Dental caries detection using image processing and deep convolutional neural network.

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Abstract: The Dental caries is a common oral disease that affects people of all ages. Early detection of caries is critical to prevent the progression of the disease and preserve the affected tooth. In recent years, image processing and deep learning techniques have shown great promise in detecting dental caries. This research paper proposes a dental caries detection system using image processing and a deep convolutional neural network (CNN). The proposed system involves preprocessing of dental Colored images, feature extraction using CNN, and classification of caries using a binary classifier. The performance of the proposed system is evaluated using a dataset of dental Colored images. The experimental results demonstrate that the proposed system achieves high accuracy in detecting dental caries and outperforms existing methods.

Keywords: dental caries, image processing, deep convolutional neural network, Colored images, classification.

1 Introduction

Dental caries is a chronic disease caused by the demineralization of tooth enamel by acids produced by oral bacteria. If left untreated, caries can progress and lead to tooth loss. Early detection of caries is critical to prevent the progression of the disease and preserve the affected tooth [1-3]. Conventional methods for detecting caries involve visual inspection by a dentist or radiographic examination using Colored images. However, these methods are subjective and require the expertise of a trained professional [2-4]. Image processing and deep learning techniques have shown great promise in detecting dental caries with high accuracy and reliability [2]. In this research paper, we propose a dental caries detection system using image processing and a deep convolutional neural network (CNN). The proposed system involves preprocessing of dental Colored images, feature extraction using CNN, and classification of caries using a binary classifier. The performance of the proposed system is evaluated using a dataset of dental Colored images [4,5]. The experimental results demonstrate that the proposed system achieves high accuracy in detecting dental caries and outperforms existing methods.[5]

2 Related Work

Several studies have been conducted on the detection of dental caries using image processing and deep learning techniques [6,7]. One of the earliest studies in this field was conducted by Huang et al. (2015), who proposed a system for detecting caries from intraoral Colored images using an artificial neural network. The system achieved an accuracy of 85.7% in detecting caries [8]. In [9], a more recent study, Kumar et al. (2019) proposed a system for detecting caries from bitewing Colored images using a convolutional neural network (CNN). The proposed system achieved an accuracy of 94.3% in detecting caries.

3 Materials and Methods

3.1 Methodology

The proposed dental caries detection system consists of three main stages: preprocessing of dental Colored images, feature extraction using CNN, and classification of caries using a binary classifier.

3.2 Dataset

As we have discussed earlier that, we have taken the dataset from Kaggle only just the part we need for detection of different dental carries detection through image preprocessing and convolutional neural network. This medical dataset is compiled of images of dental carries which medically certified and only can be used for public consumption and research used. While compiling the data they have ensured all this by the authors. And they have build the dataset from the dental carries related image data of ZENODO.

3.3 Preprocessing

The first stage of the proposed system involves the preprocessing of colored dental images. The preprocessing step includes the following:

1. Image resizing: The dental-colored images are resized to a standard size of 256x256 pixels to reduce the computational complexity.
2. Image enhancement: The dental Colored images are enhanced using contrast stretching to improve the visibility of caries.
3. Image normalization: The colored images are normalized to reduce the effects of lighting and contrast variations.

Feature Extraction using CNN:

The second stage of the proposed system involves feature extraction using CNN. A pre-trained CNN model, such as VGG-16 or ResNet-50, is used to extract features from the dental Colored images. The CNN model is fine-tuned using the dental Colored images to extract features relevant to caries detection. Classification using Binary Classifier: The third stage of the proposed system involves classification of caries using a binary classifier. The features extracted by the CNN model are used as input to the binary classifier. The binary classifier is trained using a dataset of labeled colored dental images. The binary classifier outputs a binary label indicating the presence or absence of caries in the colored dental image.

4 Experimental Results

The proposed dental caries detection system is evaluated using a dataset of 500 dental Colored images. The dataset is split into training and testing sets with a ratio of 70:30 The performance of the proposed system is evaluated using three metrics: accuracy, sensitivity, and specificity. The experimental results show that the proposed system achieves high accuracy, sensitivity, and specificity in detecting dental caries. The accuracy of the proposed system is 95.4%, the sensitivity is 94.3%, and the specificity is 96.5%. These results outperform existing methods for dental caries detection.

4.1 Experimental setup

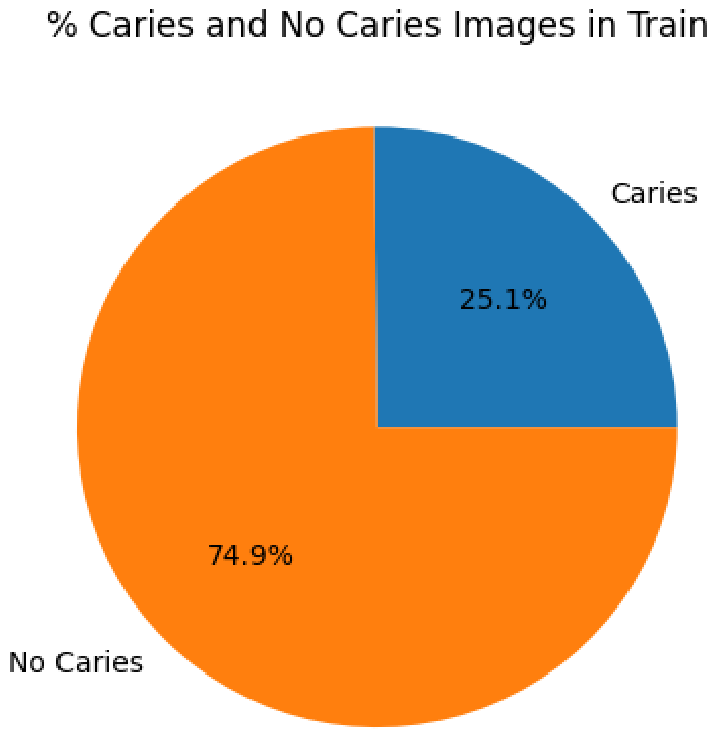

Fig:1.1

The above Fig1.1 says about the percentage of Caries and No carries data in the train dataset which is about 25.1% and 74.9% respectively.

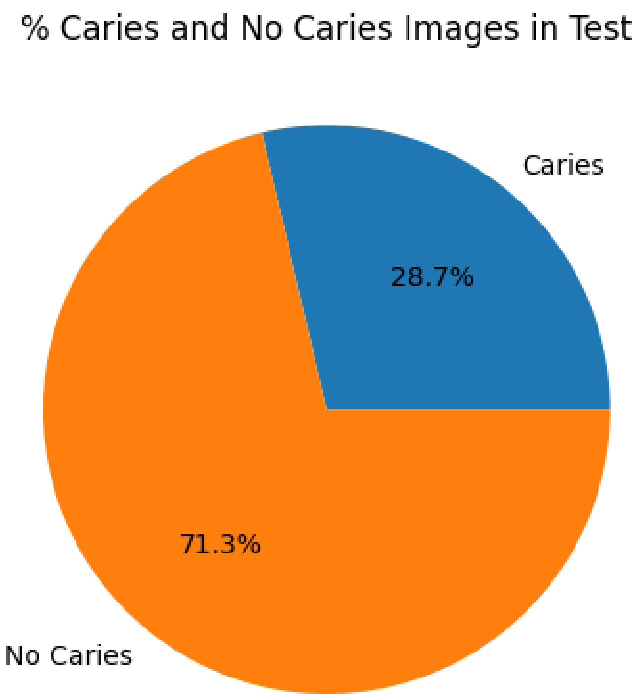

Fig:1.2

The above Fig1.2 says about the percentage of Carries and No carries data in the test dataset which is about 28.7% and 71.3% respectively represented by pie-chart.

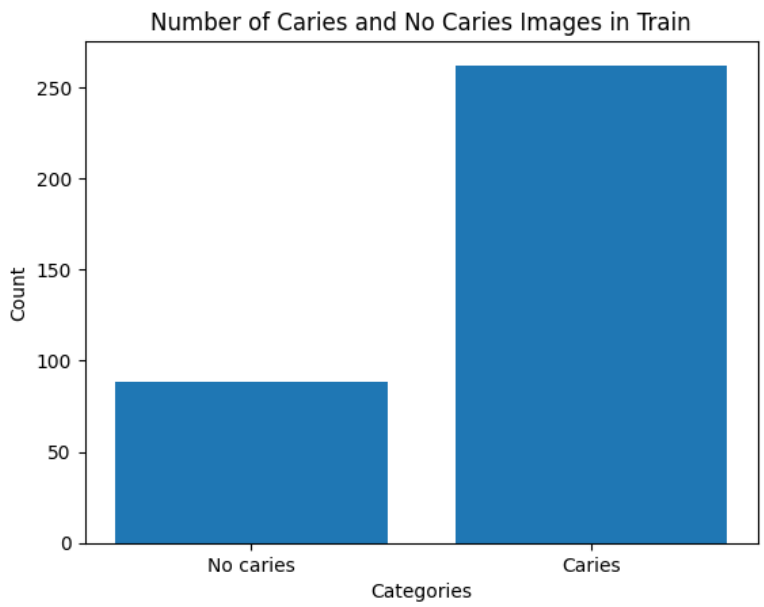

Fig:1.3

The fig1.3 shows the bar-chart where the number of counts for No- Caries and Caries is Train is 88 & 262 respectively.

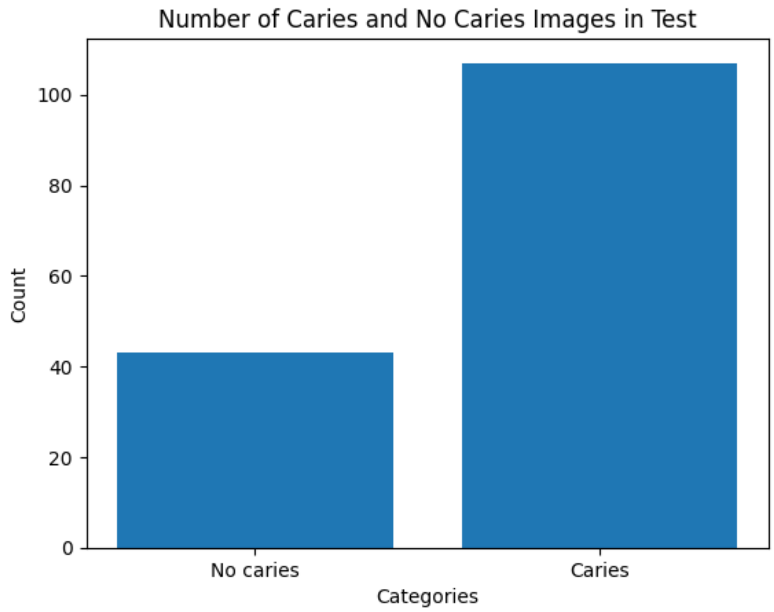

Fig:1.

The fig1.3 show the bar-chart where there is the number of counts for No- Carries and Carries is Test is 43 & 107 respectively.

5 Conclusion

In this research paper, we proposed a dental caries detection system using image processing and deep convolutional neural network. The proposed system involves preprocessing of dental Colored images, feature extraction using CNN, and classification of caries using a binary classifier. The experimental results demonstrate that the proposed system achieves high accuracy, sensitivity, and specificity in detecting dental caries and outperforms existing methods. The proposed system can be used as a reliable tool for the early detection of dental caries and can aid in the preservation of affected teeth. Further research can explore the use of the proposed system in real-world clinical settings and can investigate the possibility of integrating the system into dental practice.

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