AUTOMATIC RECOGNITION OF MUSCULOSKELETAL DISORDERS FROM RADIOGRAPHS

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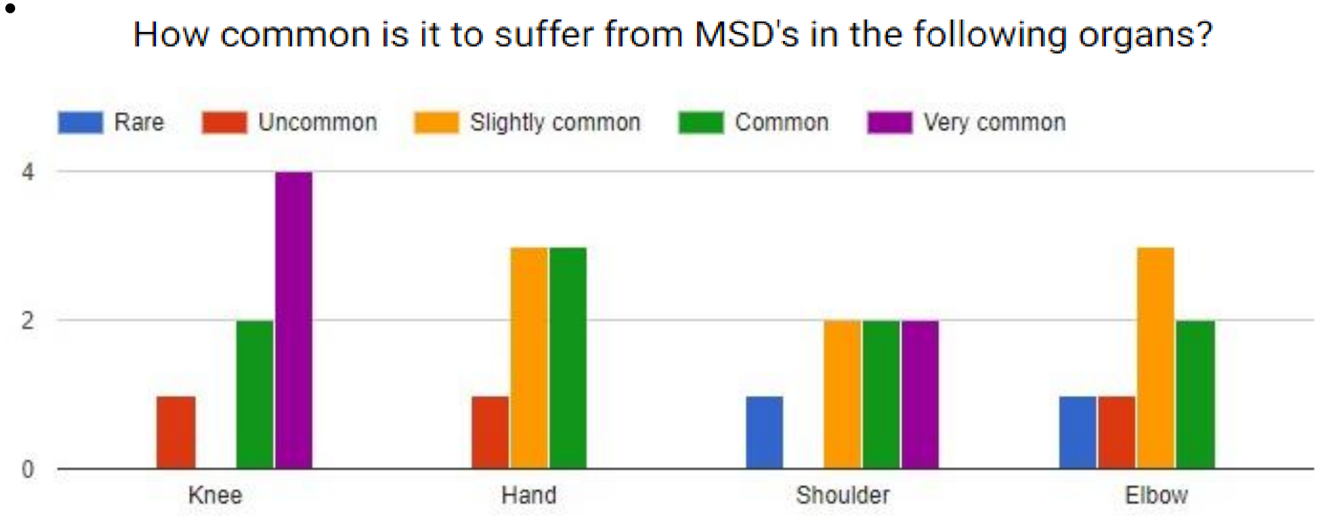
INTRODUCTION (1/2)

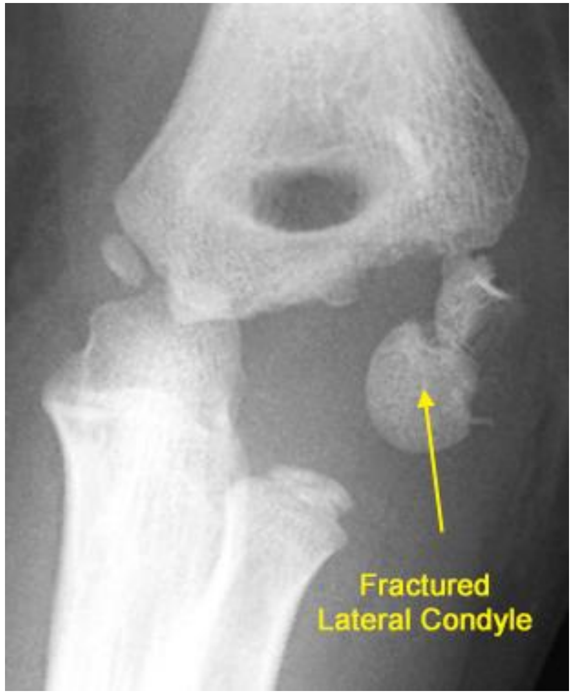
- Musculoskeletal disorders (MSDs) are conditions that affect muscles, bones, joints and the human body's movement.
- Some common types of MSDs:
  - Osteoarthritis
  - Rheumatoid arthritis
  - Fibromyalgia
  - Bone Fractures



http://www.arthritisireland.ie/go/fit_for_work/msds/types_of_msds

INTRODUCTION (2/3)

- Some common types of MSDs found in elbows:
  - Condylar fracture
  - Tennis Elbow
  - Golfer's Elbow



https://medlineplus.gov/elbowinjuriesanddisorders.html

INTRODUCTION (3/3)

- MSDs affect more than 1.7 billion people worldwide. [2]
- MSDs are more common in construction supervisors than office workers. [1]
- The elbow is a complex joint commonly injured in athletes. [3]
- Automatic recognition is being widely used for different purposes, recently for detecting abnormalities from X-rays.

1- Boschman, Julitta S., et al. "Occupational demands and health effects for bricklayers and construction supervisors: A systematic review." *American journal of industrial medicine* 54.1 (2011): 55-77.
2- http://www.boneandjointburden.org/fourth-edition/ie0
3- https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3548664/

PROBLEM STATEMENT

- Recent work used deep learning to detect abnormalities found in the upper-limb.
- Feature extraction was not included.
- Accuracies were low on the elbow.
- The reached automatic detection of abnormalities is still not equivalent to the best radiologists.

-Pranav Rajpurkar*, Jeremy Irvin*, Aarti Bagul, Daisy Ding, Tony Duan, Hershel Mehta, Brandon Yang, Kaylie Zhu, Dillon Laird, Robyn L. Ball, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren, Andrew Y. Ng. MURA: Large Dataset for Abnormality Detection in Musculoskeletal Radiographs. 2018.
-Bhargavan, Mythreyi and Sunshine, Jonathan H. Utilization of radiology services in the united states: levels and trends in modalities, regions, and populations. Radiology, 234(3):824–832, 2005.

PROBLEM STATEMENT

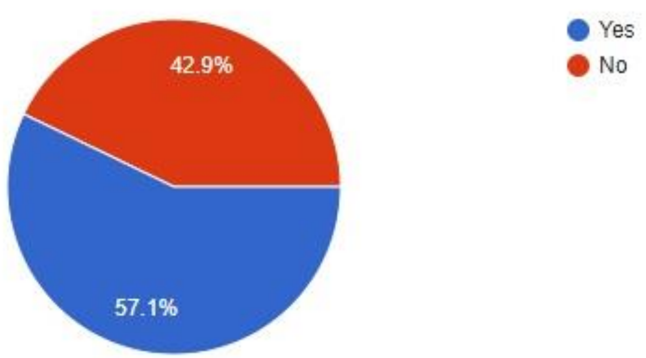
- There is no work that tackles issues on the elbow.
- Lack of databases, available databases are not labelled and they are demanded.
- Datasets are not labelled, so important features are unknown, which makes it difficult to include feature extraction which affects the performance of automatic recognition systems.

PROBLEM STATEMENT

- X-rays can have noise or can be unclear.
- Inexperienced or less experienced radiologists can also cause misdiagnosis.

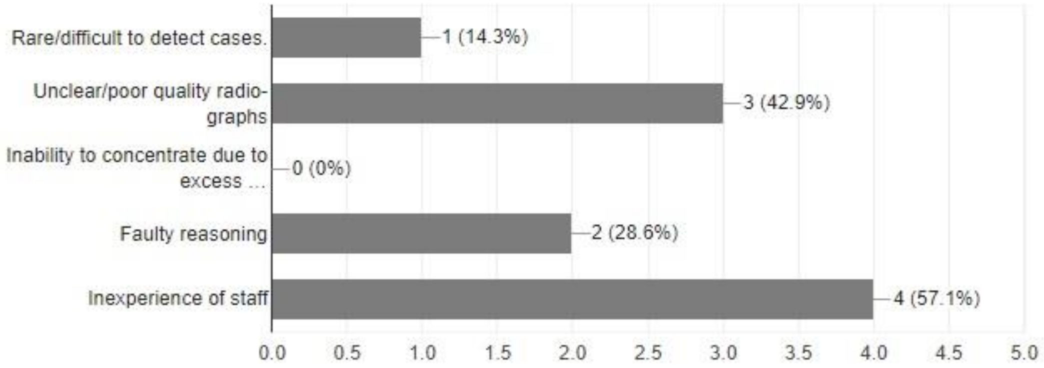
Are there any features in a radio-graph that could be difficult to notice?

7 responses



What are the problems radiologists face when diagnosing diseases from radio-graphs that can lead to misdiagnosis?

7 responses



RELATED WORK (1/3) – MURA (2017)

- The dataset has 40,561 multi-view radiographic images of bones.
- A 169 layered convolutional neural network (CNN) (Dense Convolutional Network architecture) model anticipates the probability of anomalies in each view.
- Scored a model performance of 71% on elbow studies.

Pranav Rajpurkar*, Jeremy Irvin*, Aarti Bagul, Daisy Ding, Tony Duan, Hershel Mehta, Brandon Yang, Kaylie Zhu, Dillon Laird, Robyn L. Ball, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren, Andrew Y. Ng. MURA: Large Dataset for Abnormality Detection in Musculoskeletal Radiographs. 2018.

RELATED WORK (1/3) – MURA (2017)

	Radiologist 1	Radiologist 2	Radiologist 3	Model
Elbow	0.850 (0.830, 0.871)	0.710 (0.674, 0.745)	0.719 (0.685, 0.752)	0.710 (0.674, 0.745)
Finger	0.304 (0.249, 0.358)	0.403 (0.339, 0.467)	0.410 (0.358, 0.463)	0.389 (0.332, 0.446)
Forearm	0.796 (0.772, 0.821)	0.802 (0.779, 0.825)	0.798 (0.774, 0.822)	0.737 (0.707, 0.766)
Hand	0.661 (0.623, 0.698)	0.927 (0.917, 0.937)	0.789 (0.762, 0.815)	0.851 (0.830, 0.871)
Humerus	0.867 (0.850, 0.883)	0.733 (0.703, 0.764)	0.933 (0.925, 0.942)	0.600 (0.558, 0.642)
Shoulder	0.864 (0.847, 0.881)	0.791 (0.765, 0.816)	0.864 (0.847, 0.881)	0.729 (0.697, 0.760)
Wrist	0.791 (0.766, 0.817)	0.931 (0.922, 0.940)	0.931 (0.922, 0.940)	0.931 (0.922, 0.940)
Overall	0.731 (0.726, 0.735)	0.763 (0.759, 0.767)	0.778 (0.774, 0.782)	0.705 (0.700, 0.710)

Table 1: Comparison between radiologists and mura's model on the Cohen's kappa statistic. The best (green) and worst (red) performances on each of the study types.

RELATED WORK (2/3) - DETECTING BONE FRACTURES IN X-RAY IMAGES (2015)

- The dataset consists of 98 labeled x-ray images.
- Removed different types of noise such as salt and pepper noise for preprocessing by median filter.
- Used Sobel edge detector for segmentation process.

(a) Original image. (b) The image after noise removal. (c) The image after edge detection.

M. Al-Ayyoub , et al. Detecting Bone Fractures in X-rays Images. *ResearchGate,* 2015.

RELATED WORK (2/3) - DETECTING BONE FRACTURES IN X-RAY IMAGES (2015)

- Proceeds with extracting useful features of the bone image by using Wavelets and Curvelets Features.
- Weka's supervised attribute filter feature selection technique was used with the Best-First technique which uses hill-climbing with backtracking.
- This technique selected the best 84 features.
- The Gray Level Co-occurrence Matrix (GLCM) method was used to extract additional textural features

M. Al-Ayyoub , et al. Detecting Bone Fractures in X-rays Images. *ResearchGate,* 2015.

RELATED WORK (2/3) - DETECTING BONE FRACTURES IN X-RAY IMAGES (2015)

- Four classifiers were used:
  - Neural Network (NN)
  - Naive Bayes (NB)
  - Bayesian Networks (BN)
  - Decision Tree (DT)

TABLE 1
Accuracy measures for the base classifiers using the Wavelets features.

Algorithm	Precision	Recall	F-Measure	AUC
BN	86.8%	86.7%	86.7%	93.8%
NB	82.8%	82.7%	82.6%	92.8%
NN	81.7%	81.6%	81.6%	89.4%
DT	63.3%	63.3%	63.3%	63.4%

TABLE 2
Accuracy measures for the base classifiers using the Curvelets features.

Algorithm	Precision	Recall	F-Measure	AUC
DT	46.9%	48%	43%	46.4%
NB	60.3%	59.2%	58.1%	59.7%
BN	47.4%	49%	40%	48.4%
NN	64.7%	60.2%	56.9%	61.5%

M. Al-Ayyoub , et al. Detecting Bone Fractures in X-rays Images. *ResearchGate,* 2015.

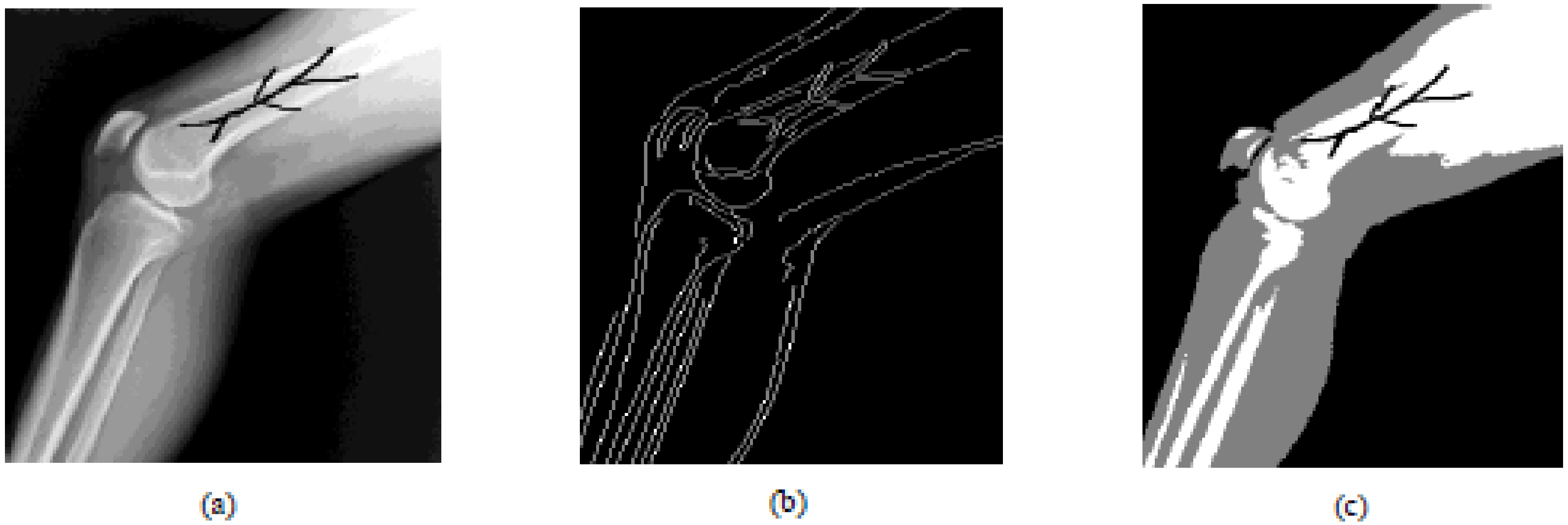
RELATED WORK (3/3) - DETECTION OF BONE FRACTURE USING IMAGE PROCESSING (2015)

- The dataset consists of 20 fractured images and 20 non-fractured images.
- Median filter and Sobel operator were used for preprocessing and edge detection respectively.
- The K-means clustering technique was used for segmentation.
- Gray-Level Co-occurrence Matrix was used for feature extraction and selection.

Anu T C, Mallikarjunaswamy M.S., et al. Detection of Bone Fracture using Image Processing Methods. *NCPSIA*, 2015

RELATED WORK (3/3) - DETECTION OF BONE FRACTURE USING IMAGE PROCESSING (2015)

- Different types of classifiers were used such as decision tree (DT) and neural network (NN).



Results of image processing steps (a) input image (b) edge detected image (c) output image

Anu T C, Mallikarjunaswamy M.S., et al. Detection of Bone Fracture using Image Processing Methods. *NCPSIA*, 2015

COMPARISON

System	Disorder	Classifier	Dataset	Accuracy
MURA	Upper Limb	CNN	MURA	AUROC of 0.929, with an operating point of 0.815 sensitivity and 0.887 specificity.
AUTOMATIC KNEE OSTEOARTHRITIS DIAGNOSIS	Osteoarthritis	CNN	MOST & OAI	0.83 kappa coefficient
[1] (2017)	Spine Segmentation	CNN & a Collision-Based Model	Spine Web Database	The Dice coefficient (DSC) 93.2±2.2%
[2] (2018)	Intervertebral discs	Fully Convolutional Network	MICCAI 2015 segmentation challenge datasets	Dice coefficient: 92.0%

1. Korez R., Likar B., Pernuš F., Vrtovec T. (2018) Segmentation of Pathological Spines in CT Images Using a Two-Way CNN and a Collision-Based Model. Lecture Notes in Computer Science, vol 10734. Springer, Cham
2. Zeng G., Zheng G. (2018) DSMS-FCN: A Deeply Supervised Multiscale Fully Convolutional Network for Automatic Segmentation of Intervertebral Disc in 3D MR Images. Lecture Notes in Computer Science, vol 10734. Springer, Cham

PUBLIC DATASETS

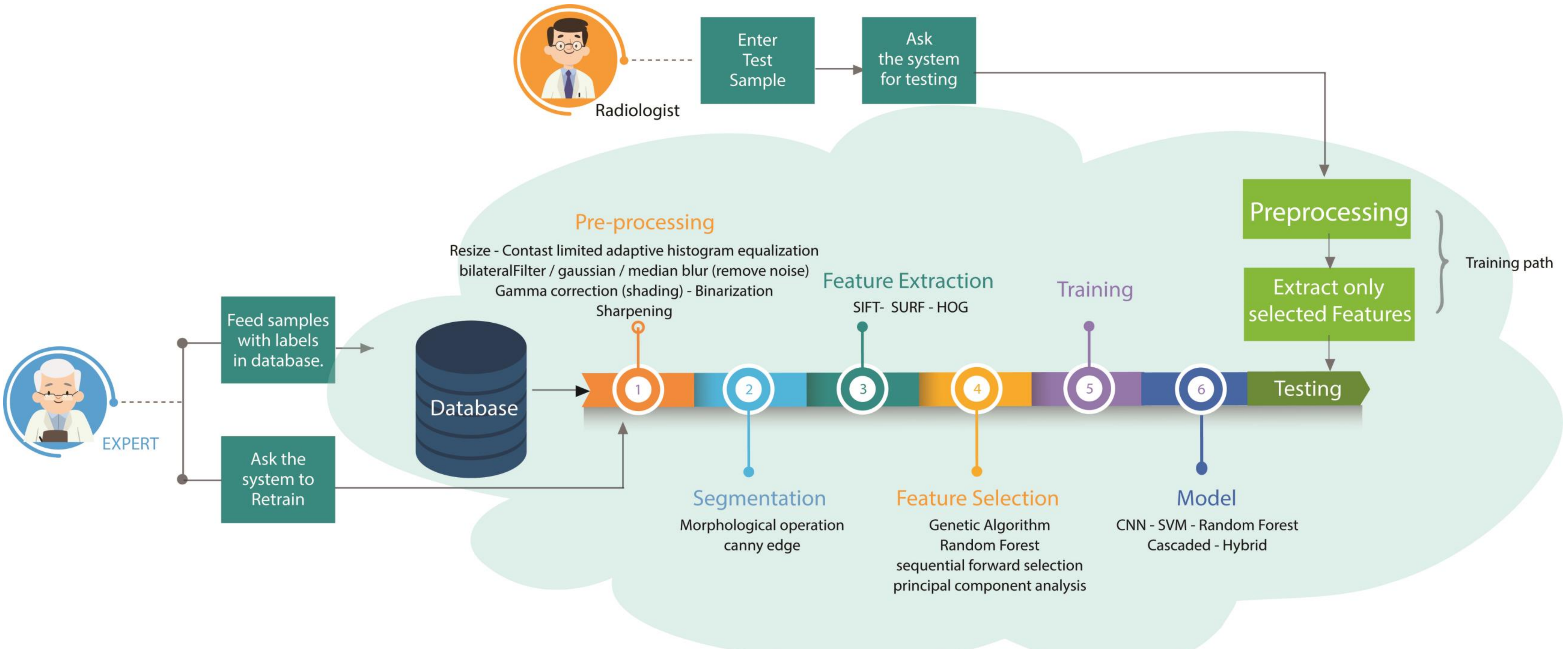
Dataset	Study Type	Images
MURA	Musculoskeletal (Upper Extremity)	40,561 (Elbow:1912)
Osteo Arthritis Initiative (OAI) [1]	Musculoskeletal (Knee)	8,892
Multicenter Osteoarthritis Study (MOST) [2]	Musculoskeletal (Knee)	18,376
Visible Korean Human [3]	Human Anatomy (Cadaver)	5000+
ChestX-ray14 [4]	Chest	112,120

1. Segal, Neil A. et al. "The Multicenter Osteoarthritis Study (MOST): Opportunities for Rehabilitation Research." *PM & R : the journal of injury, function, and rehabilitation.*
2. https://oai.epi-ucsf.org/datarelease/default.asp
3. http://vkh3.kisti.re.kr/
4. Wang, Xiaosong, Peng, Yifan, Lu, Le, Lu, Zhiyong, Bagheri, Mohammadhadi, and Summers, Ronald M. Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. arXiv preprint arXiv:1705.02315, 2017.

SYSTEM OVERVIEW (1/2) - SCOPE

- We will develop an automatic recognition system that will classify the disorders and their sub-types present from the X-ray, and also label the disorders in the dataset.
- Learning the problem areas in the images will help us with feature extraction.
- The system will be developed into an expert system.

SYSTEM OVERVIEW (2/2) - SCOPE



SYSTEM OVERVIEW - INPUT

- Radiographs are uploaded & changed to grayscale images in order to start processing.

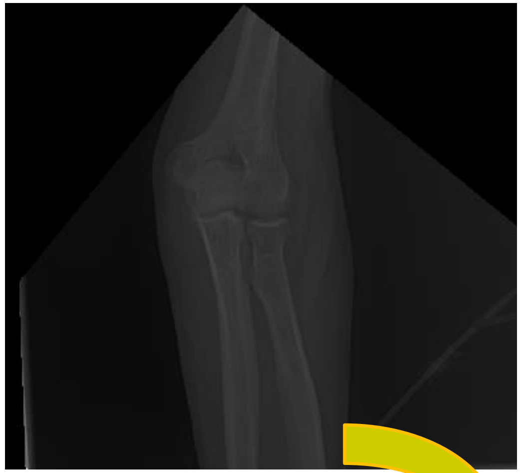
(a) Lateral radiograph of a **negative** elbow

(b) Lateral radiograph of a **positive** elbow

Obradov M., Gielen J.L.M.A. (2015) Radiologic Imaging of Elbow and Forearm Injuries. *Springer,* 2015.

SYSTEM OVERVIEW - PROCESSING

- The radiographs undergo sharpening filters such as contrast-limited adaptive histogram equalization (CLAHE) and gamma correction, in addition to bilateral filter for image smoothing.
- Morphology gradient based Bone fracture segmentation was used and Canny Edge Detection.
- For feature extraction, gradient features and Hog could be used.

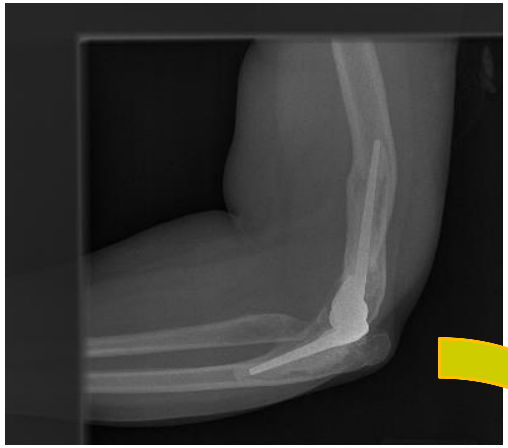


(a) A patient's elbow that contains a fracture.

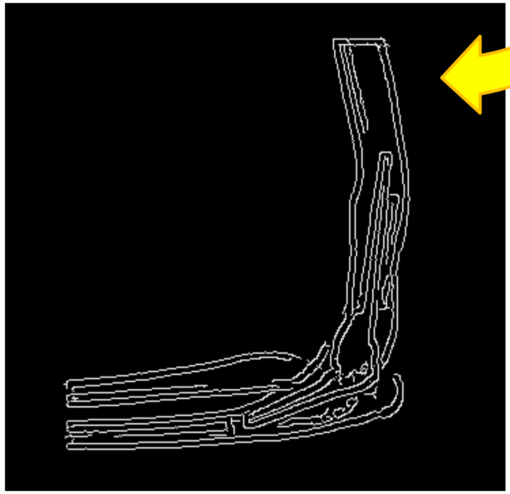
(b) Real picture after exposure.

SYSTEM OVERVIEW - PROCESSING

- Genetic algorithm, even random forest and GLCM could be used in feature selection.
- CNN is considered the most suitable classifier, since it is vastly used by several work and highly efficient in increasing accuracy.
- Hybrid Classifiers (as: CNN and random forest and HMM)



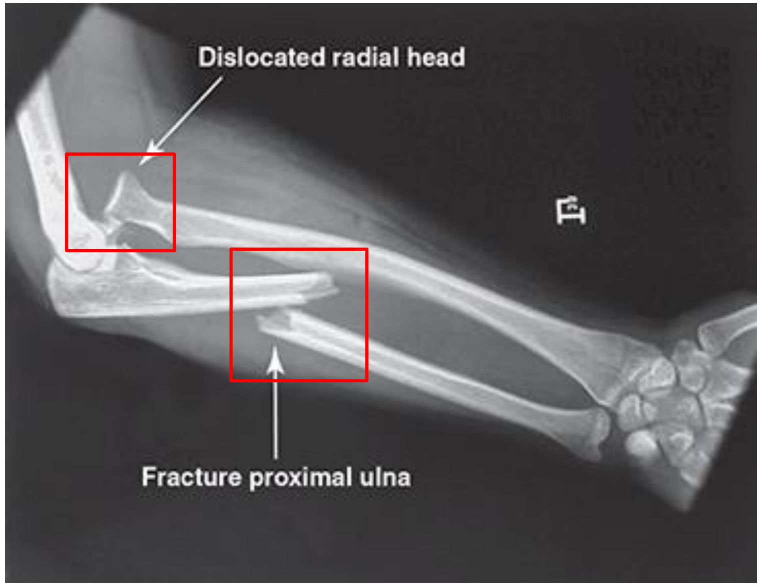
(a) A patient's elbow that contains a fracture.



(b) Real picture after Canny Edge Detection.

SYSTEM OVERVIEW - OUTPUT

- The expected output would be the probability of abnormalities in elbows and detecting the disorder.



1. Lynn N. Mckinnis: Fundamentals of Musculoskeletal Imaging, 4th Edition: www.FADavisPTCollection.com

EXPECTED RESULTS

- Different robust features will be applied to propose a **reliable** automatic system for classification to assist doctors.

- Develop automatic expert systems that save all the knowledge of experts in a centralized database and improve model's accuracy by time.

QUESTIONS?

REFERENCES

- Pranav Rajpurkar*, Jeremy Irvin*, Aarti Bagul, Daisy Ding, Tony Duan, Hershel Mehta, Brandon Yang, Kaylie Zhu, Dillon Laird, Robyn L. Ball, Curtis Langlotz, Katie Shpanskaya, Matthew P. Lungren, Andrew Y. Ng. MURA: Large Dataset for Abnormality Detection in Musculoskeletal Radiographs. 2018.