Computer Assisted Solution for bone Anomaly detection in X- Ray images

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***Abstract*—Bones are the major and essential part of the body. Disease or injuries are main reason of irregularities in the human skeletal system. There are many types of bone anomaly: fracture, Rickets, Osteomyelitis, Osteosarcoma, osteoporosis, etc. X-rays are most common and oldest types of medical images. These are preferred to analyze anomaly in bones. In this research, we have detected the abnormality in forearm with the help of X-ray. Firstly, we have applied pre-processing technique to improve the quality of the image after that we extracted our region of interest that is in forearm bones. Furthermore, using edge detection technique delineated the bone from the background and then detected the capitulum inside the elbow bone where two bones are connected, then we have recorded intensity for both bones. Afterward, the hand-crafted features which we have derived are capable of differentiating normal and abnormal bones from x-ray images. Finally, we have used feature vectors for training and testing. Support Vector Machine (SVM) is used for classification. For practicing the technique, we have used MURA datasets which are available publicly for research purpose. Ninety (90) images have been trained and the accuracy of 93.5% has been achieved. After that, 40 images have been tested and achieved 85.7% accuracy.**

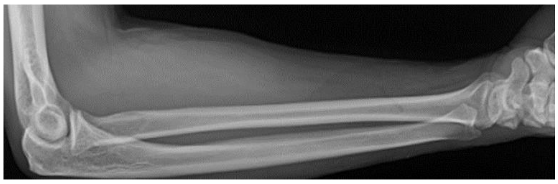
Keywords—Data Acquisition, Edge Detection, Feature Vectors, SVM Classifier, Abnormality Detection

I. INTRODUCTION

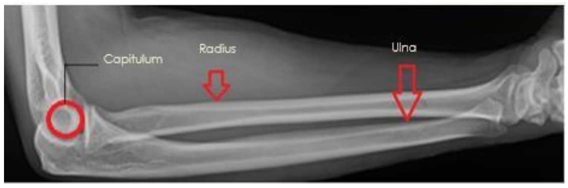
Bone fracture is a common leading problem nowadays even in developed areas, it is growing rapidly worldwide. A Bone could be fractured even by a simple accident or many disease cause irregularities in the bone like Rickets, Osteomyelitis, Osteosarcoma, osteoporosis etc. There are different types of bone fracture such as simple, compound, greenstick, oblique, comminuted, spiral, transverse and greenstick [13], [14].

X-ray (Radiographs) is one of the most common method that is used for detect the abnormality in bones and also in other organs of the human body. X-rays have few limitations. X-ray uses a small amount of radiation as compared to Computed Tomography (CT) and Magnetic Resonance imaging (MRI) which effect on their quality [15].

Among emergency department of trauma patients, the bones anomaly is one of the common problems which have been diagnosed. According to research it is indicated that about 8 to 10 percent of fractures are of elbow and forearm and it is increasing day by day [17].



(a) Forearm X-ray



(b) Forearm X-ray image with different bones

Fig. 1. Forearm X-ray Image. (a) Shows the original forearm x-ray image. (b) Shows different bones present in human forearm.

The aim behind proposing this system is to make X-rays imaging technique more efficient system for anomaly detection in bones. Other benefit of this system is saving time for patients and reduces human error. Our focus is to detect the abnormality in forearm bones by following methodology discussed below in section 3. The work flow of the proposed system is discussed in detail; in the section II Literature overview is deliberated. The section III and IV discussed methodology and its experimental results. In the last section conclusion and future directions is discussed

II. LITERATURE REVIEW

A large amount of work has been done on Computer aided diagnosis and due to noticeable betterments; it still keeps gaining the interest of researchers. Those systems which provide a highly accurate and clear diagnosis with limited resources are recommendable.

In [2], authors have proposed a technique to find fracture in bones of hand in x-ray images. They gathered the datasets that contain normal and abnormal x-ray images then enhanced them by some filtering methods that removed noise, and then edge detection methods are applied. The images are converted in to features a set using Wavelet and Curvelet Transforms, then a classification algorithm is applied on the finally extracted features. They have taken a small dataset whereas experimenting with large and diverse dataset could yield better results and established facts. Femur bone is one of the cores and largest part of human body.

In [3] authors have proposed a method to detect anomalies for finding fractures in the femur bone of human body through image processing techniques. Initially noise is extracted from the images taken as input by suppressing the background, so that the major area of interest can be highlighted by using morphological operations that is opening then edge detection techniques are applied for highlighting the foreground, then image is classified into both sides of image (normal and abnormal) by using the SVM (Support Vector Machine).

Photogrammetric techniques are commonly used for medical diagnosis and treatment; those are Computed Tomography (CT), Ultrasound and Magnetic Resonance imaging (MRI) images.

Catal Reis, H in [4] have worked on edge-based segmentation technique which is used for the detection of anomaly in CT images of foot. In this paper, author used a canny edge detection algorithm for extracting the edges, then they follow five core steps: (i) Horizontal and vertical gradient are calculated, (ii) Detect gradient direction and gradient magnitude, (iii) Application of non-maximal suppression, (iv) Calculating high and low thresholds, (v) Finally, hysteresis thresholding is applied to detect anomaly of the foot bone on CT images.

The authors in [5] proposed a technique of automatic classification of x-ray images. In this work, three main components are used first component Image Enhancement; second Feature Extraction and third Support Vector Machine (SVM). The research is limited to the usage of SVM classifier; they should also observe the effects of other practiced classification algorithms as well.

Authors in [6] have worked on dataset of digital x-ray images and divided that data into five groups that is; head-neck, upper-limb, body, lower-limb, and other. In this study state of-the-art classifier and feature selection methods are applied to improve the challenging tasks and highlight the features that indicate bone size and structure, computed nine feature extraction method that is TEXTURE, COLOR, HoG, BoVW (SIFT), BoVW (SURF), BoVW (BRIEF), BoVW (ORB), COLOR+TEXTURE, COLOR+TEXTURE+HoG and then tested the four classification methods SVM, KNN, DBN and LR. The limitation of this research is that they used only five groups of images; it should extend their research further.

In addition, a number of studies [9, 10, 11, and 12] have reported the bone anomaly detection using computer methods; however, these methods normally employ small dataset as well as they detect fracture in only horizontal images. In these papers Images are based on upper end and lower end bones.

We have discussed the related work based on x-ray, CT, MRI or ultrasound on different bones. According to our knowledge, this work has not happened in the forearm bone abnormalities.

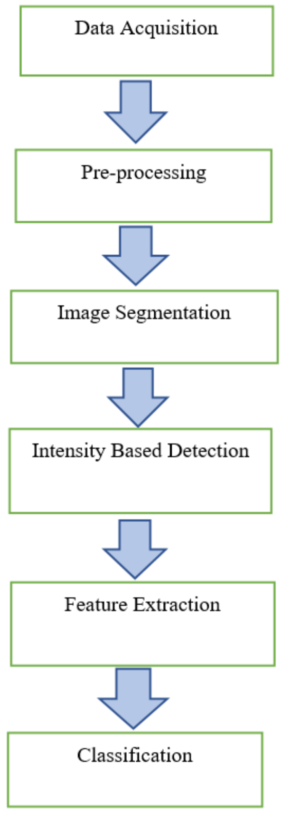


Fig.2. Flow chart of the proposed system

III. METHODOLOGY

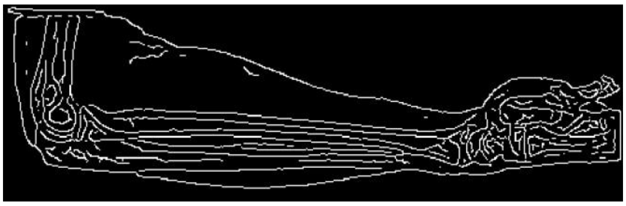
In this section, overall system design is described, Fig. 2. Shows the flow chart of our proposed system. The aim of this work is to recommend an efficient system for a quick and accurate analysis of forearm bone fractures based on the information gained from the x-ray images.

A. *Data Acquisition*

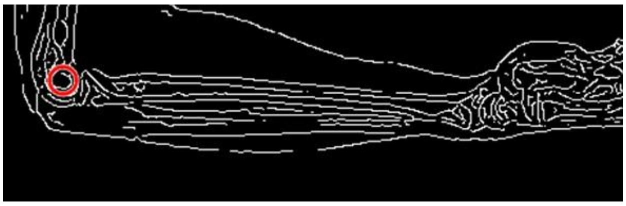
The first step is the collection of datasets and other is labeling the dataset as normal or abnormal. In this research we used publicly available dataset which is MURA and it's downloaded from MURA website [16]. MURA (musculoskeletal radiographs) is a large dataset consist x-ray images of different bones such as elbow, finger, forearm, shoulder, hand, humerus and wrist. For forearm It contained around 1000 x-ray images with the labels that is Negative (Normal) or positive (Abnormal).

B. *Image Pre-processing*

After Collection of datasets and labeling we applied basic pre-processing techniques to improve the quality of images. We converted images into gray scale; this process eliminates the color information from the image and leaves behind the luminance of every pixel in image. After that we removed all irrelevant information form the images. Now dataset was ready for further process.



a) Canny edge detected image



b) Circle detection on canny detected image

Fig. 3. Edge & Circle Detection. (a) Shows the output of canny edge detection. (b) Shows the circle detection on the edge detected image.

C. *Image Segmentation*

Image segmentation is the basic step to examine image and extract the important information from them. The main purpose of image segmentation is to suppress the irrelevant information and extract the Region of Interest (ROI). There are three main methods of image segmentation which are region-based segmentation, boundary-based segmentation and edge-based segmentation.

In our work, the best result was obtained through canny edge detection method which we applied on pre-processed image. After that, we have detected the circle by using Hough transform [18] by setting the parameters for center as 10 pixels and for radius as 18 pixels. The circle is basically the capitulum of the elbow bone where the forearm bones Radius and Ulna are connected.

D. *Intensity Based Detection*

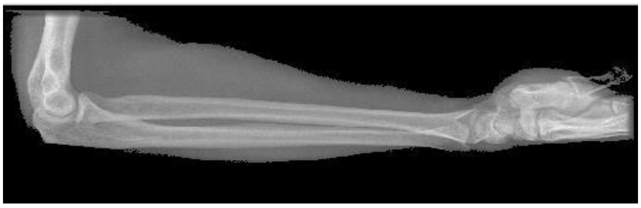
When the circle was detected on edge detected image, we have positioned that circle back on the pre-processed input image. With respect to the capitulum, we have identified new points on Radius and Ulna. These bones are joint with capitulum, which we have detected earlier. The procedure was applied on many images and at the end those images having a smooth intensity classified as normal and those having dropped of intensity were classified as abnormal.

E. *Feature Extraction*

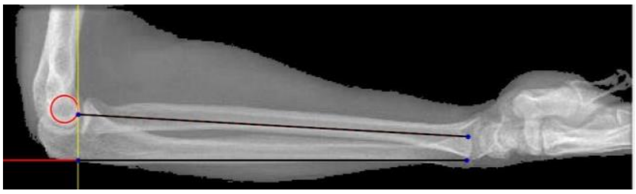
Feature extraction plays an important role in the performance of any image classification because it can produce important impact on the results of classification.

In this work, we have evaluated few features such as Circularity, Inter Bone Distance, Window mean and Maximum intensity for both Radius and Ulna bone.

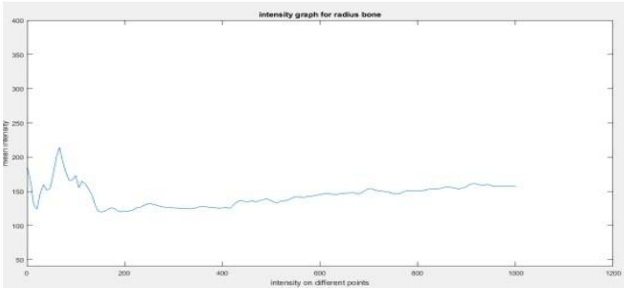
N1Cir= [0.25]
N1IBD= [48.0 40.05 34.06 18.03 13.04]



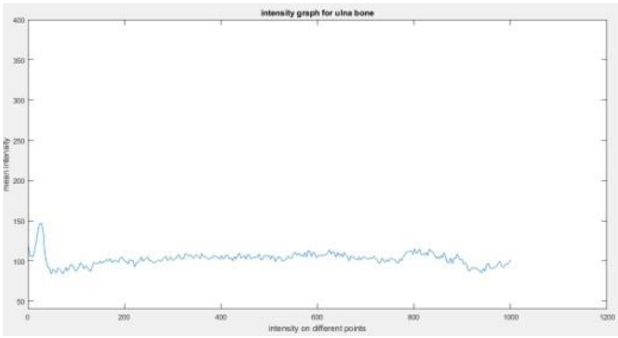
a) Input Image



b) Circle detected image



c) Intensity graph for radius bone



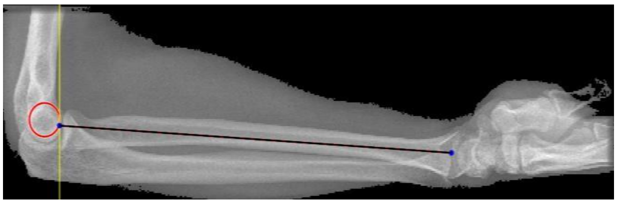
d) ***Intensity graph for ulna bone***

Fig.4. Intensity Detection. (a) Shows the pre-processed image. (b) Shows the circle detection. (c) Shows the intensity graph for radius bone. (d) Shows the intensity graph for Ulna bone.

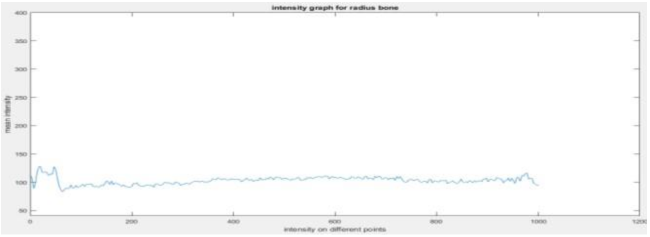
N1mvalueRadius = [211.1242 226.3298 231.9210 226.4183 220.6199 175.2065 167.0184 178.0481 177.1801 154.4360 164.3683 168.6456 140.4037 123.2496 120.4968 129.9898 130.5987 125.1200 125.6845 129.9503]
N1mvalueUlna = [171.6973 170.5667 175.8885 182.7024 160.6277 156.4823 157.1100 151.2049 153.4732 156.1554 151.9230 148.8920 147.1617 145.4742 147.5473 145.7403 146.1018 152.3880 153.3272 152.0509]
N1maxvRadius = [129.9503]
N1maxvUlna = [152.0509]
N1img = [N1Cir N1IBD N1mvalueRadius N1maxRadius N1mvalueUlna N1maxUlna]

N1Cir value shows the circularity of the X-ray image. Circularity shows that how much circle is accurate.

a) Input image



b) Circle & line detected on normal adius bone



c) Intensity graph for Radius bone

Fig.5. Normality Detection in Radius Bone. (a) Shows the pre-processing image. (b) Shows the circle and line detection on Radius bone. (c) Shows the intensity graph for Radius bone in which it can be seen as there is no any sudden drop in intensity so, Radius bone is classified s normal.

N1IBD value shows the inter bone distance. We find distance between Radius and Ulna bone by using MATLAB command. Afterward, next feature is window mean, in which we have firstly make the sample of 20 value and then find window mean values of the Radius bone. N1mvalueRadius show window mean values of the Radius bone, and then find the maximum mean value. N1maxvRadius shows the maximum mean value of the Radius bone. After that same process is done for Ulna bone, N1mvalueUlna show window mean values of the Ulna bone and N1maxvUlna shows the maximum mean value of the Ulna bone. At the last we display all the features in one row.

F. *Classification*

After finding feature vectors the dataset is ready for classification. A Classification (classifier) technique is an efficient approach to building classification models from an input dataset. Many Classifier algorithms are used to solve for these types of problems some algorithms are Decision Tree Classifiers, Rule-Based Classifiers, Neural Networks, Support Vector Machines and Naïve Bayes Classifiers [19], [2]. In this work, we used SVM classification to classified x-ray images as normal or abnormal. In this work, K-fold cross validation technique is applied, firstly it dividing the dataset into k fold of the same size. After that, it selects one of them as testing set and other as the training set based on the model which is being built. This technique is repeated for each fold and after that average accuracy is recorded. In this paper, 90 images have been trained and the accuracy of 93.5% has been achieved. Afterward, unseen 40 images have been tested and 85.7% accuracy was achieved.

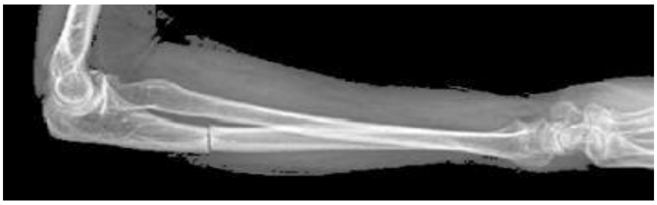
IV. Result & Discussion

The algorithm is applied on number of images for detecting normal and abnormal forearm x-ray images. For abnormal there are three different possibilities. The abnormality occurs either in Radius bone, Ulna bone or in both bones.

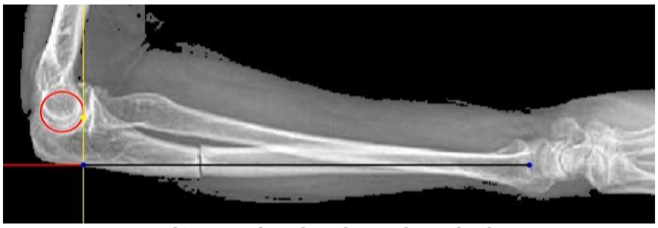
A. *Normality Detection*

B. *Abnormality Detection*

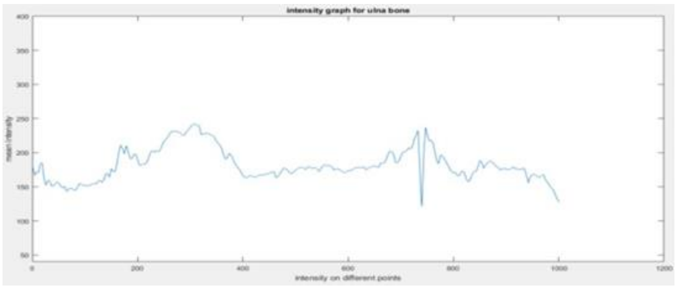
1) *Abnormality in Ulna Bone*
2) *Abnormality in Radius & Ulna Bone*
3) *Abnormality in Bone*



a) Input image



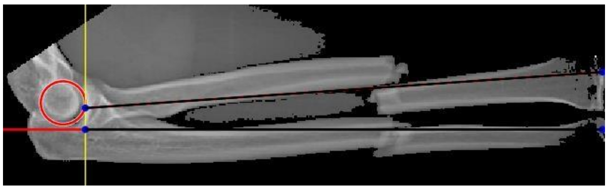
b) Circle & line detected on Ulna bone



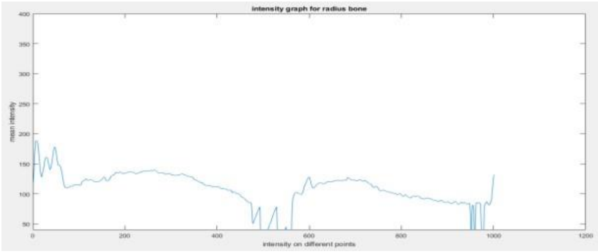
c) Intensity graph for Ulna bone

Fig.6. Abnormality Detection in Ulna bone. (a) Shows the Input Image. (b) Shows the circle & line detected on Ulna bone. (c) Shows the intensity graph for Ulna bone in which it can be seen that the intensity fluctuation in abnormal X-ray image is dropped suddenly where there is fracture in Ulna bone so, the X-ray image for Ulna bone is classified as Abnormal.

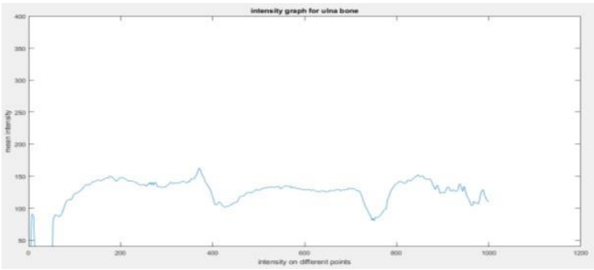
a) Input image



b) Circle & line detected on both bones

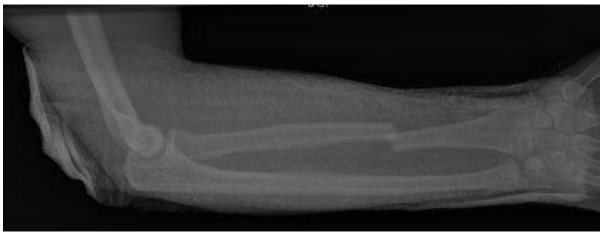


c) Intensity graph for Radius bone

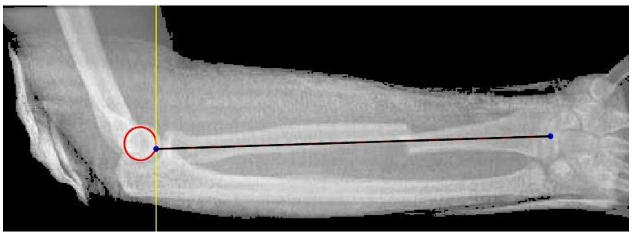


d) Intensity grapg for Ulna bone

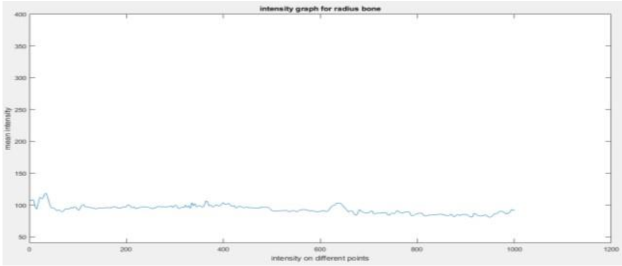
Fig.7. Abnormality Detection on Radius and Ulna Bones. (a) Shows the input image. (b) Shows the circle & line detected on Radius & Ulna bones. (c) Shows the intensity graph for Radius bone in which it can be seen that the intensity fluctuation is dropped suddenly where there is fracture in Radius Bone so, Radius bone is classified as abnormal. (d) Shows the intensity graph for Ulna bone in which it can be seen that the intensity fluctuation is dropped suddenly so, the X-ray for Ulna bone is classified as abnormal.



e) Input image



f) Circle & line detected on Radius bone



g) Intensity graph for Radius bone

Fig.8. Abnormality Detection on Radius Bone. (a) Shows input image. (b) Shows circle & line detected on Radius bone. (c) Shows the intensity graph for Radius bone in which it can be seen that there is no any change or dropped in intensity for Radius bone when there is a minor fracture in Radius bone so, here this technique is not performing well.

V. Conclusion & Future Direction

In this study, the problem of detecting abnormality in forearm X-rays has been discussed. In this system basic preprocessing techniques are applied after that; canny edge method is used to determine the ROI and then intensity-based detection is used to identify the abnormality. Moreover, different set of features are extracted and at the end SVM Classifier is used. 90 images have been trained and the 93.5% accuracy has been achieved. Afterward, unseen 40 images have been tested and achieved 85.7% accuracy. In future, different feature vectors can be extracted and used different classifier to improve the accuracy on more x-ray images.

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