

Journal of Advances in Mathematics and Computer Science

35(4): 1-11, 2020; Article no.JAMCS.57620
ISSN: 2456-9968
(Past name: British Journal of Mathematics & Computer Science, Past ISSN: 2231-0851)

Detection of Fracture Bones in X-ray Images Categorization

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/JAMCS/2020/v35i430265
Editor(s):
(1) Dr. Doina Bein, California State University, USA.
Reviewers:
(1) J. Jeevanandam, Amity University, India.
(2) H. Yildirim Dalkiliç, Erzincan Binali Yıldırım University, Turkey.
(3) Umamaheswari Duraiswamy, Vidyasagar College of Arts and Science, India.
Complete Peer review History: http://www.sdiarticle4.com/review-history/57620

Original Research Article

Received: 25 March 2020
Accepted: 02 June 2020
Published: 13 June 2020

Abstract

Fractured bone detection and categorization is currently receiving research attention in computer aided diagnosis system because of the ease it has brought to doctors in classification and interpretation of X-ray images. The choice of an efficient algorithm or combination of algorithms is paramount to accurately detect and categorize fractures in X-ray images, which is the first stage of diagnosis in treatment and correction of damaged bones for patients. This is what this research seeks to address. The research design involves data collection, preprocessing, segmentation, feature extraction, classification and evaluation of the proposed method. The sample dataset were x-ray images collected from the Department of Radiology, National Orthopedic Hospital, Igbobi-Lagos, Nigeria as well as Open Access Medical Image Repositories. The image preprocessing involves the conversion of images in RGB format to grayscale, sharpening and smoothing using Unsharp Masking Tool. The segmentation of the preprocessed image was carried out by adopting the Entropy method in the first stage and Canny edge method in the second stage while feature extraction was performed using Hough Transformation. Detection and classification of fracture image employed a combination of two algorithms; K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) for detecting fracture locations based on four classification types: (normal, comminute, oblique and transverse).Two performance assessment methods were employed to evaluate the developed system. The first evaluation was based on confusion matrix which evaluates fracture and non-fracture on the basis of TP (True Positive), TN (True negative), FP (False Positive) and FN (False

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Negative). The second appraisal was based on Kappa Statistics which evaluates the type of fracture by determining the accuracy of the categorized fracture bone type. The result of first assessment for fracture detection shows that 26 out of 40 preprocessed images were fractured, resulting to the following three values of performance metrics: accuracy value of 90%, sensitivity of 87% and specificity of 100%. The Kappa coefficient error assessment produced accuracy of 83% during classification. The proposed method can find suitable use in categorization of fracture types on different bone images based on the results obtained from the experiment.

Keywords: Fracture bones; detection; classification; categorization; X-ray images; kappa method; support vector machine (SVM); k-nearest neighbor (KNN); KNN-SVM.

1 Introduction

Digital image processing is one of the best ways that is gaining wider range of acceptance in salvaging the visual information in healthcare industry and other related fields. This plays crucial part in automatic analysis of images and assist medical experts during their diagnosis and decision making [1]. Bone fracture is one of the common diseases that affects both the young and the old in modern society. A bone disorder is the breaking up of an incessant bone that cannot endure the outer force and unable to move a part of the body. This can result to pain and displeasure by patients. The detection and correction treatment of fracture need quick action by passing through X-ray- emission machine to the body [2]. The major limitation of detecting fractured bones in X-ray Images in most Nigerian Hospitals is the inadequate availability of efficient automated detection, making it uneasy for medical personnel to interpret, classify and effectively diagnose and proffer treatment for patients. The X-Ray machine is non-invasive and it reveal the images of the human body. The vast assembly of X-ray images is captured using digital devices such as web camera, phones etc. by the improvement of the storage media [3].

The bones have different types of features, which includes; comminuted, compound, greenstick, oblique, spiral, and transverse. Medical images are stored in the standard format called Digital Imaging and Communications in Medicine (DICOM). Any effort to retrieve and display the images must pass through Picture Archives and Communication System (PACS) hardware [4]. With the development of computer skills and capabilities, medical imaging has developed the potential approach to the challenge of diagnosis of images. X-ray images cannot be read and understood by a radiologist with an open eye due to presence of inherent noise. By developing medical imaging classification, it is hoped that, this will give assistance to radiologists in detecting bones fractured abnormalities and reduce time spent in its interpretation [5].

In orthopaedic treatment, fracture classification plays a vital role in categorization of bone and it is essential for doctors to determine the severity and course of treatment of the injury. The anatomy of human bones has different features in nature which depends on its location, types and fracture-lines [6]. The core of this research is to implement a system that detect bones fracture in X-ray images based on categorization from the adoption of two classifiers. This will ease the means of diagonising patients for fracture injury and helps to eliminate inessential medical procedures.

2 Related Work

The use of image processing techniques in various medical fields have been worthwhile, embedding several applications and procedures involving compression, extraction of region of interest, segmentation, detection and categorization to mention a few. Some of the procedures employ the use of artificial intelligence tools, leading to optimal results [7]. designed SVM classifier for detection of fracture long bone types of X-ray images. Some imaging system tools were applied to eliminate salt and noise from the extracted features. 85% in the classification accuracy and testing results were recorded. [8] presented a method that can detect bone fracture types and that physical examination of X-ray images by experts take a difficult time to process

and are prone to errors. Therefore, development of automated model will help detect the nature of the fracture(s).

[9] developed an automated detection of fractures in leg bones. Hough transform technique was used for features extraction for line detection in the images. [10] implemented a combination of different classifiers for detection of fractures in Tibia bone. The system carried out preprocessing and segmentation, and then texture features were extracted. Feed Forward Backpropagation Neural Networks (FFBNN), SVM and Naive Bayes (NB), were used for classification. [11] presented a classifier decision model that predicted the type of treatment for patients with fractures based on their X-r-ay images. Hough transform and gray-level occurrence matrix (GLCM) were applied to extract features of the bone images. The techniques were evaluated in a computational experiment to construct multiple classifiers. The results show that structural features have improved predictive abilities with no statistical differences in overall classification accuracy ranging from 91.0% to 96.1%.

[12] presented image processing technique for identification of fracture bone areas from the X-ray and CT images using Laplacian method of edge detection. Some statistical parameters (such as mean and standard deviation) were calculated to analyze the accuracy and sensitivity of the used technique.

[13] presented the development of fracture detection system using digital image processing on medical X-ray image. The Non-fracture and fracture or Transverse fracture was classified using SVM classifier. Table 1 shows a theoretical review identifying the major drawback of the earlier research work on bone fracture classification. The inference form the review indicated that some of the authors adopted the use of single algorithm which resulted in degraded performance. Others did not indicate empirical values for the performance accuracy of the detection. This work however adopted KNN to complement SVM for the detection and classification of bone fracture images into its various types for improved performance accuracy.

Table 1. Comparison analysis of existing techniques[1]

S/N	Author(s)	Strategy	Limitations	Performance accuracy %
1	Mahendran, et al. (2011)	BPNN, SVM & Naïve Bayes	Shape features - not considered.	86
2	Al-Ayyoub, et al. (2013)	SVM	Segmentation.	85
3	Edward, et al. [8]	BT	Edge detection	Not reported
4	Myint & Thinzar [13]	SVM	No good performance	Not reported

3 Methodology

The block diagram shown in Fig. 1 shows the five different stages of analysis the x-ray images stored in the database would undergo (i) the acquisition of x-ray images (ii) the preprocessing is by smoothing and removing noise of the image edges. (iii) The segmentation by entropy and canny edge methods where image gray-zones are extracted from the x-ray image. (iv) feature extraction using Hough transform whereby the relevant properties of the image are extracted and analysed for detecting whether a break point exist or not in the uploaded x-ray image and a circle is drawn at the breakpoint, (v) the last step was classification of fracture bones types into categories using KNN and SVM.

3.1 Input X-ray image

Input images used were collected from the Department of radiology, National Orthopaedic Hospital, Igbobi, Lagos State, Nigeria, while others were downloaded from http://www.aylward.org/notes/open-access-medical-image-repositories. The first step scheme of classification system is the input of images. All input X-ray images collected were stored for training dataset and serve as input data to features extraction stage.

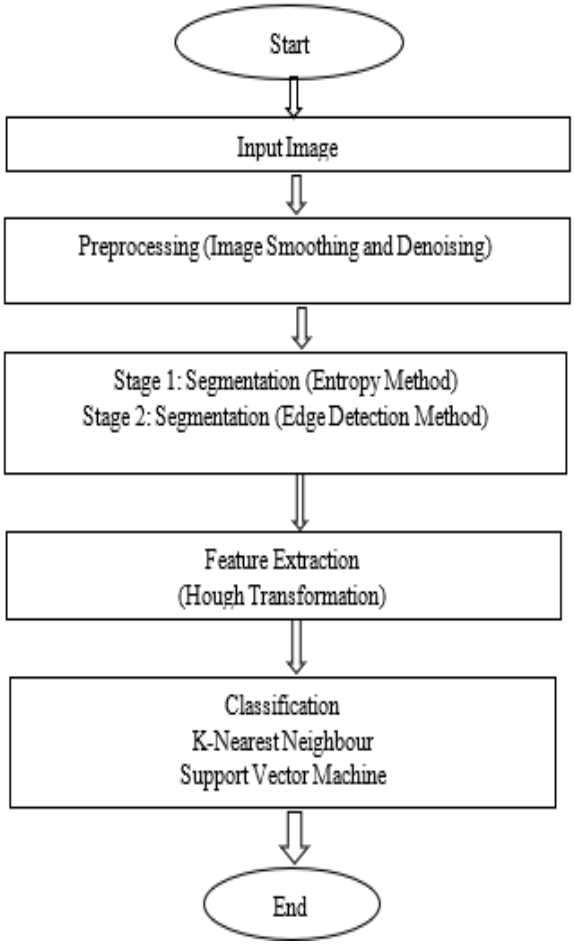
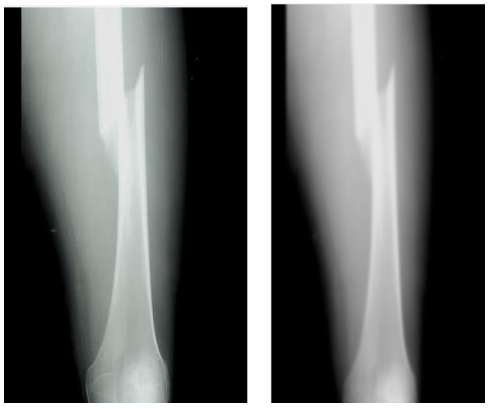


Fig. 1. Categorization of fracture bones stages



(a) **(b)**

Fig. 2. (a) Original image (b) output image for preprocessing

3.2 Preprocessing

The second step is done to improve the image data to suppress irrelevant features necessary for the next stage of processing. In this step, the X-ray image in RGB format is converted into a grayscale image for better processing and less computation time. The smoothing of the image was carried out to enhance edges and increase fine details in the image, this was done to derive a better and sharper image using basic concept of Unsharp masking (USM) tool. Gaussian blur an image denoising was used to remove noise from the x-ray image, this is to restore the true image because noise will obscure the highlights of the image and making the picture appear significantly worse.

3.3 Segmentation (Entropy)

In this research, the third step of the proposed system is the first stage segmentation which adopt the Entropy method. In x-ray images flesh are captured as darker gray while the bones are captured as brighter gray hence, at this stage the image gray-zone values are arranged into similar areas to separate the background, the flesh and the bone. It recognizes to be one of the most vital steps in the image examination system as numerous sets of pixels of image was separated hence, the gray zone areas are separated from the black background area and the flesh. This enable the analysis and interpretation of bone zones only, leaving the background and the flesh.



(a) **(b)**

Fig. 3. Result images for segmentation image (Entropy) original image on the left and first segmentation image (right)

3.4 Second stage segmentation (Edge detection)

The fourth step is the second stage of the segmentation which is the Edge Detection Method. This stage was carried out by using different mathematical methods that aim at identifying points in the x-ray image at which the x-ray image brightness changes sharply or has discontinuities, at such points a line is draw to represent the change in brightness this helps the Hough Transform to figure out if there is a break in the bone or not. Many edge detection methods are available, some of which are Canny edge detector, Prewitt edge detector and Sobel edge detector etc. In this paper the canny edge method was used to identify the accuracy of fracture bone of the X-ray images. Canny detector method produces good view of bone structure and has a better advantage over other edge detectors. This is filtered to detect fracture bone edges. The edge detection was used to obtain bone edges in image and filter out the two longest lines

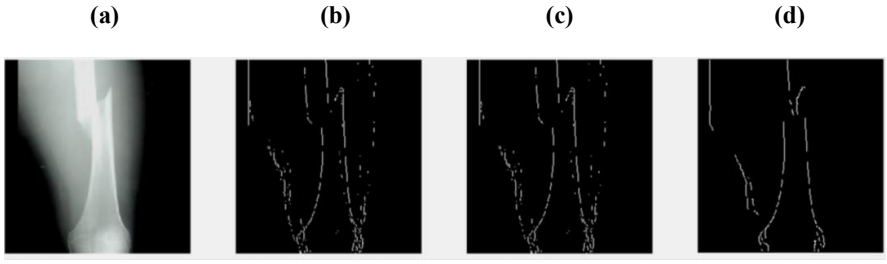


Fig. 4. a=> Original image, b=>Sobel Edge, c=>Prewitt Edge Detection, d=>Canny Edge

3.5 Feature extraction (Hough transformation)

The purpose of feature extraction is the information extracted from an image which provides more relevant feature of the image. Hough transform algorithm is used in this research to extract the features in binary form from the image. Hough transform algorithm deals with lines identification or detection of radius of fracture as it combines the basic features of the bones. The resulting edge image from the first segmentation serve as the input to the Hough transformation process. The features extracted are centroid, size, width height, boneEdges position of the cropped image, length of line to use to detect bone regions of the image and areas region The extraction of the lines was used to distinguish detecting the fracture or non-fracture image types. A straight line image can be represented as

$$r = x\cos\theta + y\sin\theta$$

where, r represents distance that is the perpendicular line from origin to the test line θ (Angle) is between the perpendicular line and the horizontal axis and then x, y are constants. A line in the image space is mapped to a point in the parameter space.. These extracted features are given as input to the KNN-SVM classifiers for classifying fracture and non-fractures image types.



Fig. 5. (a) Input image (b) Hough Transform image (right)

3.6 Classification of fracture

The next step is the classification of the image, which employs two classifiers namely KNN and SVM. These classifiers were chosen primarily because of their individual ability to decrease training time and

increase the accuracy of classification. The 2 classifiers were used sequentially, wherein the output from the feature extraction stage was fed into KNN and the output further fed into SVM for classification. K-NN was used as the first classification model due to its simplicity. The several categories of fracture bones was classified appropriately without confusion by using the multiclass SVMs classification model. The KNN-SVM improves the overall correctness and sensitivity compared with single classifier. The KNN classifies the dataset without initial training of images, reducing the dimension of the data. This is because of its simplicity and strength against noisy dataset. The SVM then perform classification on a reduced dataset which irrelevant training sample have been eliminated with similar feature pattern. The SVM trains only similar images of the dataset and displayed fractured trained successfully otherwise error training data. This ensures faster training process for SVM and improve the performance of the K-NN in the categorization of X-ray Images. The images have been segmented and resized into standard format 100 *100. The training catches the break points of the fracture bone. The SVM with radial basis function kernel was employed. SVM compared the test image with the train dataset with Euclidean distance.

Table 2. KNN-SVM algorithm

1.	compute distances of the query to all training images
2.	if the K neighbors have all the same category,
3.	then the query is labeled and exit with that particular category
4.	else, calculate the pairwise distance between the K neighbors;
5.	change the distance matrix to a kernel matrix and implement multiclass SVM;
6.	apply the resultant classifier to label the query from SVM classification

3.7 Proposed framework of categorization of fracture bones

Stage I

1) input the images to be to be categorized.

Stage II

2) Resize the X-ray image in RGB format is converted into a grayscale image and amount to denoise input image

3) The images are segmented and resized into standard format 100 *100.

Stage III

4) Canny Edge detection, smooth image using Gaussian filter

$$g(m,n) = G_\sigma(m,n) \times f(m,n) \tag{1}$$

where

$$G_\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{m^2+n^2}{2\sigma^2}\right)$$

and σ is the width of Gaussian

apply the Robert operator to compute magnitude and direction for each pixel and each pixel magnitude determines the direction using Mag[] and Dir[] values

$$fx = \left(\sum_{x=-1}^{1}\left((x,y+1) - \frac{(x,y-1)}{2}\right)\right)/3 \quad fy = \left(\sum_{y=-1}^{1}\left((x-1,y) - \frac{(x+1,y)}{2}\right)\right)/3$$
$$Mag[] = \sqrt{fy^2 + fx^2} \qquad Dir[] = tan^{-1}\left(\frac{fy}{fx}\right) \tag{2}$$

Stage IV

5) Feature Extraction using Hough Transformation

6) Classify the images using SVM and KNN algorithms with the distance measure given below:

$$d = \sqrt{(x+y)^2 + (x-y)^2} \quad (3)$$

where x, y represent image features

Detect fracture that specifies the size and position of the crop rectangle. Calculate bounding ellipse to draw ellipse around break location

4 Evaluation Results

The software tool used is MATLAB R2013b, C# on Windows 8 Operating system 64bits operating system, Hp Pavilion i5-3230M CPU @2.60GHz processor, 4.00GB Random Access Memory and 500GB hard disk drive. The evaluation was performed with 40 X-ray images. Results generated based on True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), that is, the recognition accuracy was determined by equation (5)

4.1 Evaluation of fracture and non-fracture bones

The developed system was experimented on 60 preprocessed x-ray images for training with three performance metrics: accuracy, precision (P), specificity (SP) and sensitivity (SE) were calculated using the formulas in equation (4) below: 60 bone images were used for the training set and 40 images for testing, which is done to enable the system to achieve an improved accuracy.Table.3 shows the possible outcomes of confusion matrix for the evaluation of types of fracture.

$$SE = \frac{TP}{TP+FN} \quad , \quad SP = \frac{TN}{TN+FP} \quad , \quad P = \frac{TP}{TP+FP} \quad (4)$$

$$Accuracy = \frac{TP+TN}{Total\ number\ of\ Image} \quad (5)$$

Table 3. Four possible outcomes using confusion matrix

Classifier	Truth data	
Data	**N**	**F**
N	TN = 10	FN = 4
F	FP = 0	TP = 26

N = Normal, F = Fracture

Table 4. Output of numerical data

Possible outcomes	Results	Specificity (%)	Sensitivity (%)	Precision (%)	Accuracy (%)
TN	10				
FN	4	100	87	100	90
TP	26				
FP	0				

Table 4 shows the result generated accuracy value of 90%, Sensitivity of 87% and Specificity of 100% from the numerical data that were tested to ascertain optimal detection value for fractured images. The result achieved at the first stage of the fracture detection shows that 26 out of the 40 preprocessed images were fractured.

4.2 Evaluation types of fracture

To evaluate the types of fracture, Kappa accuracy assessment (k) is applied to determine error state of the fracture bone and their classification type. The K equation is

$$k = \frac{\text{observedaccuracy} - \text{chanceagreement}}{1 - \text{chanceagreement}} \tag{6}$$

$$k = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1} x_{i+} \; X \; x_{+i}}{N^2 - \sum_{i=1}^{r} x_{i+} \; X \; x_{+i}} \tag{7}$$

The experimental result is used to compute the result of numerical tested data shown in Table 4 and Table 5 respectively. The result achieved at the first stage of the fracture detection shows that 30 out of the 40 preprocessed images were fractured. Sensitivity is 87%, and accuracy of 90% shown in Table 4.

Table 5. Confusion matrix of Kappa coefficient

Classifier Data	Truth data				
	N	**T**	**O**	**C**	**Total**
N	10	0	4	0	14
T	0	10	0	1	11
O	0	0	10	0	10
C	0	0	0	5	5
Col Total	10	10	14	6	40

N= Normal, T=Transverse, O=Oblique, C= Comminuted

$$k = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1} x_{i+} \; X \; x_{+i}}{N^2 - \sum_{i=1}^{r} x_{i+} \; X \; x_{+i}} \tag{8}$$

$$k = \frac{40 * (10 + 10 + 10 + 5) - [(10 * 14) + (10 * 11) + (14 * 10) + (6 * 5)]}{40^2 - [(10 * 14) + (10 * 11) + (14 * 10) + (6 * 5)]}$$

$$k = \frac{980}{1180} = 0.831 = 83\%$$

Table 5 shows correct labels for normal, transverse and oblique classifier data images, while 4 oblique and 1 comminuted images are falsely labelled as normal and transverse conditions respectively. Out of four possible outcomes using confusion matrix, the classification of the segmented fracture bones achieved a better false negative reduction of 10% and false positive reduction of 0%, revealing an improved process for detecting and classification of fracture bones in terms of overall performance. The generated result, shows accuracy of 83% by using the Kappa coefficient error assessment during classification.

5 Conclusion

In this paper, detection of fractured bones on X-ray images categorization is implemented using various imaging methods. The focus of this study is to provide solution to the challenges of detecting fracture or non-fracture bone images. The developed system used four main steps: preprocessing, feature extraction, segmentation and classification. The preprocessing was applied to enhance, highlights the edges in the image and to get rid of noise without losing the relevant features. The two-way segmentation is used to sharpened the image using entropy and edge detection techniques and Hough transformation and canny edge detector were used to extract the image features. KNN and SVM classification approaches were used to classify the extracted features. These classifiers were chosen primarily because of their individual ability to decrease training time and increase the accuracy of classification. The experimental results show that integration of KNN-SVM which complement one another give better classification compared to other algorithms. The

combined classifiers resulted in an improved classification accuracy compared to earlier work. The classifiers were used to detect different patterns in images as comminuted, oblique, transverse and normal five (5) fracture types. The results of the developed system are evaluated using two techniques. The evaluation results for fracture or non-fracture bones using TP, TN, FP and FN as possible outcomes and the use of kappa coefficient is employed to consider the error results to find the performance and accuracy of each fracture type. The analysis results show that the combination of KNN and SVM approach achieved an accuracy of 90 % and Kappa accuracy of 83%. The developed system can detect fracture in bones, which is a way to assist doctors and radiologists in fast and accurate diagnosis. For future study, more advanced bone fractures can be considered and a larger dataset can be examined to further investigate the suitability of the technique used in the developed system.

Competing Interests

Authors have declared that no competing interests exist.

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[e-ISSN: 2456 – 6470]

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Peer-review history:
The peer review history for this paper can be accessed here (Please copy paste the total link in your browser address bar)
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