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Detection of bone fracture based on machine learning techniques

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A R T I C L E I N F O

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A B S T R A C T

Computers have been shown to be valuable in every facet of human life, from banking and online shopping to communication, education, research and development, and even medical. To help doctors and hospitals better care for their patients, a lot of innovative technical resources have been developed. Because the typical scanner for X-rays produces a fuzzy picture of the bone component in issue, surgeons risk making an inaccurate diagnosis of bone fractures when they utilize it. Various stages such as pre-processing, edge detection, feature extraction and machine learning classifications, constitute the backbone of this system, with the end goal of making surgeons' lives easier. Among the various fields that benefit from machine learning algorithms nowadays are seismology, remote sensing, and medicine; this program is only one example. As a side note, several machine learning algorithms, such as Naïve Bayes, Decision Tree, Nearest Neighbors, Random Forest, and SVM, have been used specifically for handling bone fracture detection on a dataset with 270 x-ray images. Accuracy measures for the various algorithms employed in the study range from 0.64 to 0.92, with values obtained for Naïve Bayes, Decision Tree, Nearest Neighbors, Random Forest, and SVM. Statistically, the accuracy for SVM was found to be the highest in this research, which is higher than most of the reviewed research.

1. Introduction

A human body consists of 206 bones that vary in size, shape, and complexity. The smallest bones are found in the ear canal, while the largest are the femurs. In humans, lower-leg bone breaks are a common occurrence [1]. The use of machine learning, a pattern recognition method, to analyze medical imaging has recently gained attention. attributes are most predictive of whether [2]. Importantly, it helps physicians properly diagnose illnesses and decide on the best treatment plan for their patients. Fractures of the skeleton may happen to anybody at any time, making early detection and treatment more important. Sadly, bone fractures are on the increase worldwide, even in the richest countries [3].

The Digital Imaging and Communications in Medicine (DICOM) standard is used for the distribution of medical pictures. Among the several instruments needed to construct the biological image, X-rays are among the most extensively used for bone fracture diagnosis due to their speed, cheap cost, and ease of use. Since Wilhelm Roentgen discovered the X-ray in 1895, medical imaging has progressed at a dizzying rate, becoming an essential part of contemporary diagnostics. The mobility of digital X-ray imaging machines and developments in computerized image processing have led to their widespread use in a variety of medical contexts [4,5]. Machine Learning is an indispensable tools for medical data analytics. In order to analyze and locate abnormalities in medical imaging of the human skeleton, sophisticated algorithms are needed [6,7].

Bone fractures may be caused by a wide variety of diseases and injuries. Because of this, a timely and accurate diagnosis is crucial to the effectiveness of any treatment. If a doctor or radiologist suspects a fracture, they will likely order an x-ray to help them determine the severity and kind of break [8]. Manual inspection and the conventional x-ray method for fracture detection are inefficient. Because it was jumbled up with otherwise normal photos, a radiologist was too tired to see that one of them really showed a fracture. The use of a computer vision system allows for the screening of x-ray images for anomalies, with an alarm then being transmitted to the treating physician [9].

Since depending only on experts has resulted in intolerable errors, the idea of an automated diagnostic tool has long been enticing. Methods for detecting and classifying fractures of the leg bone in x-ray images, including preprocessing, and fracture identification [10,11]. The problem of fracture type identification by testing a variety of classification methods for spotting fractures and determining their nature. After initial processing, distinguishing features may be extracted; this is followed by the problem-solving phase. These days, bone breaks are a

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common injury. 2.7 million fractures are reported annually in the EU nations (France, Germany, Italy, Spain, Sweden, and the United Kingdom); this is an astounding number of people who are affected by this ailment, and the effects of an untreated fracture may be severe, even fatal [12]. Tibia fractures are the most common type of break in a long bone and are responsible for more than twenty percent of the patients admitted to hospital wards [13]. Therefore, the burden mostly falls on the shoulders of the doctors, who must evaluate several x-ray images daily. X-ray, a technology that has been available for over a century yet is still commonly used today, is the method of choice for making most first diagnosis [14]. [15,16]. In addition, radiographic interpretation is often performed in the circumstances without the availability of skilled peers for support.

It is essential to correctly classify a fracture into one of several recognized categories in order to determine the most appropriate treatment and prognosis. Positive effects on patient outcomes may be possible when using a cad system that may aid doctors in such a scenario. Traditional machine learning approaches, including preprocessing, feature extraction, and classification, have been widely applied in previous studies on fracture detection and classification. Recent years have seen tremendous advancements made possible by machine learning algorithms.

Noise reduction and initial picture processing are the first. Image preprocessing technologies exist in abundance, and several methods exist for dealing with various forms of noise. The second stage of the project involves the most difficult element of the process: extracting unique properties from the images. As the last step, we classify and test several machine learning classification algorithms using standard testing procedures.

2. Related works

In this work, we have conducted a comprehensive literature review, including everything from traditional approaches to state-of-the-art procedures.

Study [8] proposed a meta classifier that combines decision tree (DT) and neural network (NN) to obtain better accuracy. Several distinct processing steps, including pre-processing, segmentation, edge detection, and feature extraction, are utilized. The meta classifier has an accuracy of 85%, and the processed pictures will be further categorized into fractured and non-fractured bone.

In the study [14] long bone fracture or non-fracture classification was accomplished by first using the Bang of Words (BoW) model for feature extraction and then training the model with the Support Vector Machine (SVM) machine learning technique. Additionally, the suggested approach has a detection rate of 78% for transverse and oblique fractures, respectively.

Another study [17] proposed these steps: preprocessing, feature extraction and classification for their workflow. After that, the processed picture is used as input for classification using SVM, which has an accuracy of 84.7%.

The study [18] demonstrates that the Canny Edge Detection technique is the best algorithm for edge detection. It takes a greyscale picture (X-ray image) as input, analyzes it, and outputs an image with intensity discontinuities.

This study [12], The identification of lower leg bone (Tibia) fracture types is being explored utilizing various image processing approaches. The goal of this project is to detect fracture or non-fracture and characterize the type of fracture in an x-ray picture of the lower leg bone (tibia). The tibia bone fracture detecting system is created in three stages. To categorize fracture types and find fracture sites, they use preprocessing, feature extraction, and classification. During the preprocessing stage, Unshrap Masking (USM) and Harris algorithm have been used for sharpening and corner detection. Simple Decision Tree (DT) is utilized for fracture or not classification, while K-Nearest Neighbor (KNN) is used for fracture type classification. The four fracture types are characterized in this study as Normal, Transverse, Oblique, and Comminute. For fracture type classification, the method achieves an accuracy of 82%.

In another study [19] proposed CNN algorithm with SFCM (Spatial Fuzzy C-Means). Median filter and Discrete Wavelet Transforms (DWT) are used as preprocessing steps. It uses features like homogeneity, entropy, contrast, correlation coefficient, and energy with the accuracy of 78%.

In the study [20], suggested hybrid approach is particularly effective in identifying pediatric ulna and radius fractures. The author used a 2D sliding window to get the local Shannon entropy for each pixel in the image. This research achieved the accuracy of 91%.

Another study [21], approach to X-ray image processing was developed, which makes use of the Local Binary Pattern (LBP) feature extractor and the Support Vector Machine (SVM) classification technique. The implementation of pre-processing techniques to enhance image quality is also an important addition. The outcomes demonstrate that the CLAHE preprocessing approach achieves an accuracy of 80% in classification.

In [1] proposed a transfer learning, Faster R–CNN deep learning model for fracture detection and classification with Region Proposal Network (RPN). In addition, the author retrained the model's top layer on 50 x-ray images using the inception v2 (version 2) network architecture. This model was trained in 40 k steps and halted when the loss was just 0.0005. The suggested model for detection and classification was evaluated by the author. In terms of classification and detection, this technique has an overall accuracy of 94%.

In [22], to distinguish between fractured and healthy bone, a deep neural network model was created. Due to the little data available, the deep learning model becomes overfit. So, the size of the dataset has been increased by the use of data augmentation methods. A total of three experiments were conducted utilizing the softmax and Adam optimizers to assess the efficacy of the model. As for its classification abilities, the suggested model scores a very respectable 92.44%.

In another study [23], A comparison can also be made between the proposed method and the Harris corner detection method. For automated bone fracture identification, BPNN combined with Canny edge detection and conservative smoothing achieves the highest accuracy (91%).

3. Methods

The bone fracture detection system consists of four main modules, which are preprocessing, edge detection, feature extraction, and classification.

First, we use preprocessing techniques to the image, such as converting it from RGB to grayscale and then improving it using a filtering algorithm to get rid of the noise. The next step is for it to use edge detection techniques to find the sharp boundaries of the bones. Following that The effectiveness and precision of the proposed system are assessed as the last step. Fig. 1 illustrates the steps of the proposed method for identifying bone fractures in x-ray images.

3.1. Pre-processing

Since a majority of the real-life data acquired is noisy, in-consistent, and incomplete hence preprocessing of the acquired data plays a vital role. Image preprocessing forms a preliminary step in obtaining high accuracy of the image, followed by subsequent steps. Hence it is necessary to remove these artifacts by preprocessing procedures before further analysis. The initial step involves applying preprocessing techniques such as RGB to Grayscale conversion, followed by further noise removal by using a Gaussian Filter.

1) Noise Cancellation

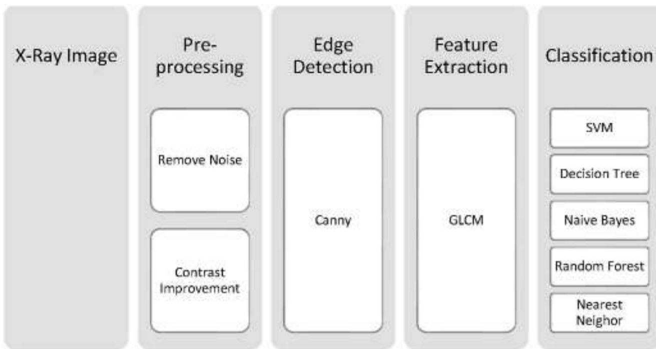

Fig. 1. Methods applied in the detection of bone fracture.

Unwanted pixels that detract from the overall quality of the image are what we refer to as noise. It's possible to express noise as:

$$f(x,y) = g(x,y) + \eta(x,y) \tag{1}$$

where f (x, y) represents the source image, g(x, y) represents the output image, and η(x, y) represents the noise model.

Noise comes in a wide variety of forms. Noise in the form of "salt and pepper" grains is a typical feature of x-ray images. Usually resulting from a malfunction during capture or transmission, this sort of noise presents as random bright and dark spots throughout the image. Applying a mathematical modification T to the x-ray image is how we deal with the salt and pepper noise [24]:

$$g(x,y) = T[f(x,y)] \tag{2}$$

where f (x, y) presents the input x-ray image with salt and pepper noise and g (x, y) presents the output image after T is applied. In our experiment, we found that the best way to decrease salt and pepper noise without losing image detail was to employ a Gaussian filter as a T. If the pixel is "too different," its value is replaced with the median value of its neighbors.

2) Contrast Improvement

Adaptive histogram equalization is a method used in digital image processing to improve picture contrast. The adaptive approach varies from conventional histogram equalization in that it boosts contrast locally. On medical x-ray images, adaptive histogram equalization has been successful in producing favorable results [25].

3) Edge Detection

Canny edge detection is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. It is based on analyzing the time-varying intensity of the picture [5]. The quality of edge detection is heavily influenced by factors like as lighting, the presence of objects with similar intensities, the density of edges in the image, and noise. Canny, Laplacian, and Sobel are only few of the edge detection techniques available. According to this research, the optimal outcome is achieved by using a modification of the Canny edge detection method that includes an adaptive histogram to boost contrast.

3.2. Feature extraction

In many different applications for image processing, the most important stage is feature extraction. When it comes to feature extraction and selection, the Gray-Level Co-occurrence Matrix is a useful tool [26], Textural properties such as contrast, correlation, homogeneity, energy, and dissimilarity are extracted using the Gray Level Co-occurrence Matrix (GLCM) approach. These characteristics are discussed in depth below [27–30].

- Contrast: determines the degree to which each pixel in the picture differs in its level of contrast.

$$\sum_{i,j} |i-j|^2 p(i,j) \tag{3}$$

- Correlation: determines the degree to which the pixels are connected with one another.

$$\sum_{i,j} \frac{(i-\mu_i)-(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \tag{4}$$

- Homogeneity: is the reverse of contrast and refers to a property that gauges the distance between individual pixels in a picture.

$$\sum_{ij} \frac{p(i,j)}{1+|i-j|} \tag{5}$$

- Energy: is a property Uniformity, uniform energy, and angular second moment are all names for energy.

$$\sum_{i,j} p(i,j)^2 \tag{6}$$

- Dissimilarity: measures the distance between two items (pixels) in the region of interest.

$$\sum_{i,j} p(i,j)|i-j| \tag{7}$$

3.3. Classification

The step of classification in data analysis is to look at a set of data and put it into different groups. Each category has its own properties, and the data that belong to that category also have those properties. The accuracy of these classifiers can be evaluated using a variety of methods, and there are many different types of classifiers available for application. By reviewing the papers written on the topic, Support Vector Machine (SVM), and Random Forest (RF).

4. Results

The dataset X-ray images obtained from the East Erbil Emergency Hospital contains 60 fractured and 210 non-fractured images of lower leg bones. After that, we applied the mentioned methodology to achieve the following results below.

4.1. Pre-processing

Fig. 2 shows an example of applying noise removal and image smoothing on an x-ray image.

Fig. 3 shows an example of applying adaptive histogram on an x-ray image.

Fig. 4 shows an example of applying canny edge detection (see Fig. 5).

Fig. 2. Gaussian filter.

Fig. 3. Adaptive histogram.

4.2. Feature extraction

As mentioned, GLCM has been used in this research for feature extractions. Took five properties (energy, correlation, dissimilarity, homogeneity, contrast) for four distances (1, 3, 5, 9) in 7 angles (0°, 45°, 90°, 135°, 180°, 225°, 270°), which means 140 features extracted per image.

Python script to extract GLCM features.

Different properties, distances, and angles have been experienced and tested, but the above combination shows the peak accuracy with the all used machine learning algorithms.

Table 1 shows a sample of extracted GLCM features for two images with distance = 1 and angle = 90°.

4.3. Classification

We randomly took 80% of the dataset for the training session and 20% for the testing. Then the dataset was used in the following machine learning algorithms to train and test the model, as shown in Table 2.

The performance of the proposed system is assessed in terms of precision, recall, and accuracy. The analysis is with respect to the observer. In this work, there are only four possible outcomes of applying the classifier on any instance. These outcomes are.

- True Positive (TP) refers to the fractured x-ray images correctly labeled as fractured.
- True Negative (TN) refers to the non-fractured images correctly labeled non-fractured.
- False Positive (FP) refers to the non-fractured x-ray images incorrectly labeled as fractured.
- False Negative (FN) refers to the fractured x-ray images incorrectly labeled as non-fractured.

The performance of this system is assessed in terms of precision, recall, and accuracy.

- Precision = TP/(TP + FP)
- Recall = TP/(TP + FN)
- Accuracy= (TP + TN)/(TP + TN + FN + FP).

Based on the assessment, the Machine Learning algorithms comparison has been presented in Table 3.

The accuracy for different algorithms such as Decision tree, Naïve Bayes, Decision Tree, Nearest neighbors, Random Forest and SVM used for the research is found as 0.64, 0.80, 0.83, 0.85, and 0.92.

Table 4 Shows the comparison with the other papers that have been reviewed in this research.

5. Conclusion

The goal of this research is to create a program that can help doctors to determine whether a patient's leg bone has been broken or not easily and quickly. This study introduces a machine learning-based strategy for the automated detection and classification of bone fractures. Both broken and unbroken human bones were used in the experiment, as were their X-ray images. The prevalence of bone fractures is rising, as reported by an increasing number of countries. The ability to recognize even a little bone fracture is very useful in medical practice. Accordingly, this technique may identify fractured bones from entire ones. The canny edge detector can accurately identify bone edges, and the GLCM

Fig. 4. Canny edge detection.

```
distance = [1, 3, 5, 9]
angles = [0, np.pi / 4, np.pi / 2, 3 * np.pi / 4, 5 * np.pi / 4,
          3 * np.pi / 2, 7 * np.pi / 4]
self.glcm_mat = graycomatrix(image, distances=distance, angles=angles)
self.properties = ['energy', 'correlation', 'dissimilarity',
                   'homogeneity', 'contrast']
[graycoprops(self.glcm_mat, prop).ravel() for prop in self.properties]
```

Fig. 5. A sample python script to extract GLCM features.

has been used to extract multi-features in an x-ray image to be classified by machine learning algorithms. This system is built on a suite of image-processing methods and machine learning algorithms to detect lower leg bone fractures. Over the duration of the study, all of the different machine learning methods (Naïve Bayes, Decision Tree, Nearest Neighbors, Random Forest, and SVM) achieved an accuracy of between 0.64 and 0.92. In this research, SVM showed statistically significant improvements over the baseline.

Table 1
Sample of extracted GLCM features Fractures

Image	Energy	Correlation	Dissimilarity	Homogeneity	Contrast
1	0.2084321	0.99656732	2.91498663	0.4241376	21.55482951
2	0.0776263	0.99842039	1.53495146	0.56196655	7.74761016

Table 2
Used Machine Learning Algorithms with parameters.

ML Algorithm	Parameters
Gaussian Naïve Bayes	Defaults
Decision Tree	Minimum sample split = 40
Nearest Neighbors	No. of Neighbors = 30
Random Forest	Defaults
SVM	Kernel = rbf, C = 10000

Table 3
Applied Machine learning Algorithms.

ML Algorithm	Precision	Recall	Accuracy
Naïve Bayes	0.882353	0.652174	0.642857
Decision Tree	0.906977	0.847826	0.803571
Nearest Neighbors	0.836364	1	0.839286
Random Forest	0.88	0.956522	0.857143
SVM	0.9375	0.978261	0.928571

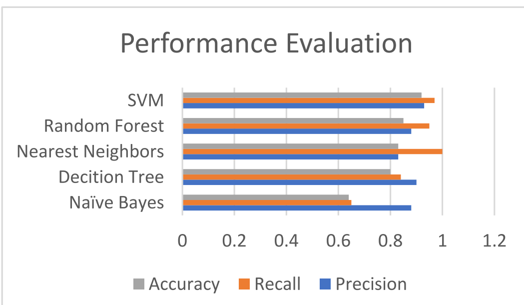

Table 4
Comparison with other papers.

Ref#	Year	Method	Accuracy
[8]	2015	Decision Tree and Neural Network	0.85
[14]	2017	SVM	0.78
[17]	2017	SVM	0.84
[12]	2018	Decision Tree and K-Nearest Neighbor	0.82
[19]	2019	CNN Algorithm with SFCM (Spetial Fuzzy C-Means)	0.78
[20]	2019	Local-Entropy Based Approach	0.91
[21]	2019	SVM with CLAHE preprocessing method	0.80
[23]	2020	Back Propagation Neural Network (BPNN)	0.91
[1]	2020	Faster R–CNN and Region Proposal Network RPN	0.94
[22]	2020	CNN	0.92

CRediT authorship contribution statement

Kosrat Dlshad Ahmed: Paper written, simultion: out put figures, related work. **Roojwan Hawezi:** English editing, references arrangement.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

References

[1] W. Abbas, S. Adnan, M. Javid, F. Majeed, Lower Leg Bone Fracture Detection and Classification Using Faster RCNN for X-Rays Images, IEEE 23rd International Multitopic Conference (INMIC), 2020.
[2] A. Al-Ghaithi, S. Al Maskari, Artificial intelligence application in bone fracture detection. Journal of Musculoskeletal Surgery and Research, J. Mach. Learn. 5 (1) (2021) 4–9.
[3] C. McCollough, J. Bushberg, G. Fletcher, L. Eckel, Answers to common questions about the use and safety of CT scans, in: Mayo Clinic Proceedings, 2015.
[4] Amin Salih Mohammed Hersh, A. Muhamad, Shahab Wahhab Kareem, A Deep Learning Method for Detecting Leukemia in Real Images, NeuroQuantology, 2022.
[5] P. Cephas, H. Hepzibah, A robust approach for detection of the type of fracture from X-ray images, International Journal of Advanced Research in Computer and Communication Engineering (2015).
[6] Sami H. Ismael, Shahab W. Kareem, Firas H. Almukhta, Medical Image Classification Using Different Machine Learning Algorithms, AL-Rafidain Journal of Computer Sciences and Mathematics, 2020.
[7] M. Al-Ayyoub, D. Al-Zghool, Determining the type of long bone fractures in X-ray images underwater wireless sensor networks view project aspect-based sentiment analysis in Arabic texts view project determining the type of long bone fractures in X-ray images, in: IEEE 23rd International Multitopic Conference, INMIC), 2013.
[8] S. College, E. Mysuru, R. Raman, Detection of bone fracture using image processing methods, Int. J. Comput. Appl. 3 (2015) 6–9.
[9] S.W. Kareem, An evaluation ALgorithms for classifying Leukocytes images, in: 7th International Engineering Conference "Research & Innovation amid Global Pandemic, Erbil, 2021.
[10] B. Czerniak, Dorfman and Czerniak's Bone Tumors E-Book, Elsevier Health Sciences, 2015.
[11] Shahab Wahhab, Kareemab Roojwan ScHawezia, Farah Sami Khoshabaa, A Comparison of Automated Classification Techniques for Image Processing in Video Internet of Things, 2022.
[12] W. Myint, Analysis on Leg Bone Fracture Detection and Classification Using X-Ray Images, Machine Learning Research, 2018.
[13] N. Umadevi, D. GeethaJakshmi, Multiple classification system for fracture detection in human bone x-ray images, IEEE (2012) 1–8.
[14] A. Vishnu, D. Prakash, S. Sharmila, Detection and classification of long bone fractures Detection and Classification of Long Bone fractures, Journal of imaging (2017).
[15] L. Tanzi, E. Vezzetti, R. Moreno, S. Moos, X-Ray Bone Fracture Classification Using Deep Learning: A Baseline for Designing a Reliable Approach, Applied Sciences, 2020.
[16] Hersh A. Muhamad, Shahab Wahhab Kareem, Amin Salih Mohammed, A deep learning method for detecting Leukemia in real images, NeuroQuantology 20 (7) (7 July 2022) 2358–2365.
[17] A. Tripathi, A. Upadhyay, A. Rajput, Automatic detection of fracture in femur bones using image processing, in: International Conference on Innovations in Information, Embedded and Communication Systems, 2017.
[18] N. Johari, N. Singh, Bone fracture detection using edge detection technique, Adv. Intell. Syst. Comput. 584 (2017) 11–19.
[19] S.S. Sinthura, Y. Prathyusha, K. Harini, Y. Pranusha, B. Poojitha, Bone fracture detection system using CNN algorithm, in: 2019 International Conference on Intelligent Computing and Control Systems, ICCS), 2019, pp. 545–549.
[20] F. Hržić, I. Štajduhar, S. Tschauner, E. Sorantin, J. Lerga, Local-entropy based approach for X-ray image segmentation and fracture detection, Entropy 21 (4) (2019) 338.
[21] E. Castro-Gutierrez, L. Estacio-Cerquin, J. Gallegos-Guillen, J.D. Obando, Detection of Acetabulum Fractures Using X-Ray Imaging and Processing Methods Focused on Noisy Images, IEEE, 2019, pp. 296–302.
[22] D. Yadav, S. Rathor, Bone fracture detection and classification using deep learning approach, in: International Conference on Power Electronics & IoT Applications in Renewable Energy and its Control, 2020.
[23] S. Karimunnisa, R. Madupu, P. Savarapu, Detection of Bone Fractures Automatically with Enhanced Performance with Better Combination of Filtering and Neural Networks, 2020.
[24] F.A. Jassim, Kriging Interpolation Filter to Reduce High Density Salt and Pepper Noise, vol. 3, 2013, pp. 8–14, *arXiv preprint arXiv*, 1.
[25] A.M. Reza, Realization of the contrast Limited adaptive histogram equalization (CLAHE) for real-time image enhancement, Journal of VLSI signal processing systems for signal, image and video technology 38 (1) (2004) 35–444.
[26] M. Al-Ayyoub, I. Hmeidi, H. Rababah, Detecting hand bone fractures in X-ray images, J. Multim. Process. Technol 4 (3) (2013) 155–168.
[27] D.A. Clausi, An analysis of co-occurrence texture statistics as a function of grey level quantization, Can. J. Rem. Sens. 28 (1) (2002) 45–62.
[28] A.E. Rad, M.S. Mohd Rahim, R. Kumoi, A. Norouzi, Dental x-ray image segmentation and multiple feature extraction, Global Journal on Technology 2 (2013).
[29] D. Aborisade, J.A. Ojo, A. Amole, A. Durodola, Comparative analysis of textural features derived from GLCM for ultrasound liver image classification, Energy 2 (10) (2014).
[30] T.K. Hazra, S. Dutta, A new approach to identify the fracture zone and detection of bone diseases of X-ray image, Int. J. Sci. Res. 5 (9) (2016).