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Automatic Bone Fracture Detection Methods : A Review

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Abstract: *Accident-related bone fractures affect peo- ple often. The doctors typically use X-ray/CT scans to manually identify fractures. But sometimes there isn't enough information in these photos to make a diagnosis. Furthermore, a high risk of false detection and subpar fracture healing may be caused by a lack of clinicians in medically underserved areas, a lack of specialised medical personnel in overcrowded institutions, or stress brought on by a large caseload. Computer vision and artificial intelligence based on image processing, deep learning, and machine learning are increasingly playing a crucial role in the identification of bone fractures. This research looks into fracture diagnosis in detail with the goal of assisting doctors in the development of models.*

Keywords: Bone Fracture.

I. INTRODUCTION

Bone fractures are a distressing condition. Al- though excessive force and stress are the main causes of fractures, they can also result from diseases like osteoporosis, cancer, or osteogenesis imperfecta, often known as bone disease, which weaken the bones. Medical diseases can lead to pathological fractures, which are those. Fractures in children, the elderly, and young people are frequently caused by falls, collisions, conflicts, and other incidents. To ascertain whether there are any bone fractures, many professionals rely on medical pictures. Imaging technology in medicine has allowed doctors to view inside the body for easier evaluation. This aided medical professionals in performing keyhole surgery to access internal organs without having to open up too much of the body.

The interior of the body may be bared with ease using a CT scanner, and abnormal spots can be recognised without causing the patient any discomfort or agony. Visualisation techniques es- tablished for assessing telemetry information could be adapted to evaluate the outcomes of medical visualisation equipment, allowing for a more effi- cient analysis of patient symptoms. It is crucial to diagnose bone fractures in the human body using X-ray medical imaging. Medical professionals use the X-ray image to make judgments and success- fully treat ailments. Medical image processing is used to further examine the stored digital images in order to improve diagnosis outcomes. Accidents cause breaks in the bones, which are known as bone fractures.

Bone x-rays are radiographs taken of a bone in the body. X-rays are among the most often used types of medical pictures. They are commonly used in the detection of bone fractures despite the minor limitations they have. X-ray scans have less detail than other types of medical pictures, but because they are inexpensive, they are still important. Both the methods used for picture ac- quisition and interpretation have advanced in the field of medical imaging. With the least amount of support from medical professionals, the research is focused on evaluating and detecting bone fractures from X-ray pictures. Computer-aided diagnosis (CAD) systems, for example, can be particularly effective for analysing vast amounts of medical information, and improving interpretation accuracy while reducing diagnosis duration. For bone frac- ture identification, imaging techniques such as X-ray, CT, and MRI are sufficient. As a result, to identify lengthy bone fractures, this research relies solely on x-ray images. The approaches used in creating CAD systems for bone fracture diagnosis are explained in the following study.

The severity of a fracture is determined by the subtype and location of the fracture. Serious fractures can result in serious complications such as damage to blood vessels or nerves, infection of the bone (osteomyelitis), or infection of the surrounding tissue if they are not treated very soon. The patient's age, health, and the kind of fracture all affect how long it takes for them to recover. Simple fractures in children can recover quickly; major fractures in elderly people can take months to recover from. By assessing the injuries and using X-rays, the majority of fractures can be found. A fracture may not always be seen on an X-ray. In these circumstances, your doctor could prescribe additional scans.

In some circumstances, such as a suspected wrist fracture not shown in a normal X-ray, then your doctor orders a second X-ray 10 to 14 days later, when the fracture may become visible due to healing. Additional imaging not only raises diagnostic expenses but also puts a strain on doctors and patients, as well as consumes resources.

II. RELATED WORK

Faster RCNN and Crack-Sensitive Convolu- tional Neural Networks were used to construct a bone fractures diagnosis system in [2]. (CrackNet). They demonstrated a novel method for accurately and quickly detecting fractures in X-ray images. The proposed device not only determines whether a bone is broken or not, but also locates the fracture. This might make it easier for medical experts to spot a fracture quickly. With an accuracy of 88.39 percent, a recall of 87.5 percent, and a precision of 89.09 percent, rigorous testing on the Radiopaedia dataset confirmed the usefulness of the proposed approach.

In order to identify and localise hand fracture in radiographs using a novel guided anchoring tech- nique, Linyan Xue et al.[3] created a deep neural network. The Fast R-CNN Classifier was used to forecast the position of fractures using proposal regions that were refined using the GA module's learnable and flexible anchors. A DenseNet Model was used by Shukla Abhilash et al. [4] to recog- nise any kind of lesions from X-ray images of bones. The MURA (Musculoskeletal Radiographs) dataset, created by the Stanford ML group, was used. Using the Classification Table and Confusion Matrix techniques, it was determined how well the DenseNet (Densely Connected Convolutional Networks) Model identified anomalies in bone from an X-Ray image. With this suggested model, accuracy of more than 85% was reached.

Two methods—two-line fracture identification and adaptive differential parameter optimiza- tion—were proposed by Y. Yang et al. [13] for identifying long bone fractures in x-ray images (ADPO). Two-line based fracture identification was used, with features retrieved based on pattern, to separate non-fracture lines from fracture lines. Fracture lines could be recognised using the Hough Transformation function because it had already been optimised using the ADPO method. The cat- egorization of fractures was done using an ANN. The accuracy of the two-line based fracture diag- nosis technique was 74.24 percent, whereas ADPO was 74.4 percent. E. Castro et al.[14] presented a method for detecting acetabulum fractures. A Lo- cal Binary Pattern (LBP) was employed to extract feature, and a Support Vector Machine (SVM) was used to classify the cracks. The overall accuracy rate was 80%. Wu, Zhengyang, et al. [15] used the convolutional neural network (CNN) algorithm to identify the degree of fracture development while building a new model that could detect cracks automatically.

Through image processing techniques, Tripathi et al. [17] proposed a method to visualise and classify abnormalities for finding fractures in the femur. The domain of interest was highlighted in the raw image after it was preprocessed. By suppressing the background information, the fore- ground, which was the main zone of interest, was found. These operations are carried out using mathematical morphological approaches. The fore- ground was illuminated using basic morphological procedures, and edge detection was employed to emphasize the items in the foreground. To separate fractured and unfractured sides of the bone, the processed picture was classified using the support vector machine (SVM). In [18], they used stacked random forests to detect fracture in X-ray image. Several methods, including the BPNN, K-Nearest neighbour, SVM, Min/Max Rule, and product rule, were combined into a new system to identify the fracture. The characteristics such as edge and shape were collected before the classification.

Using the Canny Edge Detection approach, Jo- hari et al. [16] suggested a method for determining the performance of an X-ray bone fracture identifi- cation method. Edge detection using Canny's algo- rithm has been shown to be an excellent method for finding the end of a line with a low error rate and impulsive threshold. Umadevi N et al. [19] used a multiple classification approach from plain diag- nostic X-rays to automatically diagnose fractures in long bones, particularly the leg bone (commonly referred to as the tibia). Multiple classifiers were designed using dual types of features (texture and shape) and three types of classifiers (Back Propa- gation Neural Network, K-Nearest Neighbor, and Support Vector Machine). There were 12 ensemble models in all presented. Evaluations have shown that ensemble models increase the efficiency of fracture detection substantially. An investigation of probabilistic combination techniques used to iden- tify bone fractures in X-ray pictures was presented by Lum, Vineta Lai Fun, et al. [20]. The efficiency of a technique in increasing both accuracy and sensitivity was dependent on the method's nature as well as the proportion of positive samples, according to test findings.

There are numerous object detection models available. According to the literature review, deep learning object detection models may be employed successfully for fracture detection and can provide higher performance than conventional machine learning and image processing methods.

III. IMPORTANCE OF DEEP LEARNING CONCEPTS IN THE FIELD OF RADIOLOGY

Deep Learning (DL) refers to a group of tech- niques that are part of the machine learning domain and the even larger artificial intelligence sector. Deep learning basically comes under the stream of artificial intelligence, which mainly includes layers of neurons that are artificial. Each and every layer includes more units that basically appear as neuron cells, and they are based on the structure of the human brain. The concept of deep learning changed the area of information technology and provided huge scale solutions to previously hour consuming challenges. These algorithms are united by the concept of understanding the details of the data. Deep learning has demonstrated exceptional performance when it comes to handling semantic image processing tasks..

In the current generation, the DL techniques are most commonly used to solve problems, including medical image classification, segmentation, and noise reduction. Furthermore, DL algorithms can profit from earlier accomplishments by adopting this so called transfer learning strategy. The im- portance of deep learning in the area of radiology is immense. It can help physicians make better diagnoses and provide better treatment options for their patients.

Deep learning outperforms human performance under the stream of fracture diagnosis and local- ization on medical images like radiographs and CT scans.

IV. FRACTURE DETECTION AND LOCALIZATION MODELS IN DEEP LEARNING

Single-step and two-step classifiers are the two categories of deep learning algorithms. Regions that may include objects are generated by two- stage classifiers. A neural network then classifies these regions into items. The region proposal phase is skipped in single-stage detectors, and both ob- ject localization and classification are done in the same step. As a result, single-stage classifiers are faster than multiple-stage classifiers. The R-CNN and YOLO series are two of the most popular deep learning-based fracture detection algorithms currently available. The R-CNN series has a slower detection speed than the YOLO series. It cannot meet the real-time performance of fracture detec- tion in practical circumstances.

4.1 R-CNN Series

The first deep learning-based object detection method is called the Region-Based Convolutional Neural Network (R-CNN). Faster RCNN, Faster R-CNN, and other adapted R-CNN variants are available. R-CNN cannot be used in real time since it takes about 47 seconds to analyse each test image.

The R-CNN algorithm feeds the region propos- als to CNN, whereas fast R-CNN gives the CNN the entire image to create the feature map. The feature maps are then converted to squares. Then the ROL pooling layer converts them into a defined size, and after that it feeds into the fully connected layer.

Selective search basically takes more time and is a slow-going operation that lowers performance.In faster R-CNN, the image is fed into a convolutional neural network, which outputs a feature map in the same way that fast R-CNN does. Instead of using a selective search technique on the feature map to identify the region proposals, a different network is employed to estimate the region proposals. The projected region proposals are then resized after categorising the image within the suggested region and estimating the offset values for the bounding boxes using a RoI pooling layer.

4.2 YOLO Deep Learning Algorithm

YOLO is a single-step system that detects ob- jects using a convolutional neural network. It is well known because of its quickness and perfor- mance. Various deep learning algorithms exist, but none of them can detect an object in a single run. Numerous deep learning techniques exist, but none of them can reliably identify an object in a single step. YOLO is better than any multiple-step technique because it can detect objects in a sin- gle forward propagation across a neural network, making it ideal for real-time scenarios. The main principle behind YOLO is to feed the network the full image as input and then return to the position of the bounding box and the category to which it belongs as the output.

Each bounding box in YOLO is predicted by the image's features, and each bounding box com- prises five predictions and confidences, all of which are related to the grid unit in the centre of the bounding box. w and h were the predicted width and height of the complete image (relative to the entire image) in the YOLO basic frame. YOLO is primarily made up of three components:

1. Backbone: a convolutional neural network that mixes and produces various visual fea- tures at different levels.
2. Neck: a group of network layers that mix and integrate picture characteristics before sending them to the prediction layer.
3. Head: The head is capable of categorising, identifying bounding boxes, and forecasting picture features. The accuracy with which the classification was made under the cir- cumstances is reflected in the level of confi- dence.

In YOLOv2, a fresh training algorithm is ap- plied. The k-means clustering algorithm is used to cluster the bounding boxes. Since improving the Intersection over Union is the main goal of creating the a priori box, the IOU value is used as the dis- tance indicator in the cluster analysis. Compared to YOLOv1, it greatly improves accuracy and recall rate.

ResNet, a more sophisticated basic classification network, and the classifier Darknet53 are both used by YOLOv3. Simultaneously, multiscale predic- tion is accomplished using a network topology akin to an FPN. The rate of inaccurate backdrop detection has been greatly lowered, while detection accuracy and speed have increased. While main- taining the head of YOLOv3, YOLOv4 replaces the backbone network with CSPDarknet53 and uses SPP (spatial pyramid pooling) to increase the receptive area, with PANet serving as the neck. The structure of CSPNet allows for more gradient combination information while speeding up computation. The PANet topology completely integrates the multiple feature layers, which con- siderably enhances defect feature extraction.

4.3 YOLOv5

In 2020, Glenn and his group launched YOLOv5, the latest edition of the YOLO algo- rithms. YOLO models were created using the Darknet framework.A company named Ultralystic converts previous types of YOLO to PyTorch, which is a popular deep learning structure based on the Python language. When compared to prior versions, YOLOv5 had engineering advantages. YOLOv5 is developed in Python rather than C. It's difficult to compare the performance of YOLOv4 and YOLOv5 because they're written in two sep- arate languages and run on two distinct frame- works. However, over time, YOLOv5 outperforms YOLOv4 in certain situations and has achieved some faith in the sector of computer vision.

Architecture of YOLOv5: YOLOv5 was not like the prior versions. Instead of Darknet, PyTorch is used. As a backbone, it uses CSPDarknet53. This backbone handles the repeating gradient in- formation in big backbones and the feature map incorporates gradient change, which speeds up inference, improves accuracy, and decreases model size by lowering parameters. It boosts information flow by using a structure called PANet. PANet uses a new FPN with many layers. It increases the model's transmission of bottom-level features.

V. CONCLUSION

This paper examined various approaches for detecting fractures from X-ray images. For clinical applications like bone fracture, artificial intelli- gence and deep learning must continue to advance. More work, as indicated in the study, will improve performance and assist the doctors in diagnosing the fracture. Road accidents, an unhealthy lifestyle, and a variety of other factors have all contributed to the rise in bone fractures in recent years. Bone is a vital component of the human structure. A minor fracture in the bone impairs the bone's natural function and, as a result, the person's freedom of movement. Human bones are prone to fracture. There are numerous methods for detecting frac- tures. The traditional method requires more time and is specialist-dependent. It also has a greater probability of making a mistake. When a victim is suspected of having a fracture, he or she is taken to an emergency room, where an X-ray is used to assess the condition. Fracture detection by X-ray is a cost-effective method. Patients suffer serious consequences if a fracture is missed.

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