Computer Assisted Detection of Elbow Deformation in Digital X-rays

Mashal Afzal[1], Moazzam Jawaid[2], Shahnawaz Talpur[3]

[1,2,3] Department of Computer Systems, MUET Jamshoro

Emails: mashalafzalmemon@gmail.com, moazzam.jawaid@faculty.muet.edu.pk , shahnawaz.talpur@faculty.muet.edu.pk

Abstract . Bones play a vital role in human skeleton and a large amount of emergency department visits are related with orthopedic abnormalities. Among these, one common issue of visit is elbow deformation which can be easily diagnosed through X-ray images. In this worth, we have anticipated an approach for digitizing the deformation detection in elbow X-ray images. The technique is practiced on publically available MURA dataset for elbow X-ray images. Initially, the images available in dataset for elbow X-ray were labelled and pre-processed. Later, by using 3-class probabilistic segmentation we have suppressed the background and flash in the image. Finally, we have extracted our region of interest that is the elbow bone. Moreover, using edge detection method we have distinguished the bone from the background and detected the capitulum inside elbow bone where two other bones are connected. Subsequently, with respect to capitulum, we have recorded intensity for different bone to categorize them as normal or abnormal. The technique is practiced on the available dataset and the efficiency around 82% has been scrutinized.

Keywords: Data Acquisition, Image enhancement, Object Segmentation, Edge detection, Circle detection, Deformation Detection.

1 Introduction

There is an essential role of every bone in human skeleton and a little bit of abnormality or deformation in any single bone can disturb the overall framework of the body. The deformation can occur in any bone in our body such as femur, rib, hip, ankle etc. [1] From the study, it was scrutinized that one of the common reasons for emergency department visits is Orthopedic deformation. [2] More than 1.7 billion people worldwide are effected with orthopedic abnormalities, which results in long-lasting, severe pain and disorders in human body. [3] Among emergency department trauma patients, the elbow deformation is one of the common issue which has been diagnosed. Around eight to ten percent of fractures in adults occur in the elbow and forearm and increasing gradually. [4]

Medical image diagnosing tools are indispensable in this age for the growing rate of abnormalities. One of the common scheme of deformation diagnosing is X-ray images which gives the shadow-like image as a result. There are some other methods for image diagnosing like CT and MRI which provides better results than X-ray for human body organs but X-ray images is effective to use in deformation detection due to its high speed, inexpensive and ease of use with some limitations. [5] Moreover, the end result of X-ray image is good enough to detect deformation in human bones which makes it more effective to practice.

The digitization of medical imagery is an important trend. Despite high frequency of elbow-related casualties, there is no standardized method for interpretation of digital X-rays. [6] This study focuses on digitizing deformation detection for elbow X-ray images.

(a) Elbow X-ray image (b) Elbow X-ray image representing different bones

Fig. 1. Elbow **X-ray image.** (a) shows the original elbow X-ray image. (b) referring to different bones present in human elbow.

Deformation in bone occurs in many ways depending on the number of joints and nature of the bone. [7] In this study, we will focus on categorizing elbow X-ray image as normal or abnormal by following the methodology discussed below in section 3.

To the best of our knowledge, no previous work has been done in the same context.

2 Related Work

Elbow abnormalities can be detected through many ways such as Computed Tomography, Medical Resonance Imaging, Direct Radiography and X-ray images. As X-ray images are easy to use, high speed, in expensive and provide better results in bone deformation detection. But, no any previous work has been done on digitizing elbow X-ray images. There are some works done on X-ray images in other arenas. An overview of the work done in same field is presented below.

In paper [8] the author presented the idea of fracture detection in bones of hand using X-ray images. Bones in hand belongs to the very smallest part of bones in human skeleton and are 27 in total in a single human hand. The author worked on the hand X-ray images to detect the fracture, starting with detecting edges in hand X-ray images and then extracting some meaningful features to differentiate between the normal and fractured X-ray image. After extracting features, the author builds some classification algorithm to test the accuracy which was good. However, the author limited their study by focusing on only two part of hand bones, phalanges and metacarpals and ignored all other parts of bones. Specially, a very basic and much important part of bones known as carpal bones which joint it with forearm which marked a restraint to this study.

In paper [9] the author also presented the idea of detecting fracture in femur bone on focusing image processing techniques. Femur bone is the largest and fervent bone of all bones in human body. The author worked on X-ray images of the femur bone to differentiate between the normal and abnormal bone by detecting a very thin hair line fracture. The work flow of study starts with removing noise from images and finding some logical and morphological operators, followed by edge detection methods to fix certain points. By using SVM classifier, the author classified the dataset into normal and fractured bones and tested the accuracy. Though the accuracy was 84.7% but the study was done on very small dataset and it can be improved by working with a large training data and some other algorithm can be implemented for detecting the fracture to show its shape, area of fracture or any other complex fracture.

Sometimes trauma is not clearly visible via X-ray, but it internally damages and fractures the joints. To overcome this gap of identifying the trauma in elbow joints, an idea is being proposed in paper [10] utilizing the features of computed tomography. By computed tomography these minor or neglected fractures not displayed by X-ray can be identified. For this purpose, some patients were analyzed through CT whose X-ray was clear and there were no any sign of fracture or trauma. All the CT images and X-ray were deputed by radiologists. It is extracted from the results that CT is most favorable in terms of findings elbow joint abnormalities.

Stiff elbow doesn't allow an individual to move his arm in different directions. Due to stiff elbow, one can't easily gear up the arm or lift something with the help of arm because it causes too much pain. Stiff elbow produce pain in moving elbow more than 30^o while the normal motion relies within 0^o to 145^o. The symptoms of stiff elbow involve inflammation and pain while moving arm into different degrees. For this purpose, the idea has been proposed in paper [11] which clarify the MRI discoveries of stiff elbow. The study involves MR images of 36 nonconsecutive patients and 39 stiff elbow joints which were broached to MRI section. All the patients were including surgical correlation. The surgical findings were correlated with MRI findings and mechanism of stiffness. This study results that accuracy of MRI was 100% for finding elbow abnormalities and exactness for vindicating stiffness was 96%. So, it was concluded that the boney causes of stiffness and soft tissue for multiple elbow abnormalities can be accurately diagnosed using MRI.

We have discussed the related work done on X-ray images or with CT, MRI, Ultrasound or Direct radiography on elbow images. To the best of our knowledge no work has been done on digitizing elbow X-ray images.

3 Methodology

The methodology is briefly discussed in this section. Following is the flowchart of the proposed approach which has been followed for deformation detection in elbow X-ray.

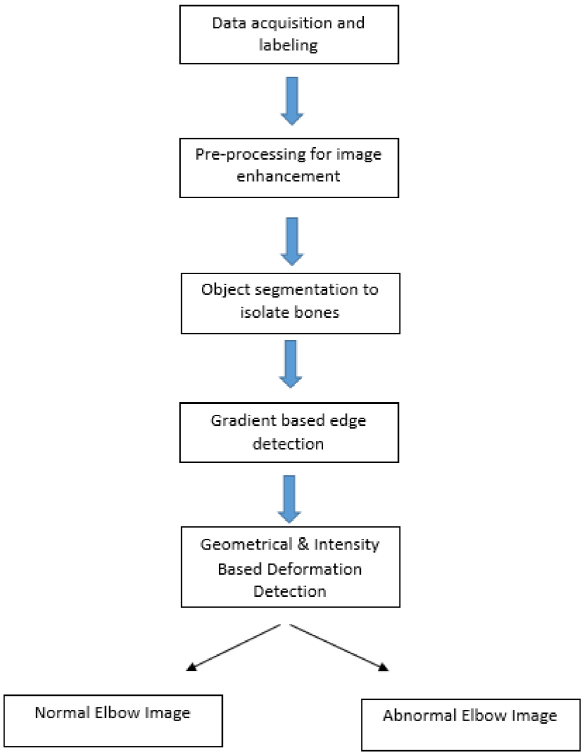


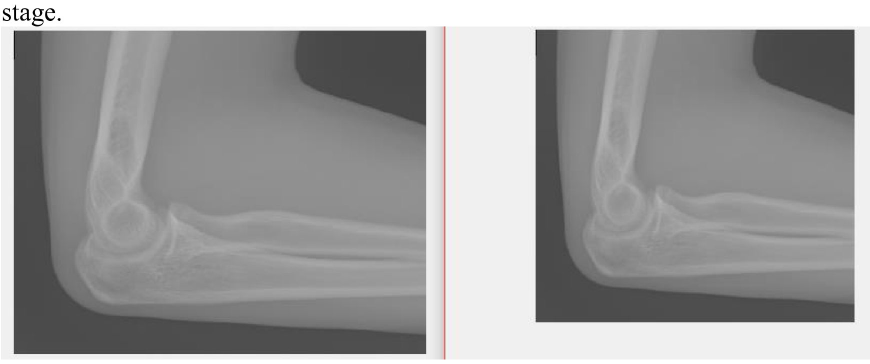
Fig. 2. Flowchart of anticipated methodology.

3.1 Data Acquisition and Labeling

The very first step in our practice is the labeling of the elbow X-ray images offered in dataset to match the results at the end. The publically available dataset which we are using for our challenging research is downloaded from the MURA website [1]. MURA the large dataset consists X-ray images for 7 different bones including elbow, finger, forearm, shoulder, hand, humerus and wrist. For elbow it contains thousands of X-ray images which are divided in two portions positive and negative. Every image is labeled as normal or abnormal, the labels are already defined as negative for normal and positive for abnormal on the website from where we got our dataset, we have labelled accordingly.

3.2 Pre-processing for Image Enhancement

After labelling all the elbow X-ray images, the images were resized and converted into gray scale. The grayscale conversion process eliminates the color information from the image and leaves behind the luminance of every pixel in image. Subsequently, when the images were resized and converted into grayscale, the dataset was ready for the next stage.



(a) Actual Image (b) Resized image

Fig. 3. Elbow **X-ray image.** (a) shows the original elbow X-ray image. (b) refers to the which is resized.

3.3 Object Segmentation to Isolate Bones

Once, all the images were pre-processed the next step was segmenting the X-ray image to get the region of interest. The image contains background, flash and bone. The major region of interest was bone from all these. By using 3-class probabilistic segmentation, the background was first suppressed to get the foreground as class 1. The resulting foreground also includes bone and flash. Again using 3- class probabilistic segmentation, we suppressed the flash which is now considered as background for the bone as class 2. In las attempt as class 3, we have segmented bone from flash which is the actual region of interest. We were finally able to suppress the flash up to some extent.

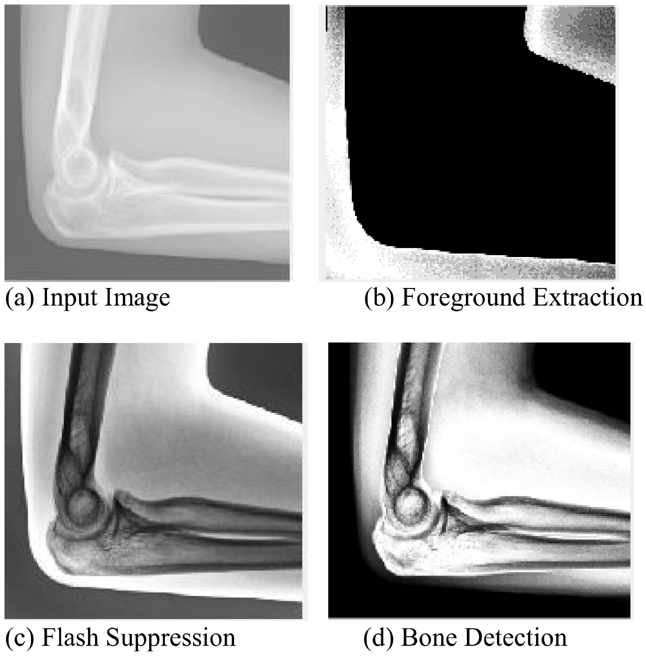
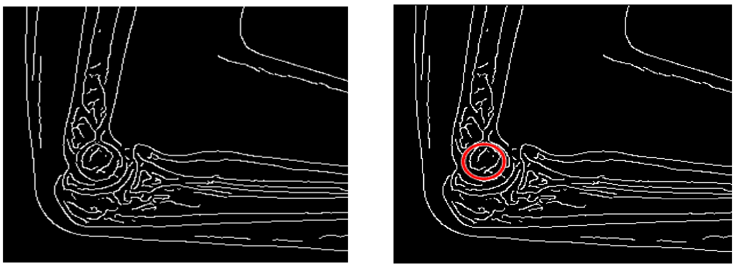


Fig. 4. Bone **Segmentation.** (a) shows the pre-processed input image. (b) referring to output image of Class 1 segmentation which shows that background is suppressed and foreground is detected from the input image. (c) referring to output of Class 2 segmentation which shows that flash is suppressed so that the bone can be further segmented. (d) referring to Class 3 segmentation which highlights the bone from the previous flash suppressed image.

3.4 Gradient Based Edge Detection

The next step was to apply edge detection method on the output image of 3-class probabilistic segmentation. Edge detection method is very useful for distinguishing the background from the region of interest. It can be used as Canny [12], Sobel [13] and Gaussian [14] edge detection methods. The best results in our study was obtained through Canny method which we have applied on segmented image 4(d). Canny edge detection results in finding sharp edges in the image which was further used for deformation detection. Subsequently, on the resulting image from Canny method we have identified the circle using Hough transform [15] by setting the parameters for center as 11 pixels and for radius as 22 ± 4 pixels. The circle is basically the capitulum of elbow bone where the other bones of elbow are connected.

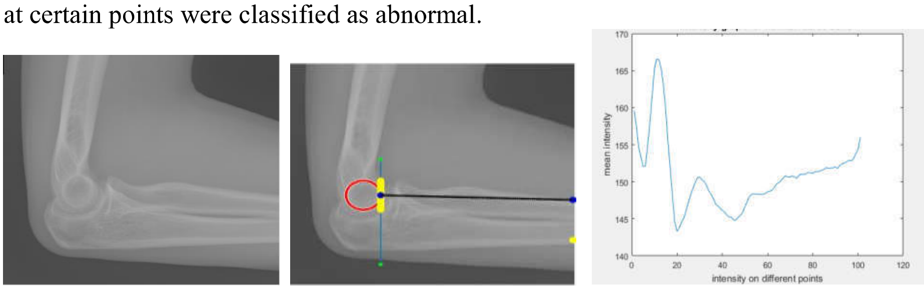


(a) Canny edge detected image (b) Circle detection on edge detected image

Fig. 5. Edge & Circle Detection. (a) shows the output of canny edge detection on bone segmented image. (b) shows the circle detection on the previous edge detected image

3.5 Geometrical & Intensity Based Deformation Detection

Once the circle was detected on the segmented and edge detected image, we have positioned that circle back on the pre-processed input image. With respect to the capitulum, we have identified new points between Radius and Ulna. These are the other bones presented in the elbow X-ray image which are joint with capitulum, which we have detected earlier. Successively connecting the points on other bones with respect to certain defined points, we have interpolated the image at every point for these bones. The algorithm was applied on many images and finally those images having a smooth intensity were classified as normal and those having rough intensity or drop of intensity at certain points were classified as abnormal.



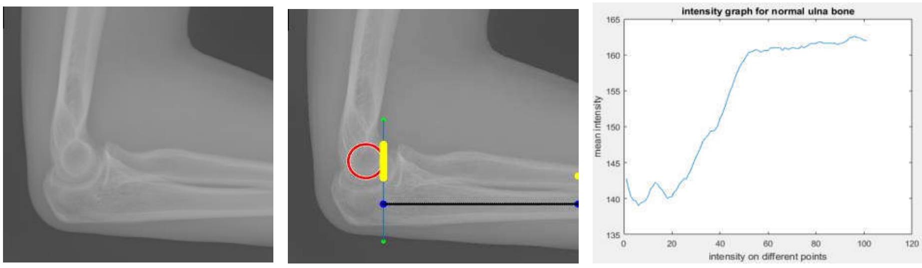
(a) Input Image (b) Circle Detected & Interpolated Image (c) Intensity Graph for Radius Bone

Fig. 6. Deformation **Detection in Radius Bone.** (a) shows the resized and grayscale image. (b) shows the processed image for deformation detection in Radius Bone. (c) refers to the Intensity Graph for the deviation in intensity.

4 Results and Discussion

The algorithm is applied on a number of images for detecting normal and abnormal elbow X-ray images. For abnormal elbow X-ray images there are two different possibilities. The abnormality can occur either in Radius or in Ulna bone.

4.1 Normality Detection

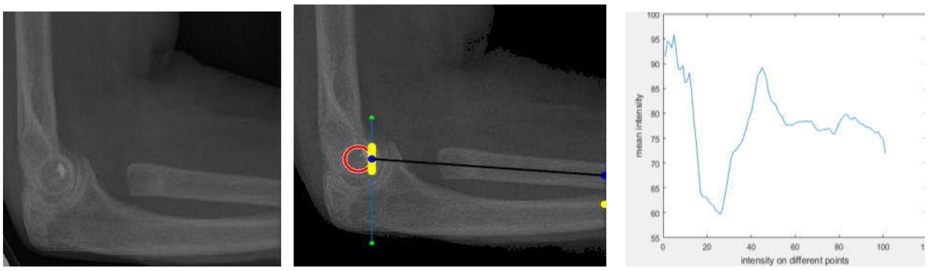


(a) Input Image (b) Circle Detected & Interpolated Normal Ulna Bone (c) Intensity Graph for Normal Ulna Bone

Fig. 7. Normality **Detection in Ulna Bone.** (a) shows the resized and grayscale image. (b) shows the processed image for deformation detection in Normal Ulna Bone. (c) refers to the Intensity Graph for the deviation in intensity which can be seen as there is no sudden drop in intensity so, the X-ray image for Ulna Bone is classified as Normal.

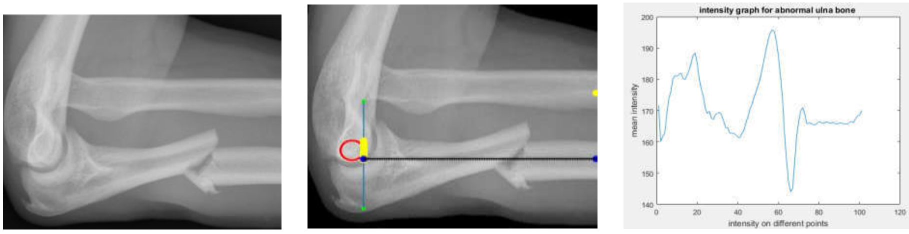
4.2 Abnormality Detection

Abnormality can occur in two different cases with respect to capitulum. It can either occur in Radius or in Ulna bone.



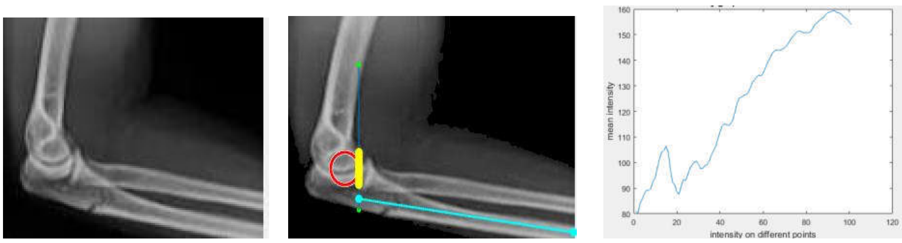
(a) Input Image (b) Circle Detected & Interpolated Abnormal Radius Bone (c) Intensity Graph for Abnormal Radius Bone

Fig. 8. Deformation Detection in Radius Bone. (a) shows the resized and grayscale image. (b) shows the processed image for deformation detection in Abnormal Radius Bone. (c) refers to the Intensity Graph for the deviation in intensity and it can be seen that the intensity fluctuation in abnormal elbow X-ray image is dropped suddenly where there's fracture in the Radius bone so, the X-ray image for Radius Bone is classified as Abnormal.



(a) Input Image (b) Circle Detected & Interpolated Abnormal Ulna Bone (c) Intensity Graph for Abnormal Ulna Bone

Fig. 9. Deformation **Detection in Ulna Bone.** (a) shows the resized and grayscale image. (b) shows the processed image for deformation detection in Abnormal Ulna Bone. (c) refers to the Intensity Graph for the deviation in intensity and it can be seen that the intensity fluctuation in abnormal elbow X-ray image is dropped suddenly where there's fracture in the Ulna bone so, the X-ray image for Ulna Bone is classified as Abnormal.



(a) Input Image (b) Circle Detected & Interpolated Abnormal Ulna Bone (c) Intensity Graph for Abnormal Ulna Bone

Fig. 10. Deformation Detection in Ulna Bone. (a) shows the resized and grayscale image. (b) shows the processed image for deformation detection in Abnormal Ulna Bone. (c) refers to the Intensity Graph for the deviation in intensity and it can be seen that there's no change or drop in intensity for Ulna bone when there's a minor fracture in the bone. So, here the technique is not performing well.

5 Conclusion and Future Work

In this study, the problem to digitize the deformation detection in elbow X-rays has been discussed. The technique is practiced on the available dataset and the accuracy for digitizing the deformation detection of 82% has been analyzed with the geometrical and intensity based detection. As this is the first trial for digitizing deformation detection in elbow X-ray. In future, other techniques can be performed by finding complex angular distance between bones and other parameters.

References

1. T. Kaur and A. Garg, "Bone Fraction Detection using Image Segmentation," *Int. J. Eng. Trends Technol.*, vol. 36, no. 2, pp. 82–87, 2016.

2. N. Kozaci *et al.*, “Evaluation of the effectiveness of bedside point-of-care ultrasound in the diagnosis and management of distal radius fractures,” *Am. J. Emerg. Med.*, vol. 33, no. 1, pp. 67–71, 2015.

3. P. Rajpurkar *et al.*, “MURA: Large Dataset for Abnormality Detection in Musculoskeletal Radiographs,” no. Midl 2018, pp. 1–10, 2017.

4. J. C. McGinley, N. Roach, B. C. Hopgood, and S. H. Kozin, “Nondisplaced elbow fractures: A commonly occurring and difficult diagnosis,” *Am. J. Emerg. Med.*, vol. 24, no. 5, pp. 560–566, 2006.

5. American Cancer Society, Imaging (radiology) tests, 2013. Accessed on: June 2013. [Online]. Available: http://www.cancer.org/acs/groups/cid/documents/webcontent/003177

6. S. M. Kengyelics, L. A. Treadgold, and A. G. Davies, “X-ray system simulation software tools for radiology and radiography education,” *Comput. Biol. Med.*, vol. 93, no. July 2017, pp. 175–183, 2018.

7. Y. Zhou *et al.*, “Computer-Aided Detection (CADx) for Plastic Deformation Fractures in Pediatric Forearm,” *Comput. Biol. Med.*, vol. 78, pp. 120–125, 2016.

8. I. Hmeidi, M. Al-Ayyoub, H. Rababah, and Z. Khatatbeh, “Detecting Hand Bone Fractures in X-Ray Images.,” *Jmpt*, vol. 4, no. 3, pp. 155–168, 2013.

9. A. M. Tripathi, A. Upadhyay, A. S. Rajput, A. P. Singh, and B. Kumar, “Automatic detection of fracture in femur bones using image processing,” *Proc. 2017 Int. Conf. Innov. Information, Embed. Commun. Syst. ICIIECS 2017*, vol. 2018-January, pp. 1–5, 2018.

10. K. Acar, E. Aksay, D. Oray, T. Imamoǐlu, and E. Gunay, “Utility of Computed Tomography in Elbow Trauma Patients with Normal X-Ray Study and Positive Elbow Extension Test,” *J. Emerg. Med.*, vol. 50, no. 3, pp. 444–448, 2016.

11. N. M. A. Hasan, M. H. Alam-Eldean, and S. S. Mousa, “Stiff elbow in adult: MR imaging findings,” *Egypt. J. Radiol. Nucl. Med.*, vol. 46, no. 4, pp. 1037–1048, 2015.

12. J. Li and S. Ding, “A research on improved canny edge detection algorithm,” *Commun. Comput. Inf. Sci.*, vol. 228 CCIS, no. PART 5, pp. 102–108, 2011.

13. S. Gupta and S. Ghosh Mazumdar, “Sobel edge detection algorithm,” *Int. J. Comput. Sci. Manag. Res.*, vol. 2, no. 2, pp. 1578–1583, 2013.

14. M. Basu and S. Member, “Gaussian-Based Edge-Detection Methods — A Survey,” vol. 32, no. 3, pp. 252–260, 2002.

15. A. O. Djekoune, K. Messaoudi, and M. Belhocine, “Incremental hough transform: A new method for circle detection,” *Stud. Comput. Intell.*, vol. 613, no. September 2013, pp. 3–22, 2016.