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BONE FRACTURE DETECTION USING FASTER RCNN

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ABSTRACT:
Bone fractures are one of the most common problems in humans because of accidents or other causes. By using the x-ray, MRI is a manual detection of bone, and ignoring the fracture may cause severe consequences to the patient that may risk their life. Automated fracture detection is an essential part of a computer-aided telemedicine system that reduces the patient's risk. It is useful to medical clinicians who lack subspecialized expertise in orthopedics, and misdiagnosed fractures account for upward of four of every five reported diagnostic errors in certain EDs. We found that the usage of CNN with edge detectors, which causes misclassification, was the main flaw in the base articles. The position and orientation of objects are not encoded by CNN. Hence, we use the deep learning model Faster RCNN to precisely detect fractures. The model detects modest bone fractures that are difficult to notice with the naked eye in x-ray pictures. In comparison to conventional approaches, the faster RCNN model is more accurate. The model in this paper uses efficient fracture location prediction and fracture accuracy visualization. The fracture location is high spotted with the bounding box. The model has a 90% accuracy rate.
Keywords: CNN, Faster RCNN, Edge detectors.

INTRODUCTION:
The human body is composed of 206 bones. Bones are vital to your body's mobility because they convey the force of muscle contractions. Accidents or certain disorders may result in fractures because they happen when a force is applied to a bone that it cannot structurally tolerate. Since bone is composed of calcium and bone cells, blood loss, edema, and immobility are complications of a bone fracture. X-rays, CT scans, and MRI scans are used to diagnose bone fractures. The goal of medical treatment is to ensure that the fractured bones are properly aligned. In this paper, we intend to develop a model of bone fracture detection using a deep learning approach that makes it easier for people to diagnose severe fractures at an early stage. Making predictions quickly and planning for future obstacles are goals of deep learning.

PyTorch is an efficient Deep Learning tensor library built on Torch and Python that is mostly used for CPU and GPU applications. Other Deep Learning frameworks are not as popular as PyTorch. An essential data type called a tensor can serve as the basis for complex mathematical computations. It could be an integer, vector, matrix, or multi-dimensional array like Numpy arrays.

The faster RCNN deep learning models are used to train computers to recognize and localize objects in images as well as to forecast bone fractures. The training and detection times of the network significantly decrease with a faster RCNN. A region proposal algorithm is used to generate "bounding boxes," or the positions of likely objects within an image; a feature generation stage, frequently utilising a CNN, is used to extract the features of these objects; a classification layer is used to predict which class this object belongs to; and a regression layer is used to increase the accuracy of the bounding box coordinates for the object. The backbone network is ResNet_50. As we know, there are many pretrained models for image classification, such as VGG_16, ResNet_50, and Inception v3. In this, for building the model, the pretrained model ResNet_50 is used to train the dataset.

The backbone network and Faster RCNN consist of 50 layers; 48 layers perform the convolution neural network, and the last two layers produce the output, which is the detection of fractures. It involves two steps. The first phase uses the region proposal network to accept the backbone layer-generated convolution feature map as input and output the anchors as a result of sliding window convolution applied to the input feature map. The initial step of rcnn is to input the image to the convolution layer, which gives the featured map, and to predict and classify the bounding box in the image. The type of image is categorized using the bounding box. The object detection network performs ROI pooling in the second step to produce the bounding box. The x-ray image dataset and bounding box image data are given to the RCNN. The output of RCNN is used to train the model. The output is the class and bounding box, which is the fractured part of the bounding box.

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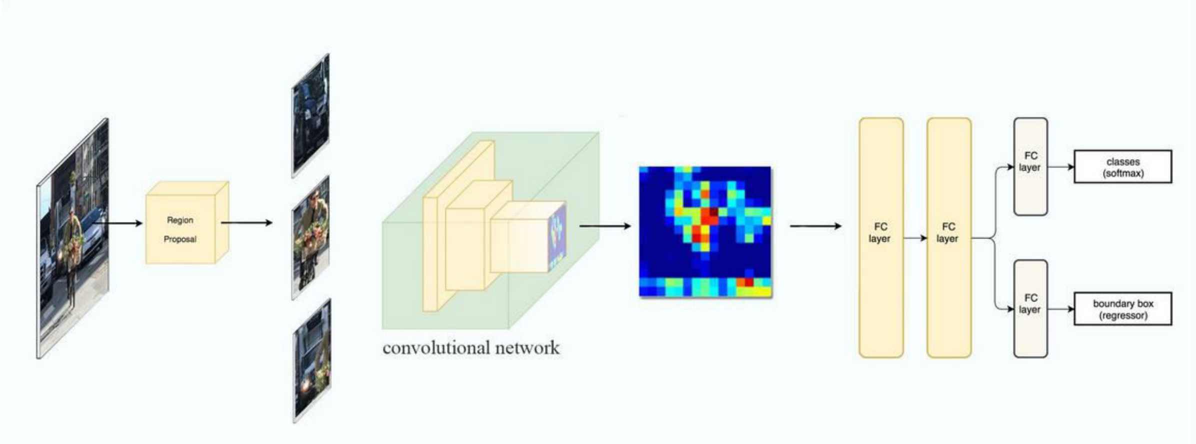

Fig1: Structure of RCNN

RELATED WORK:

Yangling ma and yixin luo[1] proposed a model of bone fracture detection through the two-stage system of a crack-sensitive convolutional neural network. In this proposed model they presented CrackNet, which is a new classification method that identifies the fracture by the fracture lines in images and it also spots the fracture. It is observed that the performance of the model is better than other methods. The model has an accuracy of 88.9%, recall is 87.5%, and precision is 89.9%. The faster rcnn with resnet gives the lowest performance, whereas the proposed model gives the best performance.

Bin Guana et al. [2] proposed an Arm fracture detection in X-rays based on an improved deep convolutional neural network. In this proposed system, an advanced deep learning technique for detecting arm fractures in X-rays has been developed, as has been noticed. The proposed method may produce an average precision of 62.04%, which is the best available today. Although the arm bone fracture is the subject of this study, the proposed framework is not limited to what may be inferred from arm bone X-rays. We want to make the dataset's annotations available in the future to support research on fracture detection and identification.

Yubin Qi et al. [3] proposed a ground-truth annotated femoral x-ray image dataset and an object detection-based method for fracture type classification. An object detection-based method for classifying fracture types is observed in this suggested system, together with a ground-truth annotated femoral x-ray image dataset. An anchor-based Faster RCNN detection model uses a multi-resolution feature pyramid network (FPN) based on the ResNet50 architecture to locate fractures and classify them according to their categories. The issue of overfitting arises from the fact that the ground truth images are not sufficiently representative. The goal of the surgical plan and the fracture reduction techniques employed during the process is to advance the surgeon's level of experience and, as a result, provide a successful fracture reduction and full healing.

Yee Liang Thian et al. [4] proposed Convolutional Neural Networks for Automated Fracture Detection and Localization on Wrist Radiographs. They provided the Inception- ResNet Faster R-CNN architecture in this proposed model. Radiology images in both frontal and lateral views might show the radius and fracture. The drawback is that they did not consider other potential components and instead only used the radius and ulna fractures, making it unable to apply to other datasets with various representations. The model's performance is shown by per-image sensitivity, specificity, and AUC values of 95.7%, 82.5%, and 0.918 for the frontal view and 96.7%, 86.4%, and 0.933 for the lateral view.

Adigun Oyeranmi et al. [5] proposed the Detection of fracture bones in X-ray image categorization. They proposed mixed classification methods such as KNearest Neighbour (KNN) and Support Vector Machine (SVM) for detecting x-ray fracture images and their different types. These classification methods decrease the training time and increase accuracy. They proposed preprocessing, segmentation, and feature extraction before the classification of images. The image preprocessing is done by using the Unsharp Masking Tool. Segmentation is carried out by using the entropy method in the first stage and the canny edge method in the second stage.

Seok Won Chung [6] proposed a model of Automated Detection and Classification of the proximal humerus fracture by using deep learning algorithms. The goal of this study was to use straightforward anteroposterior shoulder radiographs to detect and classify proximal humerus fractures. We demonstrate in this work how well deep learning CNN can distinguish between healthy shoulders and proximal humerus fractures. With 96% accuracy, 0.99/0.97 sensitivity/specificity, and 0.97 Youden indices, the CNN distinguished between healthy shoulders and proximal humerus fractures satisfactorily. With 65-86% accuracy, 0.90-0.98 AUC, 0.88/0.83-0.97/0.94 sensitivity/specificity, and a 0.71-0.90 Youden index for determining the kind of fracture, the CNN also showed good results. Furthermore, we found that CNN outperformed humans, especially for more intricate fracture types as 3- or 4-part fractures. This implies that CNN works rather well compared to humans in identifying fractures with various fracture geometries based on plain radiographs. Less images were used for the CNN training for fractures with three to four parts, thus the results seem more promising.

S.No	Author	Technique	Identification	Limitation
1	Yangling ma,Yixin luo	Faster RCNN, CNN	The strength of deep learning algorithms can be used in this to quickly and accurately automate image analysis. We introduce CrackNet, a advanced classification network that more precisely locates fractures and is sensitive to fracture lines.	Small object detection does not perform well with this approach.
2	BinGuan, JinkunYao	Dilated convolution feature pyramid network (DCFPN)	The experiment's findings demonstrate that DCFPN beats existing deep learning methods with an 82.1% precision in thigh fracture identification.	There are few fractures that cannot be detect accurately by the algorithm.
3	Yubin Ql, Jing zhao	Faster RCNN	The surgical plan and reduction processes utilised throughout the surgery are meant to enhance the degree of surgical expertise and, in the end, give a good fracture reduction and faultless fracture healing, according to the fracture type analysis.	The overfitting issue arises because the ground truth images chosen were not sufficiently representative.
4	Yee Liang Thian, Pooja Jagmohan	CNN	It detect the fracture and it is represented with boundary box and gives the confidence score of fracture.	On a wrist radiograph, they did not examine all suspected fractures, the model doesnot work on other radiographs, they tested only on emergency department radiographs but not on orthopedic outpatient radiographs.
5	Adigun Oyeranmi, Babatunde Ronke	SVM, KNN	The classifiers were used to identify various patterns in images as the five types of fractures: comminuted, oblique, transverse, and normal.	It does not work for large datasets.
6	Seok won chung, Seung seog han	CNN	The goal was to test artificial intelligence's capacity to detect and diagnose proximal humerus fractures using simple anteroposterior shoulder radiographs	First, despite being the most widely used method for classifying proximal humerus fractures, the Neer classification has only fair to moderate

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				reliability, and there is no gold standard for classifying proximal humerus fractures.

PROPOSED MODEL:

Faster RCNN is the model proposed for bone fracture detection. It is difficult to identify mild bone fractures. The proposed model detects minor fractures with proper bone fracture position and fracture accuracy. The faster RCNN is part of the neural network. The proposed model is Fig 3. The hand fracture image dataset is given to the RCNN to create the model.

A. Dataset Description

The dataset is a hand fracture x-ray image from Kaggle. The dataset consists of 277 images. The dataset is divided into two parts: training and validation. The training data consists of 237 images, and the validation data consists of 40 images. The proper dataset may decrease the overfitting of the model.

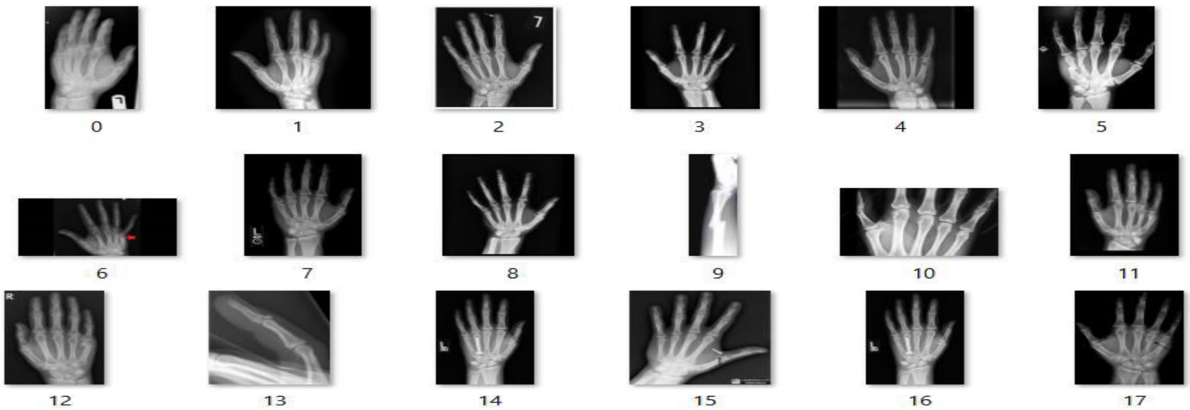

Fig2: Dataset

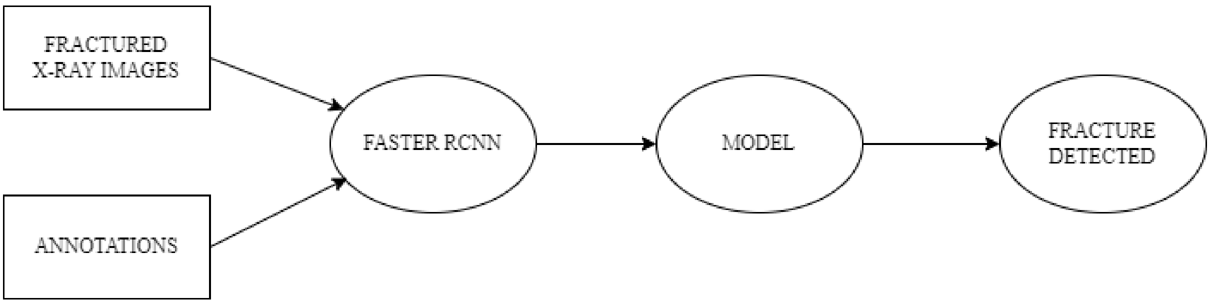

Fig3: System Architecture

Faster RCNN takes the two inputs, which are the original x-ray images and annotations. Annotations are the region proposals that are generated from the backbone network. The

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output is passed to ROI pooling to resize images. The network takes the original image, bounding boxes, and multiple categories as inputs and produces the bounding box with category and accuracy. On the website, the model's predicted output is displayed.

B.ResNet_50

A convolutional neural network with 50 layers is called ResNet-50. ResNet, which stands for Residual Network, is an architecture made up of Residual Neural Networks. The pre-trained neural network is capable of categorising photographs into 1000 different object categories, including keyboard, mouse, pencil, and several animal images. As a result, the neural network has acquired rich feature representations for a diverse set of images. A 50-layer convolutional neural network is called ResNet-50 (48 convolutional layers, one MaxPool layer, and one average pool layer). Artificial neural networks (ANNs) that use residual blocks to build networks are referred to as residual neural networks. The 50-layer ResNet architecture has 64 additional kernels with a 2-sized stride in addition to a 77 kernel convolution. A stride of two sizes with a maximum pooling layer.

C. Convolution neural network(CNN)

A machine learning subnet is the term used to describe the convolution neural network. It is one of many artificial neural network models that are used to different tasks and data sets. The have 3 primary layers, Convolutional layer, Pooling layer, and Fully-connected layer. For tasks like image identification and pixel data processing, deep learning algorithms use a specific kind of network design called a CNN. In deep learning, CNN is preferred over all other forms of neural networks for detecting and classifying objects. As a result, they are ideal for computer vision (CV) activities and for applications like face and self-driving auto systems where accurate object detection is crucial. A particular type of neural network called a CNN can be used to find important information that may be present in both time-series data and image data.

Convolutional layer:

The convolutional layer, the life of a CNN, is where the core of processing happens. Among other things, it requires a filter, input data, and a feature map. A feature detector, sometimes referred to as kernels or filters, will examine the image's receptive fields to determine whether the attribute is present. This technique is referred to as convolution. A section of the image is represented by a 2-D array of weights acting as the feature detector.

Max pooling layer:

In the convolution process known as "Max Pooling," the Kernel extracts the most value from the region it convolves. The Convolutional Neural Network is simply informed by max pooling that we will only transmit that information ahead if it is the input with the highest possible amplitude.

Fully connected layer:

Each node in the output layer of the fully-connected layer is directly connected to a node in the layer above it. Based on the features obtained from the preceding layers and their respective filters, this layer performs categorization. In contrast to FC layers, which often use a SoftMax activation function to provide a probability ranging from 0 to 1, convolutional and pooling layers typically classify inputs using Relu functions.

D. Region based convolutional neural network(RCNN)

The key concept of the R-CNN series is region-based proposals. Region proposals are used to localize objects within an image. The images are given to the RCN; before passing an image through a network, we need to extract region proposals or regions of interest using an algorithm such as selective search. Then, we need to resize all the extracted files and pass them through a network. It predicts the coordinates of the image. The training images are given to rcnn, in which the image and the region of interest (ROI pooling) are given. The faster rcnn with ResNet_50 The convolution neural network (CNN) is used first, and the last two layers are crucial in detecting the fracture; the output is the class

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and the bounding box. The model is trained with the output of the RCNN.

Region proposal

For object localisation, the region proposal algorithm Selective Search clusters regions depending on their pixel intensities. Hence, it organises pixels into groups based on hierarchical grouping of related pixels.

Bounding Box

Bounding boxes are the coordinates of the rectangular border that entirely encloses a digital image. The bounding box is illustrated by the following: [max x, max y, min x, min y] The bounding box's top-left corner's coordinates are x min (x-minimum), y min (y-minimum), and its bottom-right corner's coordinates are x max (x-maximum), y max (y-maximum).

Experimental Results

A faster RCNN approach is used by the system to process the input X-ray. A bounding box will appear at the broken region after the faster RCNN model has been applied to the X-ray images. The accuracy of the fracture will be determined after obtaining a boundary box on the broken part. We attain an accuracy of between 97% and 99% after training the network. The total number of images is 277; they undergo training and validation. We train the model with training data, and each loss index ideally converges with an increase in training iterations across the 50 epochs we specified. We adjusted the hand fracture dataset to our satisfaction and tested it on the test set, which consists of 40 photos.

Fig4: Predicted output

Our model can predict any hand fracture in real time just by submitting the original x-ray image to the website; it gives the predicted output with the percentage of fracture prediction accuracy. Fig 5 represents the structure of the website. Fig 6 represents the original image and the model's predicted fracture image.

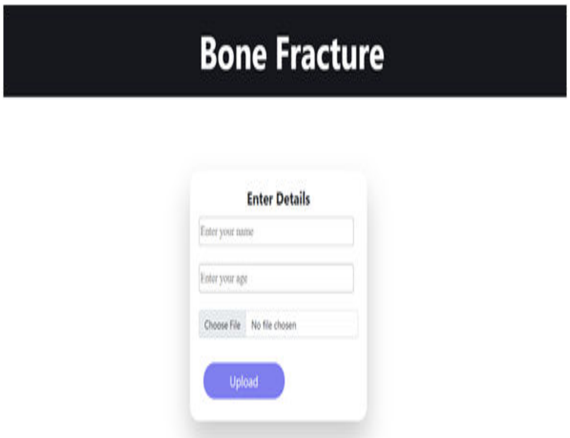

Fig5: Website

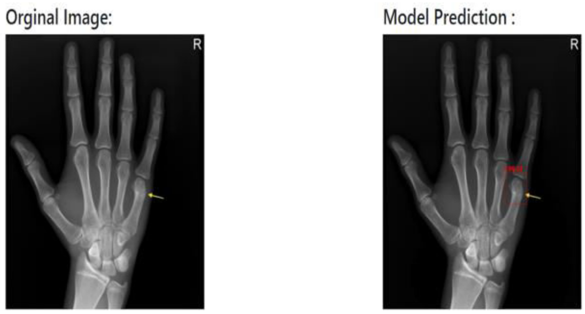

Fig6: Website output

Conclusion

In this paper, fracture detection is done using faster RCNN. By faster RCNN we train computers to recognize and localize fractures in images as well as to forecast bone fractures. We attain an accuracy of between 97% and

99%. We may draw the conclusion that our model for the detection and localization of hand fractures has a significant potential application in helping surgeons make an accurate diagnosis of fractures and avoiding further medical expenses.

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