Human Bone fracture prognosis using Income inequality based Texture Feature and Support Vector Machine

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Abstract
Bone fracture and related bone problems are most common throughout the world; people in every country are facing problems related to bone fracture. These are the prime reasons for bone fracture like due to some severe accident, or there may be chance that a person suffering from disease which weakens the bones like Osteoporosis or cancer. Therefore it is very much needed to quickly and accurately diagnose the affected area before giving any cure or treatment. Here we are proposing the technique through which we can detect and classify the fractured or healthy bones clearly, accurately and quickly. It works like a doctor’s tool and reduce his workload. Previous research work and data set is focused simply on classification of fractured bones but our research is capable of not only to classify and detect the fractured bone but the healthy bones as well, by considering data set consist of different types of human bones. The proposed approach analyzes the texture features for the bone diagnosis. In this regards, we performed performance analysis of the model using four GLCM (Gray Label Co-occurrence Matrix) texture features with and without Gini Index. The performance of the model using GLCM texture feature with Gini index is significantly improved. The proposed texture featured based SVM model have achieved the accuracy of 95% for the fracture bone.

Keywords: Bone Fracture, Classification, X-ray, SVM, Income Equality

1. Introduction
Bone is a major component of the human body and muscles are connected with the bone. Bone provides the ability to lift against gravity and movement to the body. It protects the organ and helps bone marrow to produce blood cells. The human bone is also responsible for the storage of calcium. The calcium is important for heart function. If the calcium level decrease, then the bone becomes weaker and people suffer from many diseases including a bone fracture.

The x-ray image is used for the bone fracture diagnosis. A doctor utilizes his expertise to diagnose the bone fracture manually using x-ray image, which is time-consuming and is linked with the probability of mistake. Therefore, an automated system needs to be developed to assist a doctor to diagnose the bone fracture. An automated system is quick and the likelihood of a mistake is lower. Medical imaging using digital image processing and machine learning is a very powerful technique. The main goal of the medical image processing is to obtain data that is clinically essential. Therefore, it is essential to extract an object from the x-ray image [7]. One of the significant techniques in the computer-aided simulation of comminuted fracture treatment is the bone repositioning or so-called bone reduction. A fractured bone may be broken or partially broken. Usually, the fragment sections are dislocated in orientation and position when it is broken. The broken bones should be moved to return them to the original position and orientation when the surgery is done. The problem with simulated bone repositioning is that the precision of the repositioning
consequence is not simple to verify because each broken bone has an uneven shape and the border of each
digitized model may not be sufficiently precise. The machine learning is used to train and predict the
autonomous system. Data training is carried out using a method of supervised machine learning. The overall
method of the bone fracture classification includes mapping the information to one of several predefined
classes. However, the classification methods present challenges that are due to the information overload
size and data dimension. A classification method is described by building classification models as a
systematic approach to processing input information. By evaluating texture characteristics, the fractured
bone is recognized and categorized.

Bone fracture detection and classification have been developed in the past. Dimililer and Kamil [6] have
used ANN (Artificial Neural Network) to classify fracture bone but authors have not classified the bone
into the healthy and the fracture. The study is not able to measure the other parameter like precision, recall,
f1-score to check the performance of the system Yang et al. [23] have used contour feature of x-ray image
to detect the fractured bone. The accuracy of the system is 85%, which needs to improve. In the paper of
the Chai et al. [24] Gray-Level Co-occurrence Matrix(GLCM) was used to extract the texture feature to
classify the bone into the fracture and the non-fracture. The features are extracted from the image of the
size 410×500 resolution. The classification accuracy of their system is 86.67%.

In the proposed study we, have examined that GLCM texture features are not alone sufficient for the
classification of the fractured bone. The proposed study also examines the impact of the image size on the
GLCM texture feature. Therefore, we have applied other texture feature based on income inequality along
with the GLCM texture feature. The proposed SVM based approach is better than state-of-the-arts in terms
of the classification accuracy of the fractured bone 95%. The proposed model also classifies the bone into
the healthy and the fracture with an accuracy of 91.66%.

2. Related Works

Bone fracture diagnosis using machine learning and image processing are very popular. In the past several
works have been carried out to diagnose the fractured bone. Myint et al. [1] have used an X-ray image to
detect fractures on the leg. Canny algorithm has been used for the segmentation of the image. The texture
feature Hough transforms is applied used to detect fractures in the bone. A transferable method has been
provided by Kim et al. [2]. In the many prospective applications towards medical imaging, their method
can be applied. The method can also provide support in reducing the clinical risk. For further training and
classification, first wrist data set is trained with ANN and trained information is fed to CNN. The approach
works for both moderate and large information sets and can be used for information processing in many
medical areas.

Vegi et al. [3] have used basic image processing techniques to remove noise, detect edge and extraction of
the features from an image. Finally, classification techniques are used to classify fractures and healthy bone.
They have developed a tool on the MATLAB and implemented an algorithm with a classification accuracy
of 85%. The methods of information processing are data-driven and are used inherently in radiology. In
this field, deep learning can be used as a strong instrument for imaging. The radiologist used the methods
of deep learning in this job and the technique gives more precise interpretations [4].
Mahendran et al. [5] have used the X-ray image for the bone fracture analysis. They have detected the fracture in the bone using the image processing techniques. Images are collected from a different source so noises are removed from them. After that segmentation technique followed by edge detection algorithm is applied. The author has created a GUI (Graphical User Interface) that supported the automated system to make it more efficient. Dimililer et al. [6] have created an automated system capable of detecting and comparing the various fracture phases. They also contrasted bone image classification with SHIFT (Scale-Invariant Feature Transform) and BPNN (Back Propagation Neural Networks).

Mahendran et al. [7] describes long bone fractures detection using image processing and machine learning. They have considered long bone fracture and types of fracture that happens in long bone. Their approach used an edge detection algorithm and the features are extracted for the classification. A convolution neural networks based method is developed by Ebsim et al. [8] that can detect wrist fractures. Random forest regression voting has been used in the automated system. Their model can automatically segment the radius for better performance. The CNN is trained for each view separately on the registered patches.

Umadevi and Geethalakshmi [9] have used traditional machine learning approaches like Support Vector Machine (SVM), Naïve Bayes (NB) and Feed Forward Back Propagation Neural Network (BPNN) to extract features for the classification of the fracture and the healthy bone. Korfiatis et al. [10] have developed standard line-based fracture detection. The adaptive differential parameter optimized in the line-based fracture detection. Their method is a two line-based fracture detection schemes. The two line-based fracture detection schemes extract features and detect fractured lines from X-ray images. It can easily recognize patterns to differentiate fractured lines from healthy lines. The difference between the two schemes is the detection of detailed lines.

3. The Proposed Method

The system model is described using a flow chart shown in figure1. First, the image is loaded into the system and transformed into the grayscale. Under different light circumstances, the bone images are captured using digital devices, because of which it contains noise and even pictures become blurred. Thus, image preprocessing methods need to be applied so that noise can be removed and the image intensity can be improved [7].

A median filter of a size 3x3 is applied to remove the noise. The canny algorithm based on the edge is used to obtain the object of interest. The Gini index is calculated from the matrix of the Hough accumulator. The Gini index is based on an economic notion that measures population inequality. GLCM matrix is used to calculate homogeneity, contrast, correlation, and energy. These four features are not enough to properly classify the fractured bone [24]. So entropy and skewed texture features are also calculated from the image. The system is trained with the feature vector {Contrast, Correlation, Energy, Homogeneity, Skewness, Entropy, and Gini Index}. Detection and classification of the bone fractures are performed by SVM [16].
Figure 1. The proposed feature extraction and classification system

3.1 Preprocessing of the Bone Image

Preprocessing methods for the digital image are used to enhance the image quality so that image segmentation and extraction can be efficient. The X-ray image is transformed into a gray image that requires less computation and accelerates the processing time. Using unsharp masking (USM) methods, images are sharpened [10]. A sharpened image is acquired by subtracting from the initial image as shown in equation 3.

\[
\text{Sharpened} = \text{Original image} + (\text{Original image} - \text{Blurred image}) \times \text{amount.}
\]

The amount is the percentage of contrast added to the edge so that it doesn’t affect the edge rims.

Image segmentation is an effective and rational technique of identifying a concern object from the image. The final precision rate relies on the segmentation technique's reliability. Using the segmentation image is split into a pixel set to collect data from the object concerned [8]. The Canny edge detection algorithm has been used to detect edge [13], shown in Figure 2.
Figure 2. Original Image, Sharpened image, and Canny edge Image.

Detection of the bone fracture and precision of classification rely on chosen features, so it is essential to select the image finest feature. In this research, the texture feature of the Hough transform based on the income inequality is used to identify the fractured bone. Hough transform is extracted straight line and it is a significant feature for fracture detection [11]. The binary image is used to identify the line. The equation of the line is represented as

\[ t = x\cos(\alpha) + y\sin(\alpha) \]  

where \( \alpha \) is the angle between the horizontal axis and the perpendicular line and \( x, y \) are constants, and \( t \) is a perpendicular line from the origin to the line of experiment.

3.2 Feature Extraction

The fracture and the healthy bone texture are different, so proper identification of texture characteristics is crucial. Haralick et al. suggested texture descriptors to define the texture characteristics. In the Haralick descriptor, a certain pair of pixel occurrences is calculated by each entry \((i, j)\) of the GLCM matrix \(g(i, j)\) from the gray level values of the segmented image. The GLCM matrix is used to compute four texture features: Homogeneity, Contrast, Energy, and Correlation.

Contrast: Represents the amount of variation of local gray level in an image and is calculated by the difference between max intensity and min intensity.

\[
CONSTRAST = \sum_{i,j} |i - j|^2 g(i, j)
\]  

Correlation: It measures how the pixel are co-related to each other in whole image.
$\text{CORRELATION } N = \sum_{i,j} \frac{(i - \mu_i)(j - \mu_j)g(i, j)}{\sigma_i\sigma_j}$

Where $\mu_i$= Mean pixel value in GLCM matrix.

\[ \sigma = \text{Standard deviation of pixel value in GLCM matrix.} \]

Energy: It is calculated by summation of squared elements.

$\text{ENERGY} = \sum_{i,j} g(i, j)^2$  \hfill (5)

Homogeneity: It measure smoothness of grey level distribution of elements it is inversely related to contrast.

$\text{HOMOGENEITY} = \sum_{i,j} \frac{g(i, j)}{1 + |i - j|}$ \hfill (6)

Skewness: It measure degree of distortion in an image from normal distribution. Symmetrical and asymmetrical distributions of pixel are measured by 0 and -1 to +1.

$SK = \frac{E(x - \mu)^3}{\sigma^3}$ \hfill (7)

Entropy: Entropy measure randomness of gray level pixels in image. It is calculate by formula

$H(X) = E(I(X)) = \sum_{X} p_x I(X) = -\sum_{X} p_x \log_2 p_x$ \hfill (8)

The Income inequality matrices are used in the area of economics. It is used to measure the distribution of the income. In the present study, the Hough transforms accumulator matrix is considered as income. Long line at a specified angle in the image pattern represents high income. High values distribution in the Hough accumulator matrix represents unequal texture pattern. The Gini index (GI) is frequently used to determine inequality [12]. It is calculated from the Hough accumulator matrix.

$GI = \frac{2\sum_{i=1}^{N} i x_i - N(N + 1)}{N\sum_{i=1}^{N} x_i}$ \hfill (9)

Where $N =$Total number of pixel in the accumulator matrix.

The Gini Index value is between 0 and 1. Accumulator matrix having equal distribution would yield GI value approx to 0 and maximum unequal distribution would yield GI value close to 1.
Figure 3. Feature Extraction Model

3.2.1. Mathematical SVM Model

The training data is labeled $a_i$, categories $\beta_i$, dimension $d$, therefore the relation between labeled data, dimensions and respective categories can be defined like $a_i \in R^d$, and $\beta_i = \pm 1$.

The following equation represents the hyper plane:

$$<t.\alpha + b >= 0$$

Where $b$ is real and $t \in R^d$, $<t.\alpha>$ is the inner dot product of $t$.

In this regard the two hyper planes (H1 and H2) can be defined as follows:

H1: $t.\alpha + b = +1$ (10)

H2: $t.\alpha + b = -1$ (11)

Therefore hyper plane is: $t.\alpha + b \geq -1$ when $\beta_i = \pm 1$  $t.\alpha + b \leq -1$ when $\beta_i = -1$.

The training data is formed by the a set of points (vectors) $a_i$, and $\beta_i$ is used to represent the categories with some dimension $d$, then it can be defined such that, $a_i \in R^d$, and $\beta_i = \pm 1$

Further, $<t.\alpha + b >= 0$  where $b$ is real and  $t \in R^d$, $<t.\alpha>$ is the inner dot product of $t$.

Finally H is defined such that:

$t.\alpha + b \geq \pm 1$ When $\beta_i = \pm 1$
\[ t \alpha + b \geq -1 \text{ when } \beta = -1. \]

3.2.2. Training of the Bone Image

Feature of fracture and healthy bone are extracted from the image and used to train the support vector machine. After that train system classifies the images. Identification of good feature is a difficult task because system accuracy depends up on the features. Data sets are separated into two classes, Class 1 contains the fracture bone and class 2 contains healthy bone. Further SVM is trained using features \{Contrast, Correlation, Energy, Homogeneity, Skewness, Entropy, Gini Index\}. After training system are tested on the test data set.

4. Results and Discussion

Data Set: The data set has been collected from the open repository of IIST, Shibpur [21]. A compilation of publicly available/accessible medical images is presented. It contains Healthy X-Ray images, Bone X-ray Images (Fractured Bone) and Bone X-ray Images (Cancerous Bone).

In the present study MATLAB 16a, 8GB RAM and i7 processor have been used to perform the experiment. Images are collected from different source due to which it contains noise. It is necessary to resize the image and remove noise. The texture feature extracted from the GLCM matrix depends on the size of pixels [19]. In the present study, it found that the texture feature extracted from a larger image reduces the accuracy. In figure4, x-axis contains 60 test images of size 25x25 pixels. Image ranges from 1 to 41 are of fracture bone and image ranges from 42 to 60 are of as healthy bone. The accuracy of proposed model is shown in figure4. The size of image affects the accuracy of the automated system [21]. In fracture bone test data sets out of 41 facture images 2 images are false negative and out of 19 healthy images 3 are a false positive.

![Figure 4](image-url)

**Figure4.** Test result of data set of size 25x25 pixels.

In figure5, x-axis contains 60 test images of size 500x500 pixels. In the fracture bone test data sets out of 41 facture images 15 images are false positive and out of 19 non fracture images 8 are false positive. From figure4 and figure5, it is clear that for the selected data set size of image play vital role for the classification of the bone.
Table 1: Comparison of the SVM and Random Forest Machine learning algorithm

| Measure | Random Forest | SVM  |
|---------|--------------|------|
| Accuracy | 71.66        | 91.66|
| F1 Score | 74.62        | 93.98|
| Precision | 96.15        | 92.86|
| Recall   | 60.97        | 95.12|

Figure 5. Test result of data set of size 500x500 pixels.

4.1 Comparison of SVM and Random Forest machine learning techniques

In the proposed study, we have compared the performance of the two machine learning techniques SVM and random forest on the selected feature. The performance is shown in the table 1.

The accuracy, recall, and f1-score of the SVM model are much better than the Random forest. The precision of the random forest algorithm is better than the SVM model. Indeed the precision of the random forest is better but overall the performance of the SVM is better. Therefore, we have selected SVM for the proposed approach.

Due to accidents and many illnesses, instances of bone fracture are growing day by day. It is therefore essential to develop a computer-based system capable of detecting the bone fracture. In the biomedical field, image processing, machine learning, and computer vision are common. There are noises in the images. Appropriate noise removal filter is implemented. In the present study, noise is removed by applying a median filter of size 3x3. Canny edge detection technique and Hough transform have been used by [15] to detect fractured bone. The data set is small and limited to the long bone. The classification of the healthy and the fracture bone on different types of the human can be performed.

The Hough transformed is not able to produce good result, when object is align. Therefore, in the present approach an income inequality based Hough transform technique has been used. The Gini Index is calculated from the Hough accumulator matrix [12]. In the fracture bone the distribution of pixel is unequal. The lower values of a pixel can be seen on the fractured part. An income inequality concept of economics,
which is used to find the distribution of the data, is useful to find the pixel distribution in the image, value close to zero indicates the equal distribution and close to 1 indicates maximum unequal distribution.

In the paper of [17], the authors have used the GLCM texture feature to classify the fractured bone. They also compare other texture features like LBP (Local Binary Patterns), GBP (Gradient Binary Patterns) and GLCM. The classification result of the GBP texture feature is higher than the GLCM and LBP features. The accuracy of the approach is not optimal and limited to the long bone only. The present research extracts four texture features Homogeneity, Contrast, Energy, and Correlation from the GLCM matrix. Another texture feature entropy and skewness have been taken to experiment to improve the accuracy of the system. The randomness of the gray levels is measured by the entropy.

The probability of occurrence of the gray level pixels defines the entropy. The value of entropy depends on the quantity of the gray level pixels [20]. The skewness measures the asymmetry in the image [18]. The skewness values of the fractured bone are negative and the healthy bone is positive. A negative value implies pixels are more scattered on the left side and positive value implies pixels are more scattered towards the right side of the probability density function shown in figure 6 and figure 7.

![Figure6. Skewness value of training image](image_url)

![Figure7. Skewness value of test image](image_url)

The system is first trained with the four GLCM texture features {Contrast, Correlation, Energy and Homogeneity}. The testing of the proposed model is performed on the standard data set of the 60 images.
The test result is shown in figure 8. The X-axis contains 60 images and Y-axis contains class. For the sake of simplicity 2 is considered for the fractured bone and 3 is considered for the healthy bone.

![Figure 8](image-url)  
**Figure 8.** Test Result of Image 25x25 pixels with GLCM Features.

The image ranges from 1 to 41 are of the fracture bone and 42 to 60 are of the non-fracture bone. In the experiment using GLCM texture feature classification accuracy yield by system is 73.33%. The confusion matrix of the test result using only GLCM four texture features is shown in table 2.

| Samples       | No. Of Images | Fracture | Non-Fracture |
|---------------|---------------|----------|--------------|
| Fracture Bone | 41            | 33       | 8            |
| Non–Fracture  | 19            | 8        | 11           |

The classification accuracy of the system based on the GLCM texture feature is not optimal. In the proposed approach other texture features utilize to improve the classification accuracy. Therefore the system is again trained with the feature vector {Contrast, Homogeneity, Correlation, Energy, Skewness, Entropy, and Gini Index}. The same data sets are again tested on the automated system. In figure 9, x-axis contains 60 test images of size 25x25 pixels. Image ranges from 1 to 41 are of fracture bone and image ranges from 42 to 60 are of as healthy bone. In fracture bone test data sets out of 41 fracture images 2 images are false negative and out of 19 healthy images 3 are a false positive.
The confusion matrix for the same is depicted in the table3.

Table3. Confusion matrix bone test data set with all selected features.

| Samples   | No. Of Images | Fracture | Non-Fracture |
|-----------|---------------|----------|--------------|
| Fracture  | 41            | 39       | 2            |
| Non-Fracture | 19        | 3        | 16           |

Result comparison of test data sets using feature vector { Contrast, Homogeneity, Correlation, Energy } and feature vector (Contrast, Homogeneity, Correlation, Energy, Skewness, Entropy, and Gini Index) shown in table4.

Table4. Result comparison of test data sets.

| Measure     | Feature Vector (Contrast, Homogeneity, Correlation, Energy) | Feature Vector (Contrast, Homogeneity, Correlation, Energy, Entropy, Skewness and Gini Index) |
|-------------|----------------------------------------------------------|---------------------------------------------------------------------------------------------|
| Accuracy    | 73.33                                                   | 91.66                                                                                      |
| F1 Score    | 80.49                                                   | 93.98                                                                                      |
| Precision   | 82.98                                                   | 92.86                                                                                      |
| Recall      | 82.98                                                   | 95.12                                                                                      |

From table 4, it is clear that the GLCM texture feature along with entropy, skewness and Gini index improves the classification accuracy of the system. F1-score of 93.98 of the feature selected for classification is much better than 80.49 of the GLCM texture feature vector {Contrast, Correlation, Energy, Homogeneity}. The simulations result indicates that features selected for training and classification are capable of achieving good accuracy of more than 91 % for the healthy and the fractured bone.
The proposed approach is capable of achieving 95.12% for the fracture bone classification, which is better than the approach of [6] 94.43% and 85% of the approach [24]. The approach [6] is not able to measure the other performance parameter like precision, recall and f1-score. In the proposed approach, we have measure the other performance parameter to evaluate the system. In the approach of the [24] features selected to classify the fracture and non-fractured bone is 19, which is much higher than the proposed approach of 7 features. The proposed approach classification accuracy of the healthy bone and the cancerous bone 91.66 is better than the work [24] of 86%.

5. Conclusion

The proposed texture feature using Hough transform accumulator with an income inequality matrix is a good feature for bone fracture detection and classification. It also gives a better result compared to standard GLCM texture features. In the experiment, it also found that the size of the image affects the classification accuracy. The GLCM texture feature alone doesn’t give good classification accuracy but taking the GLCM with the other texture feature like entropy, skewness, and Gini index yields better accuracy of the automated system. The objective of the present experiment is to identify and classify fractured bone using a new texture feature extracted from the Hough accumulator matrix and GLCM texture features. In the present research, the classification accuracy of the fracture bone is 95.12%, The proposed approach is also able to classify the healthy and the fracture bone with notable accuracy of 91.66%. The data set is a combination of the different types of human bone. In similar work, only one type of human bone was used for the experiment. The classification accuracy of the proposed approach is remarkable but still need to test on the large data set. In future work, we will try to implement more noise removal and texture feature techniques.

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