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Research Article

Application of infrared technique and deep learning in detecting early dental lesions

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ABSTRACT

Recently, in dentistry the infrared technique has been developed strongly to detect dental lesions, based on the fact that the optical properties of damaged tissue under infrared light are significantly different from those of sound dental tissue. Meanwhile, a number of research groups have paid attention to the application of deep learning strategies for classifying and analyzing infrared image data. The aim of the present study was to introduce the application of infrared technique and deep learning in detecting dental lesions. In this study, the optical systems with 850-nm LEDs which were applied for infrared imaging, were designed and used for diagnosing in vitro different types of early-stage lesions such as occlusal plaque, approximal plaque and white spot lesion. Two deep learning models (Unet and Mask R-CNN) were used for training and identifying the presence of lesions in 1367 near-infrared images. The results suggest the effectiveness of Unet and Mask R-CNN models in diagnosing dental lesions via infrared images.

Key words: dental lesions, near-infrared, deep learning

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INTRODUCTION

Currently, the advanced imaging techniques used for diagnosis of dental lesions have become increasingly popular in the world. However, over 90% of Vietnamese suffer from dental diseases and 85% of Vietnamese children have tooth decay, according to National Hospital of Odonto - Stomatology. The lack of professional doctors as well as hesitation to go to see dentists in time are the main reasons for these high percentages. Instead of being treated at early stages of tooth decay, people usually go to see dentists when the damages become severe or even untreatable. Early detection of tooth decay can be greatly helpful in treatment. Unfortunately, the conventional diagnostic methods such as clinical inspection or X-rays are not really effective in the early diagnosis of dental lesions.

Recently, in dentistry many new studies have been conducted and the research results show the effectiveness of near-infrared (NIR) technique in non-invasive diagnosis of dental diseases, based on the difference in the scattering and absorption properties of healthy and damaged tooth tissue in NIR region [1–4]. It has been shown that near infrared wavelengths of 780 nm to 1550 nm are effective in detecting early demineralization occurring beneath the enamel. This method has brought the significant effects in the field of dentistry. There have been many studies on the use of near-infrared imaging in early detection of dental lesions *in vitro* and *in vivo*. In this study all the experiments were conducted *in vitro*.

With the development of deep learning techniques, biomedical data analysis applications have grown strongly and brought the encouraging results. In particular, deep learning methods are being applied in medical applications such as abnormal detection in chest X-ray images [5], breast cancer detection [6], detection statistics and diagnosis. covid by X-ray image [7]. In dentistry, convolutional neural networks (CNNs) have been used to diagnose dental lesions on infrared images [8], periapical radiographs [9], computed tomography images [10]. An increasing number of studies investigated dental lesions using CNNs, with different models being employed. Reported accuracy seems promising, while study and reporting quality are currently low [11].

Unet and Mask R-CNN, which are popular with medical image segmentation applications, have been used to detect periodontitis in panoramic radiographs [12] or carious lesions in intraoral photographic images [13,14], and the results show that application of these models may help dentists increase accuracy and reliability as well as save time in detecting caries lesions. However, the studies of application of these models in infrared images of dental lesions are still limited. Therefore, the aim of this study was to apply Unet and Mask R-CNN in identifying the presence of early dental lesions such as occlusal plaque, approximal plaque and

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white spot lesions in near – infrared images; and compare the performance of the two models in order to choose the more appropriate model.

MATERIALS AND METHODS

Samples

Tooth samples were collected regularly from many sources such as Odontology Department of National Hospital of Odonto – Stomatology and Odonto - Maxillo - Facial Hospital. After being collected, tooth samples were cleansed of food, bacteria, blood and periodontal ligaments without losing dental plaque or damaging the intrinsic lesions of samples. Each tooth sample had a separate base that was made of denture adhesive powder in order to keep it in balance during diagnostic imaging. All the samples were preserved in physiological saline solution in order to keep samples from dehydrating during the study process as well as to ensure the sterilization.

The infrared imaging systems

The tooth samples were captured under 850-nm illumination with the scattering system (also known as occlusal transillumination) and the transmission system (or approximal transillumination) showed in Figure 1 [15].

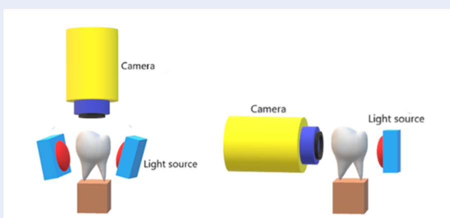

Figure 1: Schematic diagrams of scattering (left) and transmission (right) infrared imaging systems

The scattering system consists of two symmetric 850-nm LEDs and a NIR camera to capture NIR images of occlusal regions. The camera position was calibrated to get the optimal distance from tooth samples to guarantee the best image quality. The LEDs were put close to the sample so that the light did not hit the camera directly, preventing flares in the image. The LEDs had wavelength of 850 nm and power of 1 W. The NIR light emitted from 850-nm LEDs went through the sample right on top of the gum line, then was scattered and absorbed inside the tooth before reaching the occlusal surface and getting out of the tooth. Therefore, this method was used to observe the lesions on the chewing surface of the tooth samples.

With regard to approximal transillumination technique, the transmission system was designed simpler than the scattering one. It consists of one 850-nm LED put next to the lateral surface of the tooth and a NIR camera placed on the opposite side. All the components of the system were placed coaxially. With this technique, the LED light travelled through the tooth and reached the camera. The captured image was the result of optical interaction between NIR light with both enamel and dentine. Therefore, this technique was applied to the inspection of structure damages placed on the lateral surface of teeth.

Deep learning models

With the development of deep learning models, computers have become more and more capable of observing and processing highly complex images in a variety of tasks. Initially, computers could only analyze and recognize the type of object, later with more complex models, machines were able to identify the object inside the image. More advanced is determining the shape of that object (image segmentation). Image segmentation is mainly used in fault detection of products in manufacturing and medicine. The application of image segmentation in medicine is a breakthrough that supports the initial diagnosis, for example, determining the size and shape of the tumor from which it can be initially diagnosed as benign or malignant, the lesions injuries such as fractures... Two prominent models for image segmentation in medicine, namely U-Net and Mask R-CNN, were used in this study to compare their effectiveness in identifying tooth decays. The algorithms of Unet and Mask R-CNN were developed by our group.

RESULTS AND DISCUSSION

The data training process of the two models was performed with a data set of 1367 NIR images with different types of early damage. The dataset was divided into 1094 training data and 273 test data. The available tools were used to localize dental lesions to generate data for deep learning. Each image after being labeled included the coordinates of the bounding box and segmentation.

Unet results

Figure 2A shows the NIR image of sample 1 with occlusal plaque. Dental plaque or calculus is considered not damage tissue, but it is one of the main causes of tooth damage. Plaque which is not removed

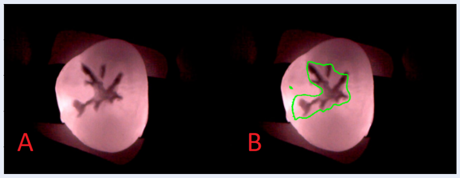

Figure 2: Sample 1: Input image (A), Output image by U-Net model (B).

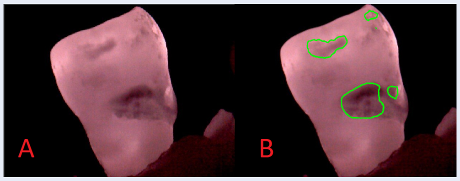

Figure 3: Sample 2: Input image (A), Output image by U-Net model (B).

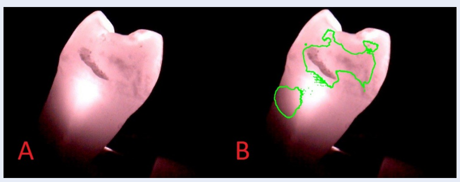

Figure 4: Sample 3: Input image (A), Output image by U-Net model (B).

at early stages could gradually calcify, leading to mineral loss and more severe damages in the long run. Because the mineral density of damaged tissue is lower than that of sound tissue, NIR light can be scattered many times in demineralized tissue and significantly attenuated before reaching the NIR camera. As a result, NIR images of lesions appear darker than that of sound tissue[8]. Figure 2B demonstrates the processing result with U-net model on sample 1, where the tooth lesions on the near-infrared image are circled as green.

Figure 3 is the test result of the tooth sample 2 with approximal plaque. Figure 3A shows that lesion regions under infrared light became darker than the surrounding enamel area, indicating that there was demineralization occurring in the tooth. And the processing result with U-net model on sample 2 is demonstrated in Figure 3B, where the tooth lesions on the near-infrared image are circled in green.

The white spot lesion of the tooth sample 3 is shown in Figure 4A. Currently, diagnosis of white spot lesions by infrared technology has become more potential than examination with radiology because X-rays are less sensitive in detecting early lesions. Meanwhile, the mineral density of damaged tissue is lower than that of sound tissue, NIR light can be scattered many times in demineralized tissue and significantly attenuated before reaching the NIR camera. As a result, NIR images of lesions appear darker than that of sound tissue. Figure 4B shows the processing result of the U-net model on sample 3, with the tooth lesions indicated by green circles.

From Figures 2, 3 and 4, it can be seen that although the position and quantity of the lesions were determined with high precision, the lesion areas detected by U-net model were not exactly the same as the original images. In case the lesion is in many angles (Figure 2), U-net model identified an area larger than the actual lesion. If the lesions are non – uniform, there are two opposite results: 1) the lesions became smaller than the actual ones while the others were even missed (Figure 3); 2) the lesions became greater whereas another sound tissue area was identified as a damage (Figure 4). The key point could be due to the limitations of the training algorithms of U-Net model.

Mask R-CNN results

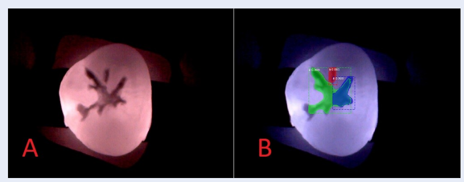

Figure 5: Sample 1: Input image (A), Output image by Mask R-CNN model (B).

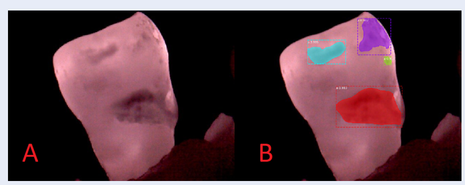

Figure 6: Sample 2: Input image (A), Output image by Mask R-CNN model (B).

Figure 5A shows the NIR image of sample 1 with occlusal plaque lesion. After inputting a NIR image, the machine proceeds to detect the lesion regions and their mask. Figure 5B demonstrates the processing result with Mask R-CNN model on sample 1, where tooth lesions on near-infrared images are identified

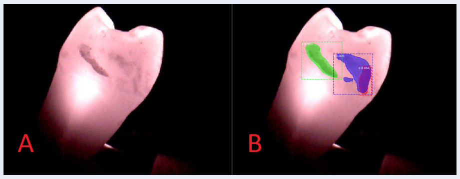

Figure 7: Sample 3: Input image (A), Output image by Mask R-CNN model (B).

by different colored regions. Besides, the IoU (Intersection over Union) values appearing with the colored regions are all greater than 0.5, proving the detection of the Mask R-CNN model is quite accurate.

Figure 6 shows sample 2 with the approximal plaque on the lateral surface of the tooth. Figure 6A shows the NIR image of sample 2 with the dark lesion, indicating the presence of demineralization on the occlusal surface of the tooth sample. Figure 6B shows the processing result for sample 2 using the Mask R-CNN model, where dental lesions in the near-infrared image are distinguished by various colored regions.

Figure 7A is the test result of tooth sample 3 with a white spot lesion. Figure 7B shows Mask R-CNN model processing results of sample 3, with the dental lesions denoted by colored regions.

In contrast to U-net model, Mask R-CNN behaved more effectively in localizing lesions with many angles like sample 1 on Figure 5, where the lesion identified by Mask R-CNN almost overlaps the actual one. However, like U-net, Mask R-CNN model had difficulty in determining non – uniform lesions. Figures 6 and 7 show that the non – uniform damages became larger or they were missed after being identified by Mask R-CNN. These results suggest that both U-net and Mask R-CNN have limitations in identification of non – uniform lesions.

Table 1: Comparison of U-Net model and Mask R-CNN models

Model	IoU	Accuracy	Average detection time / image (s)
U-Net	0.73	0.82	0.073
Mask R-CNN	0.70	0.81	0.467

Table 1 shows the results of lesion detection using two models U-Net and Mask R-CNN. The results show that U-Net model achieved values of IoU and accuracy a little better than Mask R-CNN. In addition, U-Net's average prediction time is significantly faster than Mask R-CNN.

In comparison with other studies of Unet and Mask R-CNN [12–14], the values of IoU and accuracy obtained in this study are not too high. It could be seen that the limitation of number of samples utilized in the training process or our algorithms affect the results of the models. Besides, the lesion detection results by the two models could be also affected by the quality of infrared images, causing difficulty in learning the object's attributes on models and easy confusion with other objects. To enhance the images' quality, the optical systems were continuously improved. Unfortunately, the accuracy and IoU did not remarkably change as expectations.

According to the study, there are no significant differences in IoU and accuracy between the two models, we suggest that both U-Net and Mask R-CNN are consistent with dental lesion detection in infrared images.

CONCLUSION

In this study, two deep learning models U-Net and Mask R-CNN were applied to detect early tooth lesions in near-infrared images. The two models are predicted to be a promising application of AI in detecting tooth damage at early stages. However, the accuracy of the two models is still lower than actual expectations. The results of this study can be further improved in the future by increasing the dataset of tooth sample for training and improving the algorithms of the above deep learning models.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

AUTHORS CONTRIBUTION

Pham Thi Hai Mien contributed in designing the ideas and optical systems.

Dang Thi Phuc participated in designing the ideas and deep learning models.

Nguyen Tran Kim Hoang participated in diagnosing samples' lesions.

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Bài nghiên cứu

Ứng dụng kỹ thuật hồng ngoại và học sâu trong phát hiện tổn thương răng giai đoạn sớm

Phạm Thị Hải Miền[1,*], Đặng Thị Phúc[2], Nguyễn Trần Kim Hoàng[3]

TÓM TẮT

Trong những năm gần đây, kỹ thuật hồng ngoại đã phát triển mạnh mẽ nhằm phát hiện tổn thương răng trong nha khoa dựa trên việc tính chất quang học của mô tổn thương dưới ánh sáng hồng ngoại hoàn toàn khác biệt với mô khỏe mạnh. Đồng thời, một số nhóm nghiên cứu đã hướng chú ý đến việc ứng dụng học sâu trong việc phân loại và phân tích dữ liệu ảnh hồng ngoại. Mục đích của nghiên cứu này là giới thiệu một ứng dụng của kỹ thuật hồng ngoại và học máy trong việc phát hiện tổn thương răng. Trong nghiên cứu này, chúng tôi đã thiết kế và chế tạo hệ quang học chụp ảnh hồng ngoại sử dụng LED 850 nm để chẩn đoán *in vitro* các loại tổn thương răng khác nhau như tổn thương đốm trắng và cao răng. Hai mô hình học sâu là Unet và Mask R-CNN đã được sử dụng để huấn luyện và nhận dạng sự có mặt của tổn thương trong 1367 bức ảnh hồng ngoại. Kết quả cho thấy hiệu quả của hai mô hình này trong việc chẩn đoán tổn thương răng thông qua ảnh hồng ngoại.

Từ khoá: Tổn thương răng, hồng ngoại, học sâu

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