VETERINARY BONE FRACTURE DETECTION AND FRACTURE CLASSIFICATION USING DIGITAL IMAGE PROCESSING

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ABSTRACT

This paper presents abnormality detection from segmentation techniques for leg fracture segmentation from animal x-ray images. Bone fractures are common in animals. Treatment of fractures is important. If the correct intervention is not perfom1ed, there may be complications in the fracture improvement process. So, it is essential to make a correct and quick decision. In general, x-ray images are used in the diagnosis of fracture in veterinary medicine. But, the diagnosis of bone fracture by taking X-Ray image is risky for clinicians due to radiation exposure. Gaussian filtering is used to remove the noise from the x-ray images. fracture is segmented from x-ray image by performing thresholding segmentation operations. Experiments are performed on clinical data set to present the severity of the fracture in images for threshold segmentation methods studied. Extract the Features from segmented images using GLCM techniques. SVM algorithm is use for classify the given animal x-ray image is fractured or not. Using thresholding segmentation techniques, fractures are separated from x-ray images. Utilizing GLCM techniques, extract the features from segmented images. The SVM method is used to determine whether or not the provided animal x-ray image is broken and identify its type of fracture exist in animal x-ray images.

KEYWORDS: Segmentation, Thresholding, SVM, GLCM, Transverse, Oblique, Spiral, and Comminuted

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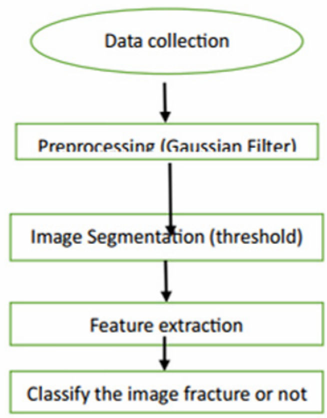
1. INTRODUCTION:

Bone fractures are common in animals. Treatment of fractures is important. If the correct intervention is not perfom1ed, there may be complications in the fracture improvement process. So, it is essential to make a correct and quick decision. In general, x-ray images are used in the diagnosis of fracture in veterinary medicine. But, the diagnosis of bone fracture by taking X-Ray image is risky for clinicians due to radiation exposure. It is also a costly and error-prone method in diagnosis. Sometimes, it may be difficult to diagnose a fracture due to the low quality of the x-ray image or fatigue cause of demanding workloads for the general orthopaedist. The quick procedure will prevent patient harm due to delayed or missed diagnosis. In veterinary medicine, fractures are a frequent occurrence, and it is often necessary to make a rapid and correct diagnosis in order to guarantee that animals get the required therapy and recover in a timely manner. Animals often suffer bone fractures. Treating fractures is crucial. The speedy process will save the patient from injury from a missing or delayed diagnosis. Fractures are common in veterinary medicine, and in order to ensure that animals receive the necessary treatment and recover in a timely way, a prompt and accurate diagnosis is frequently essential. Several researchers, among others, have used the incorporation of a denoising phase into the process of automated fracture identification. On the basis of X-ray and CT scans, there are a variety of techniques that may be used to diagnose fractures.

Support Vector Machine (SVM) classifier, X-Ray/ CT auto classification of fracture (GLCM), Novel morphological gradient based edge detection technique, Daubechies Wavelet and Fuzzy C-Means (FCM) Clustering, Using Classifiers OT, BN, NB, NN, and mixed, Fusion Classification technique, Wavelet and Haar, Combined snake and GVF, and X-Ray/ CT auto classification of fracture (GLCM) are some of the techniques that have been implemented [1]. In spite of the fact that there are a great number of retrospective studies about the automated assessment of bone fractures in humans, there are not a great number of studies that have been identified on animal fractures. Retrospective research has been conducted only with the purpose of detem1ining the frequency of appendicular fractures in canines and felines [2]. Recent developments in digital image processing (DIP) methods provide interesting possibilities to overcome these difficulties [3]. This is made possible via the use of computational techniques and machine learning models. Not only can these devices speed up the diagnosis process, but they also provide vets with objective tools that enable them to make treatment choices based on accurate information [4]. This research was prompted by the junction of veterinary medicine and healthcare technology, which presented an opportunity for investigation [5]. Significant progress has been made in the field of veterinary diagnostics with the introduction of the capability to automatically identify fractures in X-ray pictures of animals. The purpose of this study is to bridge the gap between conventional diagnostic approaches and cutting-edge technology solutions by using the potential of DIP techniques [6]. This study's major purpose is to create and assess an automated system for fracture diagnosis in animal X-ray pictures. This will be accomplished via the use of animals. Among the most important goals are, Making use of sophisticated feature extraction techniques, such as the Grey Level Co-occurrence Matrix (GLCM), in order to capture fine textural characteristics that are suggestive of fractures and using Support vector machine algorithm (SVM) to accomplish the classify the given x-ray image of animals is to be fractured or not fractured.

2. MATERIALS AND METHODOLOGY:

The proposed work flow is provided in figure I



Flow diagram 1. Block Diagram of Research Methodology

Through the use of a variety of digital image processing methods and machine learning algorithms, this research endeavor takes a methodical approach 10 the automation of fracture identification in animal X-ray pictures. The dataset is comprised of X-ray images that were gathered from a number of prestigious institutions. First phase applying preprocessing on collected animal x-ray images using Gaussian filter to remove the noise from x-ray images, in second phase applying threshold segmentation techniques to segment the fracture area. In third phase for extract the features from a segmented area using the GLCM techniques. In final phase using classification the given image fracture or not fracture use the SVM technique.

2.1. Data Set Description:

The dataset was obtained contains a variety of X-ray images of animals' legs such as dog, cat sheep, goat, cow etc. Animal's leg X-ray images were obtained from a number of authoritative veterinary institutions, including the Karnataka Veterinary Animal and Fisheries Sciences University Bidar, the Veterinary Government Hospital Mahagaon, the Veterinary Government Hospital, Kalaburagi, and the Veterinary College and Hospital Shivamogga. These institutions were used to compile the dataset that was utilised in this study. Dr. Hegga, a veterinarian in Kalaburagi, provided additional detailed descriptions and contributed insightful annotations and thorough descriptions, which contributed to the enrichment of the information. Each image was subjected to preprocessing, which included the use of a Gaussian filter for noise reduction, thresholding for segmentation, GLCM for feature extraction, and Support vector

machine (SVM) algorithm for Classification of images. The images were focused on leg areas that are prone to developing fractures. A robust automatic fracture diagnosis system that is accurate and adaptable across a variety of veterinary scenarios may be developed with the help of this diversified dataset that has been meticulously annotated. The data set consisted of minimum 50 x-ray images which are dog, cat, sheep, cow, goat leg's fractured part.

2.2. Preprocessing

Medical X-ray images often suffer from noise due to various factors (e.g., sensor imperfections, patient movement). Gaussian filters effectively reduce noise To provide high-quality inputs for further analysis, the pictures undergo preprocessing using a Gaussian filter, which smooths the images by minimising noise and highlighting essential aspect. This stage in the preprocessing process is very critical step in computer vision and medical imaging. It aims to enhance image quality, remove noise, and prepare the data for subsequent analysis. In this section, we focus on noise reduction using Gaussian blur-a co1mnon technique applied to X-ray images. necessary in order to enhance the precision of the following picture segmentation and feature extraction procedures. In the field of image processing, the Gaussian filter is a widely used method for smoothing or blurring images. It uses a Gaussian kernel, a two-dimensional matrix of weights determined by the Gaussian function, to carry out the function of a convolution filter. By lowering noise and suppressing small features, filters are mostly used to make photographs appear optically smoother. To control the level of smoothing, users can adjust a number of factors, including filter size and standard deviation. The Gaussian filter is used for pre-processing tasks in computer vision, noise reduction, and image smoothing.

One kind of linear filter used to blur (smooth) an image is the Gaussian filter. It works by utilizing a kernel that approximates a Gaussian distribution to apply a convolution operation to the image data. A smoother, more blurred version of the original image is the outcome of this process. By averaging pixel values within a local neighborhood pixel, Gaussian filters efficiently minimize noise. This method substitutes the noisy pixel in the image, which is based on a Gaussian distribution, with the average value of the surrounding or neighboring pixels.

Among the most important uses are:

- Image denoising is the process of making images less noisy at high frequencies while maintaining their edges.
- Improving the quality of a picture before proceeding with additional processing, such as segmentation, is referred to as preprocessing.

2.3. Image Segmentation:

Image segmentation is carried out after the preprocessing stage in order to separate the bone structures from the tissues that are around them the thresholding approaches that tum grayscale photos into binary images ensure that the bone structures are clearly differentiated from the background. The primary purpose of this function is to segment the input grayscale image into two regions: one representing the object of interest (foreground) and the other representing the background by thresholding the image, we create a binary mask where pixels are either O (background) or 255 (foreground) This is accomplished by converting the grayscale images into binary images. For the purpose of concentrating the study on pertinent anatomical characteristics that are symptomatic of fractures, the segmentation procedure is absolutely necessary. To compute the statistical information of each and every pixel in a picture, a square-shaped operator, which might have a size of 3x3, 5x5, or 7X7 pixels, would be used. It's possible that a picture contains more than one thing. Following the operator's division of the picture into hundreds of blocks, the amount of information contained inside each block is significantly reduced. In this method, pixels with intensity values above a certain threshold are assigned one value (e.g., white), while those below the threshold are assigned another value (e.g., black). When the threshold value is specified as 128. This means:

- **Pixels with intensity values from 128 to 255 are set to white.**
- **Pixels with intensity values from O to 127 are set to black.**

Object and background are the only two grayscale zones that are presumed to be present in each block, according to the assumption. If the size of the structural operator is sufficiently modest, then the assumption is plausible, and the experiment will provide the confirmation that the assumption is correct. \\fithin the scope of this study, the following approach is used to estimate the thresholds of the pixels that include an image. After segmentation, the segmented image is compared to the ground truth to evaluate the performance of the algorithm This comparison can be done using metrics such as accuracy, precision, recall, and the Fl-score to quantify how well the segmentation matches the ground truth labels.

Algorithm

a. **Calculate Local Threshold:** Compute r,.1 for each pixel (i,j).
b. **Classify Pixels:** Determine if each pixel belongs to the object or background based on r,.,.
c. **Compute Variance:** Calculate u1/ for each pixel's neighborhood.
d. **Detect Boundaries:** Classify boundary pixels based on grayscale value and variance.
e. **Simplify Variance Calculation:** Optionally use the difference between the brightest and darkest pixels to approximate variance.
f. **Compare to Ground Truth:** Evaluate segmentation results against ground truth using standard metrics. This approach allows for effective image segmentation by leveraging local statistics and adaptive thresholding, which can handle variations in lighting and object texture within the image.

2.4. Feature extraction

Following the segmentation of the bone stuctures, the Grey Level Co-occurrence Matrix (GLCM) is used in order to begin the process of feature extraction. The GLCM technique is a very effective way for analysing textures, since it involves quantifying the spatial correlations between the intensities of the pixels in the segmented pictures. It is possible that the existence of fractures may be inferred from the retrieved GLCM features since they capture key textural characteristics. The piece of information that is vital for solving a particular application and for representing key qualities of pictures is often referred to as features. One of the most important factors that determines the accuracy of classification and the needs for training sets is the selection of input characteristics. The technique of collecting the visual contents of x-ray image is known as feature extraction. The objective of this procedure is to reduce the number of resources that are typically needed. A grey level co-occurrence matrix, often known as GLCM, was developed as part of this research project in order to extract statistical texture properties.

The GLCM represents the statistical relationships between pairs of neighboring pixels based on their gray-level intensities. The input to this function is a preprocessed grayscale image (e.g., an X-ray image of a bone). The image has already undergone segmentation thresholding. The GLCM is constructed by analyzing the co-occurrence of pixel intensity values at specific distances and angles within the image and set the distance to I (adjacent pixels) and the angle to O degrees (horizontal direction). The grey comatrix function computes the GLCM based on these parameters. Texture characteristics are essential low-level features

that are utilised to characterise the contents of an image, such as quantifying the texture that is perceived in an image. The method is well-known for its ability to extract second-order statistical texture characteristics by making use of statistical distributions of intensity value combinations at various places in relation to one another inside an image.

It is possible to acquire a total of twenty-two texture-based characteristics, which include energy, correlation, entropy, inverse difference moment (TOM), homogeneity, sum variance, autocorrelation, contrast, maximum probability, dissimilarity, and TOM nom1alised, amongst many more. Only a handful of them are comprised of the following:

2.5. Classification

The overall classification workflow is represented in diagram. The proposed fracture type classification system significantly improves veterinary diagnostic support by reducing manual interpretation effort and minimizing diagnostic errors. It also provides a computationally efficient solution suitable for small veterinary datasets and low-resource clinical environments. Future enhancement of the system may include fracture localization, severity analysis, and deep learning-based hybrid classification models for higher diagnostic accuracy

Powerful classifiers that can be effectively used for tasks like identifying whether an X-ray image corresponds to a fractured bone or not. Let's explore how SVMs can be applied to this specific problem. Problem Statement, Given an X-ray image, we want to determine whether the bone in the image is fractured or not. Using SVMs for Classifications are well-suited for binary classification tasks. Here's how we can apply SVMs to this problem. Extract relevant features from the X-ray image by GLCM, which capture texture information. The SVM receives these features as input.

The SVM learns to find the optimal decision boundary (hyperplane) that separates fractured and non-fractured cases. Predict that given a new X-ray image, extract the same features. Use the trained SVM to predict whether the bone is fractured or not. Finaly Evaluate the SVM's performance using metrics such as accuracy, precision, recall, or Fl-score. Cross-validation can help ensure robustness. Once the SVM is trained and evaluated, it can be deployed in a medical application. Medical professionals can input X-ray images, and the SVM will provide predictions. Using the retrieved characteristics, the classifier, which was trained on labelled datasets, is able to differentiate between images that have been fractured and those that have not occurred. This automated categorisation technique considerably improves diagnostic accuracy and consistency, so providing veterinarians with trustworthy instruments for the quick diagnosis of fractures. Powerful classifiers such as Support Vector Machine (SVM) can be effectively used not only for identifying whether an animal X-ray image contains a fracture, but also for determining the specific type of fracture present in the bone structure. In the existing system, the SVM classifier is primarily used for binary classification, where the input X-ray image is classified as either fractured or non-fractured. However, in this proposed extension, the classification stage is further enhanced to identify multiple fracture categories such as transverse, oblique, spiral, and comminuted fractures. The classification process begins after pre-processing, segmentation, and feature extraction stages are completed. Initially, the X-ray image undergoes Gaussian filtering to remove noise and improve image quality. Threshold-based segmentation techniques are then used to isolate the fractured bone region from the background tissues. After segmentation, important texture features are extracted using the Grey Level Co-occurrence Matrix (GLCM). These extracted features represent variations in pixel intensity, texture complexity, edge discontinuities, and structural abnormalities within the bone region.

The extracted GLCM features are then provided as input to the Support Vector Machine (SVM) classifier. SVM is a supervised machine learning algorithm that learns the differences between multiple fracture classes by analyzing labelled training data. The classifier identifies the optimal hyperplane that separates different fracture categories with maximum margin. During testing, the trained SVM model predicts whether the given animal X-ray image belongs to the normal class or one of the fracture classes. The proposed system classifies fractures into the following categories: as shown in table.

A transverse fracture appears as a straight horizontal crack perpendicular to the bone axis. Oblique fractures are characterized by diagonal fracture lines crossing the bone at an angle. Spiral fractures occur due to twisting forces and produce curved or spiral-shaped fracture patterns. Comminuted fractures are severe fractures where the bone breaks into multiple fragments and irregular pieces. These fracture types exhibit different texture and edge characteristics in X-ray images, which can be captured effectively using GLCM texture analysis.

Table 1: classes names

Class	Description
Normal	No fracture detected
Transverse Fracture	Horizontal fracture line
across the bone	
Oblique Fracture	Diagonal fracture line
Spiral Fracture	Twisting fracture caused by rotational force
Comminuted Fracture	Bone broken into multiple fragments

The SVM classifier simultaneously determines:

- Whether a fracture is present
- The specific fracture type

This multi-class classification approach improves the diagnostic capability of the system and provides more detailed clinical information to veterinarians. Instead of simply detecting fractures, the proposed model assists in identifying the nature and severity of bone damage, which helps in treatment planning and surgical decision-making. The mathematical representation of the SVM decision function is expressed as:

$f(x) = w.x + b$

where:

- w represents the weight vector,
- x represents the input feature vector extracted using GLCM,
- b represents the bias term.

The Radial Basis Function (RBF) kernel is utilized in this work because fracture patterns are generally non-linear and complex in nature. The RBF kernel transforms the extracted features into a higher-dimensional feature space, enabling more accurate separation between different fracture categories.

3. RESULT AND DISCUSSION

It also makes a contribution to the development of digital healthcare technology in the field of veterinary medicine. In this study, we employed Gray Level Co-occurrence Matrix (GLCM) and connected regions for feature extraction from x-ray images. The experiment involved two types of x-ray images one depicting a fractured bone and another representing a normal x-ray image without any fracture presence. Feature Extraction and Analysis GLCM Texture Features We computed texture features from the GLCM to characterize the grayscale patterns within each x-ray.

These features provided insights into the texture variations associated with different fractures and the absence of fractures. Connected Regions for Shape Features: Utilizing connected regions, we extracted shape features such as circularity, area, and perimeter from segmented x-ray images. These features helped quantify the geometric properties of fractured leg and normal leg in bones. for the Figure, the GLCM features extracted from the image, the mean GLCM value was found to be very low (I.53e-05), indicating subtle variations in texture. The standard deviation of GLCM values was 0.00306, suggesting moderate variability in texture patterns across the image. The maximum GLCM value observed was 0.784, indicating areas of pronounced texture co-occurrence. These findings collectively led to the detection of a fracture in the analyzed image, highlighting the effectiveness of GLCM-based image processing techniques in identifying structural abnormalities."

The mean GLCM value of I.53e-05 indicates low overall texture complexity, while the standard deviationof0.00306 suggests moderate variability in texture patterns. The maximum GLCM value observed was 0.784, indicating areas with significant texture co-occurrence.

These findings led to the detection of a fracture in the analysed image. "The mean GLCM value of approximately I.53e-05 indicates very low texture complexity across the image. The standard deviation of GLCM values, at 0.00287, reflects relatively uniform texture patterns with slight variability. The maximum GLCM value observed was 0.736, suggesting localized areas of pronounced texture co-occurrence. These findings collectively supported the detection of a fracture in the image, underscoring the efficacy of GLCM-based analysis in identifying structural abnormalities."

The mean GLCM value of approximately l.53e-05 suggests very low texture complexity throughout the image. The standard deviation of GLCM values, measured at 0.00225, indicates minimal variability in texture patterns across the analyzed area. The maximum GLCM value observed was 0.576, indicating areas with moderate texture co-occurrence. These findings collectively indicate no fracture detected in the image, highlighting the consistent texture patterns observed.

Table: II Experimental Data

Data	Mean GLCM	STD GLCM	Max GLCM	Classification
Fig I	J.525e-05	0.002	0.590	Fracture detected in the image Complete fracture
Fig2	1.525 e-05	0.003	0.784	Fracture detected in the image
Fig 3	1.525 e-05	0.0028	0.736	Fracture detected in the image.
Fig4	1.525 e-05	0.0022	0.576	No Fracture detected in the Image comminuted fracture

Fig. I: Data I (original vs classified image)

Fig. 2: Data 2 (original vs classified image)

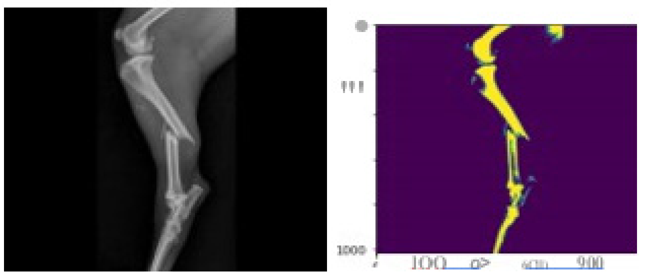


Fig. 3: Data 3 (original vs classified image)

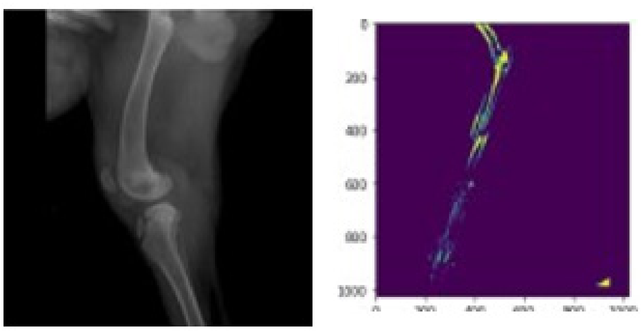
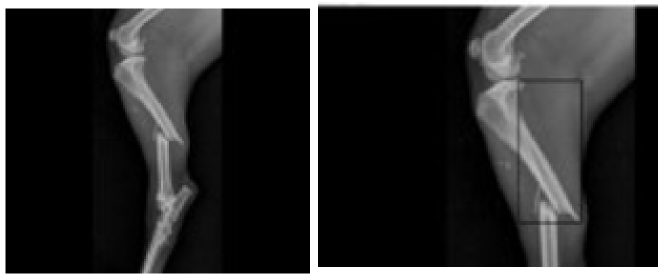


Fig. 4: Data 4 (original vs classified image)



5. CONCLUSION

The approach is able to accommodate differences in illumination and texture since it calculates local thresholds based on the mean grayscale values of nearby pixels. The use of variance analysis helps to further enhance boundary detection, which in tum ensures that edge pixels are classified accurately. The computational cost of the technique is reduced by the use of a simplified variance calculation, which makes the approach acceptable for use in real-time applications. The results of the experiments demonstrate the accuracy and resilience of the approach, indicating that it achieves the desired outcomes in a variety of imaging situations. For the purpose of improving segmentation, it is possible that future study may concentrate on finding length of fractured leg x-ray images, more details of type of fracture and optimising the algorithm for pictures that are more complex and adding extra contextual information.

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