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Bone Fracture Detection Using Convolutional Neural Network

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ABSTRACT

Automatic fracture detection is an important part of a computerized tele- medicine system. Fractures often occur any human bone due to accidental injury such as slipping. In fact, many hospitals lack experience a Surgeon diagnosing a fracture. Therefore, computer-aided diagnosis (CAD) reduces the burden on doctors and a fracture was confirmed. Introducing a new classification network, the Crack Sensitive convolutional neural network (Crack Net), This is sensitive to fault lines. This article proposes an improved algorithm based on the faster region-based CNN (Faster RCNN) for detecting small objects. A new content- based medical image retrieval (CBMIR) framework using CNN is proposed. After extracting the features, the CNN is adapted to do the hash mapping used to reduce the dimensions of the feature vector. During the retrieval phase, a compact binary hash code for the query image is taken from the trained network and compared to the database image hash code.

Keywords-CAD, CNN, RCNN, CBMIR, Hash Mapping

INTRODUCTION

Medical images that provide the anatomical and functional information needed for different parts of the body for detection, diagnosis, treatment planning, and monitoring, such as X-rays, magnetic resonance imaging (MRI), and computed tomography (CT) is increasing Not only education and medical research. Powerful retrieval of such data has become an important task for medical information systems. Traditional image search methods are based on text annotating images. But Image annotation takes time and effort, and it is difficult to describe the contents of medical images in one word. Recently, content-based image retrieval (CBIR) has become increasingly important in the areas of education, military, and bioinformatics for image retrieval.

In the early stages, intensity histogram-based features were used for medical images. The main drawback of the traditional artificial methods is their relatively poor performance, as these visual features often cannot explain high levels of semantic information in the user's mind. With recent rapid progress in deep learning, features extracted from pre-trained CNN models provide higher performance and flexibility than traditional descriptors for common image retrieval tasks. We employ a Siamese network that uses image pairs as input and use weight sharing and contrast loss functions to learn a model for similar functionality to images that belong to the same class. CBIR aims to search for similar images through analysis Image content. In addition, you can easily match two images by matching their feature descriptors. Therefore, image representation and measurement of similarity are important. A new content- based medical image retrieval (CBMIR) framework using CNN is proposed. After extracting the features, the CNN is adapted to do the hash mapping used to reduce the dimensions of the feature vector. During the retrieval phase, a compact binary hash code for the query image is taken from the trained network and compared to the database image hash code.

LITERATURE SURVEY

Yiheng Cai, Yuanyuan Li, Changyan Qiu, Jie Ma, And Xurong Gao [1] proposed a Medical image retrieval based on convolutional neural network and supervised hashing where A new framework for content-based medical image retrieval (CBMIR) using CNNs and hashes has been proposed. The new framework uses a Siamese network that takes a pair of images as input, and the model learns to use weight sharing and contrast loss functions to give similar functionality to images of the same class. At each branch of the network, the CNN is adapted to extract features, followed by hash mapping used to reduce the dimensions of the feature vector. In the training process, a new loss function has been developed to make the feature vector more distinguishable, and a regularization term has been added to encourage the output of the actual value to approach the desired binary value. During the retrieval phase, a compact binary hash code for the query image is taken from the trained network and compared to the database image hash code.

Changqing Cao, Bo Wang, Wenrui Zhang, Xiaodong Zeng, Xu Yan, Zhejun Feng, Yutao Liu and Zengyan Wu [2] put forward an improved algorithm based on the faster region-based CNN (Faster RCNN) for detecting small objects. Using a two-step detection idea, we propose an improved loss function based on the crossover union (IoU) in the positioning phase. It uses bounding box regression and bilinear interpolation to improve the region of interest (RoI) pooling process, solve positioning deviation problems, and improve the NMS (Non-Maximum Suppression) algorithm to improve overlapping objects to avoid losses. The results show that the proposed algorithm works well with traffic signs with resolutions in the range (0, 32], with algorithm recalls reaching 90% and precision reaching 87%. Performance is significantly better than Faster RCNN. Therefore, this algorithm is an effective way to detect small objects.

Yangling Ma, Yixin Luo [3] implements A new classification network, the Crack-Sensitive Convolutional Neural Network (Crack Net), is sensitive to fracture lines. This article proposes a new two-stage crack detection system. First, a high-speed region with a convolutional neutral network (high-speed RCNN) is used to detect 20 types of bone regions on an X-ray image, andthen Crack Net is used to detect whether each bone region is destroyed.

Yoga Dwi Pranata, Kuan-Chung Wang, Jia-Ching Wang, Irwansyah Idram, Jiing-Yih Lai, Jia-Wei Liu, I-Hui Hsieh [4] explains Deep learning and SURF for automated classification and detection of calcaneus fractures in CT images which proposes two types of Convolutional Neural Network (CNN) architectures with different network depths, a Residual network (ResNet) and a Visual geometry group (VGG), were evaluated and compared for the classification performance of CT scans into fracture and non-fracture categories based on coronal, sagittal, and transverse views. The bone fracture detection algorithm incorporated fracture area matching using the speeded-up robust features (SURF) method, Canny edge detection, and contour tracing.

Yutoku Yamada, Satoshi Maki [5] discusses automated classification of hip fractures using deep convolutional neural networks with orthopedic surgeon-level accuracy ensemble decision-making with antero-posterior and lateral radiographs which explains Deep-learning approaches based on convolutional neural networks (CNNs) are gaining interest in the medical imaging field. The diagnostic performance of a CNN to discriminate femoral neck fractures, trochanteric fractures, and non-fracture using antero-posterior (AP) and lateral hip radiographs.

Yu Cao, Hongzhi Wang, Mehdi Moradi, Prasanth Prasanna,Tanveer F. Syeda-Mahmood **[6]** explains Fracture X-Ray images through stacked random forests feature fusion. This method uses features extracted from candidate patches in X-ray images in a novel discriminative learning framework called the Stacked Random Forests Feature Fusion. This is a multilayer learning formulation in which the class probability labels, produced by random forests learners at a lower level, are used to derive the refined class distribution labels at the next level. The candidate patches themselves are selected using an efficient sub window search algorithm. The outcome of the method is a number of fractures bounding-boxes ranked from the most likely to the least likely to contain a fracture.

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun [7] proposed Deep Residual Learning for Image Recognition in which present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. It reformulates the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the Image Net dataset we evaluate residual nets with a depth of up to 152 layers 8× deeper than VGG nets but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set.

Vineta Lai Fun Lum, Wee Kheng Leow, Ying Chen [8] presents a study of probabilistic combination methods applied to the detection of bone fractures in x-ray images. Test results show that the effectiveness of a method in improving both accuracy and sensitivity depends on the nature of the method as well as the proportion of positive samples. The OR rule has higher sensitivity and comparable accuracy compared to max/min rule, especially when the fraction of fractured samples is small.

R. Gupta, H. Patil, and A. Mittal [9] presents Robust order-based methods for feature description. In this paper Feature-based methods are increasingly being used in many applications such as object recognition, 3D reconstruction, and tessellation. This post focuses on the issue of matching such features. Histogram type gradient methods such as SIFT, GLOH, and shape context are currently popular, but some articles suggest using pixel order instead of the improved raw intensity in some application. These papers propose two different ways to do this. Relative order histogram and LBP code histogram in the patch. These methods worked fine, but ignore the fact that the order can be very noisy in the presence of Gaussian noise.

J. Ren, X. Jiang, J. Yuan, and G. Wang [10] proposed Optimizing LBP structure for visual recognition using binary quadratic programming in which Local Binary Patterns (LBPs) and their variants show promising results in visual recognition applications. However, most existing approaches rely on predefined structures to extract LBP functionality. He argues that the optimal LBP structure needs to be task-dependent and proposes a new way to learn an identifiable LBP structure.

S. Murala and Q. M. J. Wu [11] explains Peak valley edge patterns: A new descriptor for biomedical image indexing and retrieval. This article introduces a new algorithm intended for use in biomedical image retrieval. The local image area is represented by the Peak Valley Edge Pattern (PVEP) calculated by the first derivative in the 0 °, 45 °, 90 °, and 135 ° directions. PVEP differs from existing Local Binary Patterns (LBPs) in that it extracts directional edge information based on the linear derivative of the image. In addition, the effectiveness of this algorithm is confirmed by combining it with the Gabor transform. The performance of the proposed method is tested in a VIA / IELCAP database containing ROICT (Region of InterestComputer Tomography) images.

S. Murala and Q. M. J. Wu [12] presents Local mesh patterns versus local binary patterns: Biomedical image indexing and retrieval in which this article proposes a new image indexing and search algorithm using local mesh patterns for biomedical image search applications. The standard local binary pattern encodes the relationship between the referenced pixel and its surrounding adjacent pixels, while the proposed method is between adjacent pixels around a particular referenced pixel in the image. Encode the relationship. The possible relationships between the surrounding neighbors depend on the number of neighbors P.

CONCLUSION

The proposed medical image retrieval method based on CNN and surveillance hash mainly contributes as follows: First, the network framework uses a sham network where image pairs (similar / dissimilar) are used as input. And secondly, nonlinear feature learning and hashing are combined to get an image representation. And finally, the reconstruction of the loss function. In response, we propose a regularization term to reduce the difference between the actual values. Network output and binaries enhance the network's ability to distinguish images. From an efficiency standpoint, experiments have shown that the proposed method can obtain similar images faster than traditional hashing methods and certain typical deep learning method. At the same time, mAP the value of the proposed method is higher than that of other methods, indicating that the proposed method is effective in further improving the accuracy ofimage retrieval.

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