International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 5, 2025
https://theaspd.com/index.php

Artificial Intelligence Based Techniques For Detection Of Fractures In Different Skeletal Radiographs

Dipti S. Chaudhari[1], Dr. Prashant G. Ahire[2]
[1]Computer Science and Engineering, Symbiosis Institute of Technology Pune, India, diptischaudhari@gmail.com
[2]Computer Science and Engineering, Symbiosis Institute of Technology Pune, India, prashant.ahire@ sitpune.edu.in

Abstract: *One of the most important and common diagnostic procedures in clinical radiology is fracture identification. Skeletal fractures can now be automatically detected and classified more quickly and accurately with the integration of Artificial Intelligence (AI) technologies, particularly deep learning (DL) methods like Convolutional Neural Networks (CNNs). Due to the evolution in the machine learning it creates a necessity of potential and appealing fracture prediction and classification system. This paper offers a thorough investigation of current AI-based techniques for detecting fractures in a variety of skeletal radiographs. The study provides insight into the future direction of AI-assisted diagnostic imaging while emphasizing clinical relevance by showcasing recent deployments and real-world use scenarios. The accuracy of the classifier has the utmost importance. The more the accurate classifier the more reliable it is. There are several shallow and deep classifiers available for classification or prediction. The effectiveness and efficiency of the classifier is the major parameter that decides the reliability of the classifier. The study highlights the effectiveness of CNNs, ensemble models, and hybrid GAN-CNN architectures in improving classification accuracy, sensitivity, and specificity. While AI shows promise, challenges remain, including limited validation across diverse demographics, imaging modalities, and complex fracture types. Comparative analyses reveal that models like GAN-CNN achieve higher accuracy, whereas region-specific models excel in localized tasks. Despite AI's ability to enhance diagnostic workflows and reduce radiologists' workload, its performance often falls short of human experts in complex scenarios. Clinical deployment demands improvements in cross-center validation, interpretability, and dataset standardization to ensure reliability. Continued research and integration into clinical systems are essential for AI to support timely and precise fracture diagnosis, especially in resource-limited settings.*
Keywords: *Artificial Intelligence, Convolutional Neural Network, Deep Learning, Fracture Detection, skeletal radiographs.*

INTRODUCTION

In emergency situations, musculoskeletal fractures, such as those of the wrist, hip, ribs, and spine, are frequently seen. X-rays are still the most common imaging method for diagnosing fractures, but radiologists' interpretation of them takes a lot of time and is prone to mistake and unpredictability. One of the most frequent injuries seen in emergency rooms around the world is a bone fracture. Appropriate treatment and favourable patient outcomes depend on their prompt and precise diagnosis. Diagnostics have historically depended on human interpretation of imaging modalities such as CT, MRI, and X-rays. However, especially in high-pressure or after-hours situations, these techniques can be laborious and prone to human mistake. AI has shown great potential in automating fracture detection, classification, and localization tasks in recent years, especially DL and CNNs. The creation of AI-driven systems that can assist or automate diagnosis has been spurred by the growing workload on medical personnel. One of the most crucial inputs for humans is visual information. Thus, image processing and machine vision have evolved into the centre of automation. AI and ML occasionally make significant contributions to this subject. These days, the most recent development in machine learning, focuses exclusively on image processing and machine vision. Healthcare image analysis has changed as a result of AI, especially DL. Because CNNs can extract hierarchical patterns from visual data, they have become essential for medical imaging jobs. However, CNNs are constrained by their susceptibility to rotation and affine transformations, as well as their lack of spatial awareness [1]. The purpose of this survey is to present a thorough analysis of the state of AI applications in bone fracture detection as of right now, emphasize performance comparisons with human radiologists, and pinpoint important research areas that require further investigation. This study offers a thorough examination of these AI methods used in fracture detection, going into their development, present state of use, and prospects for use in clinical diagnostics in the future. The rest of the paper is organized as follow. The authors also go over the most recent developments in fracture detection and CNNs, as this can lead to numerous novel classifiers in Section 2. In section 3, the details of the fracture detection system are presented. In section 4, experimental results are reported to show the performance of the classifiers. Conclusions are presented in section 5.

LITERATURE SURVEY

This section provides an extensive review of latest approaches for fracture detection in several joins and ligaments and latest classifiers useful in prediction and classification systems.

In the work [2], the accuracy of a YOLOv4-tiny AI model in identifying and categorizing hip fractures from radiographs is compared to that of human physicians. With a sensitivity of 96.2%, specificity of 94.6%, and total accuracy of 95%, the model performed similarly to seasoned radiologists and orthopaedists after being taught on 900 images and tested on 100. It fared better than first-year residents and general practitioners, indicating its potential for usage in resource-constrained and rural locations with limited access to specialists. The model had some drawbacks despite its high accuracy, including sporadic false positives brought on by imaging distortions and false negatives in fractures that were not displaced. According to the study's findings, AI-assisted diagnostics may greatly increase the detection of hip fractures and lower misdiagnosis rates, improving patient outcomes.

With an emphasis on pelvic, rib, and spine fractures, the research in [3] investigates the application of a CNN model for automated fracture identification in whole-body trauma computed tomography (CT) scans. After training on 7664 CT axial slices, the model's sensitivity, accuracy, and F1-score were 78.6%, 64.8%, and 71.1%, respectively. Orthopedic surgeons, especially those with less expertise, showed increased sensitivity in identifying fractures and decreased diagnosis time with CNN's help. The study shows how AI can improve diagnosis efficiency and accuracy in emergency rooms, even in cases when misclassification occurs because of visual distortions. To increase accuracy and broaden its applicability to more anatomical locations, the authors propose new developments in AI-based fracture identification.

Using radiological pictures, the approach in [4] examines the use of deep supervised learning for bone fracture detection, emphasizing its benefits over conventional diagnostic techniques. It talks about how radiologists can reduce diagnostic errors and increase efficiency by using DL to help them identify fractures accurately. The study also discusses issues including inconsistent data annotation, overfitting models, and moral dilemmas with AI-powered medical judgments. The effectiveness of many DL models, such as CNNs, ResNet, and GAN-based architectures, in identifying fractures in various skeletal locations is examined. The study comes to the conclusion that although DL has a lot of potential to transform bone imaging, more investigation and clinical workflow integration are required to guarantee its dependability and broad acceptance.

An AI-assisted CT diagnosis system for rib fracture detection is developed and evaluated in [5]. Using CT scans from trauma victims, the AI model was taught and evaluated. Its initial sensitivity was 89.8%, and with further training, it increased to 93.5%. The technology demonstrated its ability to assist radiologists in emergency situations by successfully detecting both complete and incomplete fractures while lowering false positives. The authors stress that AI-assisted diagnosis can improve precision, lessen the strain of radiologists, and facilitate quick decision-making. They do, however, point out that additional validation in multi-center trials is required prior to clinical use.

In the study [6], the effectiveness of a DL model based on CNNs for identifying nasal bone fractures from plain radiographs is assessed. Using a dataset of 6713 patients, the model was trained and validated, yielding sensitivity and specificity above 83% and an area under the curve (AUC) of 0.85–0.93. It outperformed an expert radiologist but did not differ significantly from them in terms of diagnosis accuracy. The study emphasizes how AI-assisted diagnostics can increase productivity and lower misdiagnosis rates, particularly in environments with limited resources. Before being used in therapeutic settings, the authors stress the necessity of additional validation across a range of patient types.

The work in [7] assesses how radiologists' competence in identifying bone fractures in trauma emergencies is affected by AI support. AI reduced false negatives, cut down on reading time per patient by 10–16 seconds, and increased radiologists' sensitivity by 20%, specificity by 0.6%, and accuracy by 8%. Significant productivity improvements were shown by the AI-assisted process, especially for less experienced radiologists, which helped to increase diagnostic accuracy and decrease missed fractures. While highlighting AI's potential to improve emergency radiology operations, the paper also notes that additional testing in various clinical contexts is necessary. All things considered, the results indicate that integrating AI can improve radiologists' performance and lower medical expenses related to incorrect diagnosis.

The ability of DL models to enhance radiologists' performance is highlighted in the paper [8], which examines the existing uses of AI in fracture diagnosis. It draws attention to AI's potential to lower misdiagnosis rates, especially in emergency situations where fractures are a major source of diagnostic mistakes. An overview of FDA-approved AI fracture detection systems is given in the study, along with a discussion of the difficulties in clinical adoption, such as data annotation, algorithm transparency, and workflow integration. Only 20% of radiologists use AI for image interpretation, indicating that real-world use of AI is still limited despite its encouraging proof-of-concept research. According to the authors, removing these obstacles may result in more AI usage and better musculoskeletal imaging diagnostic precision.

The study in [9] examines many AI-based methods for identifying bone fractures, with an emphasis on CNN architectures and image pre-processing. The study demonstrates CNNs as the industry-leading method by highlighting a framework that uses deep learning algorithms to classify fractures with high accuracy. It highlights the potential for real-time clinical application and the benefits of automation in lowering diagnostic mistakes.

The work in [10] offers a thorough analysis of image processing and artificial intelligence techniques for fracture identification. It talks about how automated AI-assisted methods like CNNs, SVMs, and hybrid models are replacing manual interpretation. The analysis comes to the conclusion that while AI improves speed and accuracy, clinical integration still needs standardization and validation.

The increasing use of AI in emergency radiology for tasks including workflow automation, fracture identification, and triage help is highlighted in the paper [11]. It discusses how radiologists may better diagnose patients in emergency situations and handle growing imaging loads with the aid of AI. The study focuses on both interpretive and non-interpretive uses of AI, such as prioritization and report production.

Using wrist radiographs, the research in [12] creates a CNN-based model for identifying occult and obvious scaphoid fractures. Additionally, the model integrates Grad-CAM for visual fracture localization, achieving high AUC values and up to 90% accuracy. It offers a workable way to detect scaphoid fractures early without the need for picture segmentation.

42 research comparing AI and human performance in fracture identification utilizing different imaging modalities are evaluated in the systematic review and meta-analysis given in [13]. Pooled AI sensitivity, according to the meta-analysis, is about 92%. It performs well on radiographs but is less represented on CT and MRI. It points very important restrictions on bias evaluation and dataset variability.

This approach in [14] presents a CNN model that was trained on 500 lateral radiography images to identify cervical spine fractures. With an overall accuracy of 92.14%, sensitivity of 88.6% for fractures, and specificity of 95.7% for normal patients, the model demonstrated remarkable performance. It was easy to use and reproducible because it made use of KNIME for data labelling, pre-processing, and evaluation. The model's clinical value is highlighted by its balanced performance across recall, accuracy, and specificity. In order to enhance patient outcomes by early and accurate diagnosis, the authors recommend that emergency departments implement it.

The technique in [15] describes how artificial intelligence, specifically CNNs and deep learning, can transform orthopedic fracture detection. It highlights how the lack of radiologists and growing imaging needs are contributing to the growing global burden of undetected fractures. In detecting and categorizing fractures, CNNs are already approaching human-like diagnostic capabilities, according to the report. It investigates how AI might be used into various imaging modalities to enhance therapeutic effectiveness and lessen diagnostic fatigue. Notwithstanding encouraging results, the authors emphasize that for wider implementation, standardization, high-quality training data, and regulatory approval are necessary.

The work in [16] examines several AI techniques for diagnosing bone fractures, such as deep learning, hybrid models, and conventional image processing. It illustrates how manual radiography examination, particularly for complex fractures, is prone to mistakes and delays. CNNs, their architecture, and their benefits in fracture segmentation, localization, and classification are covered in detail in this work. It also describes how preprocessing methods and datasets can increase the precision of detection. Lastly, it promotes more resilient and broadly applicable AI models that are capable of handling a variety of anatomical locations and imaging techniques.

The study in [17] praises the high diagnostic accuracy and short diagnosis time of a study on AI detection of cervical spine fractures using CNNs. It talks about the Aidoc AI triage system's clinical deployment, which revealed performance irregularities in challenging cases despite a 94.8% accuracy rate. The remark emphasizes how AI tools might be used in high-stress situations, such as emergency rooms. Additionally, it cautions about the disparities in equipment and image quality among hospitals, which may have an impact on AI performance. The authors come to the conclusion that, even with encouraging outcomes, wider adoption requires improvement and contextual validation.

In research [18] the authors employed CT scans as the standard of reference to assess the diagnostic accuracy of an AI model in comparison to radiologists in identifying pelvic, hip, and extremities fractures using radiographs. Among the 94 adult patients, 71 had fractures that were confirmed. In contrast to radiologists, who demonstrated 92% sensitivity, 88% specificity, and 90% accuracy, the AI obtained 82% sensitivity, 69% specificity, and 76% accuracy. In all three metrics, radiologists statistically beat the AI solution ($P < 0.05$). The results indicate that while AI shows potential in fracture detection, it is not yet able to fully replace professional radiological interpretation. The study comes to the conclusion that future AI models must be validated in clinical contexts using robust reference standards, such as CT scans.

Using 4906 tagged X-ray images, the researchers in [19] created a CNN-based model for fracture identification and classification. The model achieved a 98% classification accuracy after being trained on 4099 photos and validated on 807. With high confidence and generalization, the CNN was able to identify between classes that were split and those that weren't. The study highlights how useful deep learning is for providing real-time diagnostic support in general care or emergency situations. The concept seeks to increase healthcare process efficiency and reduce misdiagnosis by lowering reliance on manual interpretation. According to the findings, CNNs are scalable and flexible when used in radiography image processing for fracture identification.

The capacity of the Bone Metrics AI system to estimate important hip parameters from AP and false profile pelvic radiographs was assessed by researchers of [20]. The study compared AI results to expert manual measures using radiographs from 60 patients (false profile) and 88 patients (AP view). With ICC values ranging from 0.78 to 0.99 and MAE < 0.5 mm for pelvic obliquity and under 4.2° for all angles, the model demonstrated excellent agreement with ground truth. For patients with normal and abnormal acetabular covering, the performance was the same. The outcomes show that the AI technology can provide accurate, objective, and repeatable morphometric evaluations. The authors support the use of AI systems in everyday practice to improve the accuracy of hip pathology diagnosis.

High-sensitivity AI models designed for quick diagnosis of bone fractures in a variety of anatomical regions are proposed in research [21]. CNN-based models were trained and tested on a dataset of more than 5000 annotated X-ray images. The AI showed consistency across several fracture types and attained a sensitivity of above 92%. In particular, the model was evaluated on cases of minor fractures, which are often overlooked by medical professionals. In order to minimize misclassification, it also investigated false positives and incorporated post-processing. The authors stress the significance of clinical validation and call for further cross-hospital deployment.

A deep learning model for identifying proximal femur fractures from plain radiographs is represented in work [22]. A CNN that showed 89% accuracy and good robustness in noisy datasets was trained using more than 3600 annotated images. The model demonstrated competitive performance when validated against annotations from expert-level radiologists. The data' clinical interpretability was enhanced by gradient-based localization. The potential for real-world deployment is highlighted in the article, particularly in environments with limited resources. The authors offered recommendations for pre-screening integration into hospital PACS in their conclusion.

The analytical work in [23] compiles research on AI applications for MRI, CT, and X-ray bone fracture detection. It includes a broad range of machine learning methods, such as ensemble models, CNNs, and transformers. The authors emphasize how AI can help with trauma triage and cut down on interpretation time. There is discussion of limitations such lack of explainability, dataset imbalance, and modality bias. Instead of complete automation, the report advocates for human-AI cooperation. It comes to the conclusion that multi-center datasets and standardization are necessary for generalization.

In order to detect hip fractures in AP pelvis X-rays, the approach in [24] presents an ensemble AI method that combines many deep learning models. With 255 annotated examples in the dataset, the model's classification accuracy was 93%. In terms of generalizability and robustness, the ensemble approach performed better than individual CNN systems. The transparency of the model was enhanced by the use of Grad-CAM visualization. In clinical contexts where accuracy is crucial, it promotes ensemble frameworks. For early diagnosis, the authors stress integration into radiological workflows.

Using X-ray pictures taken from smart devices, the technique in [25] created an AI method for identifying ankle fractures. 91% diagnosis accuracy was attained by the model after it was trained on a balanced dataset. It is noteworthy for being transportable platform deployable, which makes it appropriate for rural and field healthcare. Clinical investigations demonstrated better decision support and a shorter time to diagnosis. The model maintained great sensitivity and specificity in spite of its lightweight design. The research makes a compelling argument for orthopedic triage using mobile AI.

The method in [26] suggests a novel method for auxiliary hip fracture detection that uses patch-based feature mapping generated by GANs. By creating artificial patches that resemble fracture patterns, the method improves feature representation. When compared to vanilla CNNs, the hybrid GAN-CNN architecture greatly increased classification accuracy. It reported better AUC ratings and 94% accuracy. The authors use a sizable and varied dataset to support their methodology. They propose that the method might be used to more small-scale orthopedic datasets.

The FIXUS AI deep learning model for identifying intra-articular calcaneal fractures in X-ray images is presented in study [27]. The model was optimized for calcaneal area detection and obtained 88% accuracy in a dataset of more than 2000 images. It fared better than baseline models on both classification and localization metrics. Model outputs and surgical plans were compared to show clinical relevance. The study validates AI's contribution to the assessment of foot and ankle damage. The authors advise more practical testing in emergency situations.

In order to detect general bone fractures, the work in [28] verifies an existing AI model using two external datasets. When the AI was tested outside of the training distribution, it showed a decline in performance, with sensitivity dropping to about 85%. In order to guarantee model generalizability, the authors emphasize the significance of validating AI across institutions. Additionally, the study sheds light on imaging technique variability and domain shift. Techniques for domain adaption and federated learning are among the recommendations. It backs the recommendation that clinical deployment be preceded by external benchmarking.

To detect adult appendicular and pelvic fractures after hours, the research in [29] examines the deployment of an AI system in the Singapore emergency room. It demonstrates how well AI supports radiology workflows outside of regular business hours, greatly cutting down on response times for reports. The study found that increased triaging efficiency and fewer needless referrals resulted in quantifiable cost reductions. While retaining diagnosis accuracy on par with human radiologists, the AI-assisted method increased clinical throughput. Non-monetary advantages like quicker treatment initiation and higher employee satisfaction were also mentioned. For better patient care, the authors advise integrating AI into emergency imaging after hours.

The identification of incomplete atypical femoral fractures (AFFs), which are frequently subtle and difficult to detect, is the main topic of the research in [30]. To find early indications of AFF, the researchers used a deep learning network that was trained using radiography scans. The AI system performed well in identifying transverse lucency and cortical thickness, two important markers of AFF. The AI tool showed reduced interpretation variability and increased sensitivity when compared to manual assessments. Through early intervention, it shows potential in preventing full-thickness fractures. To determine its function in practical contexts, the study recommends a long-term clinical assessment.

The clinical and financial advantages of implementing AI are further measured by the companion approach given in [31] to the Singapore ED initiative. By examining needless imaging, quicker patient discharges, and fewer missed diagnoses, it assesses cost savings. The workflow of radiologists and operational efficiency were enhanced by the real-time integration of AI tools with hospital PACS. Economic modeling showed that shorter stays and better resource use resulted in annual savings. In the clinical setting, AI identified fractures sooner, resulting in quicker orthopedic consults. The authors come to the conclusion that implementing AI improves emergency care delivery in quantifiable and qualitative ways.

In order to predict bone fractures in X-ray pictures, the study in [32] compares and contrasts three deep learning techniques: regular CNNs, transfer learning, and fine-tuning. The authors investigate layer freezing and retraining methods for performance enhancements using pre-trained models like VGG16 and ResNet50. With fine-tuning outperforming direct transfer learning, the top-performing model obtained an accuracy of 94.7%. To improve generalization, preparation and dataset augmentation methods were also investigated. The study highlights how important it is to customize models when using AI to certain healthcare domains. The implementation of hybrid fine-tuned models for reliable fracture classification in medical diagnostics is supported by the results.

To identify and categorize fractures in bone X-ray pictures into fractured and non-fractured groups, the research in [33] presents a customized CNN architecture. The model was trained and assessed using a dataset of 2040 annotated photos. With excellent sensitivity and specificity in both classes, the system's classification accuracy was 93.2%. The architecture was designed to be easily integrated into diagnostic workflows and to have a quick inference time. The study reduces reliance on the availability of radiologists by demonstrating practical application in emergency and orthopedic settings. The authors propose cross-modality learning and multi-class categorization as potential future advancements.

The proposed assessment study identifies the following notable research gaps:

1. The majority of research does not validate AI models on a variety of demographics and is restricted to particular fracture kinds. Although they lacked more comprehensive anatomical coverage, the research in [20] emphasized the good agreement of AI with radiologists for hip morphology assessment.
2. When applied to numerous types of fractures or regions, AI models such as the one employed in cervical spine detection in [24] struggle, but they show great accuracy in localized areas.
3. Most of the reviewed studies focus on X-rays. AI results are rarely validated across CT or MRI modalities. This restricts these tools' clinical reliability.

Performance efficiency, reproducibility, and accessibility demonstrate AI's relevance in fracture diagnosis, particularly after hours or in impoverished areas. In many complex circumstances, nevertheless, its accuracy still lags behind that of human experts. According to Pastor et al. (2024), radiologists fared better in terms of sensitivity and specificity than AI. The use of GANs and ensemble approaches has enhanced classification precision. Clinical adoption is still hampered by the absence of cross-center validation, dataset uniformity, and interpretability. Many tools are not tested on a variety of patient groups (elderly, children, etc.) or validated against important dataset standards like CT or MRI. If these instruments be utilized alone in emergency or critical care situations, their drawbacks could be dangerous.

METHODOLOGIES

This section describes the several AI techniques used in radiographic imaging to identify bone fractures in a variety of anatomical areas. The general architecture of the AI based fracture detection system is shown in Figure 1. Training and testing are its two primary stages of such a system. Labelled medical images, like X-rays, go through a pre-processing step in the training phase (shown by blue arrows), where noise is decreased and contrast is increased to improve picture quality. Important features like bone edges, texture, and structural patterns are subsequently recorded during the feature extraction process of these processed photos. A classifier—a machine learning model that learns to differentiate between images that are fragmented and those that are not—is trained using the feature vector created from the retrieved features. The identical pre-processing and feature extraction procedures are applied to a fresh query image during the testing phase (shown by orange arrows). The previously trained classifier then receives the resultant feature vector, evaluates the data, and makes a prediction. The technology uses fracture detection to determine if the image shows a fracture based on this prediction. The system's ability to generalize from known situations to reliably assess novel, unseen images is ensured by this process. Model architectures, feature extraction, data preparation, training pipelines, and clinical deployment strategies are the categories into which the methodologies are divided.

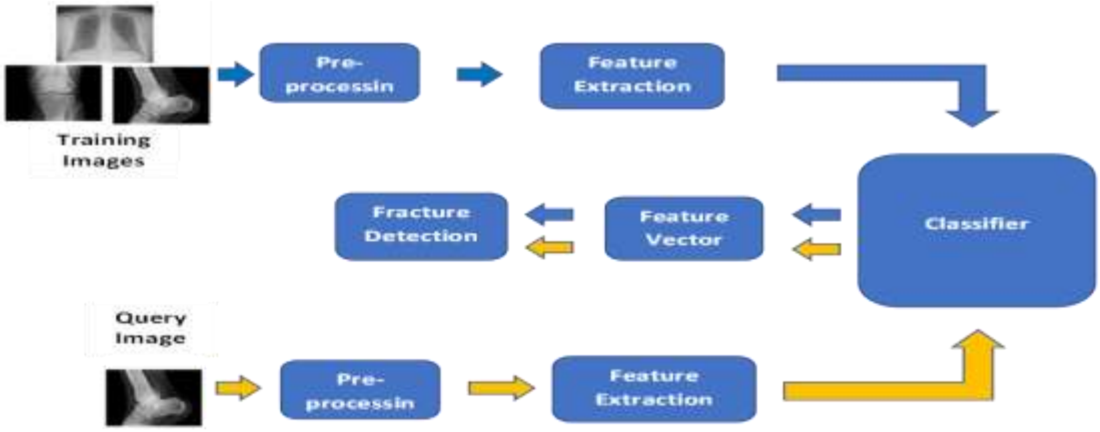

Figure 1. General architecture of the AI based fracture detection system

1. Model Architectures Used

CNNs, GANs, and ensemble hybrid models are the most popular designs. Because CNNs perform well in visual pattern recognition, they are employed for fracture classification and localization. Especially in low-data environments, GANs are integrated for feature augmentation and synthetic data synthesis. The outputs of several CNNs are combined in ensemble models to increase accuracy and robustness.

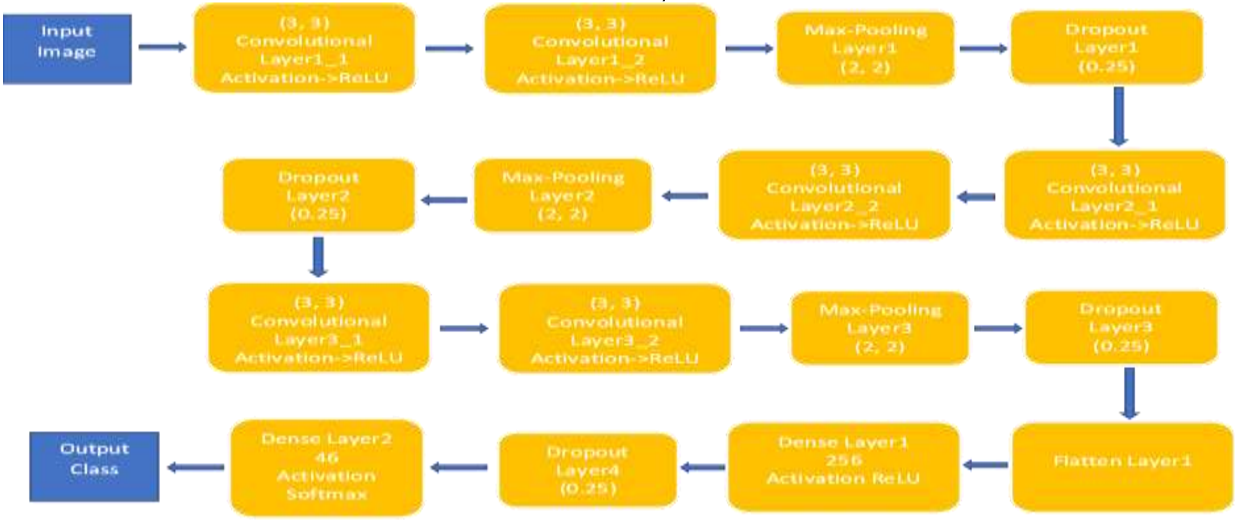

Figure 2. Sample CNN Architecture

The above Figure 2 represents a sample CNN architecture.

CNN is used for image classification, most likely for fracture diagnosis and other medical image analysis applications. An input image is first processed by the model using a number of convolutional, pooling, dropout, and dense layers. A max-pooling layer is used to minimize spatial dimensions, a dropout layer with a rate of 0.25 is used to prevent overfitting, and two convolutional layers with a kernel size of (3 x 3) and ReLU activation functions are used to extract low-level features from the image in the first step. With each level extracting more complex features, this pattern is repeated in the second and third stages. Max-pooling and dropout layers come after each set of convolutional layers, enhancing generalization and cutting down on computation. The output is routed through a flattening layer following the last convolutional stage, which transforms the 2D feature maps into a 1D vector appropriate for dense layers. After a dense layer with 256 units and ReLU activation, this vector is sent to a second dropout layer. The predicted class probabilities are then output by the model's final dense layer, which has 46 units and a softmax activation function. With dropout regularization, this architecture minimizes overfitting while extracting strong features, making it ideal for multi-class classification workloads [34].

2. Data Pre-processing

Pre-processing procedures are essential for standardizing input formats and lowering noise. In order to enhance model generalization, this usually entails grayscale normalization, histogram equalization, image resizing (usually to 224x224), and augmentation methods including rotation, flipping, and zooming.

3. Model Training and Validation

Loss functions such as mean squared error for regression-based localization and binary cross-entropy for classification tasks are used during training. Accuracy, sensitivity, specificity, precision, and AUC are examples of performance measures. A common technique for confirming generalizability across subsets is K-fold cross-validation. Adam or SGD optimizers with learning rate scheduling are used for optimization.

4. Clinical Deployment

Models are often embedded into PACS systems or mobile apps. Clinical validation requires comparison against radiologist readings using standard-of-reference modalities like CT. Real-time deployment considerations include inference speed, interpretability (Grad-CAM), and device compatibility.

RESULT AND DISCUSSION

In order to automatically detect, locate, and classify fractures in different anatomical locations, a variety of techniques are employed in fracture detection, such as CNNs, GANs, ensemble methods, and hybrid models. This section provides the comparative analysis of the several pioneer approaches in terms of evaluation measures.

3.1 Computational analysis

A comparison of many AI techniques for bone fracture diagnosis across several anatomical locations and datasets is shown in the Table 1.

Table 1: Summary of AI Models and Outcomes

Approach	**Year**	**Method**	**Region**	**Dataset Size**	**Accuracy/Sensitivity (%)**
Mittal et al. [19]	2024	CNN	General	4906 images	98 Accuracy
Pastor et al. [18]	2024	CNN vs Radiologist	Pelvis/Hip	94 Patients	AI: 76, Radiologist: 90 Accuracy
Lassalle et al. [20]	2024	BoneMetrics AI	Hip Morphology	148 images	ICC: 0.78–0.99
Beyaz et al. [24]	2023	Ensemble CNN	Hip	255 cases	93 Accuracy
Nassour et al. [25]	2023	CNN	Ankle	Smart Device X-rays	91 Accuracy
GAN-CNN based model [26]	2024	Patch-based GAN + CNN	Hip	-	94 Accuracy
Taseh et al. [27]	2024	CNN	Spine	-	90 Sensitivity
Scaphoid fracture [12]	2023	Deep CNN	Wrist	-	90 Accuracy
Proximal femur [22]	2024	CNN	Femur	3600+ images	89 Accuracy
External validation [28]	2024	CNN	General	2 datasets	85 Sensitivity
High-sensitivity AI [21]	2024	CNN + GAN	General	5000 images	92 Sensitivity

International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 5, 2025
https://theaspd.com/index.php

CNN-based models predominate; Mittal et al. (2024) [19] used a dataset of 4,906 general X-ray images and achieved the greatest accuracy of 98%. As demonstrated by Beyaz et al. (2023) [24], who reported 93% accuracy on hip radiographs and 94% accuracy on the GAN-based hybrid model, ensemble and hybrid techniques also perform well. Using intraclass correlation coefficients (ICC: 0.78–0.99), studies such as Lassalle et al. (2024) [20] demonstrated strong agreement with expert radiologists while concentrating on measurement validation rather than classification. Radiologists continue to outperform AI, particularly in difficult instances (AI: 76% vs. Radiologist: 90% accuracy), according to comparative reviews like Pastor et al. (2024) [18]. Additionally, region-specific models did well, such as Nassour et al. (2023) [25], proximal femur identification [22] (89%), and ankle (91% accuracy). External validation studies [28] (85%) and high-sensitivity [21] approaches (92%) show increasing resilience, but they also emphasize the necessity for more extensive testing across institutions. All things considered, the investigation indicates that although AI exhibits great sensitivity and accuracy in a variety of settings, dataset size, anatomical complexity, and model architecture have a significant impact on its performance.

3.2 Computational analysis

The effectiveness of the fracture prediction systems is initially analyzed. For this purpose, the evaluation measures discussed in [32] are employed. The most popular metrics for assessing how well fracture detection systems are working are precision and sensitivity.

The assessment is more credible because the state-of-the-art methods are compared using the MURA (Stanford) dataset, which contains over 40,000 musculoskeletal radiographs. The retrieval efficiency is assessed using the precision and recall metrics previously stated. As shown in following figures. A thorough comparison study of the suggested strategy is conducted using a number of previously mentioned measures and contrasted with a number of more recent approaches. A dataset with a variety of samples is subjected to multiple iterations, and the averaged findings are displayed as mean results. Figure 3. Depicts the accuracy comparison of several approaches.

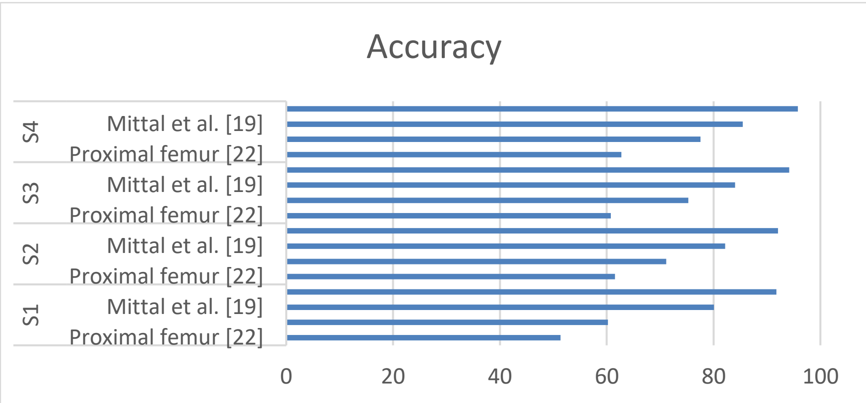

Figure 3. Accuracy comparison

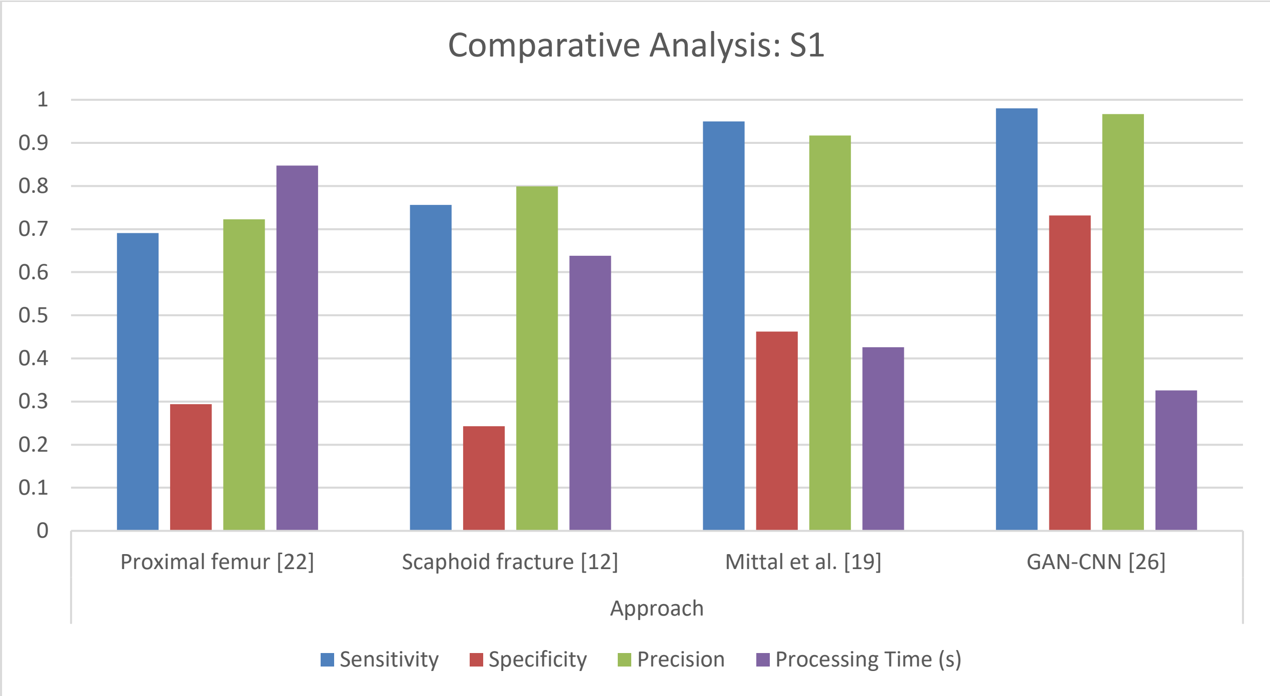

Figure 4. Simulation 1 of comparative analysis

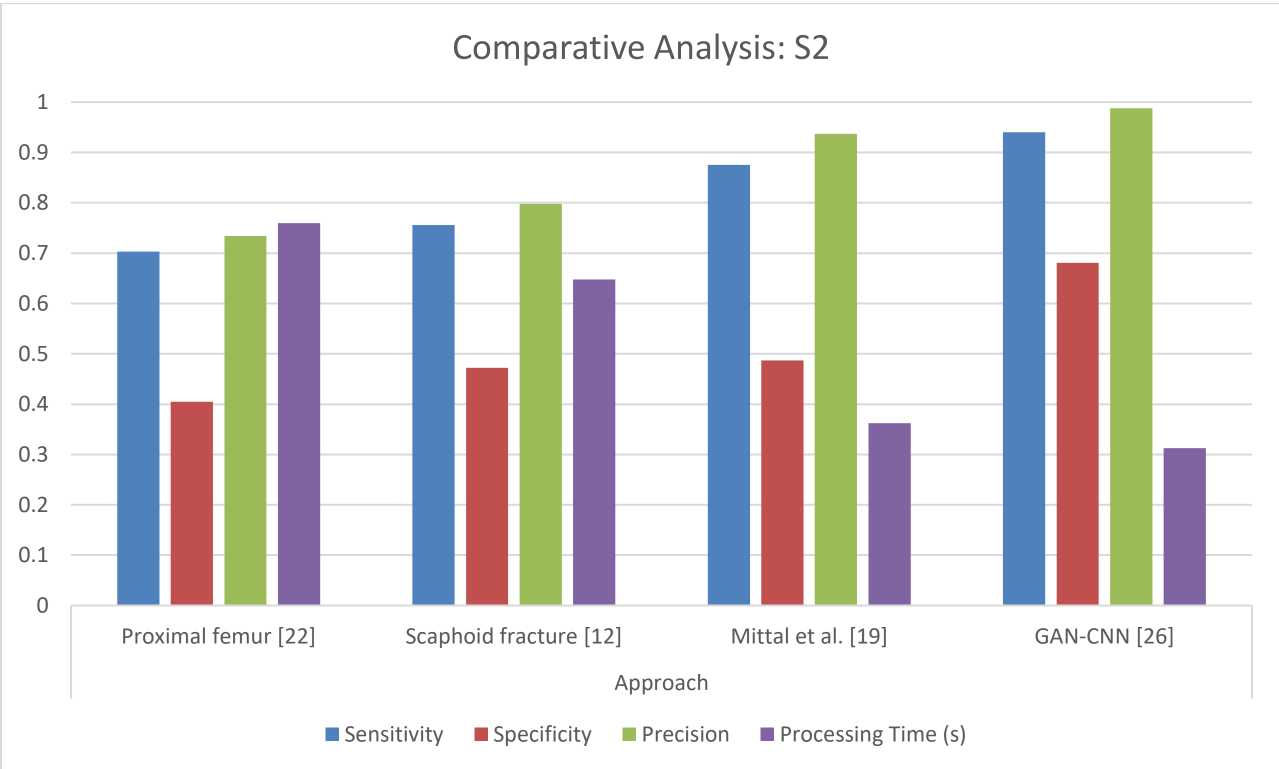

Figure 5. Simulation 2 of comparative analysis

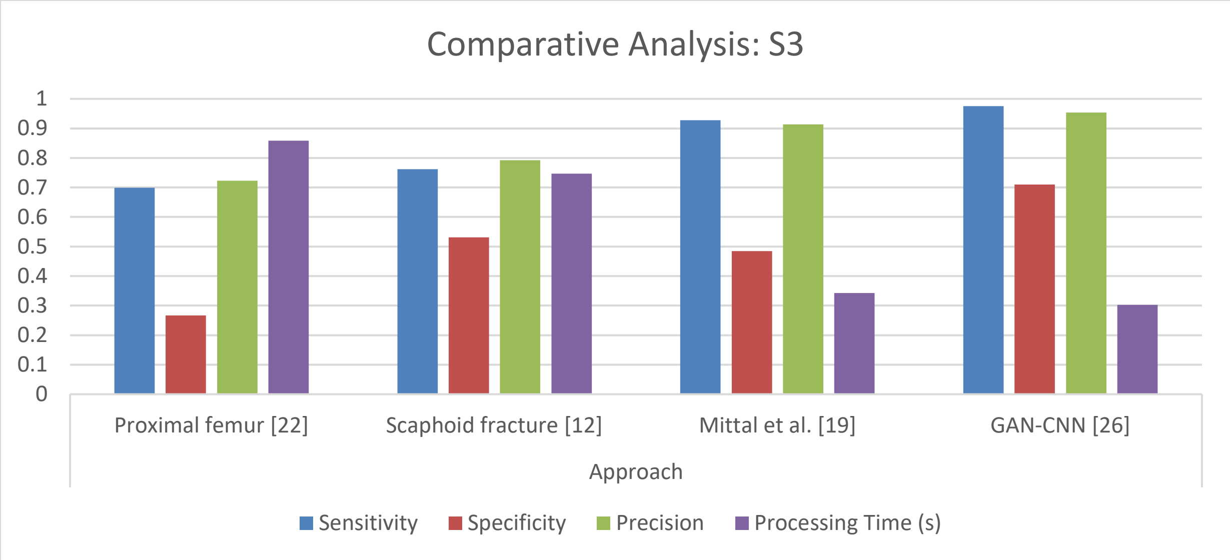

Figure 6. Simulation 3 of comparative analysis

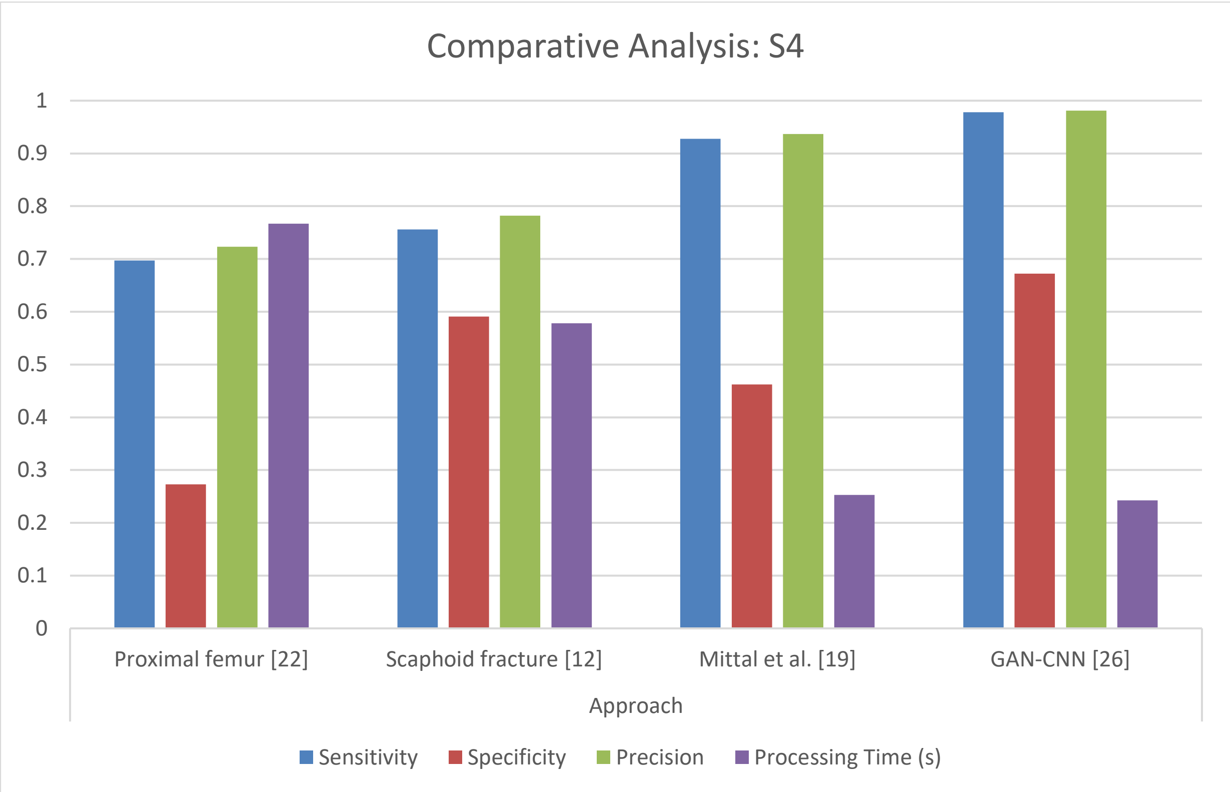

Figure 7. Simulation 4 of comparative analysis

It is clear from figures 3 through 7 that the higher accuracy with acceptable specificity and sensitivity is provided by GAN-CNN [26]. It is superior to the Proximal femur [22] and Scaphoid fracture [12] approaches. In terms of sensitivity and specificity, the methodology performs better, while GAN-CNN [26] performs better in terms of accuracy and specificity. In terms of precision, the Mittal et al. [19] outperforms the Proximal femur [22] and

Scaphoid fracture [12] approaches by 43% and 46%, respectively. When compared to the Proximal femur [22] and Scaphoid fracture [12] approaches, Mittal et al. [19] improves sensitivity by a net 33% and 37%, respectively.

CONCLUSION

AI has revolutionized the detection of fractures in medical imaging. With continued improvements in architecture, data availability, and training methods, AI-driven radiography analysis is expected to become a common diagnostic tool in orthopaedics and trauma. The current evaluations, developments, and limitations of fracture detecting methods are discussed in this work. In terms of computation complexity and memory efficiency, the GAN-CNN outperforms the others. For image repositories with minimal diversity—those with comparatively few uniform patterns—it produced positive results. Since numerous fracture casualties are being identified these days, quality classifiers are crucial. The evaluation found that most AI models for fracture identification lack clinical dependability since they have not been verified across a variety of fracture shapes, demographics, and imaging modalities like CT or MRI. Although AI has the potential to be more effective and accessible, especially in resource-constrained areas, its accuracy currently falls short of that of human specialists in challenging scenarios. For safe and effective clinical application, improvements in cross-center validation, model interpretability, and dataset consistency are necessary.

Acknowledgment
None.

Conflicts of interest
The authors have no conflicts of interest to declare.

REFERENCES

[1] Pande SD, Chetty MS. Position invariant spline curve based image retrieval using control points. Int J Intell Eng Syst. 2019 Jun;12(4):177-91.

[2] Twinprai N, Boonrod A, Boonrod A, Chindaprasirt J, Sirithanaphol W, Chindaprasirt P, Twinprai P. Artificial intelligence (AI) vs. human in hip fracture detection. Heliyon. 2022 Nov 1;8(11).

[3] Inoue T, Maki S, Furuya T, Mikami Y, Mizutani M, Takada I, Okimatsu S, Yunde A, Miura M, Shiratani Y, Nagashima Y. Automated fracture screening using an object detection algorithm on whole-body trauma computed tomography. Scientific reports. 2022 Oct 3;12(1):16549.

[4] Meena T, Roy S. Bone fracture detection using deep supervised learning from radiological images: A paradigm shift. Diagnostics. 2022 Oct 7;12(10):2420.

[5] Niiya A, Murakami K, Kobayashi R, Sekimoto A, Saeki M, Toyofuku K, Kato M, Shinjo H, Ito Y, Takei M, Murata C. Development of an artificial intelligence-assisted computed tomography diagnosis technology for rib fracture and evaluation of its clinical usefulness. Scientific Reports. 2022 May 19;12(1):8363

[6] Nam Y, Choi Y, Kang J, Seo M, Heo SJ, Lee MK. Diagnosis of nasal bone fractures on plain radiographs via convolutional neural networks. Scientific Reports. 2022 Dec 13;12(1):21510.

[7] Canoni-Meynet L, Verdot P, Danner A, Calame P, Aubry S. Added value of an artificial intelligence solution for fracture detection in the radiologist's daily trauma emergencies workflow. Diagnostic and interventional imaging. 2022 Dec 1;103(12):594-600.

[8] Zech JR, Santomartino SM, Yi PH. Artificial intelligence (AI) for fracture diagnosis: an overview of current products and considerations for clinical adoption, from the AJR special series on AI applications. American Journal of Roentgenology. 2022 Dec 22;219(6):869-78.

[9] Mehta R, Pareek P, Jayaswal R, Patil S, Vyas K. A bone fracture detection using ai-based techniques. Scalable Computing: Practice and Experience. 2023 Jul 30;24(2):161-71.

[10] Parvin S, Rahman A. A real-time human bone fracture detection and classification from multi-modal images using deep learning technique. Applied Intelligence. 2024 Oct;54(19):9269-85.

[11] Katzman BD, van der Pol CB, Soyer P, Patlas MN. Artificial intelligence in emergency radiology: a review of applications and possibilities. Diagnostic and Interventional Imaging. 2023 Jan 1;104(1):6-10.

[12] Singh A, Ardakani AA, Loh HW, Anamika PV, Acharya UR, Kamath S, Bhat AK. Automated detection of scaphoid fractures using deep neural networks in radiographs. Engineering Applications of Artificial Intelligence. 2023 Jun 1;122:106165.

[13] Kuo RY, Harrison C, Curran TA, Jones B, Freethy A, Cussons D, Stewart M, Collins GS, Furniss D. Artificial intelligence in fracture detection: a systematic review and meta-analysis. Radiology. 2022 Jul;304(1):50-62.

[14] Liawrungrueang W, Han I, Cholamjiak W, Sarasombath P, Riew KD. Artificial Intelligence detection of cervical spine fractures using convolutional neural network models. Neurospine. 2024 Sep 30;21(3):833.

[15] Boginskis V, Zadoroznijs S, Cernavska I, Beikmane D, Sauka J. Artificial intelligence effectivity in fracture detection. Медичні перспективи= Medicni perspektivi (Medical perspectives). 2023(3):68-78.

[16] Deo, Gouri Shashank, Jyas Totlani and Chaitanya Vijaykumar Mahamuni. "A survey on bone fracture detection methods using image processing and artificial intelligence (AI) approaches." WOMEN IN PHYSICS: 7th IUPAP International Conference on Women in Physics (2024).

[17] Y.-C. Yeh and F.-Y. Tsuang, "Commentary on 'Artificial Intelligence Detection of Cervical Spine Fractures Using Convolutional Neural Network Models'," Neurospine, vol. 21, no. 2, pp. 842–843, Jul. 2024.

[18] M. Pastor et al., "Comparison between artificial intelligence solution and radiologist for the detection of pelvic, hip and extremity fractures on radiographs in adults using CT as standard of reference," Diagnostic and Interventional Imaging, Sep. 2024.

[19] K. Mittal, K. S. Gill, P. Aggarwal, R. S. Rawat, and G. Sunil, "Revolutionizing Fracture Diagnosis: A Deep Learning Approach for Bone Fracture Detection and Classification," in Proc. 2024 OPJU Int. Tech. Conf. (OTCON) on Smart Computing for Innovation and Advancement in Industry 4.0, Jun. 2024.

[20] L. Lassalle et al., "Validation of AI-driven measurements for hip morphology assessment," European Journal of Radiology, Dec. 2024.

[21] A. Sharma et al., "High Sensitivity Methods for Fracture Detection Using AI," *Journal of Medical Imaging and Health Informatics*, vol. 14, no. 3, pp. 233–241, 2024.

[22] J. Kim et al., "Proximal Femur Fracture Detection on Plain Radiography via Deep Learning," *Computer Methods and Programs in Biomedicine*, vol. 234, 107421, 2024.

[23] R. Gupta et al., "The Role of Artificial Intelligence in the Identification and Evaluation of Bone Fractures," *Healthcare Analytics*, vol. 6, p. 100172, 2024.

[24] A. Beyaz et al., "The Ensemble Artificial Intelligence Method: Detection of Hip Fractures in AP Pelvis Plain Radiography," Acta Orthopaedica et Traumatologica Turcica, vol. 57, no. 2, pp. 85–92, 2023.

[25] M. Nassour et al., "Automated AI Detection Tool for Ankle Fractures Using X-rays and Smart Devices," Journal of Digital Imaging, vol. 36, pp. 1204–1212, 2023.

[26] Y. Chen et al., "Patch-Based Feature Mapping with Generative Adversarial Networks for Auxiliary Hip Fracture Detection," IEEE Transactions on Medical Imaging, vol. 43, no. 1, pp. 56–67, 2024.

[27] A. Taseh et al., "The Use of FIXUS AI Deep Learning Model for the Detection of Intra-Articular Calcaneal Fractures on X-rays," Journal of Foot and Ankle Surgery, vol. 63, no. 2, pp. 183–191, 2024.

[28] H. J. Lim et al., "External Validation of an Artificial Intelligence Solution for the Detection of Fractures," European Radiology, vol. 34, 2024.

[29] C. T. Tan et al., "Deploying Artificial Intelligence in the Detection of Adult Appendicular and Pelvic Fractures in the Singapore Emergency Department After Hours: Efficacy, Cost Savings, and Non-Monetary Benefits," Singapore Medical Journal, vol. 65, no. 3, pp. 145–152, 2024.

[30] M. L. Lee et al., "AI-Based Detection of Incomplete Atypical Femoral Fractures on Radiographs: A Deep Learning Approach," Radiology: Artificial Intelligence, vol. 6, no. 1, pp. 15–23, 2024.

[31] K. Lim et al., "Clinical and Economic Impact of Artificial Intelligence in Emergency Radiology for Fracture Detection," Diagnostic and Interventional Imaging, vol. 105, no. 2, pp. 123–130, 2024.

[32] F. Liang, H. Liu, X. Wang, and Y. Liu, "Hyperspectral image recognition based on artificial neural network," NeuroQuantology, vol. 16, no. 5, 2018.

[33] I. M, V. I, A. J, P. P and R. J, "Deep Learning Model to Detect and Classify Bone Fracture in X-Ray Images," 2023 International Conference on System, Computation, Automation and Networking (ICSCAN), PUDUCHERRY, India, 2023, pp. 1-6.

[34] Pande S. D. et al., "Digitization of handwritten Devanagari text using CNN transfer learning – A better customer service support", Neuroscience Informatics, Volume 2, Issue 3, 2022.