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IMPLEMENTATION OF DEEP LEARNING ALGORITHM FOR BONE FRACTURE DETECTION USING RADIATION IMAGES

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Abstract

A correct medical diagnosis and therapy are essential for the successful management of bone fractures, which are a common injury. Although X-ray imaging is a commonly used technique, even skilled clinicians may find it difficult to interpret the images. Convolutional neural networks (CNNs) and support vector machines (SVMs) are two examples of artificial intelligence (AI) techniques that have demonstrated potential in assisting in the identification of bone fractures from X-ray images. In order to achieve precise and effective detection, we provide a method for bone fracture detection in this paper that combines CNNs with SVMs. The system is divided into two phases: feature extraction with a CNN that has already been trained and classification with an SVM. With the use of a sizable image dataset, the CNN is trained to identify between various bone forms, including fractures, using high-level characteristics. The SVM is then fed the features in order to classify them. To categorize the images based on the characteristics taken from the CNN, the SVM is trained using a tagged dataset of X-ray images. The efficacy of the suggested approach in identifying bone fractures is demonstrated by its high accuracy of 95% on a dataset of X-ray pictures. Compared to existing methods, the suggested system has a number of benefits, such as the capacity to handle high-dimensional data, handle manual interpretation, and scale to enormous datasets. The system is a useful tool in the medical profession since it uses artificial intelligence automation to provide faster and more accurate diagnosis.

Keywords: X-Ray, Deep Learning, Convolutional Neural Networks, Support Vector Machines, Bone fracture

1. INTRODUCTION

Medical records state that 206 bones make up an adult human body. These bones differ in size, intricacy, and shape. The stapes is the smallest bone in the human body. It is difficult for doctors to determine the degradation of this bone using radiographic images. A bone fracture is a common type of injury that can cause pain, discomfort, and limited movement. In order for a medical diagnosis and treatment plan to be suitable, bone fractures need to be accurately and efficiently recognized. Radiation imaging is a regularly used technology for bone fracture diagnosis since it is non-invasive and provides detailed information on bone structure.

Radiation scan interpretation can be challenging, even for experienced medical experts, as fractures are not always visible or easily confused with other bone structures. It's critical to diagnose and classify a fracture into one of the established categories in order to determine the best course of treatment and prognosis. Patient outcomes may be enhanced by the deployment of digital technologies that could support doctors in these kinds of circumstances. Several machine learning methods have been applied in the past to identify bone fractures, including feature extraction, pre-processing, and classifications. In recent years, artificial intelligence (AI) and machine learning algorithms have shown great promise in assisting in the identification of bone fractures using radiation photographs. Noise reduction and image pre-processing are the first steps in any deep learning technique.

There are several different image pre-processing and noise reduction techniques available today. The second stage of the process involves feature extraction, which is a very difficult step. The last prediction phase consists of classifying and assessing several machine learning classification methods using industry-standard testing protocols.

This work proposes a method combining CNNs and SVMs for reliably and efficiently identifying bone fractures in radiation images. The proposed method consists of two main stages: feature extraction using a pre-trained CNN and classification using an SVM.

During the feature extraction stage, high-level features are taken from the radiation photos to allow a pre-trained CNN to distinguish between different bone forms, including fractures. After the features of the CNN are retrieved, the data is subsequently classified using the SVM. The SVM is trained using a labeled dataset of radiation picture data. There is a label on every image that indicates whether or not it has a fracture. With the help of the CNN's training features, the SVM learns how to classify images. Next, using the trained SVM, new radiation images are categorized as either not having a fracture or having one.

The proposed technology has several advantages over traditional methods for identifying bone fractures. It first removes the need for doctors to manually assess X-ray images, which may be time-consuming and prone to human error. Instead, it uses a machine learning technique to automate the detection process, allowing for faster and more accurate diagnosis. Second, the proposed method can handle high-dimensional data, such as X-ray images, which may include large amounts of information. Because SVMs are so good at handling high-dimensional data, they are a common choice for this kind of work. Finally, the large scalability of the proposed system allows it to be trained on large X-ray image datasets, which may improve its accuracy and generalization skills.

2. Related Works

In recent years, there has been increasing evidence of the potential of AI-based systems and machine learning algorithms to assist in the identification of bone fractures from X-ray images. Support vector machines (SVMs) and convolutional neural networks (CNNs) are two types of algorithms that have been used for this purpose. Applications for image analysis and recognition, such as medical picture analysis, commonly use deep learning algorithms like CNNs. The capacity of supervised learning algorithms, or SVMs, to handle substantial volumes of high-dimensional data makes them a popular option for classification tasks.

Numerous studies on the detection of bone fractures have been proposed. For example, Tanushree Meena et al. [1] give a summary of how deep learning is being applied to bone imaging to help radiologists spot a range of abnormalities, particularly fractures. The application of deep learning to bone fractures was also discussed by the author, along with its challenges and restrictions.

The study[2] looked at a number of edge detection systems, and it recommended a generalized type-2 fuzzy logic system based on the Sobel methodology. Testing it with fictitious photos yields promising results. The Pratt figure of merit is used to quantify the edge detection procedure's accuracy and illustrate the advantages of this methodology.

A different study [3] enhanced the CNN method to identify six core emotions.Preprocessing methods such resizing, face detection, cropping, adding noise, data normalization, and histogram equalization were tested in order to show the influences on CNN. The accuracy results showed a considerable improvement over the raw data and another preparation stage.

The core of the [4] suggested system is made easier for people to live by a number of phases, including pre-processing, edge detection, feature extraction, and machine learning classifications. Additionally, a number of machine learning methods are applied to the dataset comprising 270 x-ray pictures in order to detect bone fractures. According to the author's suggestion, the accuracy of SVM was found to be highest in this work statistically, surpassing that of most of the examined studies.

A further study [5] suggested using deep learning algorithms with X-ray images to identify different kinds of bone fractures and to diagnose anomalies in the bone early. Numerous significant factors are considered in order to identify the best model, such as the number of epochs, batch size, kind of optimizers, and learning rate. Among them, it is found that the CNN model has good accuracy performance.A novel system called the Crack-Sensitive Convolutional Neural Network (CrackNet) was presented in [6]. CrackNet is sensitive to fracture lines. In order to ascertain whether each bone region is broken, the author's two-stage method in this study consists of a speedier region using a Convolutional Neural Network (quicker R-CNN) and a CrackNet.

In a different study [7], a dataset comprising different bones—both normal and fractured—is used to conduct fracture detection and classification using a variety of machine learning approaches. During the preprocessing phase, Canny and Sobel edge detection techniques are applied. Utilizing Harris corner detector and Houhg line detection, feature extraction was carried out. The highest accuracy rate is achieved by accuracy, testing duration, training time, and linear discriminant analysis.

[8] looks at problems with sternum fracture diagnosis, such as low rates of small and concealed fracture detection. The author used cascade R-CNN, atrous convolution, and attention mechanism to maximize the detection of small fractures in a large set of X-ray images with notable local oscillations. This model was found to have a better detection approach than the convolution neural network-based cascade and attention mechanism models when compared to other models.

To help doctors diagnose wrist X-ray fractures, particularly in emergency rooms, deep learning is being used in another study [9] to identify fractures in these images. Using deep learning based object recognition models with different backbones, such as SABL, RegNet, RetinaNet, PAA, Libra R-CNN, FSAF, Faster R-CNN, Dynamic R-CNN, and DCN, twenty alternative fracture diagnosis processes were performed on wrist X-ray images. To further improve these processes, the wrist-fracture detection-combo (WFD-C) model was developed, which is a special model, by looking at five different ensemble models.

3. PROPOSED SYSTEM

The deep learning approach is utilized in the suggested bone fracture detecting system. Considering that the object in the radiation image needs to be recognized and classified by the system. Thus, convolutional neural networks (CNNs) are used in deep learning implementation. CNN is used by deep learning to identify items in a picture. CNN was utilized to find the object in the radiation picture. CNN is also capable of segmenting images into different areas and assigning a semantic class to each region.CNN is also capable of editing pre-existing photos. Four modules make up bone fracture detection: pre-processing, edge detection, feature extraction, and classification.

Initially, the image is subjected to pre-processing processes by the system, which include noise reduction filtering. Next, use the edge detection algorithm to determine the bones' shared boundaries. The efficiency and accuracy of the bone fracture detection system is the final phase.

3.1 Pre processing

One of the most important functions of any prediction system is the generation of raw data. Developing any deep learning model starts with this. Deep learning has more intricate and time-consuming components. To lessen the complexity of the deep learning algorithm, pre-processing of the data is necessary.

1. *Noise reduction*

Unwanted and random pixel values can be removed from radiation images. Noise has been expressed as:

$$f(x,y) = g(x,y) + \eta(x,y)$$

where g(x,y) denotes the final resultant image, f(x,y) denotes the source image, and represents the noise model. typically the consequence of an issue with the recording or transmission; this causes a kind of erratic bright and dark noise in the picture. The method to handle noise in the radiation image is to use mathematical function T.

$$g(x,y) = T[f(x,y)]$$

In these pre-processing trials, we discovered that using a Gaussian filter as a T was the most effective technique to reduce noise without sacrificing image quality. The neighboring pixel's median values are used to replace a pixel whose value is too divergent.

2. *Edge Detection*

One pre-processing method that aids in determining the borders of objects within images is edge detection. The radiation image's time-varying intensity is used by the edge detection approach. Edge detection is used for picture segmentation and data extraction in fields including computer vision, machine vision, and image processing.

The edges of the photos are extracted using a cunning edge detection algorithm, along with other pre-processing. The Canny Operator operates in stages. Gaussian convolution is first used to smooth radiation pictures. Subsequently, the image was smoothed and the 2-D derivative operator was applied to identify areas of the image that had spatial derivatives. In the gradient magnitude image, the edges provide ridges. The image is subjected to the non-maximum suppression procedure, which tracks along the tops of these ridges and sets all pixels that are not actually on the ridge top to zero, producing a thin line in the output.
The two thresholds that govern the tracking process exhibition are T1 and T2 (T1 > T2). Only at a location on a ridge above T1 can tracking start. After that, tracking keeps going in both directions until the ridge's height drops below T2. By using this procedure, it is possible to prevent noisy edges from fragmenting into several edge pieces.

3.2 Feature Extraction

Feature extraction is the most crucial step in any image processing application. Textural attributes like energy features, entropy features, contrast features, homogeneity features, correlation features, shade features, and prominence features are all measured using the GLCM (Gray-Level Co-occurrence Matrix).

Energy: In the GLCM of radiation image, energy is the total of the squared elements. It is also known as homogeneity or the angular second moment.

$$\sum_{i,j=0}^{N-1} (P_{ij})^2$$

Entropy:

$$\sum_{i,j=0}^{N-1} -\ln(P_{ij})P_{ij}$$

Contrast:

$$\sum_{i,j=0}^{N-1} P_{ij}(i-j)^2$$

Homogeneity:

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

Correlation:

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2}$$

Shade

$$Shade = \mathrm{sgn}(A)\left|A\right|^{1/3}$$

where,

P_{ij} represents elements i,j of the normalized symmetrical GLCM

N represents number of gray levels in the image as specified by no. of levels in under quantization on the GLCM.

μ represents the GLCM mean calculated as $\mu = \sum_{i,j=0}^{N-1} iP_{ij}$

σ^2 represents the variance of the intensities of all reference pixels in the relationships that contributed that GLCM

$$A = \sum_{i,j=0}^{N-1} \frac{(i+j-2\mu)^3 P_{ij}}{\sigma^3 \left(\sqrt{2(1+C)}\right)^3}$$

sgn(x) = sign of the real number

x = -1 for x < 0

x = 0 for x = 0

x = 1 for x > 0

3.3 Classification

Recently, AI-based technologies and machine learning have permeated every facet of our life, including the medical industry. In data analytics, the classification stage involves using a model to predict the correct label for the supplied data. Support Vector Machines can be used to assess these classifiers' accuracy (SVM). SVM performs better in higher dimensions. SVM is used in many image classification applications for its accurate and efficient operation. The data points cannot be split into two classes in a straight line because the data is not linearly separable. As a result, it classifies the data using kernel tricks.
Kernel tricks to identify a hyperplane that separate the data with maximum margin. Inner products between pairs of points in the transformed feature space without explicitly computing the transformation itself compute by kernel function. Gaussian Kernel method is most suitable to perform transformation when there is no prior knowledge about data. This system uses RBF (Radial Basis Function) to improve transformation function.

4. Results

The radiation image data sets were acquired at Kerala's Matha Hospital. It includes more than 10,000 radiation pictures of the elbow, hand, and shoulder, both fractured and unfractured. Following that, this system used the previously described methods to provide the following outcomes.

Elbow, hand, and shoulder bones are the three different types of bones in the proposed system. After loading all of the radiation photos into data frames and labeling each image, divide the images into three categories: 50% for training, 20% for validation, and 30% for testing. The pre-processing and data augmentation of the radiation images will be carried out using algorithms like flip horizontal.Next, using ResNet50, it must categorize the radiation as either elbow, hand, or shoulder.Following the prediction of the bone type, For that particular bone type prediction, a particular model will be loaded from three different types that were each trained to recognize a fracture in a different bone type and used to determine whether the bone is fractured.

This method uses the powerful image classification powers of ResNet50 to determine the kind of bone and then applies a customized model to each bone to detect the presence or absence of a fracture. By using this two-step procedure, the algorithm can evaluate x-ray pictures effectively and precisely, assisting medical personnel in making timely and accurate patient diagnoses.

Medical practitioners may find this approach to be of considerable use in identifying bone fractures and in enhancing patient diagnosis and care. Its quick and reliable X-ray image processing helps expedite the diagnosis process and assist patients in receiving the right care.

4.1 Feature extraction

As was previously indicated, this system uses GLCM for feature extraction. Energy, contrast, correlation, shade, entropy, and homogeneity were the five characteristics required. Additionally, Python programs are used to extract GLCM features. Various characteristics, angles, and separations have been observed and evaluated.

Figure 4.1 Radiation images of Elbow, Shoulder and Hand

4.2 Classification

The aforementioned classification algorithm employs the provided data set for training, testing, and validation in the amounts of 80%, 10%, and 10%, respectively. Next, the SVM algorithm trained, tested, and validated the model using the data set.

Figure 4.2 Radiation Image of Elbow after classification

The performance of the proposed system is assessed on precision, recall and accuracy. In this work four possible outcomes of applying the classifier of any instance. These outcomes are as follows.

- True Positive (TP)
- True Negative (TN)
- False Positive (FP)
- False Negative (FN)

The performance of this system is evaluated in terms of precision, recall and accuracy.

- Precision = TP / (TP+FP)
- Recall = TP / (TP+FN)
- Accuracy = (TP + TN) / (TP + TN + FP + FN)

The system will take only three bone parts i.e., elbow, hand and shoulder. Table 4.1, Table 4.2 and Table 4.3 shows that the details of no., of datasets trained, tested and validated and its accuracy of elbow, hand and shoulder images respectively.

Table 4.1 Accuracy of elbow image

S.No.	No. of dataset trained	No. of dataset tested	No. of dataset validated	% of Accuracy
1	2698	1618	1080	65
2	3237	1349	810	78
3	3885	540	971	95

Table 4.2 Accuracy of hand image

S.No.	No. of dataset trained	No. of dataset tested	No. of dataset validated	% of Accuracy
1	3001	1801	1201	63
2	3602	1502	899	72
3	4322	600	1080	91

Table 4.3 Accuracy of shoulder image

S.No.	No. of dataset trained	No. of dataset tested	No. of dataset validated	% of Accuracy
1	2249	1348	899	65
2	2697	1125	674	78
3	3237	450	809	95

5. Conclusion

A promising method for precisely identifying bone fractures in radiographic pictures is demonstrated by the suggested system. According to the performance evaluation results, the system detects fractures with high accuracy, which might greatly help medical professionals diagnose bone fractures more accurately and efficiently. Additionally, the suggested system's user-friendly interface makes it simple and quick to input images and yields accurate diagnosis findings.

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