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Exploring Innovations in Bone Fracture Detection Technologies : A Review

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ABSTRACT

Bone breakage or cracks occur when an external force exceeds the bone's tolerance, potentially leading to dislocations that require extensive treatment. Manual examination by experts is complex and difficult with a significant risk of false detection. This systematic review evaluates the current state of bone fracture detection technologies, focusing on the methodologies, performance metrics, dataset considerations, and clinical integration of AI- based systems, particularly deep learning (DL) algorithms. It highlights significant advancements in enhancing diagnostic speed and accuracy for detecting fractures in X-ray and CT images. Various studies demonstrate promising results, such as improved precision and reduced diagnostic time, though challenges remain, including the need for large, diverse datasets and better sensitivity in complex anatomical regions. Future research should prioritize long-term studies to assess the accuracy, cost-effectiveness, and scalability of AI- based fracture detection systems across diverse healthcare environments.

1. INTRODUCTION

Bone is a structurally rigid tissue in the human body, primarily composed of collagen protein, which forms a soft framework as shown in Figure 1. This framework gradually becomes harder due to the deposition of minerals. The hardness and strength of the bone is determined by the amount of these minerals. The human Skelton consist of 206 bones, which is categorized into two groups such as: axial and appendicular. There are eighty axial bones which include the bones of the skull, vertebral column and thoracic cage. These bones protect

the vital internal organs, such as brain, heart and lungs. The remaining bones which include the bones of the limbs, pelvis and shoulder. Bone is a fundamental part of the human musculoskeletal system, providing support for the mechanical action of soft tissues. Flat bones in the skull, thoracic cage and pelvis protect vital internal organs, facilitate movement and offer a medium for blood cell development. Due to the heterogeneity in the structure of bones, accurate identification of any bone deformity, fracture or misalignment is essential for effective treatment [1].

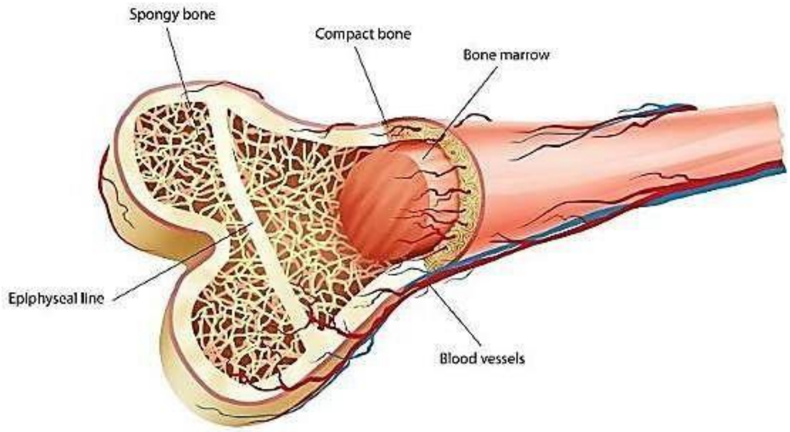

Fig. 1: Structure of Bone

A fracture can be defined as a partial or complete break in a bone, which is often caused by accidents. In case of individuals age, bone mineral density decreases that leads to a condition that weaken the bones and make them more susceptible to fractures. It is clear in conditions like osteoporosis, where the bones become fragile and brittle due to a loss of bone mass. In such cases, minor stresses or falls can result in fractures such as traumatic accidents, osteoporosis, genetic bone disorders, prolonged diseases and Aging [2].

A bone fracture can be broadly classified into two primary types: simple fractures and complex fractures. These categories help in understanding the severity and complexity of the fracture as of Figure 2. Bone fractures can vary widely in their presentation and severity, each requiring specific treatment approaches [3]. Stable fractures involve minimal displacement and typically heal with rest and bracing, while open fractures, which penetrate the skin, require urgent treatment to prevent infection. Transverse fractures occur vertically along the bone's axis, often necessitating advanced imaging for soft tissue assessment. Oblique fractures are angled and common in long bones, posing a risk of skin laceration. Longitudinal fractures extend along the bone's length, usually due to twisting forces. Spiral fractures result

from rotational forces, while comminuted fractures shatter the bone into multiple fragments, often requiring surgery. Impacted fractures occur when one bone fragment is driven into another, creating a stable yet shortened bone. Avulsion fractures involve detachment at tendon or ligament insertions, greenstick fractures involve partial bending, and torus fractures are incomplete with bending but no break. Hairline fractures, or stress fractures, result from repetitive strain, especially in athletes. Recognizing these fracture types is crucial for accurate diagnosis and effective treatment planning.

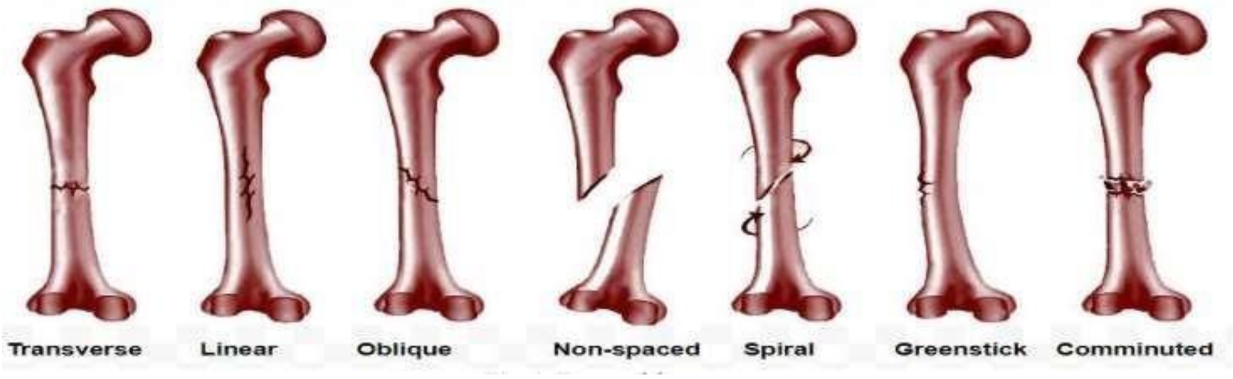

Fig. 2: Types of Fracture

Bone fractures are a common and significant health concern, often requiring timely and accurate diagnosis to ensure appropriate treatment and recovery. Traditional methods of detecting bone fractures, such as manual examination of CT scans and X-rays by radiologists, can be time-consuming and subject to human error. In recent years, advancements in technology have led to the development of automated fracture detection systems, particularly those leveraging DL algorithms. These AI-based systems have shown promise in enhancing the efficiency and accuracy of fracture detection, potentially transforming clinical practices. This systematic review aims to evaluate the current state of bone fracture detection technologies, examining the methodologies, performance metrics, dataset considerations, and the integration of these technologies into clinical settings. By synthesizing existing research, this review seeks to provide a comprehensive understanding of the effectiveness and challenges of these emerging technologies, guiding future innovations and clinical applications.

2. LITERATURE REVIEW

2.1 BONE FRACTURE DETECTION IN X-RAY IMAGES

The detection of bone fractures in X-ray images is a crucial task in medical imaging. The emergence of DL methods has led to notable progress in the development of automated systems for fracture detection. These systems analyze the X-ray images to identify the regions of fracture, resulting in advancements in processing, better performance, and reduction in radiologists. However, challenges persist in the detection of fractures, including the need for large datasets, for better training, generalizability on populations, and addressing issues related to false positives and false negatives. The development of DLmodels, their techniques, performance metrics, datasets and initiatives targeting improving accuracy are included in this analysis of bone fracture detection in X-ray images.

Xie et al. (2024) [4] presented a DL model for recognizing multiple-fracture X-ray images of bones in limbs using a dataset comprising 25,635 individuals and 26,098 images. The training set, consisting of 90% of the data, was used to create model for fracture detection, while the remaining 10% served as the validation set. Employing region based convolutional neural network (R-CNN) algorithm, the study achieved notable results. The free-response receiver operating characteristic (FROC) curve values were 0.843 for multiple fractures and 0.886 for single fractures, with an effective identification of AUC exceeding 0.920 for all parts and a notable AUC of 0.952 for wrist fractures. Despite these achievements, limitations include lower sensitivity for multiple fractures, particularly in complex anatomical areas like the hand, wrist, and foot. Not all fractures visible on radiography can be detected by the model, and its current functionality is restricted to detecting fractures in the limbs.

In their study, Dibo et al. (2023) [5] combined YOLO (You Only Look Once) with the Shifted Window Transformer (Swin), adding a recently built block to present a new method for localizing and categorizing bone diseases in wrist X-ray images. The GRAZPEDWRI-DX dataset is used in this study. Their methodology aims to address two key challenges in wrist X-ray analysis one is precisely locating bone pathologies and another one is accurately classifying abnormalities. The YOLO method is utilized to determine and pinpoint bone diseases, utilizing its capabilities for real-time object detection. Additionally, Swin transformer is employed to extract relevant features from the localized regions of interest (ROIs), enhancing the accuracy of classification. This proposed approach successfully combines the advantages of both YOLO and Swin, showing the possibility of enhancing the localization and categorization of bone diseases in wrist X-ray images.

Ju and Cai (2023) [6] employed the YOLOv8 algorithm to improve fracture detection in pediatric wrist trauma X-ray images. Utilizing the data augmentation techniques, they tried to improve the model's performance on the GRAZPEDWRI-DX dataset. Experimental results demonstrated that the model outperformed both the improved YOLOv7 and original YOLOv8 models in terms of mean average precision (mAP 50). The development of the "Fracture Detection Using YOLOv8 App" aimed to assist surgeons in fracture diagnosis, reduce error analysis, and provide valuable information for surgery.

Wang et al. (2023) [10] examined the use of plain radiographs to diagnose and grade lower extremity fatigue fractures using DL-based diagnostic models. They utilized a dataset comprising 2842 and 1151 X-ray images of fatigue fractures. They created diagnostic models for grading and detection using a triplet branch network and a ResNet-50. Evaluation metrics included AUC for detection models, and accuracy by confusion matrix for grading models. The detection model demonstrated AUC values of 0.965 and 0.877 for the tibiofibula and 0.947 and 0.911 for the foot, in the internal testing and external validation sets, respectively. Despite promising results, the study had limitations, notably its focus only on tibiofibula and foot fatigue fractures, limiting its broader applicability.

In the study, Reddy (2023) [13] presented an artificial intelligence (AI) approach comprising five pre-trained deep convolutional neural networks (DCNNs) for feature extraction, one classifier, and one cross-validation method. The framework was utilized to small exemplar sets of medical images from the MURA dataset, focusing on upper extremity body parts such as the elbow, forearm, hand, wrist, finger, shoulder and humerus, to distinguish between fractured and non-fractured bones. Results revealed that InceptionV3 and Xception combined with random forest achieved 86% accuracy in binary classification, while DenseNet169 combined with random forest attained 90.3% accuracy in multi-class classification, distinguishing fractures across different body parts. The study suggests that this integrated AI framework holds promise for providing rapid and accurate diagnosis of bone fractures from medical images.

In their study, Hardalac et al. (2022) [9] aimed to enhance fracture detection in wrist X-ray images using DL, particularly to support physicians in emergency services. They conducted 20 different detection procedures on wrist X-ray image dataset from Gazi University Hospital. Five ensemble models were created and merged to produce a new detection model known as "wrist fracture detection-combo (WFD-C)" in order to improve these processes. Among 26 models, the WFD-C model's average precision (AP) of 0.8639 was the best detection result for fracture detection.

Asma Alzaid et al. (2022) [20] conducted a study to examine the performance of object detection and classification systems on binary and multi-class problems using plain radiographs of peri-prosthetic femur fractures (PFF). Two clinical specialists collected 1272 X-ray images, labeled them with bounding boxes, and classified them using the Vancouver Classification System. Two object detection models (Faster RCNN and RetinaNet) and four classification models (Resnet50, Densenet161, Inception, and VGG) were examined. Resnet50 emerged as the top performer, with 94% F1-score and 95% accuracy in binary classification (fracture/normal) and 90% accuracy in multi-classification.

Barhoom et al. (2022) [11] emphasized the crucial role of bones in the human body, serving both structural and protective functions. However, bone abnormalities resulting from accidents or diseases can lead to fractures, chronic pain, and even mortality if not promptly and accurately diagnosed. Traditional diagnosis methods depending on X-ray imaging and human interpretation are prone to errors, prompting the exploration of DL algorithms like the VGG16 convolutional neural network (CNN). Customized to classify bone abnormalities, the modified VGG16 model was trained, validated, and tested on a dataset comprising 42,000 X- rays from the upper bones. Results showed promising precision (85.96%), recall (85.82%), and F1-Score (85.77%). However, a limitation of the study was the dataset's focus on specific upper bones, restricting the generalizability of the findings to other skeletal regions.

Jia et al. (2022) [24] developed a sternum fracture detection model using 1227 labeled X-ray images. Their CNN-based model, incorporating cascade R-CNN, attention mechanisms, and atrous convolution, aimed to optimize detection in X-ray images with local variations. Comparative analysis showed superior performance (mAP = 0.71) compared to YOLOv5 (mAP = 0.44) and cascade R-CNN (mAP = 0.55). Limitations include the use of data from a single institution; therefore, multi-center datasets are required for wider applications.

In their study, Franko Hržic et al. (2022) [13] suggested a machine learning model (ML) based on the YOLOv4 method aimed at improving wrist fracture detection. The model underwent rigorous testing across three levels, demonstrating superior performance compared to the U-Net model. Evaluation against five radiologists revealed that the YOLOv4 model, outperformed the radiologists. It achieved 0.965 AUC-ROC, while the average AUC-ROC of the radiologists was 0.831 ± 0.075.

Table 1. Summary of Recent Methods in X-ray Imaging

Author and Reference	Methodology	Dataset	Performance Evaluation
Xie et al. [4]	Faster R- CNN	Real time	FROC curve values: 0.886 (single fractures), 0.843 (multiple fractures); AUC: >0.920 (all parts), 0.952 (wrist fractures)
Dibo et al. [5]	YOLO with Swin Transformer	GRAZPEDWRI-DX	Improved localization and classification of bone pathologies
Ju and Cai [6]	YOLOv8	GRAZPEDWRI-DX	mAP =50
Wang et al. [7]	ResNet-50	Real Time	AUC: 0.965, 0.877 (tibiofibula); AUC: 0.947, 0.911 (foot)

Reddy [8]	InceptionV3, Xception, DenseNet169, Random Forest	MURA	Accuracy: 86% (binary classification); Accuracy: 90.3% (multi-class classification)
Hardalac et al. [9]	DCNN	Gazi University Hospital dataset	AP: 0.8639
Asma Alzaid et al. [10]	Densenet161, Resnet50, Inception, VGG	Real Time	Resnet50: 95% accuracy and 94% F1-score
Barhoom et al. [11]	VGG16	X-rays	Recall: 85.82%; Precision: 85.96%; F1-Score: 85.77%
Jia et al. [12]	CNN	X-ray images	mAP: 0.71
Franko Hržic et al. [13]	YOLOv4	Pediatric X-ray images	AUC-ROC: 0.965

2.2 BONE FRACTURE DETECTION IN CT IMAGES

Bone fracture detection in CT images utilizes advanced computational techniques, particularly DL algorithms, to identify the fractures. These systems analyze the intensity of the pixel and spatial relationships within the CT images to differentiate between normal bone structures and areas of fracture. This method not only enhances the diagnostic accuracy but also it simplifies the work flow, allowing for faster interpretations. However, the challenges

persist, including the need for datasets, the optimization of model performance, and the exploration of new methodologies. An examination of the diagnosis of bone fracture detection from CT scans highlights their success, drawbacks, and the need for further study to improve accuracy and clinical applicability.

In their study, Warin et al. (2023) [14] aimed to evaluate the effectiveness of CNN based models in detecting and classifying maxillofacial fractures in computed tomography (CT) images. They utilized a dataset consist of 3407 CT images, from which 2407 images consist of maxillofacial fractures. The multiclass image classification models are trained using ResNet-152 and DenseNet-169, as well as multiclass object detection models are trained using YOLOv5 and Faster R-CNN. Evaluation on an independent test dataset revealed that DenseNet-169 achieved an overall accuracy of 0.70 for multiclass classification, while Faster R-CNN demonstrated a mAP of 0.78 for multiclass detection. However, a limitation identified was that the low-quality image resolution of 512×512 pixels might have shown challenges in developing accurate fracture classification models.

Lin et al. (2023) [15] conducted a study on the possibility of employing DL methods to enhance the efficiency of rib fracture diagnosis in CT images. They examined CT scans of the chests of 2622 patients who had been hospitalized for chest injuries in outpatient and emergency departments. Before importing the various scale features into a DCNN model, the study first extracted primary features using Hourglass Net and then extracted multi-scale features using Inception. Results indicated that the DCNN model outperformed low-senior physicians

in rib fracture diagnosis, with an accuracy of 95.6% compared to physicians' 93.2%. The DCNN model also significantly reduced diagnostic time, from an average of
156.0 seconds for physicians to just 4.9 seconds. The removal of individuals with poor breath-holding and significant respiratory abnormalities from testing was one of the limitations.
A study was carried out by Nejad et al. (2023) [16] to examine the effectiveness of DL methods for identifying spine fractures, especially in the cervical region. They employed a dataset comprising CT images of the cervical spine that were both fractured and non- fractured. The study introduced a two-stage pipeline design achieving promising results, with a macro- F1 accuracy of 96% for vertebral classification and a mAP of 96% for fracture detection. These findings suggest that the algorithm can reduce the workload of radiologists while enhancing fracture detection accuracy.

Moon et al. (2022) [17] introduced a computer-aided facial bone fracture diagnosis (CA- FBFD) system aimed at enhancing the efficiency of facial fracture detection in CT images. The system employed object identification model YoloX-S for box prediction and CT image mixup data augmentation, which was trained using IoU loss. The evaluation revealed that the CA-FBFD system attained an AP of 69.8% for fractures in facials, exceeding the performance of the baseline YoloX-S model. This suggests that the CA-FBFD system can effectively reduce the workload of physicians tasked with identifying facial bone fractures in facial CT scans.
In their study, Takaki Inoue et al. (2022) [18] studied the feasibility of utilizing a CNN-based automatic localization and classification system for rib, spine, and pelvic fractures on whole- body CT axial slices. The study involved 7664 CT axial slices from 200 patients, with performance metrics including sensitivity, F1-score and precision. The CNN model helped the less experienced orthopedic surgeons perform better in terms of sensitivity and reading time for fractures in pelvis, spine, or ribs. However, several limitations were identified, as the study focused only on the axial slices of CT images, it did not examine fractures occurring in other anatomical areas such as the scapula, sternum, clavicle, humerus, femur, cervical vertebrae, which may restrict the generalizability of the findings.
Yang et al. (2022) conducted a study on the performance of a DL system for automatically diagnosing and classifying rib fractures. They examined CT data from 666 patients with rib fractures across two hospitals and utilized a CNN-based diagnostic tool. Their experiment compared the diagnostic efficiency of the DL system with that of radiologists through a human-model comparison. The DL system showed significantly superior fracture detection efficiency compared to radiologists of varying experience levels, except for senior radiologists. The classification models accurately distinguished between new and old fractures with an accuracy of 87.63% and detected misalignments in newly formed fractures with a precision of 95.22%.
Wang et al. (2022) [20] studied CNNs' accuracy and reliability in identifying and categorizing mandibular fractures on spiral CT scans. Three skilled maxillofacial surgeons categorized and analyzed the CT scans of 686 individuals who had mandibular fractures as part of the study. U-Net and ResNet CNN-based algorithm was trained, tested and validated on 222, 408 and 56 CT scans, respectively. The study diagnosed 1506 mandibular fractures across nine subregions, achieving a DICE of 0.943 for mandible segmentation using U-Net and accuracies above 90% for all subregions, with a mean AUC of 0.956. However, the study was limited by the need for uniformity in data accuracy among various devices and the difficulty in creating sufficient datasets for rare fracture forms such as mandibular ramus fractures and coronoid process fractures.
A new DL-based rib fracture detection method was presented by Yao et al. (2021) [21] with the aim of helping radiologists quickly and reliably diagnose rib fractures in chest CT scans. They developed a three-step algorithm

for the detection of rib fractures from the CT scans of 1707 patients. The Rib Fracture Detection System demonstrated promising performance, with an F1-score of 0.890 and significant reductions in diagnosis time. The study found that the DL model was trained on CT data from only one academic institution, and the size of test data was relatively small and not validated with data from other centers.

In order to detect traumatic fractures in patients, Amodeo (2021) [22] developed an innovative maxillofacial fracture detection system (MFDS) that makes use of CNNs and transfer learning (TL). The system was trained on 148 CT scans, validation was conducted on a dataset of 30 patients, while a separate test set of 30 CT scans was used for the final evaluation. The model achieved 80% accuracy in classifying maxillofacial fractures, indicating its potential to provide valuable assistance to radiologists by reducing the risk of human error and minimizing diagnostic delays. However, it was emphasized that the MFDS model cannot replace the experience of radiologists completely.

Small et al. (2021) [23] conducted a study evaluating C-spine, an FDA-approved CNN, for detecting cervical spine fractures on CT scans. They analysed 665 examinations and established ground truth by visualizing fractures on CT with additional imaging modalities. The CNN achieved 92% accuracy, with 97% specificity and 76% sensitivity, while radiologists had slightly higher accuracy at 95%, with specificity of 96% and a sensitivity of 93% . Both the CNN and radiologists overlooked similar fractures, including those in the lower cervical spine covered by CT beam attenuation, transverse processes, spinous processes, and anterior osteophytes.

Table 2. Summary of Recent Methods in CT Imaging

Author and Reference	Methodology	Dataset	Performance Evaluation
Warin et al. [14]	DenseNet-169, ResNet-152, Faster R-CNN, YOLOv5	CT images	Accuracy: 0.70 mAP: 0.78
Lin et al. [15]	DCNN	chest CT images	Accuracy: 95.6
Nejad et al. [16]	YOLOv8	Cervical spine fractures and non-fractured CT images	Macro F1 accuracy: 96%) mAP: 96%
Moon et al. [17]	YoloX-S with IoU Loss	Facial bone CT data from university hospital	Average precision: 69.8%
Takaki Inoue et al. [18]	CNN	CT axial slices	Moderate performance for pelvic, spine, or rib fractures
Yang et al. [19]	CNN	CT images of rib fractures	Accuracy: 87.63% Precision: 95.22%
Wang et al. [20]	U-Net and ResNet	CT scan of mandibles	DICE: 0.943 Mean AUC: 0.956
Yao et al. [21]	DL algorithm	CT images of rib fractures	F1-score: 0.890
Amodeo [22]	CNNs and transfer learning	Maxillofacial CT scans	Accuracy: 80%

Small et al. [23]	CNN	CT scans of cervical spine fractures	Accuracy: 92%; Sensitivity: 76%; Specificity: 97%; Radiologists: Accuracy: 95%, Sensitivity: 93%, Specificity: 96%

3. RESEARCH GAP

Although the application of DL algorithms for fracture detection has advanced significantly, there's still a gap in understanding how well these AI-based systems perform in real-world clinical scenarios. Many studies show that AI can accurately detect fractures in various parts of the body, but there's a lack of evidence on how effectively these systems can be used in everyday medical practice and whether they truly improve patient outcomes. Most research focuses on specific types of fractures or imaging techniques, leaving a gap in understanding their broader application. To address this, future research should prioritize long-term studies that not only test the accuracy of these AI systems but also their cost-effectiveness and ability to be scaled across different healthcare environments. It needs to consider factors like how different clinicians interpret the results and how these systems integrate with existing diagnostic processes without interpretation. It's essential to explore how well these systems work across various healthcare settings and patient populations to ensure they are useful and effective.

4. CONCLUSION

The present state of bone fracture detection technologies is evaluated in this systematic review, which focuses on the methods, performance metrics, dataset considerations, and clinical setting combining these technologies. The study shows promising results in improving diagnostic speed and accuracy by highlighting notable developments in AI-based systems, especially DL algorithms, for detecting fractures in X-ray and CT images. Nevertheless, there are still issues to be resolved, such as the requirement for sizable, varied datasets, enhanced sensitivity in complex anatomical regions, and greater workflow integration. Despite these improvements, challenges such as the need for large, diverse datasets, and increased sensitivity in complex anatomical regions. Moreover, a notable gap exists in understanding the real-world clinical application and effectiveness of these technologies. Future research should focus on long-term studies to examine the accuracy, cost-effectiveness, and scalability of AI-based fracture detection systems across various healthcare environments.

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