

Multi-view-enabled Deep Learning for Automated Radiographic View Classification and Fracture Detection for Elbow



Emine Doganay, PhD¹

Gene Kitamura, MD¹

Lu Yang, MD¹

Jun Luo, MS^{2*}

Shandong Wu, PhD^{1,2,3,4}



Department of ¹Radiology / ³Biomedical Informatics / ⁴Bioengineering

²Intelligent Systems Program

University of Pittsburgh

Background

- Elbow fracture is one of the fracture types that happens most frequently among people across all ages
 - Needs timely diagnosis and treatment since it could cause neurovascular damage
 - X-ray helps assessment by visualization
 - Patients often take frontal and lateral view radiographies of elbow
 - View not always labeled accurately



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- Deep learning
 - Thrives in recent years
 - Have potential benefits to reduce treatment lead-time
 - Comparable performance to human experts'

Objective

- ❑ Two-step deep learning method
 - ❑ Step 1: Develop a deep learning model that can predict view labels (frontal or lateral) given the image.
 - ❑ Step 2: Develop a multi-view deep learning method for elbow fracture classification

Method and Materials

□ Method

- View labeling (frontal/lateral)
 - Review the collected images by a board-certified radiologist
 - Correct the labels of mislabeled images
 - Train a CNN deep learning model on a binary classification task (frontal against lateral)
 - Reassign labels to images

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- Multi-view-enabled elbow fracture classification.
 - Pair the frontal and lateral view images of the same patient
 - Feed the pairs into the model for feature extraction with Inception-Resnet-V2
 - Fuse the features for classification of elbow fracture
 - Evaluate the multi-view-enabled model as well as the single view model

Method and Materials

□ Materials

- This is an IRB approved retrospective study
- 4,740 cases
- Average patient age: 50.44, standard deviation: 20.42
- Each with a frontal and a lateral view elbow X-ray image (9,480 in total)
- 1,598 images (631 frontal and 967 lateral) were mislabeled on the header
- 682 fractured cases, 4,058 non-fracture (normal) cases
- 90% data for training, 10% for testing
- Evaluation metrics: accuracy, AUC

Results

- View labeling
 - 97% accuracy

- Fracture classification
 - Single view model
 - AUC: 0.94
 - Accuracy: 89%

 - multi-view model
 - AUC: 0.96
 - Accuracy: 97%

Discussion

- ❑ We developed a two-step method to first assign correct view labels (frontal vs. lateral) to images, and then use both views to detect fractures.
- ❑ Our model is highly accurate in automatically categorizing elbow radiographic views and detecting elbow fractures.
- ❑ This kind of AI models can be helpful to assist radiologist assess multi-view images and automatically triage elbow radiographs to reduce treatment lead-time.
- ❑ Our study is a single-center study and further evaluation of the models are required.

Medical Knowledge-Guided Deep Curriculum Learning for Elbow Fracture Diagnosis from X-Ray Images



Jun Luo, MS¹

Gene Kitamura, MD²

Emine Doganay, PhD²

Dooman Arefan, PhD²

Shandong Wu, PhD^{1,2,3,4}

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Method

- Scoring of different fracture subtypes
 - Fracture images: 6 subtypes
 - Assign scores from human expert's knowledge

Table 2. Difficultness scoring of the normal cases and six subtype fractures of the elbow (1 – hardest; 100 – easiest).

	<i>(normal)</i>	<i>(a)</i>	<i>(b)</i>	<i>(c)</i>	<i>(d)</i>	<i>(e)</i>	<i>(f)</i>
Score	30	30	30	70	40	90	10



Figure 1. Six Subtypes of elbow fractures: (a) Ulnar fracture; (b) Radial fracture; (c) Humeral fracture; (d) Dislocation; (e) Complex fracture/multi-type fracture; (f) Coronoid process fracture.

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Thank you!

Questions?

jul117@pitt.edu