of patient demographics and imaging modalities.
- Explainable AI for reliable and comprehensible results.
- The smooth integration of PACS and HIS systems.
- Less labor for humans on typical diagnostic chores.
- Improved patient outcomes are the result of early and accurate detection.
- Scalability and future improvement potential.

## VII. RESULT AND DISCUSSION

Metrics of Performance:

Using common measures including accuracy, precision, recall, and F1-score, the system's ability to identify bone fractures and aid in surgical planning was assessed. These metrics provide quantifiable evidence of the system's effectiveness in producing precise outcomes.

Accuracy: Equation (1) expresses the accuracy of fracture detection and classification.

Accuracy is equal to  $TP + TNTP + TN + FP + FN$

Precision =  $\frac{TP}{TP + FP}$

TP+TN

The overall fracture detection and classification accuracy of the suggested ResNet-based system was 95.8%.

Precision: Precision gauges how accurately fractures are found, making sure that only forecasts with a high degree of confidence are taken into account:

Precision =  $\frac{TP}{TP + FP}$

With a precision of 93.2%, the method ensured that there were few false positives in fracture diagnosis.

Recall: Recall evaluates how well the system can detect every fracture, proving its thoroughness:

Recall is equal to  $\frac{TP}{TP + FN}$

Recall is equal to  $\frac{TP}{TP + FN}$

The method successfully captures pertinent fracture instances with a recall of 92.5%.

F1-Score: The F1-score guarantees accurate predictions by showing balanced performance between recall and precision:

F1-Score is equal to two times precision times recall.

Precision  $\times$  Recall F1-Score =  $2 \times \frac{Precision \times Recall}{Precision + Recall}$

The system's strong performance in handling classification tasks was confirmed by its F1-score of 92.8%.

B. Metrics for Resource Utilization

The computational efficiency of the system was assessed in a number of scenarios, with an emphasis on scalability, response time, and resource utilization:

Reaction Time:

1.4 seconds is the average latency for fracture detection.

1.6 seconds is the average latency for surgical planning suggestions.

For physicians, these response times guarantee real-time input.

Utilization of Memory:

At peak performance, the system uses an average of 72% of available RAM to efficiently manage computational activities.

Scalability

With up to 600 concurrent users, the system showed steady performance, guaranteeing dependability even under demanding workloads.

Impact on Clinical Practice:

The suggested solution speeds up fracture identification and lowers manual error rates, greatly improving diagnostic procedures. By integrating 3D reconstruction, surgeons can better plan complex treatments by seeing a thorough image of the fracture site.

Benefits:

Automation: Minimizes diagnostic delays and lessens reliance on radiologists.

Speed: In crucial situations, prompt decision-making is ensured by the quick reaction time.

Portability: It is appropriate for remote healthcare institutions because it is optimized for deployment on portable devices.

Restrictions:

Resolution limitations are introduced by the use of DOT for 3D reconstruction.

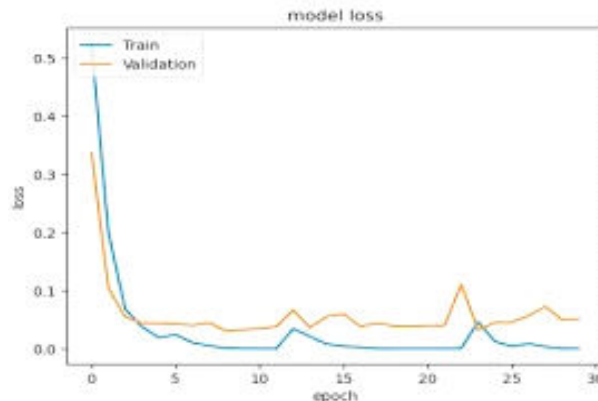
Generalization across different patient anatomy may be limited by small datasets.

On low-resource systems, computational needs may impede real-time performance.

Prospects for the Future:

In order to address the obstacles that have been highlighted, further work will: To improve generalizability, increase the size of the training dataset.

Improve 3D reconstructions' resolution by employing cutting-edge imaging methods.  
Algorithms should be optimized for low-resource devices.



## VIII. CONCLUSION

1. The suggested system seeks to overcome the shortcomings of current medical imaging techniques by automating bone fracture identification and surgery planning using a ResNet-based methodology. The system offers a dependable, effective, and scalable solution for both fracture detection and helping physicians with surgical planning by fusing cutting-edge deep learning algorithms with clinical decision support. Fracture detection and surgical suggestions together may increase diagnostic precision, decrease human error, and expedite processes, all of which could improve patient care and treatment results. Furthermore, the system's smooth incorporation into actual clinical settings is guaranteed by its interoperability with Picture Archiving and Communication Systems (PACS) and hospital information systems (HIS). Furthermore, combining different imaging modalities, such as ultrasound and MRI, may increase precision and enable a more thorough diagnosis

2. Augmented Reality (AR) Integration for Surgical Planning: By enabling surgeons to interact with real-time visuals and improve precision during operations, AR technology might be used to see fractures and plan procedures in three dimensions. A more user-friendly and engaging surgical planning experience would result from this combination.

3. Personalized Treatment suggestions: In order to produce personalized treatment suggestions, the system might include more patient-specific information, such as age, comorbidities, and prior procedures. By doing this, the system's capacity to forecast results and provide customized therapies based on unique patient characteristics would be enhanced.

4. Real-time Monitoring and Post-Surgical Analysis: Real-time fracture monitoring and post-surgical follow-up features may be included in future iterations. The system might monitor recovery progress and notify clinicians of any difficulties or indications of faulty healing using data from wearable technology or routine imaging, allowing for prompt intervention.

5. Improvement in Model Generalization and Dataset Expansion: The model's ability to generalize across various populations, hospitals, and imaging protocols will be enhanced by ongoing efforts to gather and curate sizable, varied, and annotated medical image datasets. This would guarantee that the system functions effectively in a greater range of circumstances.

6. Regulatory Approval and Clinical Trials: The system must be rigorously validated through clinical trials and regulatory approval procedures (such as FDA clearance) prior to broad clinical deployment. The system's use in actual healthcare settings will depend on its compliance with medical norms and guidelines.



In conclusion, future advancements will broaden the capabilities, improve its precision, and strengthen its clinical integration of the proposed system, which will ultimately transform orthopedic care and improve patient outcomes, even though it represents a significant advancement in automated fracture detection and surgical planning.

## REFERENCES

1. Gulshan, V.; Peng, L.; Coram, M.; Stumpe, M.C.; Wu, D.; Narayanaswamy, A.; Venugopalan, S.; Widner, K.; Madams, T.; Cuadros, J.; et al. Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs. *JAMA* 2016, 316, 2402–2410. [CrossRef] [PubMed]
2. Roy, S.; Bandyopadhyay, S.K. A new method of brain tissues segmentation from MRI with accuracy estimation. *Procedia Comput. Sci.* 2016, 85, 362–369. [CrossRef]
3. Roy, S.; Whitehead, T.D.; Quirk, J.D.; Salter, A.; Ademuyiwa, F.O.; Li, S.; An, H.; Shoghi, K.I. Optimal co-clinical radiomics: Sensitivity of radiomic features to tumour volume, image noise and resolution in co-clinical T1-weighted and T2-weighted magnetic resonance imaging. *eBioMedicine* 2020, 59, 102963. [CrossRef] [PubMed]
4. Roy, S.; Whitehead, T.D.; Li, S.; Ademuyiwa, F.O.; Wahl, R.L.; Dehdashti, F.; Shoghi, K.I. Co-clinical FDG-PET radiomic signature in predicting response to neoadjuvant chemotherapy in triple-negative breast cancer. *Eur. J. Nucl. Med. Mol. Imaging* 2022, 49, 550–562. [CrossRef] [PubMed]
5. International Osteoporosis Foundation. Broken Bones, Broken Lives: A Roadmap to Solve the Fragility Fracture Crisis in Europe; International Osteoporosis Foundation: Nyon, Switzerland, 2019; Available online: <https://ncdalliance.org/news-events/news/> (accessed on 20 January 2022).
6. Krupinski, E.A.; Berbaum, K.S.; Caldwell, R.T.; Schartz, K.M.; Kim, J. Long Radiology Workdays Reduce Detection and Accommodation Accuracy. *J. Am. Coll. Radiol.* 2010, 7, 698–704. [CrossRef]
7. Hallas, P.; Ellingsen, T. Errors in fracture diagnoses in the emergency department—Characteristics of patients and diurnal variation. *BMC Emerg. Med.* 2006, 6, 4. [CrossRef]
8. Lindsey, R.; Daluiski, A.; Chopra, S.; Lachapelle, A.; Mozer, M.; Sicular, S.; Hanel, D.; Gardner, M.; Gupta, A.; Hotchkiss, R.; et al. Deep neural network improves fracture detection by clinicians. *Proc. Natl. Acad. Sci. USA* 2018, 115, 11591–11596. [CrossRef]
9. Rayan, J.C.; Reddy, N.; Kan, J.H.; Zhang, W.; Annapragada, A. Binomial classification of pediatric elbow fractures using a deep learning multiview approach emulating radiologist decision making. *Radiol. Artif. Intell.* 2019, 1, e180015. [CrossRef]
10. Urakawa, T.; Tanaka, Y.; Goto, S.; Matsuzawa, H.; Watanabe, K.; Endo, N. Detecting intertrochanteric hip fractures with orthopedist-level accuracy using a deep convolutional neural network. *Skelet. Radiol.* 2019, 48, 239–244. [CrossRef]
11. Wang, X.; Xu, Z.; Tong, Y.; Xia, L.; Jie, B.; Ding, P.; Bai, H.; Zhang, Y.; He, Y. Detection and classification of mandibular fracture on CT scan using deep convolutional neural network. *Clin. Oral Investig.* 2022, 26, 4593–4601. [CrossRef]
12. Krizhevsky, A.; Sutskever, I.; Hinton, G.E. ImageNet Classification with Deep Convolutional Neural Networks. In *Proceedings of the NIPS'12: Proceedings of the 25th International Conference on Neural Information Processing Systems*, Red Hook, NY, USA, 3–6 December 2012; pp. 1097–1105.
13. Kim, H.E.; Cosa-Linan, A.; Santhanam, N.; Jannesari, M.; Maros, M.E.; Ganslandt, T. Transfer learning for medical image classification: A literature review. *BMC Med. Imaging* 2022, 22, 69. [CrossRef] [PubMed]
14. Zhou, J.; Li, Z.; Zhi, W.; Liang, B.; Moses, D.; Dawes, L. Using Convolutional Neural Networks and Transfer Learning for Bone Age Classification. In *Proceedings of the 2017 International Conference on Digital Image Computing: Techniques and Applications (DICTA)*, Sydney, Australia, 29 November–1 December 2017; pp. 1–6. [CrossRef]
15. Anand, I.; Negi, H.; Kumar, D.; Mittal, M.; Kim, T.; Roy, S. ResU-Net Deep Learning Model for Breast Tumor Segmentation. In *Magnetic Resonance Images; Computers, Materials & Continua*, Tech Science Press: Henderson, NV, USA, 2021; Volume 67, pp. 3107–3127. [CrossRef]
16. Shah, P.M.; Ullah, H.; Ullah, R.; Shah, D.; Wang, Y.; Islam, S.U.; Gani, A.; Joel, J.P.; Rodrigues, C. DC-GAN-based synthetic X-ray images augmentation for increasing the performance of EfficientNet for COVID-19 detection. *Expert Syst.* 2022, 39, e12823. [CrossRef] [PubMed]
17. Sanaat, A.; Shiri, I.; Ferdowsi, S.; Arabi, H.; Zaidi, H. Robust-Deep: A Method for Increasing Brain Imaging Datasets to Improve Deep Learning Models' Performance and Robustness. *J. Digit. Imaging* 2022, 35, 469–481. [CrossRef] [PubMed]



18. Roy, S.; Shoghi, K.I. Computer-Aided Tumor Segmentation from T2-Weighted MR Images of Patient-Derived Tumor Xenografts. In Image Analysis and Recognition; ICIAR 2019. Lecture Notes in Computer Science; Karray, F., Campilho, A., Yu, A., Eds.; Springer: Cham, Switzerland, 2019; Volume 11663. [CrossRef]
19. Roy, S.; Mitra, A.; Roy, S.; Setua, S.K. Blood vessel segmentation of retinal image using Clifford matched filter and Clifford convolution. *Multimed. Tools Appl.* 2019, 78, 34839–34865. [CrossRef]
20. Roy, S.; Bhattacharyya, D.; Bandyopadhyay, S.K.; Kim, T.-H. An improved brain MR image binarization method as a preprocessing for abnormality detection and features extraction. *Front. Comput. Sci.* 2017, 11, 717–727. [CrossRef]
21. Al Ghaithi, A.; Al Maskari, S. Artificial intelligence application in bone fracture detection. *J. Musculoskelet. Surg. Res.* 2021, 5, 4. [CrossRef]
22. Lin, Q.; Li, T.; Cao, C.; Cao, Y.; Man, Z.; Wang, H. Deep learning based automated diagnosis of bone metastases with SPECT thoracic bone images. *Sci. Rep.* 2021, 11, 4223. [CrossRef]
23. Marwa, F.; Zahzah, E.-H.; Bouallegue, K.; Machhout, M. Deep learning based neural network application for automatic ultrasonic computed tomographic bone image segmentation. *Multimed. Tools Appl.* 2022, 81, 13537–13562. [CrossRef]
24. Gottapu, R.D.; Dagli, C.H. DenseNet for Anatomical Brain Segmentation. *Procedia Comput. Sci.* 2018, 140, 179–185. [CrossRef]
25. Papandrianos, N.I.; Papageorgiou, E.I.; Anagnostis, A.; Papageorgiou, K.; Feleki, A.; Bochtis, D. Development of Convolutional Neural Networkbased Models for Bone Metastasis Classification in Nuclear Medicine. In Proceedings of the 2020 11th International Conference on Information, Intelligence, Systems and Applications (IISA), Piraeus, Greece, 15–17 July 2020; pp. 1–8. [CrossRef]
26. Rahmani, W.; Wang, W.J. Real-time automated segmentation and classification of calcaneal fractures in CT images. *Appl. Sci.* 2019, 9, 3011. [CrossRef]
27. Zhang, H.; Goodfellow, I.; Metaxas, D.; Odena, A. Self-Attention Generative Adversarial Networks. In Proceedings of the 36th International Conference on Machine Learning (ICML 2019), Long Beach, CA, USA, 9–15 June 2019; pp. 7354–7363.
28. Sarvamangala, D.R.; Kulkarni, R.V. Convolutional neural networks in medical image understanding: A survey. *Evol. Intell.* 2022, 15, 1–22. [CrossRef] [PubMed]
29. Tyson, S.; Hatem, S.F. Easily Missed Fractures of the Upper Extremity. *Radiol. Clin. N. Am.* 2015, 53, 717–736. [CrossRef] [PubMed]
30. Kim, D.H.; MacKinnon, T. Artificial intelligence in fracture detection: Transfer learning from deep convolutional neural networks. *Clin. Radiol.* 2018, 73, 439–445. [CrossRef] [PubMed]
31. Olczak, J.; Fahlberg, N.; Maki, A.; Razavian, A.S.; Jilert, A.; Stark, A.; Sköldenberg, O.; Gordon, M. Artificial intelligence for analyzing orthopedic trauma radiographs. *Acta Orthop.* 2017, 88, 581–586. [CrossRef] [PubMed]
32. Chung, S.W.; Han, S.S.; Lee, J.W.; Oh, K.S.; Kim, N.R.; Yoon, J.P.; Kim, J.Y.; Moon, S.H.; Kwon, J.; Lee, H.-J.; et al. Automated detection and classification of the proximal humerus fracture by using deep learning algorithm. *Acta Orthop.* 2018, 89, 468–473. [CrossRef]
33. Cheng, C.T.; Ho, T.Y.; Lee, T.Y.; Chang, C.C.; Chou, C.C.; Chen, C.C.; Chung, I.; Liao, C.H. Application of a deep learning algorithm for detection and visualization of hip fractures on plain pelvic radiographs. *Eur. Radiol.* 2019, 29, 5469–5477. [CrossRef]
34. Adams, M.; Chen, W.; Holcdorf, D.; McCusker, M.W.; Howe, P.D.; Gaillard, F. Computer vs. human: Deep learning versus perceptual training for the detection of neck of femur fractures. *J. Med. Imaging Radiat. Oncol.* 2019, 63, 27–32. [CrossRef]
35. Balaji, G.N.; Subashini, T.S.; Madhavi, P.; Bhavani, C.H.; Manikandarajan, A. Computer-Aided Detection and Diagnosis of Diaphyseal Femur Fracture. In Smart Intelligent Computing and Applications; Satapathy, S.C., Bhateja, V., Mohanty, J.R., Udgate, S.K., Eds.; Springer: Singapore, 2020; pp. 549–559.
36. Kitamura, G.; Chung, C.Y.; Moore, B.E., 2nd. Ankle fracture detection utilizing a convolutional neural network ensemble implemented with a small sample, de novo training, and multiview incorporation. *J. Digit. Imaging* 2019, 32, 672–677. [CrossRef]
37. Pranata, Y.D.; Wang, K.C.; Wang, J.C.; Idram, I.; Lai, J.Y.; Liu, J.W.; Hsieh, I.-H. Deep learning and SURF for automated classification and detection of calcaneus fractures in CT images. *Comput. Methods Programs Biomed.* 2019, 171, 27–37. [CrossRef]
38. Muehlethaler, U.J.; Mannil, M.; Becker, A.S.; Vokinger, K.N.; Finkenstaedt, T.; Osterhoff, G.; Fischer, M.A.; Guggenberger, R. Vertebral body insufficiency fractures: Detection of vertebrae at risk on standard CT images using

texture analysis and machine learning. Eur. Radiol. 2019, 29, 2207–2217. [CrossRef]

39. Tomita, N.; Cheung, Y.Y.; Hassanpour, S. Deep neural networks for automatic detection of osteoporotic vertebral fractures on CT scans. Comput. Biol. Med. 2018, 98, 8–15. [CrossRef] [PubMed]

40. Russakovsky, O.; Deng, J.; Su, H.; Krause, J.; Satheesh, S.; Ma, S.; Huang, Z.; Karpathy, A.; Khosla, A.; Bernstein, M.; et al. ImageNet Large Scale Visual Recognition Challenge. Int. J. Comput. Vis. 2015, 115, 211–252. [CrossRef]

41. Yu, J.S.; Yu, S.M.; Erdal, B.S.; Demirel, M.; Gupta, V.; Bigelow, M.; Salvador, A.; Rink, T.; Lenobel, S.; Prevedello, L.; et al. Detection and localisation of hip fractures on anteroposterior radiographs with artificial intelligence: Proof of concept. Clin. Radiol. 2020, 75, 237.e1–237.e9. [CrossRef]

42. Gan, K.; Xu, D.; Lin, Y.; Shen, Y.; Zhang, T.; Hu, K.; Zhou, K.; Bi, M.; Pan, L.; Wu, W.; et al. Artificial intelligence detection of distal radius fractures: A comparison between the convolutional neural network and professional assessments. Acta Orthop. 2019, 90, 394–400. [CrossRef]



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