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Automatic Detection of Humerus Deformation in X-ray Imagery

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***Abstract*—People worldwide suffer from skeletal deformity which intrudes the overall function of the human skeleton. It's the leading cause of acute and chronic pain, as well as disability. About 8-10% of adult fractures occur in the arms. Although high Arm-related casualty frequency, no standard method exists for interpreting digital X-rays. We propose a Humerus Automatic Deformation Detection Model with computer vision technology. The technology is applied to the Publicly Available Musculoskeletal Radiographs (MURA) data set. First, the X-ray images are preprocessed to reduce noise, and the region of interest is extracted using multiclass Probabilistic segmentation. The segmented bone features are then improved which helps in differentiating among normal and deformed humerus X-rays. The Upper and lower peaks of the humerus are calculated to categorize them as normal or abnormal. 300 humerus X-rays from the dataset were examined. Overall, the proposed method shows promising results in terms of accuracy.**

***Keywords* —Data acquisition, deformation detection, probabilistic segmentation.**

I. INTRODUCTION

Every year, 30 million individuals visit the emergency department, and the number is growing. More than 1.7 billion people globally undergo skeletal deformity, it's the major cause of infirmity. About 8-10% of adult fractures occur in the arms. The frequency of these fractures rises with the commonness of osteoporosis and the incidence begins to increase significantly from the age of 40 years [1].The bones in the body act as a structure. Every bone plays a very stimulating role equally important throughout the skeleton. One-minute abnormality or fracture of any bone will affect the general human bone structure. Orthopedic irregularities are the most common reasons for emergency unit visits [1]. Skeletal human arm abnormality is one of the issues seen in emergency units trauma patients.

Fractures of the proximal humerus are the third most common fracture which affects people over the age of 65 [2]. Although high arm-related casualty frequency, no standard methods for interpreting digital X-rays exist [3]. Causes for skeletal deformation in the human arm include osteoporosis, sports, vehicle accident, electric shocks, etc.

For this growing abnormality rate, medical imaging diagnostic tools in this era are necessary [4]. One of the modalities for abnormal bone diagnosis is X-ray. The result gives a shadow-like image. When compared with other image diagnosis procedures, X-rays are mostly used because of easy availability, cheapness, harmlessness, and high speed [5]. Fractures of the proximal humerus are primarily identified by conventional methods-radiographs, the type of fracture is determined by anatomical areas and levels of rupture and displacement. However, since non-orthopedic surgeons or the less experienced orthopedic surgeons are often the first doctors for evaluation of fractures, misdiagnosing proximal humerus fracture is very common and fractures are easily mistreated. Furthermore, even experienced orthopedic doctors may misunderstand fracture types because of variable representation [7] [8]. Thus, a more capable and precise way of detecting and categorizing fracture type is the need for time.

Digitization of X-ray imagery is a significant trend. Regardless of the high occurrence of arm-related fractures, no consistent technique for the detection of digitalized X-rays is developed [6]. This study emphasizes digitalizing abnormality recognition for humerus X-ray imageries. Fig.1 and Fig.2 show normal and abnormal humerus digital X-rays, respectively.

Fig.1.Normal Humerus X-ray

Fig.2.Abnormal Humerus X-ray

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The flow for this research consists of four more sections. The literature reviews to identify deformation in the humerus bone and intelligently decipher the X-ray imageries have been briefly discussed in Section 2. In the third section we've elaborated on the methodology that helped in achieving our objective, the fourth section shows the results of this research. Moreover, the conclusion of this research and the forthcoming work is presented in the last division.

II.LITERATURE REVIEW

Humerus abnormalities can be detected through many methods of medical imaging, but because of the easily accessible X-ray imageries, this procedure is extensively used and recommended by orthopedics [5]. Earlier, abnormality recognition in X-ray imageries of the humerus was achieved manually, but as technology has advanced, methods have been suggested to interpret X-ray imageries digitally, and these will be discussed below.

In [9] researcher presented the model where he evaluated the ability of AI to identify and categorize proximal humerus abnormalities by simple radiographs. The authors intended to assess the analytical accuracy of a deep learning process combined with a CNN algorithm for the recognition and sorting of proximal humeral fractures by using anterior-posterior (AP) shoulder plain X-rays. He has associated the outcomes with those in humans. 1,891 common shoulder AP films (1,376 proximal humerus abnormalities cases and 515 normal shoulders) from 1,891 patients (591 men, 1,300 women), 1,083 from Konkuk University Medical Center, 209 taken from Kyungpook National University Hospital, 165 from Myongji Hospital, 203 people from Gangwon National University Hospital, 41 from National Police Hospital, 25 from Seoul St. Mary's Hospital, and 165 from Wonkwang University Sambon Hospital) as the complete dataset for this research. He reduced the over-performance of deep learning by including very similar images of the same patient in each test and training set, using only 1 image per person. The mean age of the patients was 65 (24-90) years.
Among all fracture types, CNN presented the maximum performance in classifying proximal humerus abnormalities types but only high-quality X-ray images were used and idle scenarios were considered.

In [14], the author has tried to digitalize the abnormality detection in elbow X-rays imageries. The method implemented on the available dataset is based on geometrical features and intensity of the bone in images. The study starts with labeling and pre-processing of X-ray imageries, suppressing irrelevant components in images, identifying the bone, detecting edges of the elbow bone, and finally detecting capitulum in the elbow. Then, recording the intensities of bones in the images distinguishes them between normal and fractured elbow bone. The efficiency observed is 82%. The author limited the study by considering images with the same bone pose.

In [15], the researcher identified the fractures in the bones of the hand using X-rays imageries. Hand bones are the smallest type of bones in a skeleton. In the human hand, there are a total of twenty-seven bones. The author started his research by identifying the edges, extracting significant geometrical features for distinguishing between normal and deformed hand X-rays. The algorithm built by the researcher for classification gave a decent accurateness but was limited by addressing only 2 sections of hand bone(phalanges & metacarpals) ignoring other sections of hand bones.

In the paper [16], the researcher focused on image processing methods for identifying fractures in the bone femur. The femur is the major and largest bone of all human bones. The researcher distinguished between normal and deformed femur bone by identifying the tiniest hairline deformation in X-ray imageries. The research starts with reducing noise from images and analyzing important and logical features, then detecting edges. He used an SVM classifier. The accuracy observed for the classification of normal and deformed bone was 84.7% but a small amount of dataset was worked on. This research can be improvised by using a large dataset and by using some other techniques available.

In [10], 116(One hundred and sixteen) humerus fractures (among them 90 proximal) were recovered by computer-assisted randomization with the help of SFR and reconsidered individually at two incidents, after 6 weeks, by 3 experienced orthopedic specialists unaware of patient statistics and consensus "gold standard" grouping was settled. Comparing this to the classifications that have been plugged into the record. In SFR (Swedish Fracture Registry), all kind of abnormalities is entered by the attending surgeon, usually the junior physician. For most fractures, an altered AO/OTA sorting/classification method is used. The research is meant to authenticate the correctness of humeral fracture classification in SFR and deliver awareness into inherent classification ambiguity. The data sets used in this model should belong to the same design.

In [11], multiplex abnormalities in ninety-six consecutive patients were studied by making a fast classification prototype model from computed tomography "Digital Imaging and Communications in Medicine" (DICOM) imaging data. The research assessed numerous classification methods and skillful doctors' anatomical thought for multifaceted injuries centered on a sequence of the patients. The hypothesis said that the current classification system for proximal humerus abnormalities, irrespective of the imaging approach, is insufficient to help in the clinical organization of these abnormalities. Currently, existing proof recommends that, despite the use of imaging modalities, fracture classification in use has poor intra- and inter-observer reliability, so the difficulty of treating these injuries is as weak as it affects scientific research. The research aims to assess the consistency of numerous structures using rapid sequence prototype models.

The major issue of analyzing X-ray imageries manually can be

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resolved by computerizing deformation detection approaches. There are a lot of other studies besides the ones mentioned for interpreting humerus deformation with the help of image processing methods. Our research emphasizes the computerized interpretation of humerus X-ray imageries using the procedures elaborated in the coming section.

III.METHODOLOGY

In this portion, the suggested methodology is elaborated to detect the abnormality in humerus bone automatically. If the experiment performed has clear results, the X-ray image will be classified to be normal otherwise the X-ray image will be considered abnormal. Fig.3 shows the step of the methodology followed in this research.

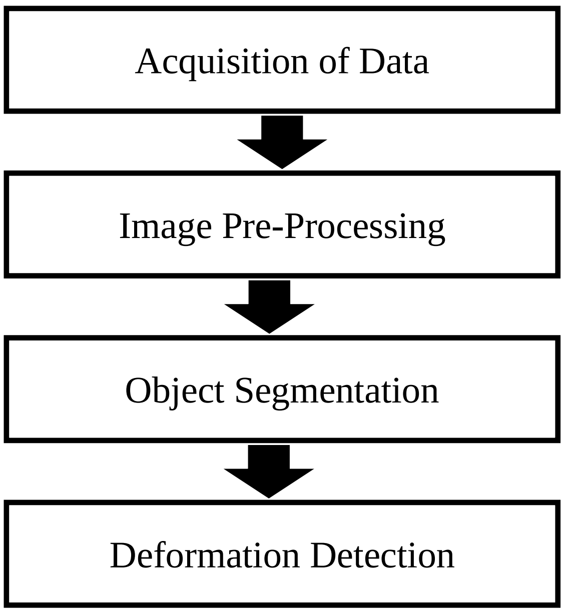

Fig.3.Flow chart of the proposed model to detect deformity in X-ray images

A. Data Acquisition

Firstly, we have collected a dataset from the Stanford ML group website. Stanford ML Group released the MURA dataset, a large dataset of musculoskeletal radiographs containing 40,895 imageries from 14,982 pieces of training [12]. MURA, a dataset of the bone radiographs, tags imageries as 1-(abnormal and positive) or 0-(normal and negative) [13]. The dataset comprises X-ray imageries of dissimilar bones containing (HumerusX-rays, HandX-rays, ShoulderX-rays, ElbowX-ray, and FingerX-rays), etc.

B. Image Pre-processing

The images of humerus X-ray are preprocessed with the help of image-improving methods. The imageries were resized and transformed into gray-scale, the gray-scale imageries reduce noises like color information and in the end, provide an image where the value of each pixel represents only the intensity information of the light. Fig.5 shows the image which is now resized and converted into gray-scale, making it ready for the next stage.

Fig.4.Original Image

Fig.5.Gray-Scale Image

C. Object Segmentation

In the dataset imageries, our region of interest is the humerus bone. The X-ray imageries show background, flash, and bone. To fragment humerus bone, multi-class probability segmentation is implemented on the gray-scale image. Three-class probability segmentation first calculates the probability of each pixel of the image, collects pixels of the same probability, and determines the sign of the similarity of the pixel with the next one. The below figures show three-class probability segmentation. Fig.6 is the normal humerus bone, Fig.7 shows class-1, where all pixels of background having the same standard are highlighted. In the remaining part, the resulting possibilities are recalculated and the outcome of class-2 is presented in Fig.8. For the outcome of class-3, pixels having similar statistics for the bone are emphasized as shown in Fig.9. With the assistance of three-class probability division, the humerus is taken out from digital X-ray imageries, further treated in the coming stage. Fig.11, 12, 13 also shows the probability segmentation but of fractured/abnormal humerus bone.

Fig.6.Input Image, Normal Humerus X-ray

Fig.7. Result of Class1, Foreground Extraction

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Fig.8. Result of class2, Flash Suppression

Fig.9.Result of Class3, Bone Detection

Fig.10.Input Image, Abnormal Humerus X-ray

Fig.11. Result of Class1, Foreground Extraction

Fig.12. Result of class2, Flash Suppression

Fig.13.Result of Class3, Bone Detection

D. Deformity Detection

Once we get our region of interest i.e. humerus bone, we fill the vacant space in the bone area, convert the image into a binary matrix which removes all linked components that have fewer than P pixels, this eliminates all the irrelevant modules around the bone from the image as shown in Fig.14 and Fig.15. The next step is to crop and rotate an image. Image is cropped manually because of different bone sizes and locations of bone in an x-ray image. The cropped image is then rotated to a certain angle. The width of the humerus is examined and an outline is observed. The gradient is imposed on a designated region of an image to calculate the modification. For better visual output, the color map is implemented on the outcome of the gradient, and the bone is divided into two portions. Using geometric features examination, boundaries are identified at every point. The distance between the upper part of the bone and the lower part of the humerus bones is calculated and noteworthy structure is analyzed. A similar procedure is implemented on abnormal X-rays as well. Many X-rays imageries are examined and the outcomes are displayed in the coming segment.

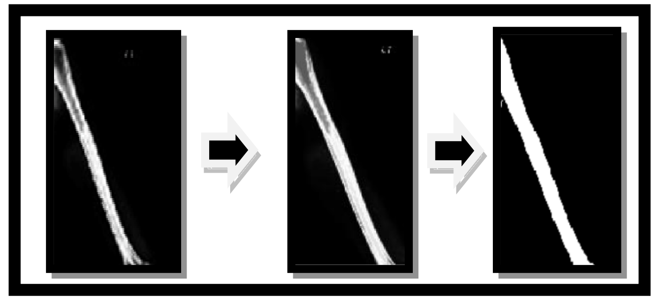

Fig.14.Binary-Image of Fig.9

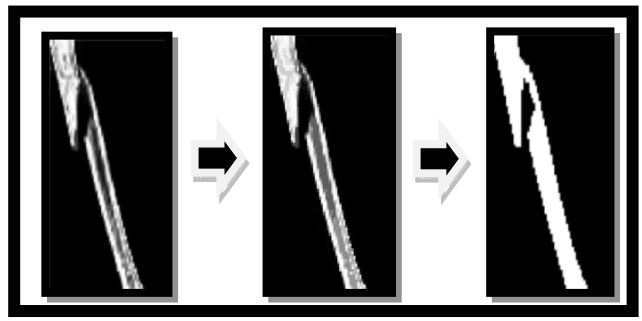

Fig.15. Binary-Image of Fig.13

IV.RESULTS AND DISCUSSION

Geometric features examination is applied on output images of Fig.14 and Fig.15 after rotating them. Local-maxima are discovered at every single point for getting the boundaries of bones as shown in Fig.16 and Fig.18 for normal and abnormal X-rays, respectively. The distance between the upper part of the bone and the lower part of the bone is observed by boundaries detection as shown in Fig.16(c) and Fig.17(c). Fig.16(d) shows the output of the technique observed in a normal X-ray. A related technique is implemented on abnormal X-rays having abnormalities and output can be seen in Fig.17(d), the noteworthy patterns in the graph are analyzed in many normal X-rays isn't found in abnormal X-rays. The visible difference in terms of pattern fluctuation can be observed between normal and abnormal humerus X-rays, sudden drop in the graph indicates the abnormality in the bone, and hence bone is identified as fractured. The X-ray which passes this method with no abrupt change in the graph is considered a normal X-ray.

The procedure is implemented on several imageries for identifying normal and abnormal humerus X-rays. The figures below show the results of the technique used on normal and abnormal bone.

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A. Normal Bone Detection

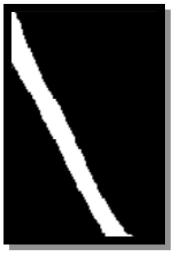

Fig.16(a)

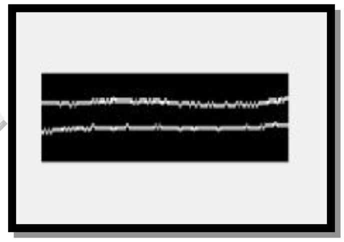

Fig.16(b)

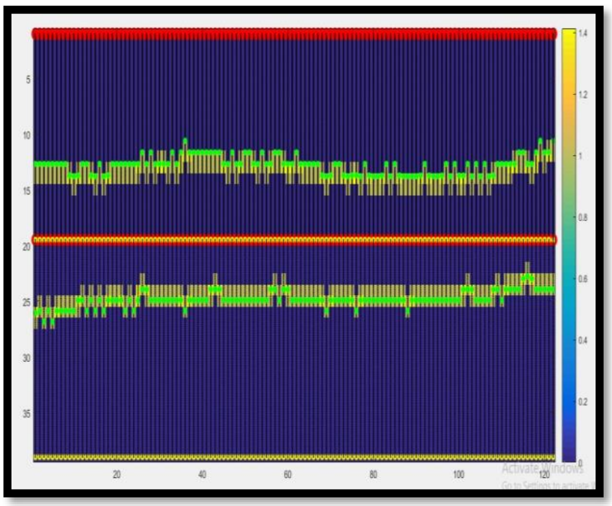

Fig.16(c)

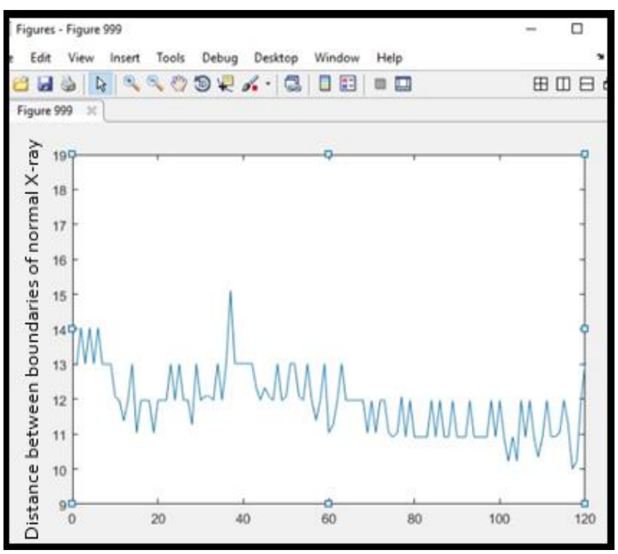

Fig.16(d)

Fig.16. (a) Shows the segmented normal humerus bone. (b) Displays the result of the image gradient. (c) Shows colored form of gradient image with peaks of the normal humerus bone detected. (d) Point out the distance between lower and upper edges/boundaries of the normal humerus bone.

B. Abnormal Bone Detection

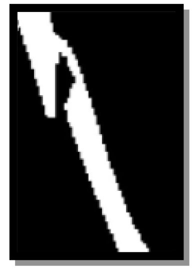

Fig.17(a)

Fig.17(b)

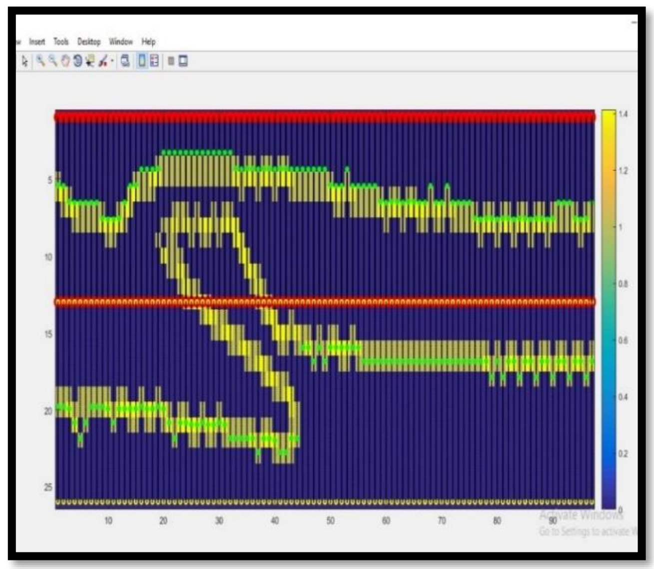

Fig.17(c)

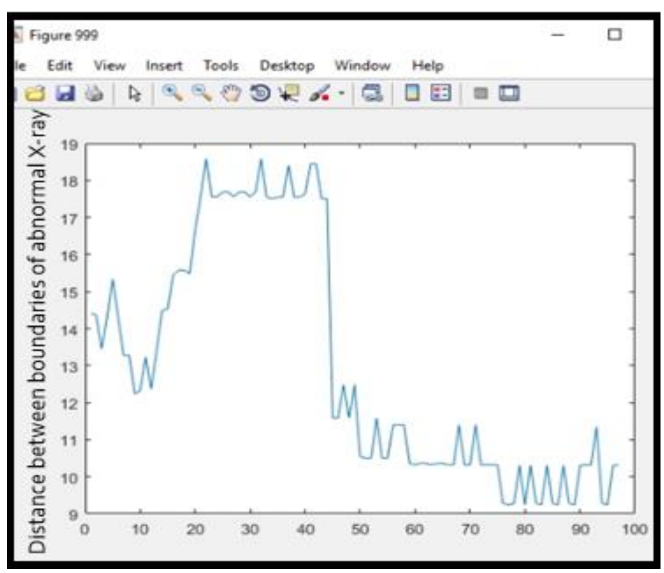

Fig.17(d)

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Fig.17. (a) Displays the segmented abnormal humerus bone. (b) Shows a result of the image gradient. (c) Displays the colored type of gradient output with peaks of Abnormal Bone detected. (d) Points out the distance between the upper and lower boundaries of the abnormal humerus bone.

C. *Experimental Results*

Image Size	Labeled As	Detected As
292x450	Positive	Positive
145x190	Negative	Negative
348x512	Positive	Negative
512x509	Positive	Positive
421x512	Negative	Negative
420x512	Positive	Positive
301x512	Positive	Positive
512x512	Positive	Positive
420x512	Positive	Positive
295x512	Negative	Negative
421x512	Positive	Positive
512x512	Positive	Negative
352x512	Negative	Negative
301x512	Positive	Positive
100x189	Positive	Positive

Table.1.Shows some experimental results obtained from the geometric feature examination technique.

D. *Accuracy*

TOTAL NUMBER OF IMAGES = 300

- True Positive (TP) = 170
- True Negative (TN) = 72
- False Positive (FP) = 8
- False Negative (FN) = 50

ACCURACY: 80%

V.CONCLUSION AND FUTURE WORK

In this research, the goal is to digitalize the deformity recognition in humerus X-rays Images which minimizes human dependency as the repeating and manual tasks are automated, the probability of human error is also greatly reduced. The model is implemented on the publically available dataset(MURA) and the accuracy observed is 80%. In the future, techniques with complex features of bone can be considered for automatically detecting the deformation efficiently and thus improving the accuracy.

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