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# Bone Deformity Identification Using Machine Learning

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**Abstract - The effectiveness of machine learning algorithms in medical imaging has underscored the necessity for proficiently trained models to expedite and optimize their application within the medical domain. This project proposes a methodology for identifying bone fractures using machine learning algorithms, aiming to alleviate the workload for orthopedic professionals. Leveraging machine learning's substantial potential in the era of vast medical data could streamline the process of extracting insights from available X-ray images, thereby reducing the need for prolonged stays in radiology departments. The project introduces imaging technologies tailored for bone fracture identification in human subjects, promising prompt results following X-ray procedures.[1]**

**Keywords: Machine Learning, Regression, clustering, K-means clustering.**

## I. INTRODUCTION

Broken bones are a common issue in humans, stemming from various causes such as falls, accidents, diseases like pathological fractures, and injuries to the skin, including hairline fractures. While conventional methods like X-rays and CT scans are utilized for fracture identification, they may not always precisely pinpoint the location. Integrating machine learning and artificial intelligence (AI) into diagnostics could substantially enhance accuracy in fracture diagnosis. Orthopedic physicians frequently rely on X-ray imaging for fracture detection, and machine learning tools can efficiently extract pertinent information from these images. Advances in hardware and software technology further facilitate this integration.[1]

Recognizing that a single method may not universally apply to all body parts, the exploration of new technology capable of identifying fractures using a unified approach is crucial. The proposed computerized diagnostic assistance system presents an innovative solution to this challenge. Relevant for individuals of all ages encompassing men, women, and children, the CAD system delivers summarized and evaluated results of identified deformities or fractures in image obtained through X-ray. Project aims to implement an efficient a system with the capability of processing images accurately detecting fractures throughout the human body.[1]

Medical science divides health risks into two major categories: those that are unchangeable and those that are changeable. Age, family history, sex, etc. are unchangeable factors.[9]

## II. AIMS AND OBJECTIVE

**a) Aim:** The main goal of this project is to achieve precise detection and proper treatment of fractures. Incorrect diagnoses can result in ineffective patient care, increased dissatisfaction, and costly legal ramifications. Detecting bone fractures presents a significant challenge, particularly in environments with high levels of noise. The incorporation of sophisticated machine learning algorithms and deep learning techniques can enhance both the precision and effectiveness of fracture detection. This involves the system learning from an extensive dataset of medical images, continuously refining its diagnostic abilities over time. By harnessing state-of-the-art technology, this project aims to bridge the gap between traditional diagnostic methods and modern computational approaches, thereby revolutionizing the field of orthopaedic radiology and leading to better patient care outcomes. By leveraging real-time feedback mechanisms, the system can adapt dynamically to new cases and evolving medical knowledge, ensuring continuous improvement in diagnostic accuracy. Ultimately, the overarching goal is to establish a standardized framework for fracture detection and treatment, fostering consistency and reliability across medical practices globally.

**b) Objective:** The preliminary algorithm for fracture detection is based on deep learning, particularly utilizing the

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Region-Based Convolutional Neural Network. This architecture consists of three primary steps: - Producing around 2000 region proposals via Selective Searching. Passing each region through a CNN for extracting its feature map. Classifying each region according to its feature map utilizing Support Vector Machine. Adjusting the bounding box around the object.

## III. LITERATURE SURVEY

**Paper 1: Improved version of graph-cut algorithm for CT images of lung cancer with clinical property condition**

Detecting lung cancer during clinical assessments presents a formidable challenge, particularly when it comes to pinpointing proliferating nodules through segmentation techniques. The early identification of lung cancer is essential in clinical research. Nevertheless, accurately segmenting the initial stages of lung nodules, which primarily comprise exceedingly soft tissues, remains an arduous endeavour. Conventional graph cut method often falter in precisely delineating these soft edges within medical images. In response, the article suggests an advanced algorithm aimed at enhancing the segmentation process's accuracy, surpassing the capabilities of conventional graph cut methods. The investigation detailed here seeks to showcase the elevated precision attained in lung segmentation, marking a significant advancement in the field's methodology.[2]

**Paper 2: Bone fracture detection from x-ray image of human fingers using image processing**

Orthopaedics encompasses the surgical and therapeutic management of the human musculoskeletal system, addressing a spectrum of issues including degenerative conditions, trauma, sports injuries, tumours, and congenital abnormalities. Orthopaedic practitioners often rely on X-ray imaging to aid in diagnosing injuries. X-rays utilize electronic radiation to capture images of bones within the body, which are then interpreted by radiologists to identify any abnormalities or fractures. However, manual examination of X-ray images by doctors can be labour-intensive and prone to oversight. Detecting major bone-related diseases or issues solely through visual inspection of X-ray images is challenging, as many conditions may go unnoticed until they progress to more advanced stages, such as bone fractures. Moreover, X-ray images can suffer from various imperfections like blurriness, improper brightness, and noise, further complicating the diagnostic process. To address these challenges, computerized image processing techniques offer promising solutions. By leveraging algorithms and computational methods, researchers can enhance the quality of X-ray images and automate the detection of fractures. In this paper use image processing techniques to provide a novel algorithm specifically made for identifying bone fractures in human fingers. Our strategy uses advanced algorithms that can precisely locate fractures in X-ray pictures in order to get around the drawbacks of manual examination and image defects.[3]

**Paper 3: Automatic identification of fracture region within bone in x-ray image**

Bone fractures is a prevalent issue in humans, often resulting from high pressure on the bone or accidents, and in some cases, conditions like bone cancer or osteoporosis. Consequently, accurate diagnosis of bone fractures holds paramount importance in the medical field. This paper focuses on utilizing X-ray images for bone fracture analysis. The objective is to devise a processing technique capable of identifying fracture regions within bone structures in X-ray images sourced from medical institutions. The results obtained showcase the effectiveness of the proposed processing technique.[4]

**Paper 4: Fracture detection in x-ray images through stacked random forests feature Fusion**

Fractures are a common occurrence in injuries affecting the musculoskeletal system and are often overlooked in radiological assessments, highlighting the essential need for support tools to aid radiologists. Previous research in automated bone fracture detection has primarily concentrated on identifying specific fracture types within a single anatomical area. This paper introduces an innovative method for detecting bone fractures across various fracture types and bone structures throughout the body. The proposed technique utilizes features extracted from candidate patches in X-ray images within a distinct discriminative learning framework. This framework employs a layered learning approach where class probability labels generated by random forest learners at a lower level contribute to refining the class distribution labels at the subsequent level. Candidate patches are selected using an efficient sub-window search algorithm. The result of the approach consists of multiple fracture bounding boxes ranked in descending order of likelihood to contain a fracture.[8]

## IV. EXISTING SYSTEM

In the medical field, identification of broken bones and deformity assessment are crucial areas of study. While fractures are often invisible to the naked eye, X-ray and CT imaging serve as indispensable tools for their detection. However, the intricacies of these images can sometimes overwhelm human perception, leading to potential oversight of multiple fractures and complicating treatment protocols. It is imperative to create intelligent categorization algorithms that can quickly identify and highlight bone fractures to address the challenge of difficulty. One promising approach involves the creation of a computerized diagnostic assistance system designed to identify fractures within medical images, particularly X-rays, with speed and accuracy. Such a system would greatly assist radiologists and orthopedic specialists in interpreting these images promptly, facilitating comprehensive and effective treatment strategies.[1]

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## V. COMPARATIVE STUDY

*Table.1: Comparative Analysis*

| Sr. No. | System Title | Authors | Main Objective | Methodology/ Technique | Results/Performance |
|---|---|---|---|---|---|
| 1 | Quantitative examination and fracture identification of x-ray images of the pelvis | Vijayakumar and G. Gireesh | Aims to locate fractures in X-ray pictures. | Gray level cooccurrence matrix is used. | Effectively identifies both large and small fractures. |
| 2 | Fracture Region Identification | Ghosh and S. Saha | Focuses on identifying fracture regions in X-ray images | Methodology not explicitly mentioned | Shows effectiveness in identifying regions of fractures. |
| 3 | X-ray Fracture Detection | Y. Cao, H. Wang, M. Moradi, P. Prasanna, and T. F. Syeda-Mahmood | Develops a generalized approach for fracture detection | Applies Feature Fusion with Stacked Random Forests | Achieves high accuracy, capturing 81.2% of fractures with top ranking bounding-boxes |
| 4 | Enhanced Lung Cancer Detection | Manoharan | Aims to improve lung cancer detection in CT images | Implements an advanced graph-cut algorithm | Enhances accuracy in segmenting lung edges compared to conventional methods |
| 5 | Finger Bone Fracture Detection | A. K. Bharodiya and A. M. Gonsai | Detects bone fractures in human finger X-ray pictures | Utilizes image processing techniques | Suggests a unique approach for identifying bone fractures in finger X-ray pictures. |

## VI. PROBLEM STATEMENT

X-ray radiography, often known as radiographs or x-rays, generates pictures of bones and specific organs and tissues by capturing their silhouettes. While x-rays excel at detecting bone abnormalities, their depiction of delicate tissues and organs may lack the intricacy offered by CT and MRI scans. However, due to their rapidity, accessibility, and cost-effectiveness, x-rays are commonly employed for swift data acquisition. X-ray radiography proves effective in detecting various conditions like broken bones, tumours, pneumonia, traumas, calcifications, foreign objects, and dental issues. When employed judiciously, x-rays can diagnose crucial conditions such as obstructed blood vessels, bone malignancies, and infections, potentially saving lives.[1]

## VII. PROPOSED SYSTEM

The fracture identification process relies heavily on two essential methodologies: the ridge regression framework and the edge delineation approach. One notable advantage of employing a ridge regression model lies in its capacity to introduce a nuanced bias, reminiscent of linear regression, thereby often enhancing predictive accuracy over extended durations. Furthermore, the role of edge detection proves pivotal in automatically discerning object boundaries, facilitating the segmentation of images into distinct and analyzable regions. This delineation of boundaries serves as a cornerstone in fragmenting images into individually serializable sectors, thereby augmenting the precision of subsequent analyses. Consequently, the amalgamation of edge detection with a ridge regression. [1]

## VIII. ALGORITHM

**Operational procedures inside the machine learning architecture**

```
data = load_medical_image_data() features,
labels = preprocess_data(data)
X_train,X_test,y_train,y_test=train_test_split(features,labels,test_size=0.2,random_state=42)

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)

regression_model = RegressionModel()

regression_model.fit(X_train, y_train)

kmeans = KMeans(n_clusters=2)

kmeans.fit(X_train)

cnn_model = Sequential()

cnn_model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(image_height,

image_width, num_channels)))

cnn_model.add(MaxPooling2D(pool_size=(2, 2)))

cnn_model.add(Flatten())

cnn_model.add(Dense(128, activation='relu'))

cnn_model.add(Dense(2, activation='softmax'))

cnn_model.compile(optimizer='adam',
loss='categorical_crossentropy', metrics=['accuracy'])

cnn_model.fit(X_train_images,y_train_labels, epochs=10)

regression_results= regression_model.predict(X_test)

kmeans_clusters = kmeans.predict(X_test)

cnn_predictions= cnn_model.predict(X_test_images)

regression_performance=evaluate_regression_model(regression_results, y_test)
```


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kmeans_performance=evaluate_kmeans_clusters(kmeans_clusters, y_test)

cnn_performance=evaluate_cnn_model(cnn_predictions,y_test_labels)ifregression_performance>kmeans_performance and regression_performance> cnn_performance:

print("Using Regression Model: Bone fracture detected.")

ifkmeans_performance>regression_performance and kmeans_performance> cnn_performance:

print("Using K-Means Clustering: Bone fracture detected.")

else:

print("Using CNN Model: Bone fracture detected.")

## XI. MATHEMATICAL MODEL

### 1. Convolutional Neural Network (CNN):

CNNs serve the purpose of automatically extracting distinctive features from images. The cornerstone operation within CNNs is convolution, which amalgamates input characteristics and filter coefficients. The convolutional operation at a given pixel coordinate (x, y) is computed as follows:

(Convolution)(x, y) = ∑(m) ∑(n) f(x - m, y - n) * g(m, n)

(Convolution)(x, y) calculates the aggregated sum of the local element-wise products of two matrices, denoted as f and g, having respective offsets represented by m and n, with their center situated at the position (x, y).[6]

### 2. Artificial Neural Network (ANN):

ANNs are pivotal in tackling intricate classification tasks. The foundational equation of a single-layer perceptron can be denoted as follows:

ANNs Output = σ(∑(i=1 to n) w_i * x_i + b)

Here, σ symbolizes an activation function (such as sigmoid or ReLU), w_i corresponds to the weights associated with input characteristics x_i, and b represents the bias term.[6]

### 3. Loss Function for Classification:

When it comes to binary classification assignments, the cross-entropy loss emerges as a standard choice. This specific loss function measures the disparity between the anticipateds likelihood and (hat{y}) and the actual label (y).L(y, ŷ) = - [y * log(ŷ) + (1 - y) * log(1 - ŷ)]

Employing this loss function aids in the training process by encouraging the model to make precise classifications.[7]

## X. SYSTEM ARCHITECTURE

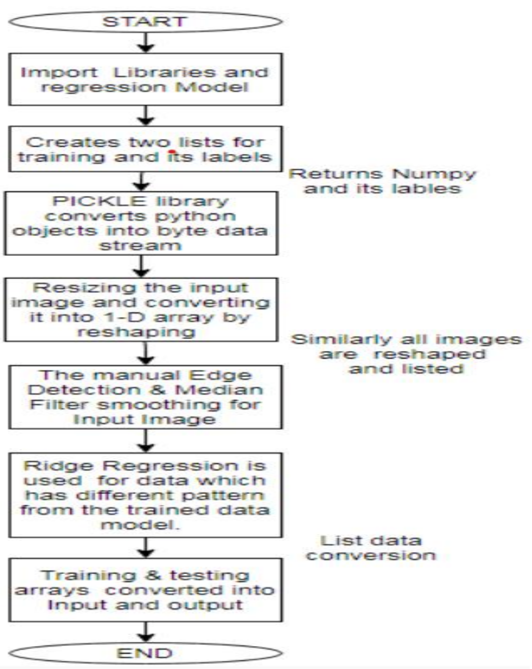


*Fig 1. System Architecture*

**Description:** The system architecture illustrates the procedure for teaching a machine learning model for image analysis. It starts by importing necessary libraries and regression models, followed by creating separate lists to store the training images and their corresponding labels. Once the images and labels are imported, the images are preprocessed, which might involve resizing and converting them into a format suitable for the model. Interestingly, the diagram indicates a step for manual edge detection and applying a median filter, likely for noise reduction in the image data.[5]

## XI. ADVANTAGES

**a)** Simplified diagnostic process.

**b)** Efficient utilization of computational resources, including RAM, CPU, GPU, or TPU, resulting in minimal resource requirements.

**c)** Superior performance compared to existing pre-trained systems.

## XII. DESIGN DETAILS

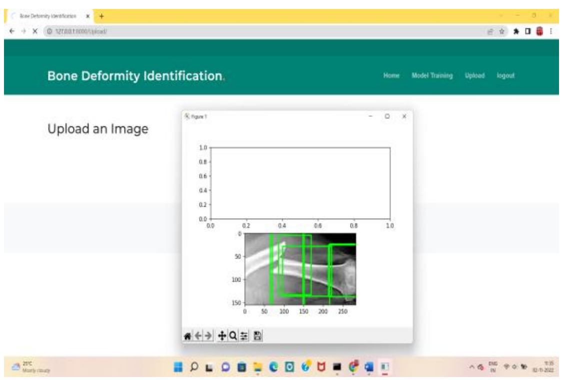


*Fig 2. Bone fracture detection*


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## XIII. CONCLUSION

Thus, we have tried to implement the paper of Authors: R. Vijayakumar and G. Gireesh, "Quantitative analysis and fracture detection of pelvic bone x-ray images," in 2013 fourth international conference on computing, communications and networking technologies (ICCCNT). IEEE, 2013, pp. 1–7 and according to the implementation, this paper creates a machine learning-based method for identifying bone deformities. which makes main contributions is identifying bone deformities with convenience and accuracy is presented. It is crucial to identify abnormalities, such as overlapping cracks, in different body parts.

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