



Artificial intelligence versus radiologist in the accuracy of fracture detection based on computed tomography images: a multi-dimensional, multi-region analysis

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Background: Extremities fractures are a leading cause of death and disability, especially in the elderly. Avulsion fracture are also the most commonly missed diagnosis, and delayed diagnosis leads to higher litigation rates. Therefore, this study evaluates the diagnostic efficiency of the artificial intelligence (AI) model before and after optimization based on computed tomography (CT) images and then compares it with that of radiologists, especially for avulsion fractures.

Methods: The digital X-ray photography [digital radiography (DR)] and CT images of adult limb trauma in our hospital from 2017 to 2020 were retrospectively collected, with or without 1 or more fractures of the shoulder, elbow, wrist, hand, hip, knee, ankle, and foot. Labeling of the fracture referred to the visualization of the fracture on the corresponding CT images. After training the pre-optimized AI model, the diagnostic performance of the pre-optimized AI, optimized AI model, and the initial radiological reports were evaluated. For the lesion level, the detection rate of avulsion and non-avulsion fractures was analyzed, whereas for the case level, the accuracy, sensitivity, and specificity were compared among them.

Results: The total datasets (1,035 cases) were divided into a training set (n=675), a validation set (n=169), and a test set (n=191) in a balanced joint distribution. At the lesion level, the detection rates of avulsion fracture (57.89% *vs.* 35.09%, $P=0.004$) and non-avulsion fracture (85.64% *vs.* 71.29%, $P<0.001$) by the optimized AI were significantly higher than that by pre-optimized AI. The average precision (AP) of the optimized AI model for all lesions was higher than that of pre-optimized AI model (0.582 *vs.* 0.425). The detection rate of avulsion fracture by the optimized AI model was significantly higher than that by radiologists (57.89% *vs.* 29.82%, $P=0.002$). For the non-avulsion fracture, there was no significant difference of detection rate between the optimized AI model and radiologists ($P=0.853$). At the case level, the accuracy (86.40% *vs.* 71.93%, $P<0.001$) and sensitivity (87.29% *vs.* 73.48%, $P<0.001$) of the optimized AI were significantly higher than those of the pre-optimized AI model. There was no statistical difference in accuracy, sensitivity, and specificity between the optimized AI model and the radiologists ($P>0.05$).

Conclusions: The optimized AI model improves the diagnostic efficacy in detecting extremity fractures on radiographs, and the optimized AI model is significantly better than radiologists in detecting avulsion fractures, which may be helpful in the clinical practice of orthopedic emergency.

Keywords: Artificial intelligence (AI); deep learning; fracture; diagnostic efficiency

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Introduction

According to reports, the incidence of traumatic fractures is as high as 0.32% in the United States (1) and up to 1.3% in China (2), which has become a public health problem of global concern. Avulsion fracture, which is the avulsion and displacement of bone fragments due to the traction of tendons and ligaments after trauma, is easy to be missed clinically. A study by Haraguchi *et al.* (3) showed that the incidence of avulsion fractures is high in patients with severe inversion injury, especially in children and patients over 40 years old. Diagnosis of avulsion fracture is usually difficult on digital radiography (DR) images. Missed fracture on radiograph in the emergency department is a common cause of medical incident and litigation (4,5). It is reported that the annual litigation rate experienced by orthopedic doctors is 14%, which is higher than the national average of 7% for physicians (6,7).

Recently, convolutional neural networks (CNNs) in deep learning have achieved remarkable results in automatic detection of various non-avulsion fractures, ligament injuries, and classification of bone tumors, including upper and lower extremities fractures [e.g., distal radius (8), proximal humerus (9), intertrochanteric hip (10)], calcaneofibular ligament injuries in the ankle joint (11), and pelvic and sacral osteosarcoma classification (12). For avulsion fractures, the imaging presentation of fracture signs is often challenging to determine, making it difficult to obtain a sufficient number of labeled samples for artificial intelligence (AI) training to improve their detection. At present, there only a few studies have reported the application of deep learning in avulsion fractures (13). Moreover, most of the studies used imaging reports or interpretations of DR images by radiology experts as the evaluation reference (14-16), which may be affected by individual experience.

Therefore, this study used computed tomography (CT) images to verify the lesion labeling on X-ray radiographs and then optimize an AI model for detecting extremity fractures. The diagnostic efficiency of the AI model before and after the optimization was evaluated and compared with

radiologists, especially in the aspect of avulsion fractures. We present this article in accordance with the STARD reporting checklist (available at <https://qims.amegroups.com/article/view/10.21037/qims-23-428/rc>).

Methods

Data generation

The CT and DR images of adult limb trauma in China-Japan Friendship Hospital from 2017 to 2020 were retrospectively collected. Each X-ray examination followed the conventional projection views, consisting of 1-4 radiographs. Anatomical areas included the shoulder, elbow, wrist, hand, hip, knee, ankle, and foot. The exclusion criteria were as follows: (I) no initial radiological report (42 cases); (II) no corresponding CT examination of the same anatomical area was performed within 2 weeks (2,317 cases); (III) postoperative radiography of the fracture (937 cases); and (IV) poor radiographic quality (5 cases). Totally, 1,035 cases (anatomical areas) with 3,167 radiographs were extracted in this study, including 666 positive cases and 374 negative cases, which were divided into a training set (n=675), a validation set (n=169), and a test set (n=191) in a balanced joint distribution (*Figure 1*). The number of individual components of the total datasets is shown in *Figure 2*. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The study was approved by the China-Japan Friendship Hospital Institutional Review Board (Medical ethics number: 2019-94-k62-1) and the requirement for individual consent for this retrospective analysis was waived.

Image labeling

Firstly, 2 radiologists with more than 10 years of experience reviewed the CT images to define the site and scope of the fractures as a gold standard and then labeled the fractures on DR images. DeepWise software (<https://label.deepwise.com/>) was applied for annotation. A rectangular bounding box was drawn to enclose the fracture line. For a non-

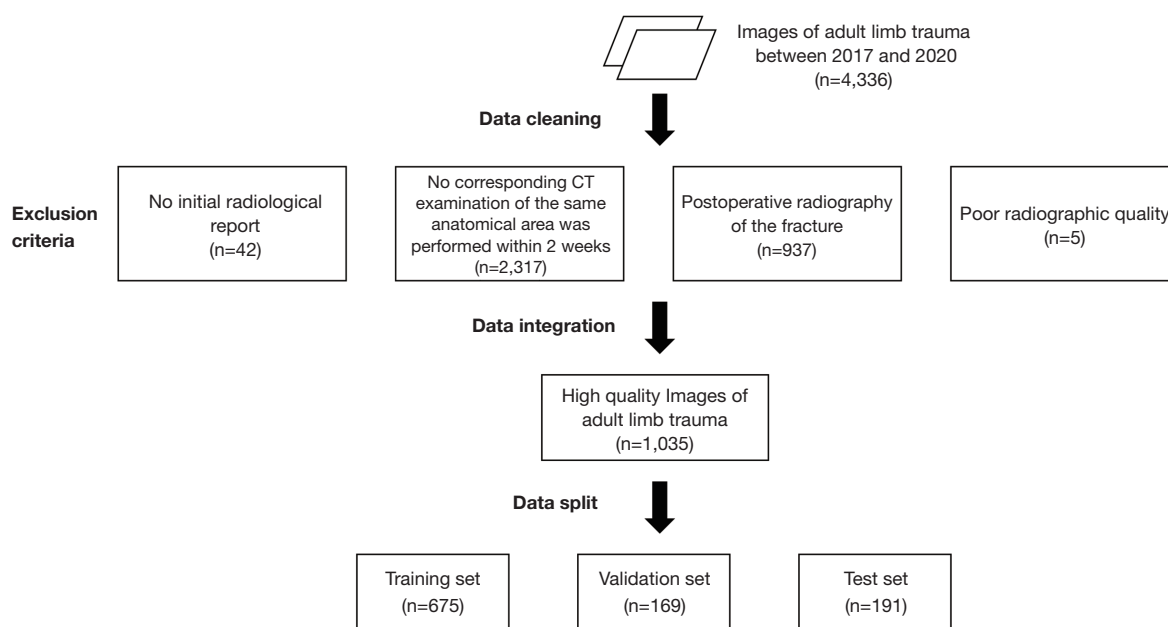


Figure 1 A flow diagram of the enrollment process for patients with fractures. CT, computed tomography.

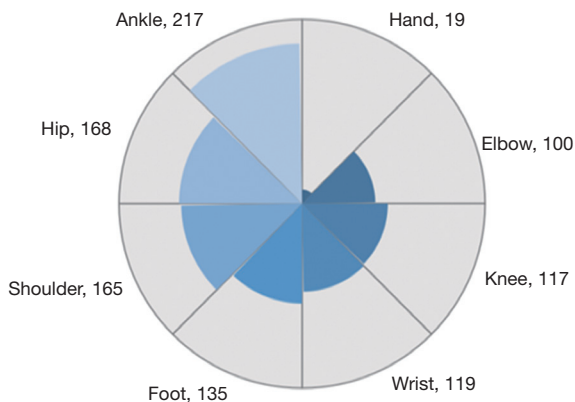


Figure 2 The number of individual components of the total datasets.

avulsion fracture, multiple rectangular bounding boxes can be labeled for 1 fracture site.

Preprocessing

Image arrays in 16-bit integer format were extracted from Digital Imaging and Communications in Medicine (DICOM) files. Then, all the images were resized to the scale so that the short side length was close to 1,200 pixels while maintaining the aspect ratio. Augmentations were employed during training, including random rotation,

random flip, random brightness, random crop, and contrast distortion.

Model architecture and learning policy

In this study, an AI diagnosis system for fracture was used for auxiliary diagnosis. The algorithm we propose in this paper was based on the ResNeXt-101-32x4d + feature pyramid networks (FPN) + Mask-region-based CNN (RCNN) model (17), and the adaptive optimization was carried out on the above annotation data set of DR images. Firstly, pre-processed training data were sent to the ResNeXt-101 backbone with FPN to extract multi-scale features (P2–P6 in Figure 3). Secondly, these features from different scale levels were fused to generate global features and sent to the region proposal network (RPN) to make preliminary box predictions and obtain the proposals. In this stage, positive and negative samples were balanced by a data balancing method to adapt to the distribution of the dataset. Thirdly, the region of interest (ROI) alignment was applied to obtain the feature map of the possible lesion area, and then the fully connected layers were used for classification and box regression to predict fractures precisely. In addition, the prediction results were optimized through adjustments such as anchor scale and aspect ratio, the FPN stages and channels, and gradient learning strategies. Finally, label balance was added to shield bad

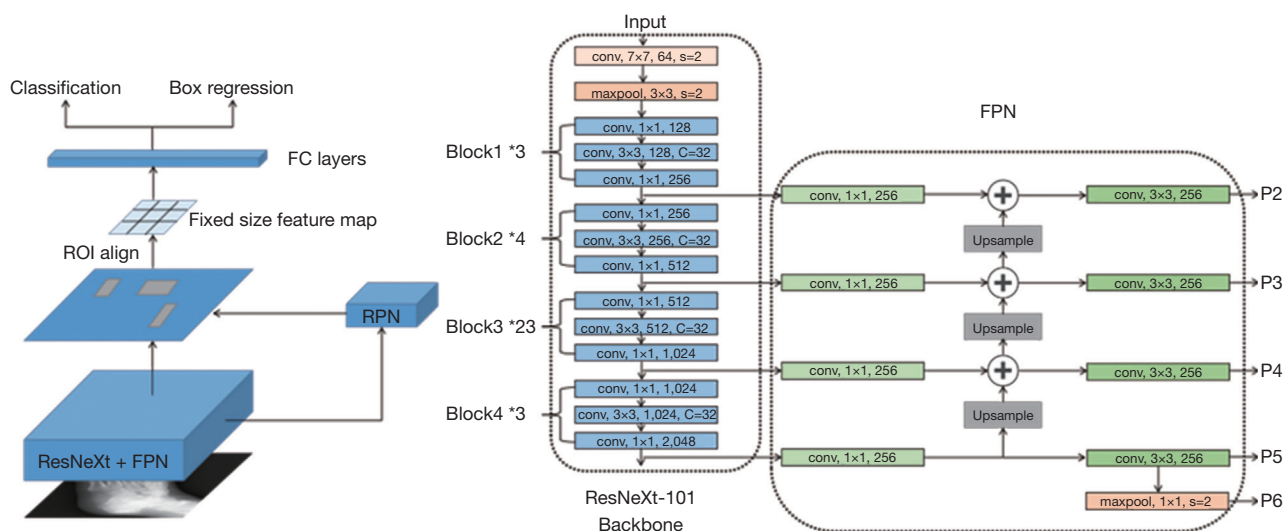


Figure 3 Flow chart of the main algorithm designed for this study. Left: the fractures detection pipeline based on Mask-RCNN. Right: the model architecture of ResNeXt-101 backbone and FPN. FC, fully connected; ROI, region of interest; RPN, region proposal network; FPN, feature pyramid network; conv, convolution.

gradients, the proposal was relocated and corrected, and then the multi-scale fused features of the corresponding region were obtained, resulting in a more robust model training. A global learning rate of 0.002 was initially used with 0.9 momentum and 0.0001 weight decay, divided by 10 at 15 epochs and 30 epochs, and then the training stopped after 45 epochs.

The proposed method was developed using PyTorch 1.7 open-source deep learning library (<https://pytorch.org/get-started/previous-versions/>), a server with 24 Intel(R) Xeon(R) E5-2685 v3 @ 2.60 GHz CPUs, and 8 NVIDIA TITAN Xp GPU (<https://www.nvidia.com/en-au/titan/titan-xp/>). The version of CUDA was 10.1.

Model evaluation

The performances of pre-optimized AI model, optimized AI model, and radiologist are evaluated at the lesion and case (anatomical area) level, respectively. For the lesion-based assessment, all fracture lesions were classified as avulsion fractures and non-avulsion fractures. True positive required 1 box of true positive on any of the projected views. For fracture lesion level, since all parts except the fracture can be considered negative, the resulting specificity was meaningless. Therefore, the detection rate was considered as the true positive rate. For case (anatomic area) level, true positive required only 1 box of true positive, regardless of

the number of fractures present.

For the performance of the radiologists, initial radiological reports were evaluated. Reports that indicated a fracture with unequivocal diagnosis or probability were rated as positive, whereas description of unspecific signs without conclusion was treated as negative results.

Statistical methods

The study was statistically analyzed using SPSS 26.0 (IBM Corp., Armonk, NY, USA) software, and the count data were expressed as n (%). The detection rates of avulsion fractures and non-avulsion fractures by the pre-optimized AI model, the optimized AI model, and the radiologist were compared, respectively, as well as their accuracy, sensitivity, and specificity for fractures at each anatomic area by using the quality test for paired samples. Significance tests were used to compare detection rate, accuracy, sensitivity, and specificity. Statistical significance was indicated by a two-tailed $P < 0.05$.

Results

Lesion-based diagnostic efficacy

In the test set (191 cases), a total of 266 lesions were identified, including 57 (21.43%) avulsion fractures and 209 (78.57%) non-avulsion fractures. The detection rate

Table 1 Comparison of AI diagnostic efficacy before and after optimization of the test set based on lesion

| Fracture type | Detection rate | | t value | P value |
|-------------------------------|----------------------|------------------|---------|---------|
| | Pre-optimized AI (%) | Optimized AI (%) | | |
| Avulsion fracture (n=57) | 35.09 | 57.89 | -2.871 | 0.004 |
| Non-avulsion fracture (n=209) | 71.29 | 85.64 | -4.196 | <0.001 |

AI, artificial intelligence.

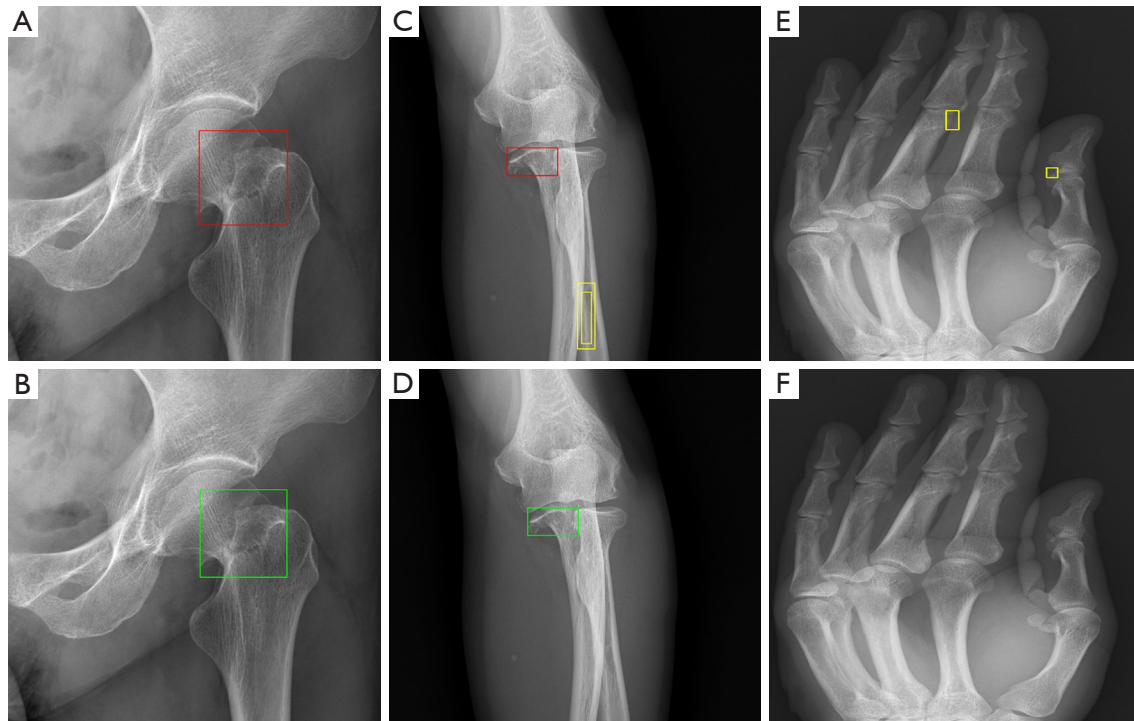


Figure 4 Results of femoral neck, ulna, and hand detection in pre-optimized model (A,C,E) and optimized model (B,D,F). Fractures that were not identified by the pre-optimized model (A and C, red boxes) were detected by the optimized model (B and D, green boxes). Optimized AI models (D and F) may help eliminate false positives (C and E, yellow boxes). AI, artificial intelligence.

of avulsion fracture by the optimized AI was significantly higher than that by pre-optimized AI (57.89% *vs.* 35.09%, $P=0.004$), increasing by 22.80%. The detection rate of the optimized AI model for non-avulsion fractures was significantly higher than that of the pre-optimized AI model (85.64% *vs.* 71.29%, $P<0.001$), with an increase of 14.35% (Table 1 and Figure 4). The average precision (AP) of optimized AI model for all lesions was higher than that of pre-optimized AI model (0.582 *vs.* 0.425) (Figure 5).

The detection rate of avulsion fracture by the optimized AI model was significantly higher than that by radiologists (57.89% *vs.* 29.82%, $P=0.002$), with 28.07% difference. For the non-avulsion fracture, there was no significant

difference of detection rate between the optimized AI model and radiologists ($P=0.853$). The results are presented in Table 2 and Figure 6.

Case-based diagnostic efficacy

At the case level, the accuracy (86.40% *vs.* 71.93%, $P<0.001$) and sensitivity (87.29% *vs.* 73.48%, $P<0.001$) of the optimized AI were significantly higher than those of the pre-optimized AI model, with an increase of 14.47% and 13.81%, respectively, as shown in Table 3. There was no statistical difference in accuracy, sensitivity, and specificity between the optimized AI and the radiologists ($P>0.05$) (Table 4).

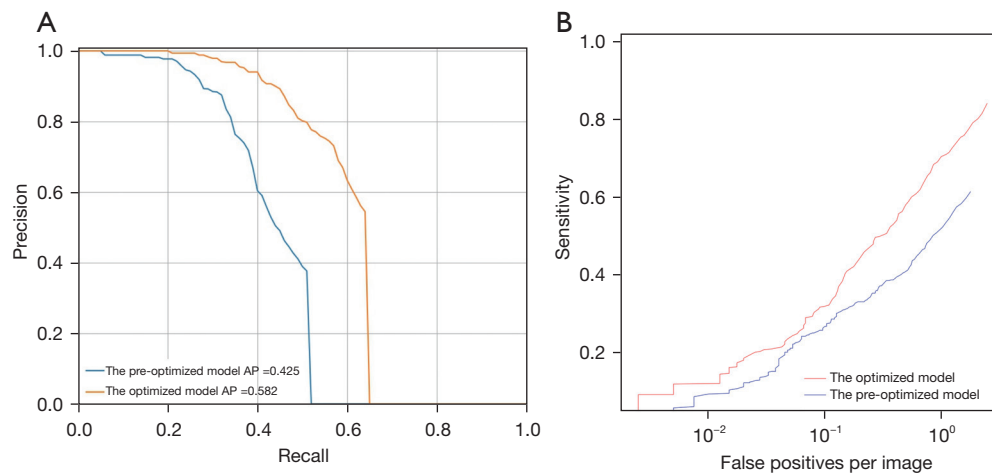


Figure 5 The PR curves (A) and FROC curves (B) of pre-optimized and optimized AI model at lesion level analysis. AP, average precision; PR, precision-recall; FROC, free-response ROC; ROC, receiver operating characteristic; AI, artificial intelligence.

Table 2 Comparison of the diagnostic efficacy of radiologists and optimized AI of the test set based on lesion

| Fracture type | Detection rate | | t value | P value |
|-------------------------------|-----------------|------------------|---------|---------|
| | Radiologist (%) | Optimized AI (%) | | |
| Avulsion fracture (n=57) | 29.82 | 57.89 | -3.066 | 0.002 |
| Non-avulsion fracture (n=209) | 86.12 | 85.64 | 0.185 | 0.853 |

AI, artificial intelligence.

Discussion

The study used CT image-based fracture identification as the “gold standard” to label and train AI models, and then evaluated the diagnostic efficacy of the AI models in detecting avulsion fractures and non-avulsion fractures in multiple anatomical areas on DR images. The results found that the optimized AI model greatly improved the diagnostic performance for different anatomical areas and different types of extremity fractures compared to the pre-optimized AI. The optimized AI model improved the detection rate of avulsion fractures compared to radiologists (29.82% *vs.* 57.89%, $P=0.002$). Inagaki *et al.* reported that an AI model improved the detection rate of sacral fractures compared to specialists by labeling and training an AI model using the results of CT images (accuracy 93.5% *vs.* 55.3%) (18). This study demonstrated the feasibility of using AI for fracture detection.

This study used CT images as the gold standard to label radiographs for the training set. Most published datasets for automated fracture detection have been labeled by orthopedic surgeons (19), general radiologists (20-23),

specialized musculoskeletal radiologists (20,21), or orthopedic specialists (16). Tobler *et al.* (14) used radiology reports to label distal radius fractures on radiographs for the training set. Another study showed that a considerable part of fractures were missed at the initial diagnosis (24). Since partial radiology reports and clinicians are susceptible to error, the data labeling based on reports had some level of inaccuracy. In contrast, the fracture areas were manually labeled by radiologists based on the visualization of lesions on the corresponding CT images in our study. A previous study suggested that subtle fractures are difficult to detect on plain films, and CT imaging may be required (25). The bounding boxes used to train, validate, and test the models were labeled according to each instance corresponding axial CT and 3-dimensional (3D) reconstruction images in our study; this method could harvest more accurate bounding boxes than expert-based data annotations. It is more difficult to identify subtle imaging findings for avulsion fractures than non-avulsion fractures, so CT localization for small fragments and translucent lines can make the labeling more accurate.

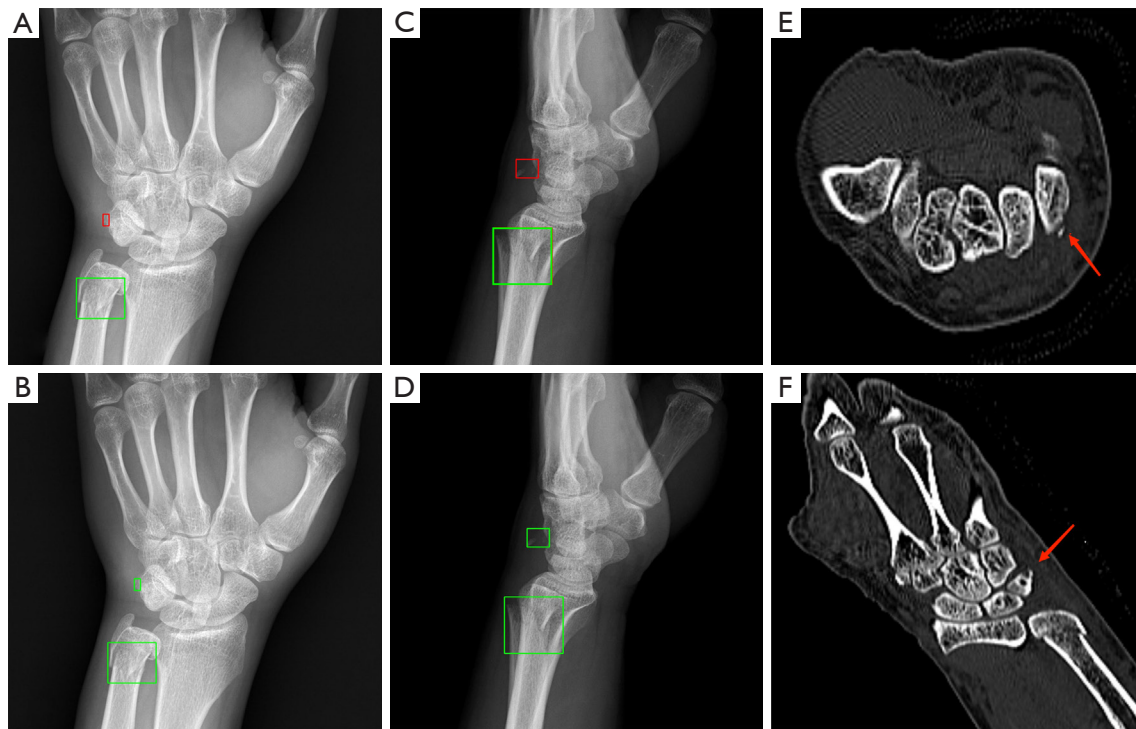


Figure 6 A case with a distal ulna fracture and a triquetral avulsion fracture. Both the initial radiology report (A and C, green boxes) and the optimized model (B and D, green boxes) correctly identified the distal ulna fracture. The triquetral avulsion fractures (A and C, red boxes) missed on radiographs from the initial radiology report were detected by the optimized model (B and D, green boxes), and the corresponding reconstructed CT images showed the fragment of the avulsion fracture (E and F, arrows). CT, computed tomography.

Table 3 Comparison of the diagnostic efficacy of the pre-optimized AI and optimized AI of the test set based on case

| Diagnostic efficacy | Pre-optimized AI (%) | Optimized AI (%) | <i>t</i> value | P value |
|---------------------|----------------------|------------------|----------------|---------|
| Accuracy | 71.93 | 86.40 | -4.391 | <0.001 |
| Sensitivity | 73.48 | 87.29 | -3.964 | <0.001 |
| Specificity | 65.96 | 82.98 | -1.940 | 0.058 |

AI, artificial intelligence.

Table 4 Comparison of the diagnostic efficacy of radiologist and the optimized AI of the test set based on case

| Diagnostic efficacy | Radiologist (%) | Optimized AI (%) | <i>t</i> value | P value |
|---------------------|-----------------|------------------|----------------|---------|
| Accuracy | 83.33 | 86.40 | -1.068 | 0.725 |
| Sensitivity | 85.64 | 87.29 | -0.538 | 0.725 |
| Specificity | 74.47 | 82.98 | -1.159 | 0.252 |

AI, artificial intelligence.

Olczak *et al.* (26) used a Visual Geometry Group (VGG)-16 network to identify fractures. Their dataset contained 256,000 hand, wrist, and ankle radiographs. The model detected fractures with accuracy of 83%. This study is considered the first to show that deep learning works for orthopedic radiographs. The VGG-1618 network is a CNN that classifies entire radiographs into fracture or nonfracture categories. This study used a ResNeXt-101 network and achieved an accuracy of 86.4% in diagnosing extremity fractures, which is higher than that of the study by Olczak *et al.* Our study also used the Mask-RCNN architecture (17), which is a proposal-based object detection CNN. The region proposal-based models mainly include the RCNN (27), Faster-RCNN (24), and Mask-RCNN (17). In a study performed by Wu *et al.* (28), the RCNN was used to identify fractures from hand, wrist, elbow, shoulder, pelvic, knee, ankle, and foot radiographs. In addition, a Feature Ambiguity Mitigate Operator (FAMO) model was introduced to mitigate feature ambiguity. This model finally achieved a sensitivity of 77.5% and a specificity of 93.4%. The Mask-RCNN method achieved a sensitivity of 87.29% in our study, which is higher than that in the study by Wu *et al.* Increased sensitivity is important to reduce the missed diagnosis for clinical practice.

The most important result of this study was the finding that the optimized AI model improved the detection of avulsion fractures, which has important implications for clinical practice given that avulsion fractures are easily missed. Published studies investigating deep learning approaches for fracture detection have focused on non-avulsion fractures, such as those of the hip (29,30), wrist (31), shoulder (9), and ankle (20). However, there have been few applications of deep learning for the detection of avulsion fractures. Ren *et al.* (13) developed and evaluated a 2-stage deep CNN system that mimics a radiologist's search pattern for detecting 2 minor fractures: triquetral avulsion fractures and Segond fractures. The specially designed training program has greatly improved the detection rate of the minor fractures. In our study, the total detection rate of avulsion fractures at multiple anatomical areas by the optimized AI model was 57.89%, whereas the detection rate of radiologists was only 29.82%. These avulsion fractures were mostly misdiagnosed in the initial radiological reports, and were only identified by the optimized AI model. Therefore, the results of our study show that CNNs can be trained to improve the detection of avulsion fractures.

Our study had several limitations. Firstly, we concluded that CT-based labeling was superior to labeling based

on a team of experts, but we did not further compare the differences between them. Secondly, selection of only examinations that had CT follow-up may have created spectrum bias toward more severe injuries, and the number of negative samples in the test set was relatively small, especially for the hand bones; more multi-center data in the future are required for testing our model. Thirdly, our radiology reports were written by radiology residents and radiologists with varying expertise in musculoskeletal imaging and were unstructured, which may have influenced the diagnostic results. Finally, whether this AI will improve the ability of professionals to diagnose fractures needs to be tested further in clinical practice.

Conclusions

In conclusion, this study showed that the optimized AI model significantly improved the diagnostic efficacy of extremity fractures compared with the pre-optimized AI model, and the optimized AI model significantly outperformed the radiologists in detecting avulsion fractures. Therefore, the AI model trained on CNN with CT-based labels to detect extremity fractures (especially avulsion fractures that are easily missed) on radiographs are suitable as an assisted reading tool.

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Footnote

Reporting Checklist: The authors have completed the STARD reporting checklist. Available at <https://qims.amegroups.com/article/view/10.21037/qims-23-428/rc>

Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at <https://qims.amegroups.com/article/view/10.21037/qims-23-428/coif>). HC, YY and XL are employees of DeepWise AI Lab Company. The other authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki

(as revised in 2013). The study was approved by the China-Japan Friendship Hospital Institutional Review Board (Medical ethics number: 2019-94-k62-1) and the requirement for individual consent for this retrospective analysis was waived.

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