A Computer-Aided Diagnosis System Using Artificial Intelligence for Proximal Femoral Fractures Enables Residents to Achieve a Diagnostic Rate Equivalent to Orthopedic Surgeons—multi-institutional joint development research—

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Abstract

Objective
To develop a CAD system for proximal femoral fracture for plain frontal hip radiographs by a deep learning model trained on a large dataset collected at multiple institutions. And, the possibility of the diagnosis rate improvement of the proximal femoral fracture by the resident using this CAD system as an aid of the diagnosis.

Materials and methods
In total, 4851 cases (include bilateral cases) of proximal femoral fracture patients over 20 - year - old who visited each facility between 2009 and 2019 were included. 5242 plain pelvic radiographs were extracted from a DICOM server, and a total of 10484 images, 5242 including the fracture site and 5242 without the fracture site, were used for machine learning. A convolutional neural network approach was used for machine learning. We used the EffectivNet-B4 framework with Pytorch 1.3 and Fast.ai 1.0. In the final evaluation, diagnostic accuracy, sensitivity, specificity, F-value, and AUC were evaluated. Grad-CAM was used to conceptualize the basis of the diagnosis by the CAD system. For resident of 31 persons and orthopedic surgeon of 4 persons, the image diagnosis test was carried out by 690 photographs of proximal femoral fracture randomly extracted from test image data set used in the accuracy verification, and (1) diagnosis rate in the situation without the diagnosis support, (2) diagnosis rate in the situation with the diagnosis support by the CAD system were evaluated respectively.

Results
The diagnostic accuracy of the learning model was 96.1%, sensitivity 95.2%, specificity 96.9%, F value 0.961, and AUC 0.99. Grad-CAM was used to show the most accurate diagnosis. In the diagnostic imaging test, the resident acquired the diagnostic ability equivalent to that of the orthopedic surgeon by using the diagnostic aid of the CAD system. (Residents: 84.7% without diagnostic support, 91.2% with diagnostic support. Orthopedic surgeons: 91.3% without diagnostic support, 93.0% with diagnostic support)

Conclusions
The CAD system using AI for the thighbone proximal part fracture which we developed could offer the diagnosis reality, and it became an image diagnosis tool with the high diagnosis accuracy. And, the possibility of contributing to the diagnosis rate improvement was considered in the field of actual clinical practice such as emergency ambulatory treatment in which the non-orthopedic surgeon is supposed to deal with the initial correspondence.

Index Terms: Artificial Intelligence, Deep learning, Hip fracture

I. Introduction
In Japan, it is said that as many as 13 million patients suffer from age-related osteoporosis [1,2]. Fragility fractures such as proximal femoral fractures and vertebral body fractures associated with osteoporosis are also increasing. Patients are over 200,000 patients suffer from proximal femoral fractures annually [3]. Patients with proximal femoral fracture are required to be hospitalized for bed rest as soon as possible and undergo surgery as soon as possible because of the significant decrease in walking ability and daily life and the significant impact on their vital prognoses [4,5].

Many patients with proximal femoral fractures visit the emergency department because pain makes them unable to walk. In such an environment, clinicians are exposed to excessive time and mental stress, which can lead to fatigue and misdiagnosis [6,7].

In the previous study, the misdiagnosis rate in the initial diagnosis for proximal femoral fracture is said to be 7 - 14% [8,9]. Delayed diagnosis and treatment worsen prognosis [10], and misdiagnosis can also cause medical litigation [6].

In order to prevent misdiagnosis, in addition to plain radiography, additional radiographs, radionuclide bone scans, CT, and MRI scans are recommended as routine diagnostic modalities [8,11], but these are not effective, efficient, or economical methods in routine examinations. It is necessary to avoid the disadvantage of these patients and to reduce the burden on the primary care physicians and orthopedic surgeons in the emergency department. Recently, due to the advent of Deep Learning and Convolutional Neural Network, the accuracy of image recognition by Artificial Intelligence (AI) has improved, and its application is also advancing in the medical field [12]. In the field of orthopedics, several reports have been made on the development of Computer-Aided Diagnosis (CAD) systems that utilize Deep Learning for fracture diagnosis [13]. Retrospective studies have also been conducted on the assumption that the drug will be used in clinical settings, such as in the emergency department. It has been reported that, when a CAD system using AI for wrist fracture was developed and a diagnostic test was conducted for clinicians, the diagnosis rate was significantly improved by the combined use of this CAD system [14]. Thus, the CAD system by AI applying image recognition will be able to improve the diagnosis rate and reduce the misdiagnosis.

Results of valid medical studies are required to show equivalent results even for data obtained from different conditions and environments, but most of the published AI studies were conducted in a single institution [15]. Also, small sample sizes can cause overlearning and impede proper machine learning [13]. To solve these problems, multicenter studies with large sample sizes will be necessary.

In this study, we hypothesized that by creating a CAD system with a deep learning model trained on a large dataset collected in a multicenter collaboration, proximal femoral fractures can be diagnosed with high accuracy by plain radiography. Furthermore, we hypothesized that residents using this CAD system would significantly improve the fracture diagnosis rate for their proximal femoral fractures.

II. Materials and methods

Patient registration

It has been approved by the ethics committee of each hospital. This multicenter collaborative development study collected medical images from 3 institutions (Gamagori City hospital, Tushima City Hospital, Nagoya Daini Red Cross hospital) in Aichi Prefecture, Japan. Gamagori City hospital and Tushima City Hospital are secondary emergency medical institution in local cities with a population of 5 - 70,000, respectively, and Nagoya Daini Red Cross Hospital is a tertiary emergency medical institution with a lifesaving emergency center in a city with a population of 2.3 million.

Subjects were 4851 cases of proximal femoral fracture patients over 20 years old, who visited each facility and underwent surgical treatment between April 2009 and March 2019. These patients were diagnosed with femoral neck fracture or trochanteric fracture and treated by orthopedic surgeons in their respective institutions using plain frontal hip radiographs or CT or MRI. 5242 (Include 391 bilateral fractures) plain frontal hip radiographs taken at the time of injury were extracted as anonymized image data from a Digital Imaging and Communications in Medicine (DICOM) server. The file format in the data extraction is “.jpeg” data of Gamagori city hospital and Nagoya Daini Red Cross hospital, and “.dcm”.
data of Tsushima City folk hospital. The sex in counting by the image is man of 1290 examples, woman of 3952 examples, and the average age is $80.7 \pm 10.1$ years old. Regarding photographing equipment of simple X-ray photography, MODEL TF-6 TL-6 (Tokyo, Japan) is used for Gamagori City Hospital, and UD 150 L-40 (SHIMADZU, Japan) is used for Tsushima City Hospital, and DHF-153 HII (Hitachi, Japan) is used for Nagoya Daini Red Cross Hospital. Both images were captured using an imaging plate and stored as digital images.

### Image selection (radiograph dataset)

2 orthopedic surgeons (Yoichi Sato MD, Takamune Asamoto MD) evaluated the fracture type. The classification used the Garden classification [16] for femoral neck fractures and the conventional AO/OTA classification for femoral trochanteric fractures, considering the inter-rater reliability in the previous study [17]. Fractures of the greater trochanter of the femur in which the fracture line does not reach the medial bone cortex in MRI were classified as greater trochanter fractures [18]. On the diagnosis of the fracture type, the image of CT and MRI in DICOM server in each institution was referred, if necessary. 2665 hip fractures and 2577 trochanteric fractures (Table 1). Patients with occult fracture diagnosed only by MRI, pathological fracture due to tumor, and osteoarthritis of the hip joint were also included. And, the image which included hip joint implant in the opposite side, image which included spine implant, image which included obsolete or combined damage in the traumatism were also made to be an object. Periprosthetic fractures were excluded.

### Image preprocessing

We used Intel Core i7 8700 K, Ubuntu 18.04, and Python 3.7 to perform image processing on the target image data. The images extracted from the DICOM server were converted into JPEG images of 3 channel * 8 bit, and both were resized to 380 px * 380 px. No data compression is performed. All of the resized images were checked by two orthopedic surgeons and given a rectangle that included the entire fracture site. In order to cut the image of the wider area, the vertical division line was put in the position which provided the margin of 50 pixel for the rectangle, and the image of the side which did not include the rectangle was adopted as the non-fracture side data, and the image which did not include the fracture position of 5242 images was made. And, the image of the side including the rectangle in the size equal to the non-fracture side data was adopted as the fracture side data, and the image including 5242 fracture positions was made. A total of 10484 images were prepared for machine learning (Figure 1).

It was randomly divided into 3 data sets: training image data set (4242 images on the non-fractured side and 4242 images on the fractured side, for a total of 8484 images), validation image data set (500 images on the non-fractured side and 500 images on the fractured side, for a total of 1000 images), and test image data set (500 images on the non-fractured side and 500 images on the fractured side, for a total of 1000 images).

### Learning environment

I used Intel Core i7 8700 K, 32 GB memory, and Ubuntu 18.04. Python 3.7 was used to create the analysis algorithm, and the deep learning libraries Pytorch 1.3 and Fast.ai 1.0 were used. Nvidia’s RTX 2070 GPU was used for deep learning learning and inference. We also used EfficientNet-B4, which we have already learned in ImageNet, to perform transition learning [19] (Figure 2).

### Learning method

A deep convolutional neural network (DCNN) approach was used for the learning. The model was made to learn as a problem of binary classification, making the image with the fracture to be positive and the image without the fracture to be negative. The data used in the learning are training image data set and validation image data set.

### Table 1. All data sets

|                     | Gamagori | Tsushima | Nagoya red cross | overall |
|---------------------|----------|----------|------------------|---------|
| Average age at the  | 81.8     | 81.4     | 80.1             | 80.7    |
| Time of injury      | ±11.4    | ±10.5    | ±12.5            | ±10.1   |
| Sex                 | Male     | 368      | 310              | 612     | 1290   |
|                     | Female   | 1249     | 895              | 1808    | 3952   |
| Fracture            | Garden I / II | 275     | 191              | 583     | 994    |
|                     | Garden III / IV | 450     | 324              | 897     | 1671   |
| Type                | A031-A1  | 489      | 383              | 509     | 1381   |
|                     | A031-A2  | 253      | 185              | 322     | 760    |
|                     | A031-A3  | 54       | 48               | 76      | 178    |
|                     | Great trochanter | 96     | 74               | 88      | 258    |
| Number of images    | 1617     | 1205     | 2420             | 5242    |

※Age at injury and fracture type were evaluated for each image when there were multiple images in bilateral cases and time series.

Figure 1. Image preprocessing

Step 1) A rectangle including the fracture was added to all 5242 plain radiographs.

Step 2) A space of 50 pixels was provided from the rectangle, dividing lines were inserted, and the image without the rectangle was taken as the image on the non-fracture side.

Step 3) The image of the fracture side was made to be the image including the rectangle in the same size as the non-fracture side.

Figure 2. EfficientNet-B4 model structure

The EfficientNet used in this study is the most efficient combination of the depth, width, and input resolution of the neural network in the performance ratio in the existing research. Compared with other learning models, the number of parameters is small, the model is simple, and it is optimum for transfer learning.
Learning process
Learning process in training image data sets and validation image data sets. 1 batch = 40 plain X-ray images, 8484 training image data sets were repeated 6 times. A error confirmed by the validation image data set converged to be small every time the training was repeated, and the progress of the learning was confirmed. The training took about one hour.

The initial learning coefficient was WarmStartup from 0, and it was raised to about $10 \cdot 10^{-3}$ in 1 cycle from there to Decay. The learning time is about 10 minutes per 1 epoch, and it is about 1 hour for 6 epochs in total. Adam was used as the optimizer. The batch size was set at 40, and the curve of the validation loss was confirmed in about 1200 batches in the trial of multiple learning, and it was judged that the plateau of the performance mask was reached. Annealing (annealing) of LR was scheduled, and learning rate decay was carried out in 1 cycle (Figure 3).

In addition to the use of Dropout ($p = 0.4$) in EfficientNet, which is included in the model adopted as a countermeasure against overlearning, mirroring and light and dark changes on a random vertical axis were randomly performed during learning as Data Augmentation. Early stopping is not used for LR decay.

**Items to be considered**

1. **Accuracy verification of learning models**
   For the test image data set, the diagnostic accuracy of the trained learning model was evaluated. Evaluation items are diagnostic accuracy, sensitivity, specificity, and F value. We also calculated the ROC curve and measured the AUC. Sikit-Learn was used for data analysis. A 95% confidence interval was calculated for each value.

2. **Visualization of grounds for judgment**
   We attempted to conceptualize the concept to show the reason why AI judged fracture, and we adopted gradient-weighted class activation mapping (Grad-CAM) [20]. The show _ heatmap function of FastAI was performed on the learning model to obtain a heatmap and evaluate whether it differed from the fracture site.

3. **Diagnostic test for clinicians**
   In order to evaluate the practicability in the actual clinic, the diagnostic test was carried out for resident of 31 persons and orthopedics major of 4 persons who got agreement and cooperation in each institution. 300 images (133 images on the non-fractured side and 167 images on the fractured side) randomly extracted from the above 1000 test image data were adopted. Those including postoperative implants were excluded. The accuracy of the CAD system for 300 images used in the test was diagnostic accuracy 96.1% (95% CI, 94.9 ~ 97.3%) for diagnosis, 95.2% (95% CI, 93.9 ~ 96.5%) for sensitivity, 96.9% (95% CI, 95.9 ~ 98.0) for specificity, and 0.961 (95% CI, 0.949 ~ 0.970) for F value (Table 2). The ROC curve was as shown, with an AUC of 0.992 (95% CI, 0.973 - 0.997) (Figure 4).

On the other hand, the CAD system misdiagnosed 39 images in total (Table 2). A total of 24 images were diagnosed as “false negative”. The image consists of 21 relatively less displaced fractures, such as femoral neck fracture (G/S 1,2), femoral trochanteric fracture (AO 31 · A1), and femoral greater trochanteric fracture, and 3 relatively more displaced fractures, such as femoral neck fracture (G/S 3,4) and femoral trochanteric fracture (AO 31 · A2,3) (Figure 6). And, it was diagnosed as “false positive” for 15 images in total. The breakdown is 1 image with the deformation after the conservative treatment progress of the thighbone proximal part fracture, 1 image after the nail removal, 13 images of the image with the normal image. No patient-specific changes such as deformative changes were observed in these 13 normal images, and the basis for this judgment is unclear (Fig. 7).

Figure 3. Learning process
Learning process in training image data sets and validation image data sets. 1 batch = 40 plain X-ray images, 8484 training image data sets were repeated 6 times. A error confirmed by the validation image data set converged to be small every time the training was repeated, and the progress of the learning was confirmed. The training took about one hour.

Figure 4. ROC Curve
ROC curve of the EfficientNet-B4 model. The AUC is 0.992.

1) Duplicate each of 300 images
2) Show the same duplicated image in sequence
3) The first image is presented as a non-diagnostic image of AI, along with the option with or without fracture, and an answer is sought.
4) As the second image with the diagnosis support of AI, the answer is required, after the result diagnosed by AI is described together in the option with fracture/without fracture.
5) The above 2 sets of diagnostic tests are performed on 300 images. A total of 600 images were tested to determine the accuracy, sensitivity, and specificity of each diagnostic. A statistical analysis using the Mann-Whitney U test was performed using the statistical software EZR on the change in the diagnosis rate with or without diagnostic aid of AI, with a significance level of 0.05.

**III. Results**

1. **Accuracy verification of learning models**
   The accuracy of the learning model was 96.1% (95% CI, 94.9 ~ 97.3%) for diagnosis, 95.2% (95% CI, 93.9 ~ 96.5%) for sensitivity, 96.9% (95% CI, 95.9 ~ 98.0) for specificity, and 0.961 (95% CI, 0.949 ~ 0.970) for F value (Table 2). The ROC curve was as shown, with an AUC of 0.992 (95% CI, 0.973 - 0.997) (Figure 4).

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Figure 5. Visualization of fracture judgment area using Grad-CAM. On the image which diagnosed the fracture by the CAD system in this study, the features were appropriately extracted (left: original image; right: Grad-CAM image with heat map showing the basis of fracture site). From yellow to red, the part as a diagnosis reason of the CAD system appears strongly.
oral fractures obtained at each proper diagnosis rate.

Table 3. Result of the diagnostic test

| -B4 | Residents Without support | Residents With support | Orthopedic surgeons Without support | Orthopedic surgeons With support |
|-----|---------------------------|------------------------|-----------------------------------|---------------------------------|
| accuracy(%) | 96.1 | 84.7 | 91.2 | 91.3 | 93.0 |
| (95%CI)   | (94.9-97.3) | (82.2-87.2) | (89.5-92.8) | (89.5-92.8) | (89.9-96.1) |
| sensitivity(%) | 95.2 | 83.5 | 90.5 | 95.5 | 95.2 |
| (95%CI)   | (93.9-96.5) | (76.0-91.1) | (83.7-97.2) | (94.8-96.3) | (92.9-97.5) |
| specificity(%) | 96.9 | 88.7 | 93.2 | 89.5 | 92.5 |
| (95%CI)   | (95.9-98.0) | (81.9-95.4) | (89.4-97.1) | (87.0-92.1) | (89.1-95.9) |

In the meantime, the proper diagnosis rate of the clinician for 10 images (7 false-negative images and 3 false-positive images) in which the CAD system misdiagnosed was also calculated. For these 10 images, the residents’ proper diagnosis rate were significantly reduced by diagnostic support of AI (resident 43.2% → 28.1%; p = 0.01, orthopedic surgeon 57.5% → 50.0%; p = 0.20).

IV. Discussion

Through this study, CAD system using AI for proximal femoral fracture which we developed could offer the diagnosis reason, and it became an image diagnosis tool with the high diagnosis accuracy. And, the possibility of contributing to the diagnosis rate improvement was considered in the field of actual clinical practice such as emergency room in which the non-orthopedic surgeon is supposed to deal with the initial correspondence. The diagnosis of fracture by AI using the deep learning approach is reported by Olczak et al. for the first time in 2017 [21], research on various regions is progressing [13], and proximal femoral fracture [22,23,24]. Though high diagnostic accuracy is reported in all preceding studies for proximal femoral fracture, it is a development research carried out respectively in single institution, and the image number used for the learning is under around 3500 images. And, the case including the implant in the opposite side and the case of obsolete pelvic fracture, etc. are omitted from the data for the learning, and the restriction will remain, when the use in the actual clinic is assumed.

We tried to solve the above problem by the cooperative research in multiple institutions. Since a large data set is considered to be a key to the success of DL [25], approximately 10,000 learning data images were generated from approximately 5000 cases for almost all images of proximal femoral fractures obtained at each institution. By this, it was possible to make the data set which widely included the condition of the hip joint of each patient such as individual difference of pelvis and thighbone and deformation of the hip joint. By preparing sufficient learning data, the learning model could correctly judge patient-specific information other than fracture, such as implants in the contralateral femur and spine, as "negative".

As an advantage of the multi-institutional joint research, it is also mentioned that the validity is ensured. For the result of the appropriate medical science research, it is required that the equivalent result is shown even in the data acquired from different conditions and environments. On the other hand, most of the published research on AI was conducted in a single facility, and only 6% of the reports evaluated its practicability in different environments [15]. In this study, the high accuracy was able to be obtained even in X-ray machine and image storage type which differed in the multiple institutions. It seems to be an aid of the practicability, even if it is considered that it is used with the generality as a CAD system in future.
On the assumption of practical application, it was necessary to solve the “black box problem” peculiar to AI [26]. The DL used in the image recognition realizes the classification for the data which can not express the feature quantity explicitly originally, and the reason of the judgment is uncertain, and it can not be understood and interpreted by the human. It becomes a problem from the viewpoint of the accountability of the medical practice, if the reason can not be explained in the diagnosis by the medical AI. In this study, using Grad-CAM, it was possible to explain the reason of AI judgment. Such efforts will be the minimum necessary for safe use of medical AI in the future. And, it may have the aspect as an education to offer the decision reason to the resident.

The fact that it could be developed with a comparatively light learning model will be a factor to support the practical application. The efficiency improvement of learning by the transfer learning of the pre-learned model has been reported in the past [27]. There are a variety of pre-learned models [28]. Models with many parameters require a lot of time to adjust the performance because of the large storage area and long learning time. EfficientNet-B4 used in this study has a relatively small number of parameters [19], but its diagnostic accuracy was higher than that of previous studies [22,23,24]. The inference time per 1 image was about 0.1 seconds. Therefore, the EfficientNet-B4 is a model with superior performance in comparison with the number of parameters, and can provide diagnostic imaging results in a short inference time in a real environment. And, it may be comparatively easy to apply this algorithm to other fracture diagnosis by transfer learning in future.

Many medical care support systems by machine learning show high accuracy in the research level, and it seems to be useful for medical care. However, there is a problem that the effect when it is actually applied to the clinical field is not evaluated [15]. In this study, it was possible to carry out the diagnostic test on the assumption of the use of the CAD system in the actual situation. The diagnostic rate of proximal femoral fracture in the plain frontal hip radiographs is said to be 95.6% in the radiologist [29], and the diagnostic rate of the orthopedic surgeon seems to be also equivalent. However, in clinical practice, radiographic images are often interpreted in situations where a second opinion to an expert cannot be obtained [9], which may lead to misdiagnosis. This tendency is particularly strong in emergency departments where patients with proximal femoral fractures present and residents are treated for the first time [30]. In this context, AI tools could be used as complementary tools to review and validate clinician questions and decisions [31]. In this study, the residents were able to obtain a high diagnosis rate equivalent to that of orthopedic surgeons by using the CAD system jointly and desiring for image diagnosis. And, it was indicated that there was a possibility of demonstrating the usefulness especially in the environment such as emergency ambulatory treatment, because the result which could prevent the case which could become the missing by the diagnosis support of AI was obtained.

In the meantime, it is also necessary to note that the image diagnosis by AI is not always perfect. In this study, in the accuracy verification of the learning model, 39 images (3.9%) out of 1000 test image data were erroneously diagnosed as false positive or false negative. And, within 1000 images used for the diagnosis test for the clinician, 10 images have been erroneously diagnosed as false positive or false negative. Notably, residents' use of diagnostic support with AI reduced the accuracy rate for these 10 images (43.2% → 28.1%). Thus, it was suggested that overreliance on diagnostic imaging by AI may lead to misdiagnosis, because the diagnosis may be erroneous following the diagnosis result of AI, although it should be possible to diagnose correctly.

There are some limitations to this study.

First, it is necessary to divide images as a preprocessing of images. On this, at present, whole plane pelvic radiographs of similar age group and sex ratio without recognizing the thighbone proximal femoral fracture are collected, and it is necessary to redevelop the CAD system which can diagnose the proximal femoral fracture from both hip joint front simple radiograph without the pretreatment using the learning model got in this study.

Second, the applicability in the actual clinical field as a prospective study has not been evaluated. This study is a retrospective evaluation performed through a web interface similar to PACS used by clinicians for medical imaging. It is also possible that the incidence of "with fracture" images in clinical practice differs from the diagnostic frequency in clinical practice. On these, it is necessary to carry out the prospective study in the actual clinical environment using the actual PACS system in future.

V. Conclusion

Through this study, CAD system using AI for the thighbone proximal part fracture which we developed could offer the diagnosis reason, and it became an image diagnosis tool with the high diagnosis accuracy. And, the possibility of contributing to the diagnosis rate improvement was considered in the field of actual clinical practice such as emergency ambulatory treatment in which the non-orthopedic surgeon is supposed to deal with the initial correspondence.

VI. Acknowledgements

All experiments were conducted in accordance with the ethical standards set out in the revised Declaration of Helsinki. The author declares that there is no conflict of interest.

VII. Reference

1. Yoshimura N, Muraki S, Oka H, et al. Cohort Profile Research on Osteoarthritis/osteoporosis Against Disability (ROAD) Study. Int J Epidemiol. Int J Epidemiol 2010; 39: 988-95
2. Yoshimura N, Muraki S, Oka H, et al. Prevalence of knee osteoarthritis, lumbar spondylosis and osteoporosis in Japanese men and women: the research on osteoarthrosis / osteoporosis against disability study. J Bone Miner Res 2009; 27:620-8
3. Osimo H, Yaegashi Y, Onoda T, et al. Hip fracture incidence in Japan: estimates of new patients in 2007 and 20-year trend. Arch Osteoporos 2009: 4: 71-7
4. Boonen S, Autier P, BaretteM, et al. Functional outcome and quality of life following hip fracture in elderly women: a prospective controlled study. Osteoporos Int 2004: 15:87-94
5. Grimes JP, Gregory PM, Noveck H, et al. The effects of time-to-surgery on mortality and morbidity in patients following hip fracture. Am J Med 2002: 112: 702-709
6. Berlin L. Defending the “missed” radiographic diagnosis. Am J Roentgenol 2001: 176: 317-322
7. Hallas P, EllingsenT. Errors in fracture diagnoses in the emergency department: Characteristics of patients and diurnal variation. BMC Emerg Med 2006: 6:4
8. Hakkarianen DK, Bang KV, Hendey GW: Magnetic resonance imaging identifies occult hip fractures missed by 64-slice computed tomography. J Emerg Med 2012: 43: 303-307
9. Chellam WB: Missed subtle fractures on the trauma-meeting digital projector. Injury 2016: 47: 674-676
10. Tarrant SM, Hardy BM, Byth PL, et al. Preventable mortality in geriatric hip fracture inpatients. Bone Joint J 2014: 96-B:1178–1184.
11. Rehman H, Clement RGE, Perks F, White TO: Imaging of occult hip fractures: CT or MRI? Injury 2016: 47:1297-1301
12. Kermany DS, Goldbaum M, Cai W, et al. Identifying medical diagnoses and treatable diseases by image-based deep learning. Cell 2018: 172:1122–1131.e9.
13. Kalmet PHS, Sanduleanu S, Primakov S, et al. Deep learning in fracture detection: a narrative review. Acta Orthop. 2020: Jan 13:1-6
14. Lindsey R, Daliski A, Chopra S et al: Deep neural network improves fracture detection by clinicians. PNAS 2018: 115(45): 11591-11596,
15. DW Kim, HY Jang, KW Kim et al: Design characteristics of studies reporting the performance of artificial intelligence algorithms for diagnostic analysis of medical images: results from recently published papers. Korean J Radiol 2019: 20: 405-410
16. Bjorgul K, Reikeras O : Low interobserver reliability of radiographic signs predicting healing disturbance in displaced intracapsular fracture of the femoral neck. Acta Orthop Scand 2002 ; 73 : 307-310
17. Jin WJ, Dai LY, Cui YM, et al. Reliability of classification systems for intertrochanteric fractures of the proximal femur in
experienced orthopaedic surgeons. Injury 2005; Jul;36(7):858-61
18. Moon NH, Shin WC, DoMU, et al. Diagnostic strategy for elderly patients with isolated greater trochanter fractures on support. BMC Musculoskelet Disord 2018; Jul 25;19(1):256
19. M Tan, Q V.Le. EfficientNet: Rethinking Model Scaling for convolutional neural networks. Mathematics, Computer Science ICML arXiv 2019: 1905.11946
20. Selvaraju R.R, Cogswell M, Das A et al: Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization. Int J of Comput Vis 2019: doi:10.1007/ s11263-019-01228-7
21. Olczak J, Fahlberg N, Maki A et al: Artificial intelligence for analyzing orthopedic trauma radiography. Acta Orthop 2017: 88: 581-586
22. Cheng CT, Ho TY, Lee TY et al: Application of a deep learning algorithm for detection and visualization of hip fractures on plane pelvic radiographs. European Radiology 2019: 29: 5469-77,
23. Urakawa T, Tanaka Y, Goto S, et al: Detecting intertrochanteric fractures with orthopedist-level accuracy using a deep convolutional neural network. Skeletal Radiol 2019: 48: 239-244
24. M Adams, W Chen, D Holcdorf, et al. Computer vs human: Deep learning versus perceptual training for the detection of neck of femoral fractures. J Med Imaging Radiat Oncol. 2019: 63(1):27-32
25. Giger ML. Machine Learning in Medical Imaging. J Am Coll Radiol. 2018; Mar;15(3 Pt B):512-520
26. Fogel AL, et al. Artificial intelligence powers digital medicine, NPJ Digit Med 2018: 15
27. Kim DH, MacKinnon T: Artificial intelligence in fracture detection: transfer learning from deep convolutional neural networks. Clin radiol 2018: 73: 429-556,
28. Image classification on Image Net (https://paperswithcode.com/sota/image-classification-on-imagenet)
29. Dominguez S, Liu P, Roberts C et al : Prevalence of traumatic hip and pelvic fractures in patients with suspected hip fracture and negative initial standard radiographs—a study of emergency department patients. Acad Emerg Med 2005 : 12 : 366-369
30. Leeper WR, Leeper TJ, Vogt KN, et al. The role of trauma team leaders in missed injuries: does specialty matter? J Trauma Acute Care Surg. 2013; Sep;75(3):387-90
31. Liew C. The future of radiology augmented with artificial intelligence: a strategy for success. Eur J Radiol 2018: 102: 1526.