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ORIGINAL ARTICLE

Evaluation of an artificial intelligence system for diagnosing scaphoid fracture on direct radiography

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Abstract

Purpose The aim of this study is to determine the diagnostic performance of artificial intelligence with the use of convolutional neural networks (CNN) for detecting scaphoid fractures on anteroposterior wrist radiographs. The performance of the deep learning algorithm was also compared with that of the emergency department (ED) physician and two orthopaedic specialists (less experienced and experienced in the hand surgery).

Methods A total 390 patients with AP wrist radiographs were included in the study. The presence/absence of the fracture on radiographs was confirmed via CT. The diagnostic performance of the CNN, ED physician and two orthopaedic specialists (less experienced and experienced) as measured by AUC, sensitivity, specificity, F-Score and Youden index, to detect scaphoid fractures was evaluated and compared between the groups.

Results The CNN had 76% sensitivity and 92% specificity, 0.840 AUC, 0.680 Youden index and 0.826 *F* score values in identifying scaphoid fractures. The experienced orthopaedic specialist had the best diagnostic performance according to AUC. While CNN's performance was similar to a less experienced orthopaedic specialist, it was better than the ED physician.

Conclusion The deep learning algorithm has the potential to be used for diagnosing scaphoid fractures on radiographs. Artificial intelligence can be useful for scaphoid fracture diagnosis particularly in the absence of an experienced orthopedist or hand surgeon.

Keywords Scaphoid · Fracture · Deep learning · Artificial intelligence · Radiography

Introduction

Approximately 29% of all injuries treated in emergency departments are hand and wrist injuries. Fractures account for 42% of these injuries [1]. Scaphoid fractures are the most common carpal bone fractures [2]. Although scaphoid fractures are not life-threatening, early diagnosis is very important to start appropriate treatment as early as possible. The initial assessment of these fractures is usually done in emergency departments (EDs). The first-line imaging method for diagnosis is plain radiographs, which is a simple, inexpensive, and easily accessible imaging method. It is quite possible to miss the scaphoid fracture on these radiographs or to see a fracture that does not actually exist [3]. Because, it is difficult, particularly for physicians inexperienced in hand surgery, to accurately evaluate and interpret wrist radiographs due to its complex anatomical structure.

Plain radiographs are usually first evaluated by ED physicians or less experienced orthopedists in EDs. This situation may affect the quality of evaluation of the radiographs, causing these fractures to be missed [4]. Neglected scaphoid fractures can lead to wrist arthritis known as collapse arthritis with non-union, persistent wrist pain and loss of function [5, 6]. Therefore, early diagnosis and appropriate treatment are essential to maintain wrist kinematics and function [5]. Cross-sectional imaging (CSI) techniques such as computed tomography (CT) and magnetic resonance imaging can be

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used for early diagnosis, but this leads to additional costs and radiation exposure for CT. In addition, accessibility to CSI techniques is not always possible in all EDs such as local emergency hospitals. For this reason, it is extremely important to develop new and easily accessible methods that can be used by less-experienced doctors for early and accurate diagnosis of fractures on plain radiography.

Deep learning is a machine learning approach that is based on training artificial neural networks. For image analysis, usually convolutional neural network (CNN) layers that learn a set of image filters are used, leading to a more efficient analysis of the image data. Such neural networks are called CNNs. CNNs may be trained to start from randomly initialized filter weights, or alternatively, weights from a pre-trained network are tuned for the target image set and problem. The latter approach is known as transfer learning and requires much less image data, and it has been successfully applied to clinical problems and data sets.

In recent years, it has been shown in limited studies that deep learning with the use of CNN can be used for diagnosing bone fractures [7–9]. However, to the best of our knowledge, there are no studies investigating and comparing the diagnostic performances of deep learning and ED physician for diagnosing scaphoid fractures.

We hypothesized that the diagnosis of scaphoid fractures on plain radiography may increase with deep learning CNN model. It is important to test the sensitivity and specificity of this model in the diagnosis of these fractures. Because models such as deep learning CNN can be very useful in EDs, especially in local emergency hospitals without experienced hand surgeons.

The aim of this study is to determine the diagnostic performance of the deep learning algorithm with the use of CNN for detecting scaphoid fractures on anteroposterior (AP) wrist radiographs. We then compared the performance of the deep learning algorithm with that of ED physician and two orthopaedic specialists (less experienced and experienced in the hand surgery).

Methods

This retrospective study was approved by the Institutional Review Board of our hospital. Due to the retrospective nature of the study, informed consent by patients and providers was not required.

Patient inclusion

A total of 192 consecutive patients with a diagnosis of scaphoid fracture (fracture group) and 198 normal patients without scaphoid fracture (normal group) evaluated by wrist CT scans in the past 6 years were identified via a radiology information system keyword search, using the reference words "scaphoid fracture" on the imaging reports. Wrist AP standard radiographs were available for all patients. All radiographs were evaluated by a radiologist, with 10 years of experience, for the presence or absence of the scaphoid fracture. Then, the presence or absence of the fracture was confirmed via CT. Scaphoid fractures were classified as a proximal third (pole), middle third (waist) and distal third scaphoid fractures according to the anatomical localization of the fracture [10], and non or minimally displaced (≤ 0.5 mm) and displaced (> 0.5 mm) scaphoid fractures according to the displacement of the fracture [11, 12].

Dataset

A program to help with the selection of region of interest (ROI) containing the scaphoid was written in Python 3 using OpenCV 3.0 library for image processing and Tkinter library for Graphical User Interface elements. The program helped the radiologist to mark a rectangular area tightly wrapping around the scaphoid region. The selection and detail windows of the program are shown in Fig. 1.

Once the radiologist marked all 390 images, each image was cropped to size ($2 \times$ ROI width) by ($2 \times$ ROI height) with the scaphoid region centered within the image. These cropped images were then resized to 196 by 196 pixels by scaling, as necessary. Because the ROI size is roughly proportional to scaphoid dimensions, this scheme helps to reduce the anatomical size differences between subjects by stretching smaller ROIs and squeezing wider ROIs.

This dataset of cropped images was then split into training, validation, and test sets. Thereafter, 50 images containing scaphoid fractures (6 displaced proximal pole, 6 non-displaced waists, 21 displaced waist, 6 non-displaced distal third, 4 displaced distal third and 7 occult scaphoid fractures) and 50 images containing healthy scaphoids were randomly picked and placed in the test set. These 100 images in the test set were set aside and did not play any part in the training procedure. Indeed, these images were used only once at the end to evaluate the expected performance of the trained network on the novel patient data.

The remaining 290 images formed the training and validation sets. We used 70% of these for training the neural network and 30% for validation purposes. The training set was used to tune the weights of the neural network. The validation set was repeatedly used to assess the training quality and the selection between alternative neural network architectures and hyperparameters such as the number of training epochs and learning rates.

Training and validation

We used the prepared dataset to train neural networks by transfer learning repurposing a network pre-trained on the

Fig. 1 To aid in the selection of a rectangular area containing the scaphoid region, each radiogram is displayed together with a detail window showing a zoomed version of the image area around the mouse cursor. The radiologist marks a tight rectangular area around the scaphoid, which is later expanded with a border, cropped and scaled to the final dataset image size of 196 by 196 pixels

ImageNet dataset for scaphoid classification purposes. Thus, we downloaded a pre-trained ResNet50 network and replaced the uppermost layers with a set of layers that performed two class classifications. The procedure takes approximately a day using a Nvidia GTX 1050 Ti graphics card. We selected one of the best performing networks that achieved 90% correct classification on the validation set.

Test

Because the validation set was used multiple times during training runs, the accuracy achieved on the validation set was not representative of the real-life performance of the network on novel patient data. A separate set of 100 images was used to measure the actual performance of the network. These 100 images were also interpreted by ED physician and two orthopaedic specialists (less experienced and experienced in the hand surgery) [13] to compare the performance with a deep learning algorithm. These three physicians evaluated the radiographs in separate rooms and were unaware of each other.

Evaluation of diagnostic performance

The data were analyzed using Medcalc 14 (Acacialaan 22, B-8400 Ostend, Belgium) software. CNN, ED physician, and orthopaedic specialists' diagnostic performance results were compared with CT results, which were accepted as the reference standard. The area under the receiver operating curve (AUC), sensitivity, specificity, F-Score and Youden index of CNN, ED physician, and orthopaedic specialists for differentiating scaphoid fractures from normal scaphoid were statistically analyzed [14, 15]. Then the values of each group were compared with the CNN. AUC is generated by plotting sensitivity versus 1-specificity, which reported the best sensitivity and specificity that maximizes the sum of sensitivity and specificity. Higher the AUC, better the model is at distinguishing between patients with fracture and no fracture. Thus, the larger the area under the curve, the higher the success rate of the model.

The Youden index was calculated as follows; sensitivity + specificity − 1.

F score was calculated as follows; 2 × (positive predictive value × sensitivity)/(positive predictive value + sensitivity).

Results

A total of 390 patients were included with a mean age of 42 (range 24–70) years.

When the CNN results were evaluated, considering the CT results as the reference standard for determining scaphoid fractures, 12 false negative, 4 false positive, 46 true negative, and 38 true positive results were determined. According to these results, the deep learning CNN model was calculated to have 76% sensitivity (CI 0.618–0.869) and 92% specificity (CI 0.808–0.978) in distinguishing between normal and fractured scaphoids. The deep learning CNN showed diagnostic performance with an AUC of 0.840 (CI 0.753–0.906) for differentiating normal scaphoids from fracture cases. The Youden index of CNN model was calculated 0.680 (CI 0.540–0.820) and *F* score was 0.826 (CI 0.712–0.940).

To compare the performance in diagnosing the scaphoid fracture between the CNN model, ED physician and orthopaedic specialists (less experienced and experienced in the hand surgery), the same information was provided to them as the CNN. We calculated the same values for each group of ED physician and orthopaedic specialists as with CNN and then compared the values. The diagnostic performance and types of missed scaphoid fractures of each physician group was summarized in Tables 1 and 2.

Experienced orthopaedic specialist had the highest AUC value (0.920) among all the groups and this difference was statistically significant in all pairwise comparisons (Table 1, Fig. 2). CNN had higher AUC value (0.840) than the less experienced orthopaedic specialist (0.820) and ED physician (0.760). But this difference was significant only between CNN and ED physician (experienced orthopaedic specialist > CNN ≅ less experienced orthopaedic specialist > ED physician) (Table 1).

When compared in terms of sensitivity, the sensitivity of CNN (0.760) was significantly higher than ED physician (0.620), but there was no significant difference between the CNN and orthopaedic specialists (0.720 for less experienced, 0.860 for experienced orthopaedic specialist) (Table 1).

When the specificity and *F* score values were compared, no significant difference was found between the groups (Table 1).

Discussion

The present study showed that the deep learning CNN model has an acceptable performance in distinguishing plain radiographs from scaphoid fractures. The deep learning CNN model had 76% sensitivity and 92% specificity, 0.840 AUC, 0.680 Youden index and 0.826 *F* score values in identifying scaphoid fractures. The experienced orthopaedic specialist showed the best performance when evaluated in terms of AUC. The diagnostic performance of CNN was similar to the less experienced orthopaedic specialist but better than the ED physician. Given that there are no experienced hand surgeons in every hospital, this is promising for the future of CNN because of the higher the AUC value, the higher the success rate of the model.

Wijetunga et al. stated that the prevalence and effectiveness of direct radiographs in scaphoid fractures are not proportional, and radiographs do not guarantee accurate diagnosis in these fractures [16]. Smith et al. reported that 16% of scaphoid fractures were missed on the first radiograph, although direct radiographs are the preferred method for initial evaluation [17]. In addition, many studies have stated that direct radiographs have a sensitivity of 60–70% for diagnosing scaphoid fractures, and sensitivity can increase up to 95% only by using CSI methods [18–20]. In the present study, 38 of 50 (76%) scaphoid fractures were accurately diagnosed with the deep learning CNN model. This rate was better than ED physician and less experienced orthopaedic specialists (62%, 72% respectively). Although there is no significant difference between CNN and less experienced orthopaedic specialist, the potential for improvement in the deep learning CNN model should not be overlooked. The diagnostic performance of the deep learning CNN model will further increase as new scaphoid fractures are added. Therefore, we believe that the model may perform even better than orthopedists or hand surgeons in the future. This is because the machine can potentially observe more radiographs than any orthopedist or hand surgeon can over a lifetime, and the system can be automatically trained with these radiographs. This provides CNN with a broad scope of learning opportunities at a low cost.

One of the most important factors in the diagnosis and treatment of scaphoid fractures is the experience of the physician who performed the evaluation [4, 21]. Gäbler et al., in their prospective studies evaluating patients with wrist trauma, stated that many injuries not seen by junior doctors in the initial X-rays were seen by senior surgeons [4]. They even stated that 70% of the scaphoid fractures that could not be seen in the first radiographs by the junior doctors and therefore defined as occult can be seen by senior surgeons. Therefore, the authors suggested that senior doctors should be included in the diagnosis process as soon as possible. In this study, we found that the diagnostic performance deteriorated as the experience in hand surgery decreased. The experienced orthopaedic specialist had the highest, and the ED physician had the lowest diagnostic performance in terms of AUC value (experienced orthopaedic specialist > CNN ≅ less experienced orthopaedic specialist > ED physician). These results showed that being experienced in hand surgery is an important factor for the diagnosis of scaphoid fractures on plain radiographs but it may take several years for a doctor to gain this experience. However, CNN can be trained in a much shorter time and quickly incorporated into the diagnostic process of these patients. For this reason, the development and use of methods such as CNN can be very useful in centers where there are no experienced hand surgeons, and it can be a practical solution for these centers.

In the present study, 12 of 50 scaphoid fractures were misdiagnosed by CNN as normal. These false-negative cases were 19 for ED physician, 14 for a less experienced orthopaedic specialist, and 7 for experienced orthopaedic specialist. These results were interpreted as missed scaphoid fracture rates were higher in physicians without sufficient experience in hand surgery than CNN. Missed scaphoid fractures can cause nonunion and permanent wrist pain that

Table 1 Diagnostic performances of CNN, ED physician and orthopaedic specialists

	CNN (I)		ED physician (II)		Less experienced orthopedist (III)		Experienced orthopedist (IV)		p value for pairwise comparisons					
	Normal	Fracture	Normal	Fracture	Normal	Fracture	Normal	Fracture	(I–II)	(I–III)	(I–IV)	(II–III)	(II–IV)	(III–IV)
CT														
Normal (*n*)	46	4	45	5	46	4	49	1	–	–	–	–	–	–
Fracture (*n*)	12	38	19	31	14	36	7	43	–	–	–	–	–	–
Statistics														
AUC (95% CI)	0.840 (0.753–0.906)		0.760 (0664–0.840)		0.820 (0.731–0.890)		0.920 (0.840–0.965)		**0.014**	0.206	**0.034**	**0.041**	**0.001**	**0.014**
Specificity (95% CI)	0.920 (0.808–0.978)		0.900 (0.782–0.967)		0.920 (0.808–0.978)		0.980 (0.894–0.999)		0.999	0.999	0.256	0.999	0.141	0.258
Sensitivity (95% CI)	0.760 (0.618–0.869)		0.620 (0.472–0.753)		0.720 (0.575–0.838)		0.860 (0.733–0.942)		**0.024**	0.480	0.075	0.076	**0.001**	**0.024**
F-score (95% CI)	0.826 (0.712–0.940)		0.721 (0.591–0.850)		0.800 (0.680–0.920)		0.915 (0.800–0.970)		0.206	0.413	0.289	0.272	0.127	0.244
Youden index (95% CI)	0.680 (0.540–0.820)		0.520 (0.341–0.660)		0.640 (0.500–0.780)		0.840 (0.720–0.920)		0.166	0.389	0.118	0.233	**0.019**	0.068
p value	**< 0.001**		**< 0.001**		**< 0.001**		**< 0.001**		–	–	–	–	–	–

p values in bold indicate statistically significant differences between groups

CT computed tomography, *AUC* area under the receiver operating curve, *CNN* convolutional neural network, *ED* emergency department

Table 2 Types of missed scaphoid fractures according to the groups

	Types of missed scaphoid fractures						False-negative (*n*)
	Displaced proximal pole (*n*)	Non-displaced waist (*n*)	Displaced waist (*n*)	Non-displaced distal third (*n*)	Displaced distal third (*n*)	Occult (*n*)	
ED physician	1	5	1	6	0	6	19
Orthopedist[a]	0	3	0	3	1	7	14
CNN	1	3	0	1	0	7	12
Orthopedist[b]	0	0	0	0	0	7	7

n number of patients, *ED* emergency department, *CNN* convolutional neural network

[a]Less experienced in the hand surgery

[b]Experienced in the hand surgery

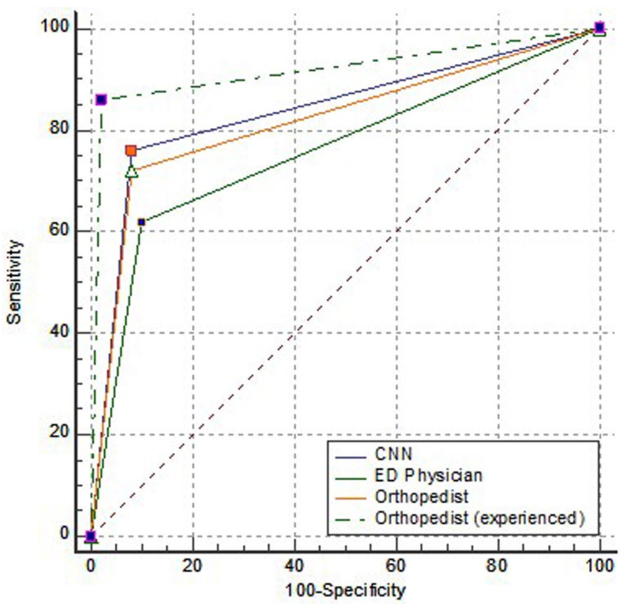

Fig. 2 The diagnostic performances of the convolutional neural network (CNN), emergency department (ED) physician and orthopaedic specialists in diagnosing the scaphoid fractures were compared with the area under the receiver operating curves (AUC). The experienced orthopaedic specialist had the highest AUC value among all the groups

develops in a short time and lead to functional loss in the wrist [4]. This is a common and important cause of litigation [22–24]. When the related literature is analyzed, it is seen that 57–77% of the litigations associated with scaphoid fractures are related to diagnostic errors [22, 24]. CSI techniques can prevent delays in the diagnosis of these fractures [25]. However, due to the higher cost of CSI techniques, even during repeated patient visits, direct radiographs are still the initially preferred imaging method in most EDs and outpatient clinics [17, 25, 26]. Therefore, presently, direct radiographs are still important for diagnosis. Considering the possible potential of the deep learning CNN model, improving this simple and inexpensive method and increasing its use, especially in local emergency hospitals, can help prevent some of these potential medicolegal issues.

Although it seems that the sensitivity of this system will increase as the training data increases, it appears that the diagnosis of occult scaphoid fractures will still continue to be a problem. When 12 false-negative radiographs for CNN, missed in this study, were examined, it was found that five were radiographically distinct fractures (1 displaced proximal pole, 3 non-displaced waists, 1 non-displaced distal third) and seven were occult fractures that were completely normal in radiographic terms. These seven fractures were diagnosed as scaphoid fractures via CT on clinical suspicion. None of the occult scaphoid fractures could be diagnosed with this model. However, we believe that this should not be interpreted as a failure of the deep learning CNN model. This is because occult fractures may not be diagnosed even if optimal radiographic images are obtained and these radiographs are evaluated by an experienced specialist [27]. Therefore, it is not expected that these fractures, which are not characterized by any findings on direct radiography, would be accurately diagnosed with CNN. When the diagnostic performances of ED physician and orthopaedic specialists in this study were evaluated in the occult fractures, it was seen that the orthopaedic specialists missed 7 occult scaphoid fractures and reported as normal, just as in the CNN model. Although the ED physician generally performed worse than orthopaedic specialists and CNN, he correctly reported one occult fracture as a scaphoid fracture. We think this is a coincidence for ED physician. In conclusion, regardless of who evaluates these radiographs, it seems that the diagnosis of occult scaphoid fractures will continue to be a problem in the future.

The present study has several limitations. Primarily, it was a retrospective study. One of the other limitations was the relatively small sample size of the study. Another limitation was the diagnosis of scaphoid fractures based on AP wrist radiographs only.

Scaphoid fractures are usually evaluated on standard wrist X-rays (AP and lateral) or scaphoid series radiographs. Thus, the fracture that does not appear in a single projection can be observed in other projections. However, in this study, the deep learning CNN model was tested only with AP radiographs. Because this was the easiest and simplest way for CNN. In addition, the superposition of carpal bones on lateral and oblique radiographs was the biggest problem in the training of CNN. Another problem was that CNN perceives each radiography (AP, lateral, oblique) as a separate case. If a patient's AP, lateral and oblique radiographs can be integrated into the AI system at the same time and if these graphs can be evaluated by the system as a single case and an average single decision can be made, the diagnostic performance of CNN may increase. In addition, evaluations based on CT images can improve the diagnostic performance of CNN.

In conclusion, this study is important because it shows the potential of using deep learning algorithms in the field of hand surgery. Artificial intelligence can accurately diagnose scaphoid fractures on wrist AP radiographs. Because this system can be operated in multiple centers at the same time, the training of the system can be quickly completed because of the additional data, and its current sensitivity can be increased. With this artificial intelligence-based automatic diagnosis system developed for the diagnosis of scaphoid fractures, wrist radiographs can be accurately interpreted, and the results can be reported almost instantly. Therefore artificial intelligence can be useful for scaphoid fracture diagnosis in the absence of an experienced orthopedist or hand surgeon. This is highly promising for the future. However, further studies are needed on the reliability and clinical applicability of artificial intelligence. For such models to be used in routine clinical practice, these results should be supported by future large-scale studies.

Author contributions EO, TB and MG researched literature and conceived the study. EO, FET, TB, MG, MO and ZK were involved in protocol development, gaining ethical approval, patient recruitment and data analysis. TB, MG, MO wrote the first draft of the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This retrospective study was approved by the Non-Interventional Clinical Studies Institutional Review Board of Izmir Katip Celebi University (IRB #440). Since the study was retrospective, informed consent by patients and providers was not required.

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