Intelligent Auxiliary Diagnosis System for Oral Caries Images

Qichang Chen,[1] Shuwen Niu,[2] Siyang Chen[3]

Xiamen University[1,2,3]

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Abstract

In recent years, the prevalence of dental caries has become higher and higher, affecting more than 3 billion people worldwide. It is becoming one of the main threats to human health. Therefore, the recognition of dental caries in oral apical radiographs is a work of great significance.Deep learning-based marking of tooth decay areas can assist professionals in determining areas of decay that are not easily detected.

We propose an intelligent assisted diagnosis system for oral caries images based on deep learning to study how to better predict the caries lesion area. Because the caries feature information of x-apical slice is not obvious, the tooth imaging angle is different, and the caries grading is many, the recognition effect is poor, so this paper explores two traditional image processing methods of image segmentation and edge extraction for enhancing feature information. Finally, this system is expected to be put into the primary hospital to guide the doctors who are not yet rich in clinical experience and help to diagnose the early adjacent surface caries.

Introduction

More than half of the world's population suffers from oral diseases, and caries, commonly known as tooth decay, is often neglected as a common disease in the field of medical dentistry(Cheng et al. 2019; Tafere et al. 2018). The caries is divided into superficial, medium and deep caries, and when the caries penetrates into the tooth pulp, it can lead to periapical inflammation. Superficial and intermediate caries cannot be detected clinically only by visual and tactile examination of the physician. The extent of lesions on apical radiographs is often overlooked due to the lack of obvious imaging changes in early adjacent caries. Studies have shown that when identified by the naked eye, the rate of missing caries in the adjacent surfaces of permanent teeth in apical radiographs is 58% and the rate of misdiagnosis is 11% (Schwendicke, Tzschoppe, and Paris 2015; Yang et al. 2018).

Currently, due to the continuous iterations of deep learning technologies, especially in the field of imaging, people are trying to apply them to medical image analysis (Li et al. 2020), making them the "third eye" of doctors, thus improving the speed and accuracy of diagnosis, helping to achieve intelligent diagnosis and remote diagnosis, enabling patients to get the correct treatment quickly. In addition, it can make up for the inevitable error of doctors' visual observation. The computer-aided caries diagnosis system enhances the image feature information by using computer vision technology, which mainly includes quantifying the gray value change, contrast shape, edge extraction in the image, and also using convolutional neural network for migration learning and prediction, which largely improves the effectiveness and reliability of identifying the dental caries area. However, a lot of manpower is still needed to extract and label image features for machine learning.

This paper focuses on the identification of carious lesion areas in apical x-ray slices using deep learning methods. The image segmentation, edge extraction and image superimposition are included in the pre-processing work of image enhancement of carious region using python-opencv. In order to explore whether deep learning technology can improve the diagnosis rate of early caries area in apical radiographs, this paper compiled the normal and caries marker images of apical radiographs, trained a deep learning model that can predict the caries area using faster RCNN, built an intelligent assisted diagnosis system of oral caries images based on deep learning model using PyQt5, and performed the preprocessing of original images and A cross-sectional comparison of two image pre-processing modes, image segmentation and edge extraction, was carried out to provide a reference for the diagnosis of caries. Using the graphical interface development tool of PyQt5, the intelligent auxiliary diagnosis system is designed and implemented to provide a simple and efficient tool for professionals to improve the reliability of professionals in identifying early caries areas and better solve the disadvantages of the difficult work of caries detection and numerous operations nowadays.

Related work

Image segmentation

Image segmentation techniques divide digital images into various subgroups (pixels) called image objects, and divides them into several specific regions with similar unique properties and obtain ROI (target of interest) regions, which is a key step combining pre-processing to image analysis. Nowadays, there are three main categories of image segmentation methods most commonly used(Wang, Zhang, and Zhu 2019): threshold-based segmentation methods, region-based segmentation methods, edge-based segmentation methods, and specific theory-based segmentation methods. In this paper, we use the threshold-based segmentation method, which is the most basic but most powerful technique for identifying the desired objects in an image. The pixels in an image are segmented by comparing the intensity of the pixel with the threshold value. The thresholding method proves to be beneficial when it is assumed that the objects in the discussed image have higher intensity than the background (and unwanted components) of the image

Image edge extraction

Edge detection is an image processing technique used to identify discontinuous points in digital images and also called sharp changes in image brightness. These points where the image brightness changes sharply are called the edges (or boundaries) of the image. When dealing with high resolution images, convolution techniques can be used to solve this problem. Therefore, an efficient algorithm needs to be chosen to perform the convolution or even use deep learning to determine the optimal value of the filter. There are several methods for edge detection(Zhao et al. 2020), and the commonly used operators are Prewitt edge detection Sobel edge detection, Laplace edge detection, and Canny edge detection. Sobel computes the image difference by performing a convolution operation on the image with the corresponding kernel, and since the Sobel operator uses both Gaussian smoothing as well as differentiation, its results are robust to noise on many images Canny is a multi-stage algorithm, which is the most commonly used complex but extremely efficient method for detecting a large range of edges compared to many other methods(Xu, Qin, and Chen 2014).

FasterRCNN

FasterRCNN can be simply regarded as a system of "region generating networks RPNs + FastRCNN", replacing the selective search of the previous generation with region generating networks. The brief process of FasterRCNN: consistenting with its predecessors, it use CNN to extract the convolutional features of the image, and then obtain featuremaps. The RPN network is relied on to obtain the ROIs from the featuremaps, and to bifurcate the ROIs, discriminate whether the content of the candidate frame is foreground or background, leave the foreground candidate frame, discard the background candidate frame, and fine-tune the foreground bounding box to a reference value close to the label by regression. ROI pooling is used to obtain the feature and t he prior frame, and then send it to the multi-classifier. Multi-classify the candidate frames by the multi-classifier, i.e., the reference value has several categories, and this will be divided into corresponding categories. Finally, the bounding box regression is performed.

Computer-aided diagnosis system

A computer-aided diagnosis system with artificial intelligence applied to CT analysis (Zhang 2017) has been demonstrated to be more accurate for the diagnosis of early caries areas in CT(Liu 2019) images compared to the physician's visual diagnosis. However, CT is more expensive in terms of equipment and detection cost and high radiation intensity compared with apical radiographs. At the same time, cone beam CT does not significantly improve the diagnostic accuracy in the diagnosis of adjacent enamel caries, and although cone beam CT is superior to apical radiographs in the diagnosis of caries areas, it is not recommended for the diagnosis of adjacent dentin caries due to its high radiation dose (Cheng et al. 2012). In medical experiments, fluorescence and laser methods are often used, which are relatively complicated and expensive. Previous studies have shown that the use of computer-aided caries diagnosis system is beneficial to improve the accuracy of the diagnosis of adjacent surface caries in apical radiograph images (Cheng et al. 2012; Heaven, Firestone, and Feagin 1992).Compared to traditional machine learning, deep learning compensates for the need to manually extract image features and has been widely used in fields such as medical image recognition, where artificial intelligence will provide complementary advice to dentists when determining care methods.

Proposed solution

Image segmentation

We use the OpenCV library of python to preprocess the root tip slice. Firstly, we pass in the grayscale binarization image, which plays an important role in image processing, and the binarization of the image greatly reduces the amount of data in the image, thus highlighting the contours of the image. In OpenCV, you can use the function: threshold() for image binarization. This article uses cv.THRESH_BINARY|cv.THRESH_OTSU two square threshold types to segment the original root and apex slices. The BINARY method is shown in formula (1). OTSU lets the system use the otsu algorithm to automatically select the best threshold(Wang, Zhang, and Zhu 2019).

$$dst(x,y) = \begin{cases} maxval & if \quad src(x,y) > thresh \\ 0 & otherwise \end{cases} \tag{1}$$

In order to better protect and transmit the characteristic information of the original image, this paper sets the Alpha transparency of the original image after image segmentation to 20% and 50% weighted fusion of the original image. In practical applications, experiments have found that based on threshold segmentation, most images can effectively separate the foreground and background, but there are some apical slices as shown in Figure 1 that will lose the root part and retain the crown after preprocessing. The mold where the tooth root is located is incorrectly classified as the foreground. Since the decayed area mostly occurs in the crown, this classification error is within our acceptable range (Zhao et al. 2020).

Edge extraction

In target detection, the edge can well reflect the characteristics of the object. Compared with the normal area, the edge of the caries area will have a certain light and dark change

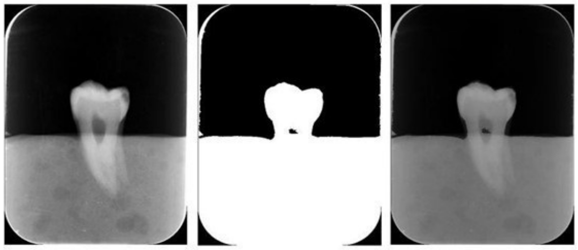

Figure 1: The left is the original image, the middle is the image after image segmentation, and the right is the result of image weighted overlay

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and shape difference (Xu, Qin, and Chen 2014). This difference information can be effectively obtained through the edge extraction of the image. Extract it and use it.

The image is also converted to a grayscale image, and then the sobel operator is used to calculate the vertical and horizontal gradients of the input image. After the convolution calculation is performed using the sobel 3*3 filter, the image edge will be less than 2 layers. Usually If the size of the input image is n*n and the filter size is r*r, the output image size will be (n-r+1)*(n-r+1), because the size of the output image is larger than that used as the input The original image is much smaller, so a lot of valuable information may be lost, especially the information at the edges of the input image. The technology to overcome the shortcomings of edge computing, in order to prevent the loss of such valuable information due to image reduction, usually "padding" the input image before applying edge detection to avoid losing valuable information in the input image.

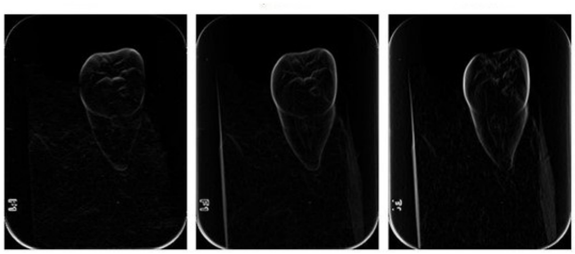

Figure 2: The left side uses the sobel operator to find the x-direction gradient of the original image, the middle is the y-direction gradient, and the right side is the result of superimposing the gradients in both directions

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Use canny to find the edge of the root apical x-ray slice. The steps are: filter with Gaussian filter to remove noise points; suppress the sobel gradient size and direction obtained in the previous step (retain the maximum value) to eliminate The noise impact caused by edge detection (Girshick et al. 2014). Double thresholds (tested, 50 and 90 are used) to determine the true and potential edges, and further selections are made. If the current gradient value is greater than the given maximum threshold, the system will It is classified to the boundary, and when the gradient value is less than the minimum threshold, it is discarded. If the current gradient value is between the given maximum and minimum values, if the surrounding points are boundary points, then the current point is retained, otherwise discarded and passed Suppress weak edges to complete the final edge detection(He et al. 2015). In order to preserve the characteristics of the original image, image weighted overlay is used here, and the alpha transparency of the original image is 50% and the edge 30% is superimposed (Ren et al. 2015).

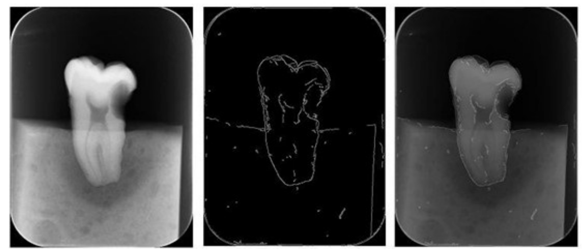

Figure 3: The left is the original image, the middle is the image after edge extraction, and the right is the result of image weighted overlay

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Labeled data

The process of labeling the original image is very important for target detection. In this article, LabelImg is used to annotate multiple categories and generate an xml file to generate an image data set in PASCAL VOC format. Its function is to mark the position of the target object in the original image and export it as an xml file with a priori box of position information. . This article only detects the caries area and does not divide the caries grades, so it is strictly a two-class problem, namely normal and dental-caries. By selecting the ROI area on the picture, select The label can complete the labeling. Save it as an xml file. The content of the xml file is information such as the area, size, type, and whether it is close to the border of the image.

The Pascal Voc format data set consists of five parts, Annotations (store xml files, each xml file corresponds to a marked picture), imageSets (store picture names in txt files, stored according to human actions, postures, training, and testing) , JPEGImages (store original pictures including training pictures, test pictures), SegmentationObject and SegmentationClass (store the data after instance segmentation, not used in this article).

Network implementation

In this paper, we first choose a lighter weight and faster training speed SSD to train the target detection network, and find that its recognition effect is not good, and the caries area cannot be identified. Since the characteristics of oral apical radiographs are relatively inconspicuous, and the number of data sets is only a hundred or so, the Faster RCNN network, which sacrifices time but has higher accuracy, is used [16].

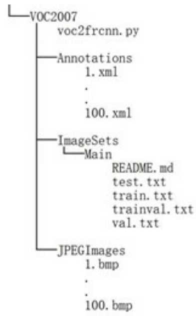

Figure 4: Pascal Voc format dataset

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This network consists of two main bodies: (1) the RPN network used to generate the suggestion frame (2) the predecessor network Fast R-CNN used as a detector, where the predecessor model is decoupled to serve specifically for target detection.Faster-RCNNN can be embedded with multiple total pre-trained backbone feature extraction networks, commonly used are VGG, Resnet, Xception, etc. In this paper, the VGG backbone feature extraction network is used for subsequent experiments, where the idea of migration learning is used to accelerate the training of the model (Yang et al. 2018).

System development

Before developing the GUI, the user's usage logic was simulated and the development was carried out with the operation logic shown in Figure 5. After loading the apical slice, the image was pre-processed to get two types of processed images and the original image, and the caries area was predicted and displayed to the interface using three pre-trained models, and the image was saved to tmp folder for subsequent review again.

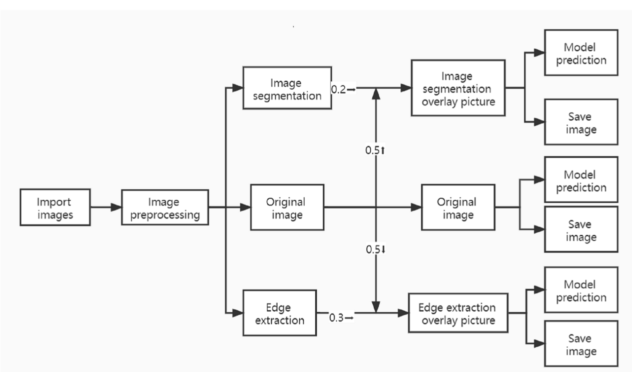

Figure 5: Flow chart of the intelligent auxiliary diagnosis system for oral caries images

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In the process of image manipulation, if other formats are imported by mistake, they can be automatically converted to ".bmp" format for subsequent pre-processing work. The system has set global variables to store the previous work status, so if you import other photos, you can revert to the previous work by closing the system and restarting it, which can prevent misuse to a certain extent.

Experiments

Dataset source

With the written consent of the patient, the isolated teeth were collected from the Dental Hospital of Fujian Medical University. The teeth were embedded in an alginate impression material with a root length of 3/4, and the apex of the isolated teeth was photographed using an oral and maxillofacial X-ray machine Films, shooting angles include front, side, and top view, and the pictures are saved in the ".bmp" format. After the shooting is completed, the tooth sample is sliced and observed by two dental professional doctors with a microscope at 20 times, and the caries area is manually marked as a verification set for evaluating the performance of the intelligent auxiliary diagnosis system (Lin et al. 2020).

Network deployment

The training process of Faster-RCNN is composed of two modules like its prediction process. The first part is to train the RPN suggestion box network, and the second part is to train the network that uses the ROI area to obtain the prediction result.

In the training process, in order to correlate the prediction results of RPN, we need to calculate the loss function smoothing L1. It is necessary to input the picture into the network of the current Faster-RCNN suggestion box to get the network's suggestion. At the same time, we also need to encode, that is, to convert the position information format of the real box to the prediction result format of the Faster-RCNN suggestion box information.

The suggestion box network obtained through training in the previous step will provide some position suggestions. In the ROI network part, it will generate suggestion boxes and obtain corresponding prediction results. In fact, it uses the suggested box in the previous step as the a priori box for the ROI network. Therefore, we need to calculate the overlap between all suggested boxes and actual boxes and filter them. If the degree of overlap between the actual box and the suggested box is greater than 0.5, the suggestion box is regarded as a positive sample. If the overlapping box is less than 0.5, it is regarded as a negative sample. Finally, we need to encode the results. This encoding is relative to the suggestion box. When we have these suggestion boxes, what kind of prediction results our ROI prediction network needs to adjust these suggestion boxes to true frame.

Network training

The Faster RCNN used in this paper is based on the PASCAL VOC dataset format (20 categories are predefined), and the dataset we use has only two types of annotations: normal and caries. The number of categories needs to be modified accordingly.

In addition, the preliminary work also includes importing vgg-16 weights that have been pre-trained with a large amount of data as the backbone feature extraction network.

At the same time, using the optimization function Adam, set the initial learning rate to 0.0001, the batch size to 2, the network epoch to 100, and also set the frozen epoch It is 50, which can speed up the training speed in the early stage and prevent the weights from being destroyed in the initial training stage.

Figure 6 shows that the loss of the network based on the original image is about 0.85 at 100 iterations, and the same test is conducted with the dataset based on image segmentation overlay and edge extraction overlay, and it is found that the network based on image segmentation also converges to 0.85 at 100 iterations, while the network based on edge extraction converges better to 0.7 at 100 iterations, indicating that the edge extraction can reflect the feature information of dental caries region to a certain extent.

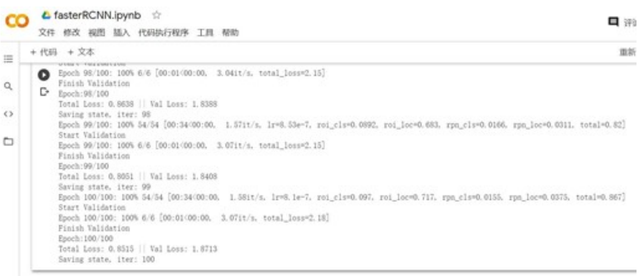

Figure 6: Training results for 100 iterations

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Figure 7 below shows that the edge extraction-based network has a map of 0.83 for the carious region, which is better than the manual recognition (0.61-0.78).

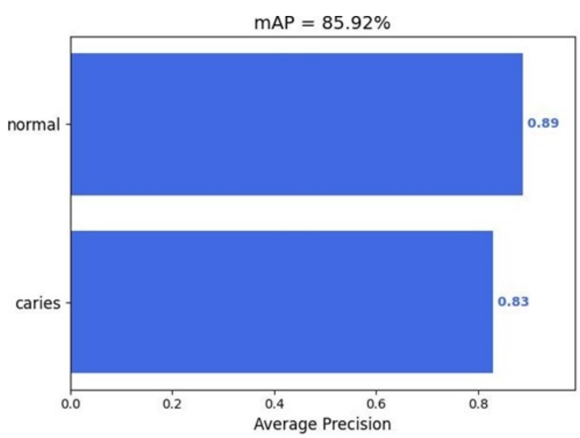

Figure 7: Validation results

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Intelligent Auxiliary Diagnosis System for Oral Caries Images

Click to import the original picture, select ".bmp" format, after the system receives the picture, it will judge the number of bits of the picture, if it is a 24-bit three-channel color picture, the image overlay will generate errors, and the system will automatically convert it to 8 single-channel grayscale pictures before pre-processing. After clicking the button on the right, the system will display the pre-processed and model predicted pictures in the corresponding position on the left after the corresponding operation, and save the pictures in tmp file, and print out the operation step information and error message in the debug window on the right.

Figure 8: System interface of intelligent auxiliary diagnosis system of oral caries image

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The main work of the oral caries project has been basically completed. The GUI can interact with the background stably, providing professionals with a simple and efficient tool.

Conclusion

In this paper, it mainly introduces the hazards of dental caries and the current research status of computer-assisted dental caries diagnosis systems at home and abroad, and the feasibility and cost-effectiveness of using computer-aided caries diagnosis are analyzed as well as the aspects that can be further explored. Then, the sources and generation methods of the dataset used in the deep learning network are explained, and the effects of two pre-processing methods, threshold-based image segmentation and canny-based edge extraction, are analyzed in turn from the original image. By training the Faster RCNN network for prediction, it is found that the dataset based on the edge extraction overlay image is more conducive to the convergence of the model and better reflects the characteristics of the oral caries region. Finally, the development of the intelligent assisted diagnosis system is introduced, the implementation of each part is described, and the specific aspects of the system operation and the recovery of the misoperation snapshot are discussed.

The feasibility of using deep learning to predict the area of oral caries is discussed, and it is concluded that edge extraction is more advantageous in reflecting the characteristic information of the area of oral caries. Developed an intelligent auxiliary diagnosis system for oral caries images, which is expected to be used in primary hospitals to guide doctors with insufficient clinical experience and help professionals diagnose early adjacent caries.

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