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A Deep Learning-Based System for the Assessment of Dental Caries Using Colour Dental Photographs

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Abstract. D[1]ental caries remains the most common chronic disease in childhood, affecting almost half of all children globally. Dental care and examination of children living in remote and rural areas is an ongoing challenge that has been compounded by COVID. The development of a validated system with the capacity to screen large numbers of children with some degree of automation has the potential to facilitate remote dental screening at low costs. In this study, we aim to develop and validate a deep learning system for the assessment of dental caries using color dental photos. Three state-of-the-art deep learning networks namely VGG16, ResNet-50 and Inception-v3 were adopted in the context. A total of 1020 child dental photos were used to train and validate the system. We achieved an accuracy of 79% with precision and recall respectively 95% and 75% in classifying `caries' versus `sound' with inception-v3.

Keywords. Oral health, dental caries, remote health

1. Introduction

Dental caries, commonly referred to as tooth decay, remains the leading childhood chronic disease, affecting almost half of children's population [1]. The temporary shutdown of dental services due to COVID-19 is likely to have worsened the already significant dental disease burden and further overburdens the health systems.

To assist in visual examination of dental caries, recent research has used smart phone photos as input data to deep learning models [2]. If deep learning technology is combined with a smartphone camera, this has the potential to play a vital role in expediting remote dental screening and early classification of tooth decay, even during the times of crisis-related dental services shutdown.

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Therefore, this study aimed to develop and validate a deep learning system for the assessment of dental caries. A comparative evaluation involving three widely used deep learning-based networks, namely, 16-layer version of VGG (VGG-16) [3], 50-layer version of Residual Network (ResNet-50) [4] and version 3 Inception network (Inception-v3) [5] was performed to classify “caries” vs. “sound” Regions of Interest (ROIs) in the context.

The images were collected from the existing records of University of Western Australia Dental School and from private dental practices in Perth, Australia, in 2021. Images were reviewed and annotated by calibrated dental reviewers to create ground truth data that were used in the training and validation of the deep learning models.

2. Methods

The reporting of this study followed the Checklist for Artificial intelligence in dental research [6]. Ethical approval for this study was obtained from the Human Research Ethics Committees at the Commonwealth Scientific and Industrial Research Organization (CSIRO - Ref no 2021-008-LR).

2.1. Dataset Preparation and Annotations

A total of 1,020 color intraoral dental images of children (up to 15 of age) were used in this study. The dental images collected were of different oral views, frontal, upper occlusal and lower occlusal views. All collected dental images were anonymous and obtained in JPG format.

Dental images were reviewed by a calibrated dental reviewer to detect carious lesions as per the International Caries Detection and Assessment System (ICDAS 1-6). The ICDAS system is intended to provide a consistent and reliable method for evaluating lesions across populations, clinical settings, and research studies. It uses a numerical code from 0 to 6 to indicate the severity of caries lesions, with 0 indicating no visible evidence of caries, and 6 indicating extensive cavitation. In our study, ICDAS 3 was used as cut off point for identifying dental caries in dental images in line with epidemiological criteria. Using the developed Simple Image Annotation tool (SIANNO) platform, the dental reviewer was asked to draw a rectangle around a suspected carious lesion on dental images. The label for each carious lesion, which contained coordinates of the ROIs, was obtained in text form for each item of the imaging data using a functional module operating at the backend of the SIANNO system.

Out of 1020 dental images included in the training dataset, 359 images were caries-free, and 661 images had dental caries. Of the images with caries, 588 had caries with ICDAS equal or above 3. Out of 588 images we eliminated another 144 images that had the frontal view of the mouth. In the images containing caries we identified 242 lesions with ICDAS-3, 297 lesions with ICDAS-4, 1082 lesions with ICDAS-5 and 280 lesions with ICDAS-6.

2.2. Proposed System

The proposed system has 2 modules: 1) ROIs localization with human input, and 2) deep learning-based ROI classification. We provide further detail of each module in sections 2.2.1 and 2.2.2.

2.2.1. ROI Localization with Human Input

We developed a graphical user interface (GUI) that allows humans to load color dental images and draw rectangles (ROIs) on them. They can then adjust the size and location of the ROIs. Once the delineation is complete, each of the ROIs are then independently and automatically sent to the deep learning-based module (described in section 2.2.2) for assessment of dental caries. The output of the classification gets displayed beside each ROIs along with the confidence of the classification.
The GUI displays the worklist to the user. The user can open each record to view each dental image.

2.2.2. Deep Learning-based ROI Classification

Three most common classification deep learning-based networks, namely, VGG-16, ResNet-50 and Inception-v3 were independently trained and evaluated for the proposed “caries” vs. “sound” ROI classification task. ICDAS 3 and above were considered as “caries”, and others as "sound". Leveraging the power of transfer learning, the network parameters for all three CNNs were initialized using pre-trained models and their learned representations on large-scale image datasets. This approach was particularly advantageous in working with limited data. Other learning parameters that were used including the exponential decay, learning rate of 0.001 and batch size of 64, which were equally applicable to all the CNNs, and we trained each for 100 epochs. The ROIs were resized to 224×224 pixels and we fine-tuned the top 70% of the networks to optimize performance [7].

A total of 13,684 ROI images generated from 947 color dental images were used to train and validate the CNNs. The images consisted of 6,952 “caries” and 6,732 “sound” ROIs. The ROI for dental caries images were generated based on the reference standard annotations (dentist’s review). The ROIs for the ``sound" images were generated randomly from the caries free images. In both cases, ROI images were produced by cropping the original color dental images based on the expert defined/randomly generated bounding box coordinates. We used image augmentation which included rotation (in the range of 15 degrees), height and width shift (in the range 0.2), scaling (in the range of 0.2), and horizontal and vertical flips to maximize the data set [8].

A 10-fold cross-validation was the used to evaluate the performance of the systems [9]. The final reported performance is the average of the 10-training performance of each network.

2.3. Evaluation Metrics

In line with previous studies [9], recall (sensitivity), precision (positive predictive value), accuracy and F1 score were used to evaluate the performance of the proposed system.

3. Results

Table 1. Performance of the caries classification task using three CNN networks.

Performance criteria	VGG-16 (95% CI)	ResNet-50 (95% CI)	Inception-v3 (95% CI)
Recall	0.87(0.81-0.93)	0.50(0.5-0.5)	0.75(0.70-0.80)
Precision	0.82 (0.76–0.88)	1.0 (1.0–1.0)	0.95 (0.93–0.97)

Specificity	0.81 (0.75–0.88)	1.0 (1.0–1.0)	0.94 (0.91–0.97)
Accuracy	0.72 (0.66–0.78)	0.47 (0.45–0.50)	0.79 (0.75–0.82)
F1 Score	0.79 (0.67–0.83)	0.66 (0.66–0.66)	0.83 (0.80–0.85)

4. Discussion

The results presented in Table 1 demonstrate the performance of the three deep learning-based networks, VGG-16, ResNet-50, and Inception-V3 – on the proposed “carries” vs. “sound” ROI classification task. Overall, the results show that the Inception-v3 outperformed the other two networks in most performance criteria, including recall, precision, specificity, accuracy, and F1 score. Specifically, the recall for Inception-v3 was 0.75 (95% CI: 0.70-0.80), which was higher than VGG-16 (0.87, 95% CI: 0.81-0.93) and ResNet-50 (0.50, 95% CI: 0.5-0.5). In terms of precision, Inception-v3 had a score of 0.95 (95% CI: 0.93-0.07), which was higher than VGG-16 (0.82, 95% CI: 0.76-0.88) and equal to ResNet-50 (1.0 95% CI: 1.0-1.0). Similarly, Inception-v3 also achieved higher scores for specificity, accuracy, and F1 score compared to VGG-16 and ResNet-50. Overall, these results suggest that Inception-v3 is the most suitable network for the proposed “caries” vs. “sound” ROI classification task.

5. Conclusions

Deep learning-based networks are found to be reasonably accurate in classifying "caries" vs "sound" ROIs in dental images, with the best preforming Inception-v3 model achieving an accuracy of 79%. The resulting automated system can be a valuable tool in the early detection and assessment of dental caries in childhood using color dental photographs. However, further research is needed to evaluate the performance of these models on larger and more diverse datasets to determine their generalizability and clinical utility. Continued investigation in this area could have significant implications for the future use of deep learning in dental imaging.

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