Dental Caries Detection: A Review

-Team REVxRETRO

Content

Introduction

Dentistry image classification is a rapidly growing field that involves the use of machine learning models to accurately identify dental conditions in medical images. This technology has significant potential for enhancing the quality of dental care and improving patient outcomes. Dentists and dental technicians can use this technology to detect dental issues at an early stage, which can prevent the progression of the disease and lead to more effective treatment.

One of the main advantages of using machine learning models for dentistry image classification is that they can identify dental conditions with a high degree of accuracy. These models can be trained to identify different types of dental conditions such as cavities, gum disease, and oral cancer. Once trained, these models can quickly and accurately analyze dental images, providing dentists and dental technicians with valuable diagnostic information. Another advantage of using machine learning models for dentistry image classification is that they can improve the efficiency of dental care. These models can quickly analyze large numbers of images, allowing dentists to diagnose dental conditions more quickly and accurately. This can lead to more effective treatment plans and faster recovery times for patients.

Motivation

- Traditional dental diagnosis can be time-consuming and may not always be accurate.
- Machine learning models can accurately and quickly identify dental conditions, allowing for more effective treatment plans and improved patient outcomes.
- This technology has the potential to revolutionize the field of dentistry, making dental care more accessible, efficient, and effective.

Problem Definition

Dental care is important for maintaining oral health and overall well-being, but traditional methods of dental examination have limitations in accuracy and cost-effectiveness. Machine learning-based dental image analysis has emerged as a promising solution to automate disease detection, diagnosis, and treatment planning. However, there is a need to review existing solutions and assess their effectiveness, limitations, and challenges.

This presentation aims to provide a comprehensive overview of current knowledge on dental care using ML-based dental image analysis, including the methods, techniques, and algorithms used. The presentation will focus on existing solutions, such as CNN, SVM, and deep learning algorithms, and their advantages over one another.

Using a deep learning-based CNN algorithm, 2018

Datasets:

- 3000 periapical radiographic images were selected and resized to 299 x 299 pixels.
- All maxillary teeth images were flipped vertically to match mandibular teeth.
- Randomization sequence was created to divide dataset into training and validation (80%) and test dataset (20%).

Architecture:

- Pre-trained GoogLeNet Inception v3 CNN network was used for preprocessing.
- Transfer learning was used to train the dataset.
- 9 inception modules, an auxiliary classifier, two fully connected layers, and softmax functions were used.
- Fine-tuning was used to optimize the weights and adjust hyperparameters.

Statistical Analysis:

- Keras library on top of TensorFlow in Python was used to implement all deep CNNs.
- Diagnostic accuracy, sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), receiver operating characteristic (ROC) curve, and area under the ROC curve (AUC) were assessed.
- P values < 0.05 were considered statistically significant and 95% confidence intervals (CIs) were calculated.

Results:

- For premolars, diagnostic accuracy was 89.0%, sensitivity was 84.0%, specificity was 94.0%, PPV was 93.3%, and NPV was 85.5%.
- For molars, diagnostic accuracy was 88.0%, sensitivity was 92.3%, specificity was 84.0%, PPV was 85.2%, and NPV was 91.3%.
- For both premolars and molars, diagnostic accuracy was 82.0%, sensitivity was 81.0%, specificity was 83.0%, PPV was 82.7%, and NPV was 81.4%.

Dental health-IoT platform , 2019

Datasets:

- 300 subjects used dental image acquisition device to sample dental disease video data.
- Algorithm analyzed each frame of video, resulting in 3835 images of dental cases.
- 7 types of dental diseases: dental caries, dental fluorosis, periodontal disease, cracked tooth, dental calculus, dental plaque, and tooth loss.
- 4/5 of data used for training and 1/5 for model testing.

IoT System Architecture:

- Three network layers: dental medical service layer, smart dental service layer, dental image data acquisition layer.
- Dental Medical Service Layer connected to professional medical facilities.
- Smart Dental Service Layer provides analysis results of dental symptoms or aesthetic needs.
- Dental Image Data Acquisition Layer serves as the basis of the entire platform.
- Data uploaded to smart dental service layer via network (Wi-Fi, 3G/4G).

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Development of Research in 2019 over 2018

CRITERIA	2018	2019
Larger dataset	3000 images	3835 images
Variety of diseases	Focused on premolars and molars	Analyzed 7 types of dental diseases
Real-time data acquisition	Relied on pre-existing dataset	Used IoT system for real-time data acquisition
Recognition rates	Overall accuracy of 82%	Recognition rates of over 90% for 7 major dental diseases
Practical applicability	No information on practical implementation	Tested in 10 private dental clinics and showed high reliability
Transfer learning	Used transfer learning but did not report any improvement in accuracy	Achieved improved accuracy of 87.5% for classification of dental caries and periodontitis using transfer learning
Classification accuracy	Lower accuracy rates for dental caries and periodontal disease	Higher classification accuracy with 90.1% for dental caries and 94.3% for periodontal disease

Using back-propagation neural network , 2020

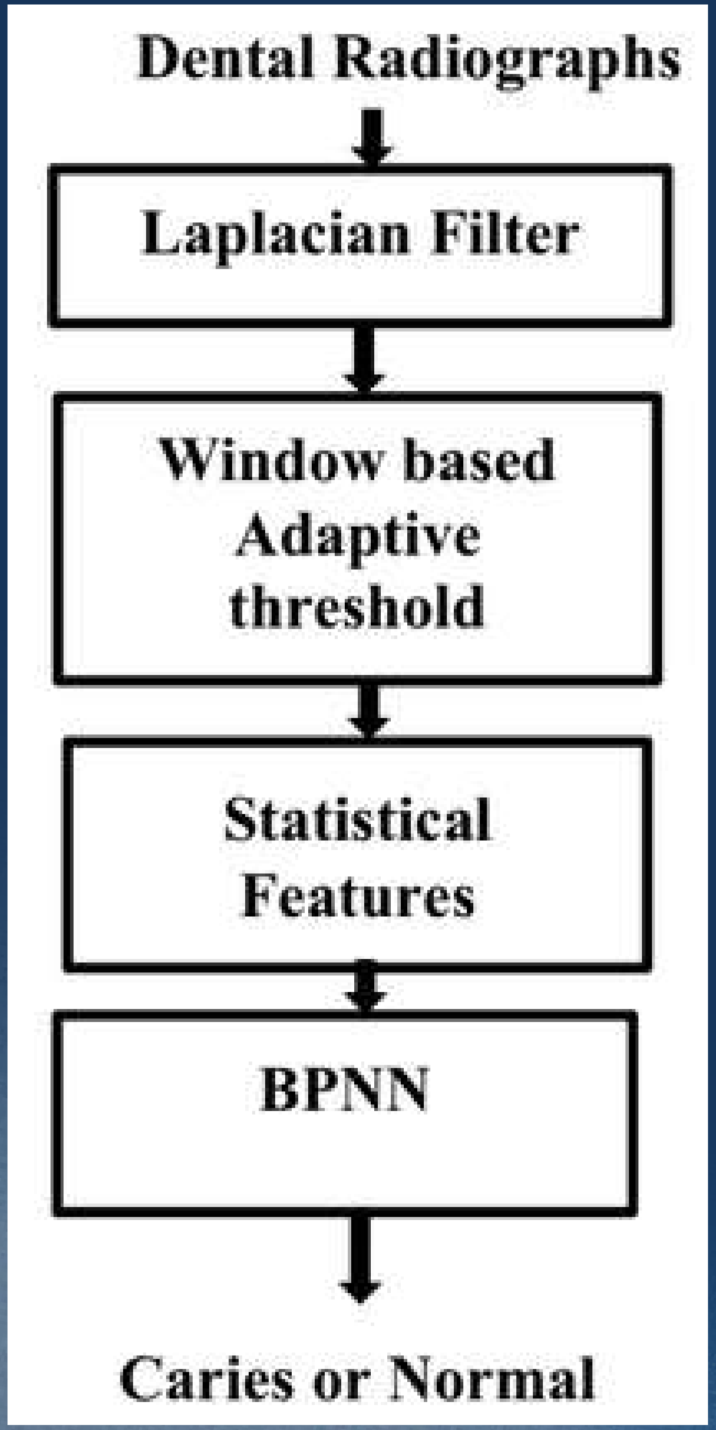
Datasets:

- 105 images derived from intra-oral digital radiography, to train an artificial neural network with 10-fold cross validation.
- Where the dataset consists of 49 caries and 56 sound dental X-ray images.
- The dental X-ray images are saved as bmp files, resized to 256x256 of class double.
- The resized image is enhanced using Laplacian filter to get sharpened image.
- The edges of the image are highlighted, and low frequency components are removed.
- For segmentation adaptive threshold and morphological processing algorithm were used.

Architecture:

- Feed forward back propagation neural network (FFBPNN) is used to classify a tooth surface as normal or having dental caries.
- Sigmoid function is used as activation function.
- The inputs for the input layer nodes are the sixteen feature vectors extracted from segmented image i.e, 16 input nodes have been used.
- The features extracted are contrast, correlation, energy, homogeneity, mean, standard deviation, entropy, Root Mean Square (RMS), variance, smoothness, kurtosis, skewness, Inverse Difference Moment (IDM), area, centroid and bounding box.

Methodology



Results:

- The system gives an accuracy of 97.1%.
- False positive (FP) rate of 2.8%.
- Receiver operating characteristic (ROC) area of 0.987.
- Precision recall curve (PRC) area of 0.987 with learning rate of 0.4, momentum of 0.2 and 500 iterations with single hidden layer with 9 nodes.
- This study shows that caries and normal images could be distinguished more accurately with BPNN rather than SVM and KNN classifier.

Development of Research in 2020 over 2019

CRITERIA	2019	2020
Dataset	Dental video frames with 7 types of dental diseases	Intra-oral digital radiography images of dental caries and sound teeth
Algorithm	CNN based Algorithm	Feed forward back propagation neural network (FFBPNN)
Feature Extraction	Algorithm analyzed each frame of video	16 feature vectors extracted from segmented images
Accuracy	Over 90% for seven dental diseases	97.1% accuracy was obtain by the system

Using score-based multi-input deep CNN , 2022

Datasets:

- 380 periapical images were analyzed, 40 excluded.
- Dataset contains 340 images of carious and non-carious teeth.
- Images were gray channels of variable sizes, contrast adjusted.

Architecture:

- CNN architecture has input, hidden and output layers.
- Hidden layer consists of convolutional, pooling, and fully connected layers.
- Pre-learned weights of AlexNet architecture were used for transfer learning.
- Score-based fusion process used in Softmax output layers of multiple CNN architectures.

Score-Based Fusion:

- MxN output matrix obtained from Softmax layers of deep CNN architectures.
- Class label determined based on maximum value of each line.
- Two-CNN models based on two input images used in proposed system.

Results:

- Experimental work carried out on a computer equipped with NVIDIA Quadro M4000 GPU.
- MATLAB software used for all coding.
- Training/testing datasets were randomly separated with 70% for training and 30% for testing.
- Proposed score-based multi-input CNN ensemble model obtained a 99.13% accuracy score.

Development of Research in 2022 over 2020

CRITERIA	2020	2022
Dataset	105 images, derived from intra-oral digital radiography with 49 caries and 56 sound dental X-ray images	340 images of carious and non-carious teeth, gray channels of variable sizes, contrast adjusted
Architecture	Feed forward back propagation neural network (FFBPNN)	More advanced convolutional neural network (CNN) architecture with input, hidden and output layers, and pre-learned weights of AlexNet architecture for transfer learning
Score-based fusion	Not used	Used a score-based fusion process in the Softmax output layers of multiple CNN architectures
Accuracy	Accuracy of 97.1%, False positive (FP) rate of 2.8%, ROC area of 0.987, PRC area of 0.987	Accuracy of 99.13%, No false positive rate reported, No ROC or PRC areas reported

Using a semi-supervised learning approach , 2023

Datasets:

- 229 dental X-ray images for caries detection with 90% training and 10% testing split.
- MyRay X-ray scanner used for data collection.
- Tool "Labelme" used for annotation.
- Centroid cropping sampling method used for caries region extraction.
- Segmentation into background and foreground components.
- Horizontal flip, shear, rotation, and vertical flip techniques used.
- 635 images in the training set after augmentation

Results:

- Deeplab-v3 with ResNet-101 achieved highest avg. accuracy of 98.38% among other models using fully supervised learning.
- Standard self-training model without CCS achieved highest avg. accuracy of 93.22%.
- CCS-based self-training models achieved highest avg. accuracy of 99.43%, much better than fully supervised model.

Architecture:

- A student-teacher self-training framework is presented for caries detection using both labelled and unlabelled images.
- Teacher model trained with labelled dataset in supervised learning fashion while student model is trained with unlabelled dataset in self-training method.
- Binary cross entropy loss used to improve performance of student model in segmenting caries region in unlabelled dental radio-graphic images.
- Six different state-of-the-art models evaluated for caries detection with generative and backbone classification models.
- Generative models used for final segmentation mask including Deeplab-v3, FCN, and LRASPP.
- Classifier models used as backbone of segmentation models include ResNet-50, ResNet-101, and Mobilenet-v3.
- All models trained with a batch size of 8 and learning rate of 10^-3 for maximum of 100 epochs.
- Deeplab-v3 with ResNet-101 backbone achieved the highest average accuracy of 98.38% among fully supervised learning models.
- CCS based self-training models achieved an average accuracy of 99.43% which is significantly better than the fully supervised model.

Development of Research in 2023 over 2022

CRITERIA	2022	2023
Dataset	Less specific and diverse, consisting of only periapical images of carious and non-carious teeth.	More focused on dental caries detection, consisting of annotated dental X-ray images. A centroid cropping sampling (CCS) method is used for extracting caries regions in dental X-ray images.
Architecture	Transfer learning is used with pre-learned weights of AlexNet architecture. Score-based fusion process used in Softmax output layers of multiple CNN architectures.	A student-teacher method-based self-training framework is used to leverage both labelled and unlabelled images, which improves the accuracy of the model.Six different state-of-the-art models for caries detection are evaluated.
Experimental Work	Experimental work carried out on a computer equipped with NVIDIA Quadro M4000 GPU.	MyRay X-ray scanner used for data collection.
Accuracy	The model achieved an accuracy of 99.13%.	The model achieved an accuracy of 99.43%.

Future Scope

This presentation on Dentistry image Classification using ML highlights several areas for future research and development. Firstly, hardware design can be improved by using better lenses to enhance image quality, expanding the lens angle, and covering larger teeth. Secondly, image capturing devices can be enhanced by increasing data collection efficiency and automating image processing activities to avoid human error.

In addition, improving the efficiency and accuracy of algorithms used for data analysis is necessary. This can be done by exploring new deep learning models such as convolutional neural networks and support vector machines, as well as incorporating transfer learning techniques to leverage pre-trained models for training. Finally, a larger and standardized dataset of dental disease images is required for training the ML models, which can be obtained from various sources such as dental clinics, hospitals, and research institutes.

These advancements have the potential to significantly improve the accuracy and efficiency of dental disease diagnosis and treatment planning, ultimately enhancing the quality of patient care in dentistry.

Conclusion

Machine learning (ML) algorithms have shown great promise in improving the accuracy and efficiency of dental care through image categorization in dentistry. However, challenges remain, such as the limited availability of dental image databases and poor picture quality. Future research should focus on hardware design, image acquisition device efficiency, and developing algorithms with improved recognition rates and lower false alarm rates.

ML-based dental image analysis has potential applications in early identification and diagnosis of dental disorders, treatment planning, and patient monitoring, leading to better patient outcomes. Future research in this area can make significant contributions to the field of dentistry, ultimately enhancing the quality of dental care.

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Thank you!