Using Deep Learning to Detect Tooth Decay in Children-To what extent can a convolutional neural network be used to detect tooth decay in images of children's teeth accurately?

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Abstract

Approximately 530 million children have untreated cavities, which could affect future permanent teeth if not treated well. Researchers have enhanced X-ray detection of tooth decay to improve the detection of cavities. However, dentophobia and lack of insurance and dentist availability are barriers that constrain thousands from receiving proper dental care. This study used a deep learning convolutional neural network model to address this problem to detect cavities. Three hundred twenty-two photos taken by a camera of child patients were used. The dataset was classified into two classes: cavity and no cavity. The MobileNetV2 architecture was used for feature extraction and cavity detection. The model was then trained and tested so that it classified photos into two categories. The model achieved an accuracy of 93.5%.

Keywords: Deep Learning, Tooth Decay, MobileNetV2, Dental caries

Introduction

Dental caries is a significant problem in many countries [1], as it is an irreversible dental disease. A large number of people suffer from this disease, including many children. In 2021, around 52% of children aged 6 to 8 had cavities in their primary teeth [2]. When a child has severe cavities in the primary teeth, the bacteria may infect the developing permanent teeth. It is a challenging issue; it should be identified, treated, and followed by appropriate oral hygiene habits [3].

There have been many approaches to diagnosing cavities more precisely using X-rays [4]. However, it is not an accessible approach to many people since it could be costly if health insurance is not acquired. Multiple studies have attempted to solve this problem by detecting tooth cavities from intraoral photos. However, many studies focused on detecting caries on one tooth, filling the frame of an image, which would not be applicable nor efficient if people were to use this system from their phones. They also did not have a high accuracy suitable for medical measures. The studies that included multiple teeth in a photo might have come across misclassifying cavity severity and needed appropriate accuracy for medical purposes. In addition, there were numerous pieces of research where the data was insufficient to amount. My contribution to the present work is to build a machine-learning system that detects tooth decay in children using photos with multiple teeth. This is to explore the extent to which a convolutional neural network model may accurately detect tooth decay in images of children's teeth.

2. Background

A machine learning (ML) model is a file that learns to make predictions and recognize patterns. This is done by implementing an algorithm trained to learn from datasets. For instance, image recognition teaches machine learning models to differentiate between particular objects. Two main categories of machine learning models are supervised and unsupervised learning. Supervised learning involves training models with labeled data. Models in supervised learning must discover a mapping function to connect the input variable to the output variable. It aims to train the model to predict the outcome when new data is provided. Classification is one subcategory of supervised learning. It is when the algorithm seeks to understand and recognize the input data to group it into categories. Unsupervised learning infers patterns from unlabeled input data. Unsupervised learning aims to extract the structure and patterns from data. Human intervention is optional since it uses data to identify patterns.

In addition, machine learning has a subset called deep learning. This technique uses artificial neural networks (ANN), which adapt and learn from large amounts of data [5]. One example of a neural network is a convolutional neural network (CNN). Node layers comprise a CNN, consisting of an input layer, at least one hidden layer, and an output layer. Each node has a threshold and weight connected to the other. Any node with an output that exceeds the defined threshold value is activated and begins sending data to the network's next layer. Otherwise, no data is sent. CNNs aim to resize photos so they may be processed more quickly while retaining the essential details for predicting [6]. Therefore, they are used for image recognition and processing.

Feature extraction is when raw data gets converted into numerical figures, which are processed to extract information (features) from an image's data. This improves the accuracy of learned models. It is helpful since it can reduce processed resources but keep the original data's information. Then, the machine will issue an understanding of the image. Feature extraction is a subcategory of dimensionality reduction. Dimensionality reduction reduces the number of features in review. Feature Extraction is essential in Region of Interest (ROI) identification. ROI is commonly used in medical imaging. It is a part of an image to be filtered or performed on. In the medical field, feature extraction is implemented on X-rays, cardiograms, intraoral images, etc. [7]. Feature extraction has been used in the dental area for tooth decay detection.

Tooth decays (cavities or caries) are holes or gaps on the hard surface of the teeth that are permanently damaged. Tooth decay occurs when bacteria produce a plaque-like film on the teeth. Over time, this results in surface damage. If left untreated, cavities get larger, harming the teeth' deeper layers. That can result in tooth loss, infection, and excruciating pain [8].

3. Problem

Machine learning and deep learning have been commonly used in medicine to study diseases. In recent years, ML has been applied to dental disease diagnosis, specifically tooth decay. In dentistry, ML has significantly been used to detect tooth cavities on oral X-rays. However, constraints, including dentophobia, unavailability of dentists, and lack of dental insurance, prohibit thousands from seeking dental care using X-rays [4]. In addition, the Alliance for a Cavity-Free Future states that around 530 million children have untreated tooth cavities. This could affect their future permanent teeth or need expensive surgery if not noticed or treated well [9]. Therefore, a more applicable solution will be improved by training a deep learning model to detect cavities on real-life images of children's teeth.

4. Objective

The main contribution of this research is to develop a system that can provide a diagnosis for detecting tooth decay in children from real-life photos using deep learning.

5. Literature Review

Machine learning has become widely used in medicine. Dental disease diagnosis is one emerging field of machine learning application [10]. In several classification and object detection tasks, deep convolutional neural networks (CNNs) have demonstrated performance better or comparable to a human's in recent years [3]. Convolutional neural networks and deep learning have recently been used in the first studies to detect caries on dental X-rays [11, 1]. However, multiple efforts have lately been made to detect tooth decay in intraoral images using Artificial Intelligence [4, 11, 9, 12].

Srivastava et al. [1] developed a computer-aided diagnosis (CAD) system that improves dentists' abilities to identify a variety of dental cavities from bitewing radiographs. A deep, fully convolutional neural network with more than 100 layers is trained to detect caries on a dataset of 3,000 bitewing radiographs. They evaluated the effectiveness of the suggested technique for identifying dental caries against that of three licensed dentists. The findings show that this approach performs significantly better than dentists regarding both the F1-score and sensitivity in predicting caries. The relatively poor accuracy of the system indicates that there are more false positives, but these also include ambiguous patches that, in some circumstances, might be read as possible caries.

Kühnisch et al. [11] used a CNN to build a deep learning methodology for caries detection and categorization on 2,417 images taken by a camera. The CNN was trained using image augmentation and transfer learning. MobileNetV2 was chosen as the architecture for the model as it was expected to achieve high performance with low complexity on the CNN. The performance of the CNN was compared to an expert's evaluation. The results showed that the accuracy was highest for caries-free surfaces (90.6%), then for non-cavitated caries lesions (85.2%), then for cavitated caries lesions (79.5%). However, the existing methodology still has to be improved. The study hypothesizes that future work should include additional and correctly segmented images to improve results. Zhang et al. [9] also used a MobileNetV2 backbone, but it was used for a Single Shot Mobile Detector (SSD). This model's performance was compared to a Faster Region-Based Convolutional Neural Network (Faster R-CNN) using a ResNet50 backbone and dentists. This study aimed to detect Early Childhood Caries using RGB oral images. The SSD+MobileNetV2 model couldn't see teeth in a photo with multiple teeth.

In contrast, the R-CNN model works faster and classifies more teeth. Although the R-CNN occasionally misclassified teeth, it was only for unclear severity levels. The authors suggest that it was because of the different lighting of the images. They conclude that clinical testing will be conducted for future work to assess the deployed system's effectiveness and look at methods to make additional deep learning models more effective. The detection model is expected to diagnose posterior teeth.

Mai et al. [12] built a cavity detector using deep learning models. The study tested four deep learning models—You Only Look Once version 3 (YOLOv3), Faster R-CNN, RetinaNet, and Single-Shot Multi-Box Detector (SSD)—using 1,902 photos of the teeth's smooth surface to identify early caries lesions and cavities. The accuracy of the four models was over 71% for visually non-cavitated and over 86% for cavitated caries.

Bhattacharjee [4] included a 12-layer Convolutional Neural Network and various modifications of previously trained image classifiers among the backbones experimented with ResNet-18 and ResNet27. By using curriculum learning, the ResNet27 architecture achieved the highest accuracy of 82.8%. The system's diagnosis was also visually explained using Local Interpretable Model Agnostic Explanation (LIME).

6. Methodology

The structure of the methodology for dental cavity detection models is illustrated in Figure 1.

6.1 Dataset

In the methodology, I gathered 322 photos taken by a camera of Saudi child patients at King Fahad Military Medical Complex. The images showed teeth that did or did not have cavities. Since the photos were first obtained unlabeled, they were sent to a professional dentist, who examined them and annotated them into two groups: cavity and no cavity. The photos went into preprocessing to cut out unnecessary background features. A total of 190 images were classified as cavities, and 132 were classified as no cavities. The data was then split into training and testing. For training, 255 photos were used, 152 cavity-infected teeth, and 103 non-infected teeth. The test data consisted of 67 photos, with 39 sorted in the cavity group and 28 photos in the no-cavity group.

6.2 Feature Extraction and Deep Learning Model

This paper builds a tooth cavity detection model using deep learning. In deep understanding, a computer model learns to perform classification tasks directly from images. The model is trained using a large set of previously explained labeled data and neural network architectures containing many layers. I specifically used a Convolutional Neural Network (CNN), and the model is written in Python and created using TensorFlow and Keras libraries [13]. Keras is a Python library that provides powerful, consistent, simple APIs to build deep learning networks.

For Image features, MobileNetV2 (an open-source neural network) was employed [14]. MobileNetV2 was chosen because it is faster, more accurate, and uses fewer steps and parameters than MobileNetV1. MobileNetV2's architecture has 32 filters and 19 residual bottleneck layers. It is also an effective mobile-oriented model suitable for detecting objects in photos. The model was implemented to detect and extract features from the training dataset. To make a prediction, a feature vector was used to characterize and numerically analyze a picture's contents. After the feature extraction process, the model was trained and then tested. As shown in Figure 1, the model will go through classification, where it will classify the dataset into a cavity and no cavity. The model's accuracy and error rate in classifying will be observed.

7. Experiment & Results

The methodology was evaluated using 322 digital color images belonging to Saudi child patients at King Fahad Military Medical Complex. The CNN model was developed for the classification of dental caries and non-caries. I tested the CNN model by tuning hyperparameters and achieved a maximum accuracy of 93.5%. The performance of the system is visualized in the plot in Figure 2. Figure 2 shows two line plots: one for the learning curves of the loss on the train and test sets and one for the classification of the train and test sets.

8. Conclusion and Future Work

The study is addressed to develop a solution to decrease the barrier keeping children away from dental health. This research used a deep learning convolutional neural network model which detected cavities in photos of children's teeth. The model achieved an accuracy of 93%, showing that using a convolutional neural network with a MobileNetV2 architecture detecting holes in real-life photos of children's teeth in different lighting is adequate. This can help make detecting tooth cavities in children accessible for millions, regardless of any constraints. However, the results could be further improved. In the future, a larger dataset will be used to increase the accuracy. Other deep learning and machine learning models may also be developed, which will be compared to enhance the performance. To make the model more accessible to the public, it could be implemented into an app.

9. References

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10. Diagrams

Figure 1: Framework of the methodology.

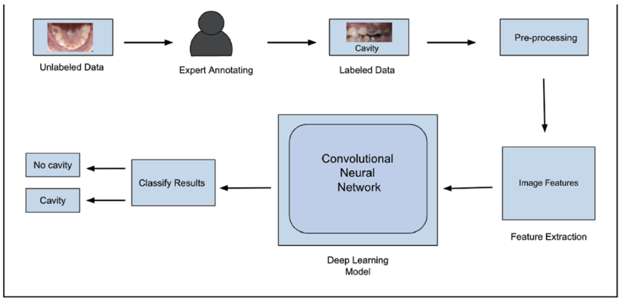

Figure 2: Training and Testing accuracy and loss with epochs.