



## FEATURE EXTRACTION OF LONG BONE (TIBIA) USING TWIST KERNEL INVARIANT DISPARITIES(TKID)

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### Abstract:

Orthopaedic treatment requires proper classification of bone fractures. This helps doctors to assess the injury and plan the treatment accordingly. Different bones have different shapes, sizes and features. Therefore, fractures vary depending on the type, location and pattern of the bone.. Before classification accurate feature extraction is most important to improve the accuracy. This research proposed a new Twist Kernel Invariant Disparities(TKID) method to extract features after segmentation. This research extracts the following features are identified from this segmented image: Mean, SD, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Energy, Homogeneity, colour, size, shape, dimensions, convex and concave.

**KEYWORDS: CLASSIFICATION, FEATURE EXTRACTION, SEGMENTATION, RMS, VARIANCE, SMOOTHNESS, KURTOSIS**

## I.INTRODUCTION

Long-bone fractures are very common among elderly people. They may fracture their bones due to osteoporosis, stress or accidents. Automated fracture detection can help

doctors and medical staff to quickly evaluate the situation and decide the best course of action. Also, many computer-based training (CBT) programs in medical science focus on orthopaedics [22]. Moreover, virtual reality simulators [8,9,29] are becoming more popular for self-learning among medical students and interns. A tool for automated fracture detection can be useful for orthopaedic diagnosis, treatment and management.

Feature extraction is an important step in various image processing applications. It is a useful tool for image texture analysis [7]. Image textures are complex visual patterns composed of regions or entities with sub-patterns that have characteristics such as brightness, shape, colour and size. Feature extraction is the process of reducing the dimensions of the image and representing the relevant parts as a feature vector [6]. This is very important when the data size is large and image retrieval or matching is performed. There are different types of features that can be extracted from images, such as spatial, histogram, transform, edge, shape, colour and size.

## **II RELATED WORK**

Fracture detection was improved by fuzzy index measures from radiographs in the work of Linda and Jiji (2021) [12]. They used image processing techniques such as gridded information, local thresholding, threshold interpolation, segmentation by fuzzy index measures, background subtraction and morphological filtering. They located fractures and compared their method with two other standard methods. Our work differs from theirs because we detect fractures instead of locating them.

Wang et al (2021) [3] designed customized plates by extracting bone morphological features. They followed three main steps: bone feature extraction, plate under-surface feature representation and customized plate construction. The plate under-surface feature combined different bone features with different anatomical morphologies into a semantic feature parameter set. This set captured the generic relationship between the plate and bone features.

Vandana et al. (2020) [1] studied the basic bone tumor. They enhanced the graph cut-based clustering algorithm to identify the cancerous and healthy parts. Their method assessed the risk attributes and classified them as normal, benign or malignant using multiclass irregular texture.

Shrivastava et al. (2020) [2] reviewed various techniques to classify the cancerous and healthy bone. They used bone computed tomography (CT) dataset in Digital Imaging and Communication in Medicine (DICOM) format. They discussed different AI methods for tumor detection and classification. AI is a broad research area, and medical image processing is a significant subarea. Image processing can help in diagnosing diseases like ulcer, fracture, tumor, etc. and finding the best solution. AI methods can be applied to medical images for anomaly detection. They showed that machine learning techniques

achieved a good level of success. They discussed different AI methods for clustering.[24,25]

Siam et al.(2019)[26] proposed adaptive restriction factors that cooperate via neural network (NN)-based trained factors and used them to build a software restriction factor to detect long bone fractures. The results showed that the cooperating factor NN could help preserve the performance of automated fracture detection. The method is user-dependent as the user can select which process should be applied to the loaded image. Unlike Syiam et al., we presented an automated method to detect bony ridges without having to select this method as it is suitable for the tibial images input to the system.

### **III.FEATUREEXTRACTIONMETHODS**

Neville has suggested that features can be extracted using various methods such as statistical, structural, model-based and transforming information..

#### **i.StructuralBasedFeatureExtraction**

Texture can be described by structural approaches, which use distinct primitives and their spatial arrangements in a hierarchy. This requires a new way of classification. The advantage of this method is that it gives a good symbolic description of the image. [4,25]

#### **ii.StatisticalBasedFeatureExtraction**

Texture features can also be described by statistical methods, which use the non-deterministic property of the grey level relationships in the image. These methods compute local features at each pixel and use their distributions to define statistical measures. The statistical methods can be divided into three types: (1) First order - statistics of one pixel, (2) Second order - statistics of two pixels and (3) Higher-order - statistics of three or more pixels. The first-order statistics ignore the spatial interaction between pixels and only use the pixel values. They include (1) Mean - Average, (2) Variance, (3) Skewness and (4) Kurtosis.[5,20]

#### **iii.Model-BasedFeatureExtraction**

Another way to describe texture is by model-based feature extraction, which uses the structure of the image. For example, the fractal model and Markov model can describe the texture. These methods represent the image as a probability model or as a linear combination of basic functions. [6]

#### **iv.TransformBasedFeatureExtraction**

Transform feature extraction is another method that represents the image in a space that has a meaning related to the texture features. Some examples of transform

methods are Fourier, Gabor and wavelet transform. Fourier transform has a problem with spatial localisation. [9,10]

#### **IVPROPOSEDWORK**

#### **TWIST KERNEL INVARIANT DISPARITIES(TKID)**

Local image features are useful for recognising objects in images. Sometimes, the feature vector has many dimensions that describe the image better. The object recognition system matches these local features with a database based on the query. When there are more images, the database also needs more space to store millions or billions of vectors. Therefore, a hybrid technique is needed to reduce the space and increase the speed of feature extraction.

Figure 1 shows the proposed feature extraction method. The feature vectors are made from the relevant features of the training data. The segmented image has these features: Mean, SD, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Energy, Homogeneity, colour, size, shape, dimensions, convex and concave.

The proposed feature extraction method uses binary space to process the feature vector, which reduces storage and increases processing speed.

### TWIST KERNEL INVARIANT DISPARITIES(TKID)

**Input:** Segmented Image

**Output:** Feature vector

**Step 1:** Laplacian of Gaussian widths of 0.35,0.60,1 and 2 are considered.

**Step 2:** Convolved image by 3x3 Kernel(7 Features are extracted)

**Step3:** Texture features are extracted from grey level image by using

$$k1 = \sum_{i=0}^{N-1} \sum_{j=0}^{k-1} p_{\mu}^2(i, j)$$

**Step4:** Gaussian kernel function is used to extract the bidirectional features such as Heterogeneity and homogeneity

$$g(x, y, \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) \times \cos\left(2\pi \frac{x'}{\lambda} + \psi\right)$$

$$\text{where } x' = x \cos \theta + y \sin \theta, y' = -x \sin \theta + y \cos \theta$$

**Step 5:** Rotational invariant texture features which are given by:

$$g(x, y, \lambda, \theta, \psi, \sigma) = \exp\left(-\frac{D(x, y)^2}{2\sigma^2}\right) \cdot \cos\left(2\pi \frac{D(x, y)}{\lambda} + \psi\right)$$

$$\text{where } D(x, y) = \sqrt{(x - \bar{x})^2 + (y - \bar{y})^2}$$

**Step 6:**The following edge features are extracted Step edge, Ramp edge, Line and Roofing gradient deviation feature indicates the amount that the current gradient deviates from the most frequently occurred gradient,  $\theta_{Ref}$ . The gradient deviation is obtained using below equation

$$\Delta\theta = |\theta_{Ref} - \theta_L|$$

ColourFeatures are calculated by using the statistical formulas

a. Mean is the average of the pixel values in the image. It is calculated using equation(1).

$$\mu = \frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N P_{ij} \text{ Eqn. (1)}$$

b. StandardDeviation (SD) is the measure of deviation every pixel has from the average.

$$\sigma = \sqrt{\frac{1}{MN} \sum_{i=1}^M \sum_{j=1}^N (P_{ij} - \mu)^2} \text{ Eqn.(2)}$$

c. Kurtosis is the relative peak of flatness found in the image

$$\theta = \frac{\sum_{i=1}^M \sum_{j=1}^N (P_{ij} - \mu)^3}{MN\sigma^2} \text{ Eqn. (3)}$$

d. Skewness is the measure to find the lopsided nature of pixels

$$\gamma = \frac{\sum_{i=1}^M \sum_{j=1}^N (P_{ij} - \mu)^4}{MN\sigma^4} \text{ Eqn. (4)}$$

The texture Features such as Energy, Entropy, Homogeneity, Variance, RMS, Smoothness, IDM, Correlation is calculated.

e. Energy depends on the ASM known as AngularSecondMoment, which denotes the pixels' uniformity or texture pattern.

$$ASM = \sum_{i,j=0}^{N-1} P_{i,j}^2 \text{ Eqn. (5)}$$

f. The square root of ASM calculates energy Eqn. (6)

$$Energy = \sqrt{ASM} \text{ Eqn. (7)}$$

g. Entropy indicates the randomness of the image. It becomes small when elements are unequal. When the Co-occurrence metrics have the same element, then the value of entropy becomes high.

$$Entropy = \sum_{i,j=0}^{N-1} P_{ij} (-\ln P_{ij}) \text{ Eqn. (8)}$$

h. Root Mean Square (RMS) is modelled as a Gaussian random process with amplitude modulation whose RMS is related to the constant force and no fatiguing contraction. It

relates to standard deviation, which can be expressed as  $RMS = \sqrt{\frac{1}{N} \sum_{n=1}^N x_n^2}$  Eqn.

(9)

i. DM Inverse difference moment is a measure of image texture, called homogeneity. IDM features measure how close the distribution of GLCM elements is to the GLCM diagonal..

$$m_k = E(x - \mu)^k \text{Eqn. (10)}$$

j.Smoothness is a measure of relative smoothness of intensity in aregion.

k.Correlation is the measure of the degree and type of relationship between adjacentpixels.

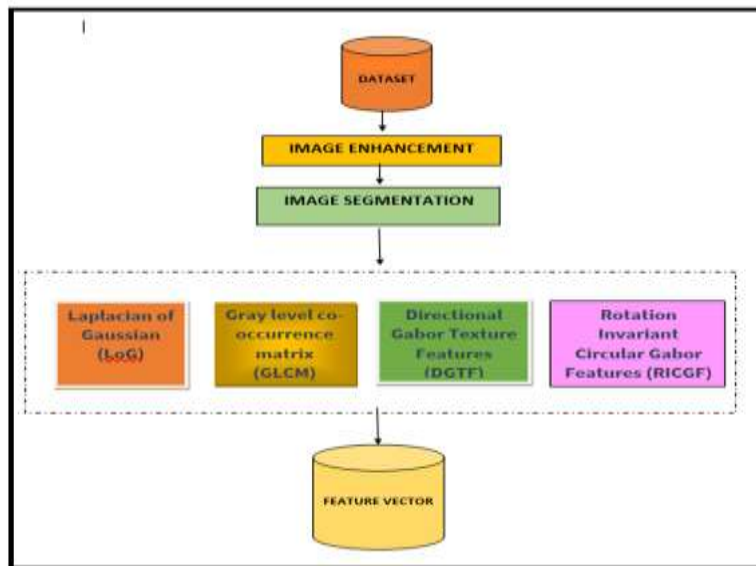
$$\text{Correlation} = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i\sigma_j} \text{Eqn. (11)}$$

l. Homogeneity defines how close the element is to the diagonal of GLCM. When homogeneity increases, the contrast decreases.

$$\text{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \text{Eqn. (12)}$$

m.Variance for the horizontal and vertical directions is calculated asfollows

$$\sigma^2 = \sum_{i,j=0}^{N-1} (i - \mu_i)(P_{ij}), \sigma^2 = \sum_{i,j=0}^{N-1} (i - \mu_i)(P_{ij}) \text{Eqn. (13)}$$



**Figure1: ProposedFeatureExtractionMethod**

## V.RESULTSANDDISCUSSIONS

The proposed algorithm's result is shown in Figures 1 and 2. It uses MATLAB to compute the values of Mean, SD, Entropy, RMS, Variance, Smoothness, Kurtosis, Skewness, IDM, Contrast, Correlation, Energy, Homogeneity, colour, size, shape and dimensions. The values of the feature extraction are labelled by their disease category and used to create the training set. The features are stored in CSV format in an Excel file. This data is used for training when the classification algorithm detects the fracture. The feature extraction process is also applied to the testing data when the classifier runs on a random image and identifies the fracture.



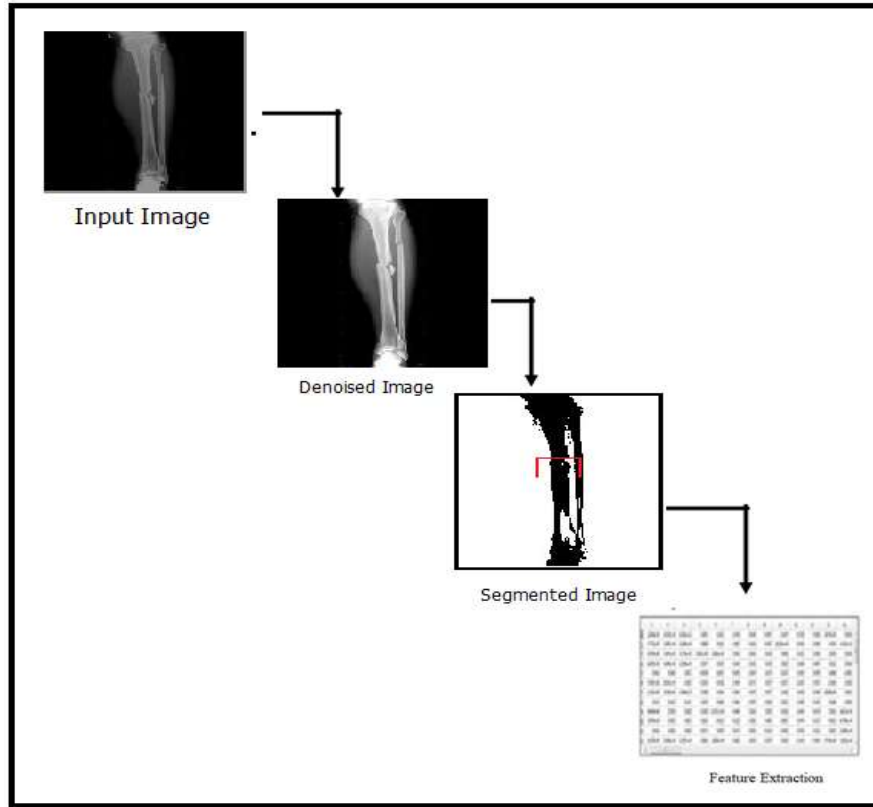
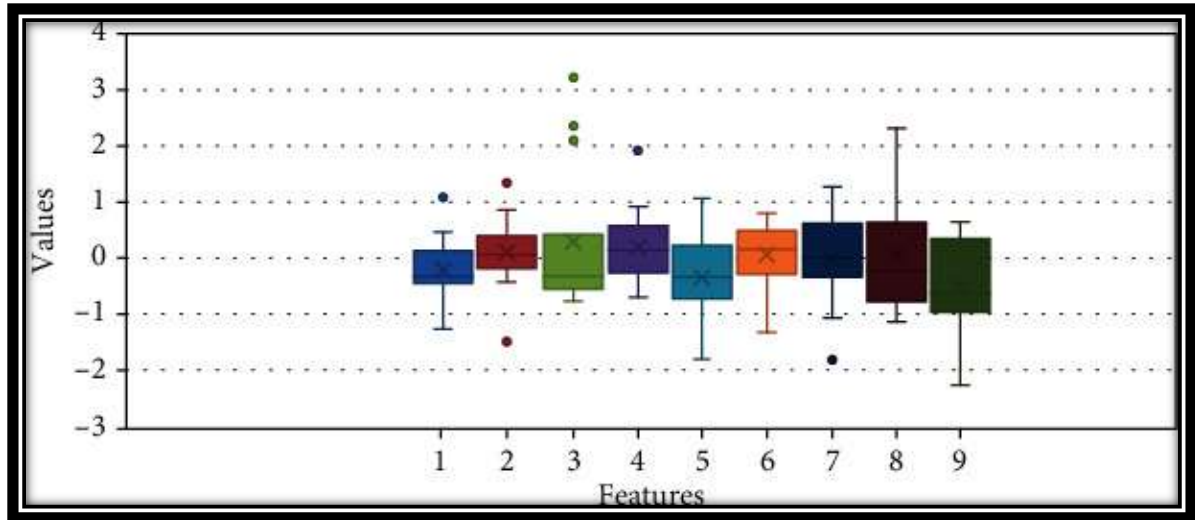


Figure2: FeatureExtraction of ProposedMethod

File	Mean	SD	Entropy	RMS	Variance	Smoothness	Kurtosis	Skewness	IDM
Image 1	2.6458e-05	4.0355e-04	6.1044e-05	0.0607	0.0031	0.0709	0.0048	-0.0017	-0
Image 2	-7.7752e-05	2.3807e-04	1.9294e-04	0.0696	0.0101	0.0697	0.0104	-0.0307	4.823
Image 3	-3.4738e-04	2.4972e-04	3.4738e-04	4.3267e-04	2.9565e-04	0.0018	0.0016	0.0148	0
Image 4	-4.6355e-05	4.2642e-04	2.2096e-04	0.0137	0.0333	0.0140	0.0335	0.0278	0
Image 5	-0.0014	0.0034	0.0072	-0.0029	0.0027	0.0191	0.0437	0.0175	0
Image 6	-3.7897e-06	8.4541e-04	0.0010	-0.0193	-0.0328	0.0404	0.0373	0.0357	-0
Image 7	-2.1261e-05	2.0339e-04	4.7946e-05	0.0508	0.0054	0.0914	0.0075	0.0037	0
Image 8	0.0121	0.0145	0.0121	0.0105	0.0084	0.0944	0.0787	0.0019	-0
Image 9	9.9459e-04	0.0018	0.0028	0.0200	-8.3571e-04	0.0485	0.0163	0.0254	0
Image 10	2.8760e-04	0.0052	0.0021	0.0141	-0.0223	0.0225	0.0301	0.0403	-0
Image 11	0.0014	0.0014	0.0020	-0.0172	0.0078	0.0179	0.0160	-0.0124	-0
Image 12	-3.1378e-05	2.3080e-04	1.3557e-04	0.0662	2.6030e-04	0.0662	0.0024	-0.0170	0

Figure3: Result of the ProposedAlgorithm





**Figure 4** Box plot of Important Features

The box plot analysis is performed to find the importance of the features. Figure 4 shows the box plot of the 9 features. It extracts gradient and orientation to find the shape and direction of a pixel in the image. The gradient in the x and y direction is calculated for every pixel to check the intensity change of the image. These features are trained by classification method to predict the types of bone fracture.

## VI CONCLUSION

The texture of the cracked bone and healthy bone are different. The cracked bone region has more scattered pixels than the non-cracked bone. Therefore, texture feature extraction from the bone is important. In this research, GLCM based texture features are extracted. The Laplacian Gaussian extracts the gradient features. The Gaussian kernel function extracts the bidirectional features such as heterogeneity and homogeneity. Rotational invariant features are also extracted. Edge features such as step, ramp line and roof are also extracted. These are new features introduced in this research. They can help to predict the bone crack accurately by the classification method.

This research described the fast matching of binary feature-based feature extraction to get energy, entropy, contrast, inverse difference and directional moment. These texture features are used as input to classify the image correctly. Therefore, selecting multiple features of the image and a suitable classification method are important for improving classification accuracy.

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