G.V Black Classification of Dental Caries Using CNN

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Abstract. Dental caries is one of the most predominant pathologies in the world. Early detection of dental caries leads to the prevention of tooth decay. According to G.V Black classification model dental caries can be classified into six classes (Class I–Class VI) based on the location of caries. The proposed work classifies caries infected tooth based on G.V black classification using deep convolution network architecture (DCNN). In the proposed approach, feature extraction of the preprocessed images is done using Local Ternary Pattern (LTP) and feature reduction is done using Principal Component Analysis (PCA). The pretrained models used in the study are AlexNet architecture and GoogleNet architecture. AlexNet is 8 layer DCNN and classifies the tooth with an accuracy of 93%, 90% sensitivity and 92% specificity. GoogleNet is a 22 layer DCNN and classifies with an accuracy of 94%, 91% sensitivity and 93% specificity.

Keywords: Deep convolutional network · AlexNet · GoogleNet

1 Introduction

Dental caries is one of the most widespread tooth problems of today. Dental caries is formed by the acid that is produced by the bacteria, that breaks down the food. Most of the dental caries is formed on the occlusal surface and interproximal surface. The demineralization of the enamel and formation of the tiny holes is the first stage of dental caries. Dental caries can be classified into six classes based on G.V Black Classification. Figure 1 shows the various classes of caries based on G.V Black classification.

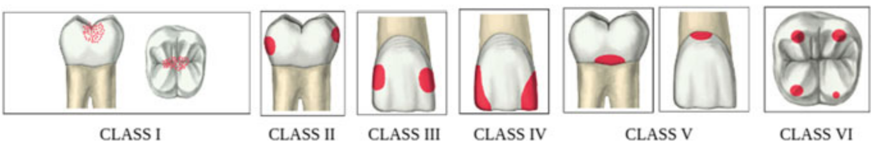

Fig. 1. Various classes of G.V Black classification

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The Class I caries affects the occlusal surface, buccal surface and lingual surface of molar and premolar teeth. The class II caries affects the near or the far surface of molar and premolar. The class III caries affects the proximal surface of incisor and canine teeth. The class IV caries affects the angle of canine and incisor teeth. The class V caries affects the one-third of anterior and posterior teeth. The class VI caries affects the tip of molar and premolar teeth.

In this paper, the G.V Black classification of caries infected dental images is done using deep convolution network (DCNN). One of the most important uses of CNN is to find patterns in the images to recognize objects. CNN is one of the best algorithms for deep learning. The pretrained models of AlexNet architecture and GoogleNet Architecture have been used in the proposed work. The pretrained AlexNet architecture consists of five convolutional layers, two fully connected layers and one softmax layer. The images were classified into 6 G.V black classes. The pretrained GoogleNet architecture consists of 22 layers with various inception modules. The performance of the proposed approaches has been shown in the result section.

The paper is structured as follows:- Sect. 2 contains the related work. Section 3 defines the proposed work using pretrained models AlexNet and GoogleNet. Section 4 defines the result of the proposed work. Section 5 covers the conclusion.

2 Related Work

Dental caries is portrayed as multifactorial sickness that results in demineralization of the tooth. Datta et al. [1] developed an optical image technique to detect dental caries. Here the optical images are filtered, the tooth region is segmented. The model was also successful in monitoring the growth of the lesion with respect to its size. These techniques used visible light thus eliminating the risk of the patient being exposed to harmful radiation. It was observed from the results that the accuracy of the system was 93% but it failed in detecting the conditions where a tooth is broken. Also, it was unsuccessful in detecting the depth of caries. Naebi et al. [2] developed an image processing approach along with particle swarm optimization (PSO) algorithm for detecting dental caries.

Prerna et al. [3] developed an automatic caries detection model based on Discrete Cosine Transformation (DCT) and Radon Transformation (RT). The extracted features in the proposed approach were applied to different classifiers such as k-Nearest Neighbor (k-NN), Decision Tree (DT), Random Forest, Radial Basis Function (RBF), AdaBoost classifiers, Naive Bayes and neural network classifiers. From the results, it was observed that the accuracy of all the classifiers was in the range of 80 to 86% and random forest classifiers gave the highest accuracy of 86%. The main shortcoming of this technique was that it was designed to classify only non-cavitated and cavitated teeth. Prajapati et al. [4] used the small dataset of 251 Radiovisiography (RVG) x-ray images for dental image classification into 3 different classes i.e.dental caries disease, periapical infection and periodontitis classes using pretrained convolutional neural network VGG 16. The overall accuracy of 88% was achieved. Miki et al. [5] investigated the use of Deep CNN for the classification of the different types of tooth on dental cone-beam CT (computed tomography) images. The CT slices were used for extracting the ROI inclusive of the single tooth. The accuracy achieved was 88%. The accuracy of classifying the augmented data for training showed an improvement of about 5%. This technique classified the tooth into seven different types and can be used for automatically filling the dental charts for the case of forensic identification. One of the drawbacks of this technique was the amount of data considered for evaluation was less.

The effectiveness of a deep CNN algorithm for detecting and diagnosing the dental cavities was assessed by Lee et al. [6]. 3000 periapical radiographic images were considered of which 80% were used as training data and the remaining 20% as test data. The accuracy of diagnosing the molar teeth, premolar teeth and both molar and premolar teeth was found to be 88%, 89% and 82%, respectively. Even though the obtained efficiency and accuracy was considerably good, however, there are some drawbacks. This technique was not designed to differentiate between the proximal, early and root caries. A technique that combined deep CNN and optical coherence tomography (OCT) imaging modality for detecting the occlusal cavity lesions was developed by Salehi et al. [7]. Fifty-one permanent tooth were collected and were categorized into the three classes, i.e. the non-carious teeth, caries extending into enamel and caries extending into the dentin. The specificity and sensitivity of differentiating among the non-carious and carious lesions were 100% and 98% respectively. This model classified the carries into just three classes, hence practical application of this technique may not help the dentists to diagnose accurately since the treatment varies with the intensity of damage to the tooth. It is observed from the literature survey that all the techniques discussed above have been used only in the process of detecting and classifying dental caries, most of them having a further scope for improving the accuracy of classification. Classification of dental caries using G.V Black classification has not been explored much by the researchers. Prerna et al. [8] performed the classification of dental images into six G.V Classes using machine learning algorithms. 400 dental x-ray images were used as dataset. The features were extracted using GIST (Graphics and Intelligence based Script Technology) descriptors. Marginal features analysis was used for feature reduction. Later, the features were subjected to the various classifiers. The accuracy of the Adaboost classifier with Marginal fisher analysis feature reduction was 88%. Later the Wilcoxon Signed Ranked test was applied for feature selection. Then, the selected features were subjected to the various classifiers. The Adaboost classifier gave the highest accuracy of 92%. In this paper, we further explore the possibility of G.V black dental caries classification using DCNN with improved performance.

3 Proposed Work

The dataset used for the proposed model for classifying the dental images into six different classes i.e. Class I–Class VI consists of the collection of 1500 images. The dental images are Radio Visiography(RVG) digital x-ray images obtained from various dental clinics. 250 images for each class were considered. The proposed model for G.V Black Classification using the two pretrained model AlexNet and GoogleNet is shown in Fig. 2 and is detailed below.

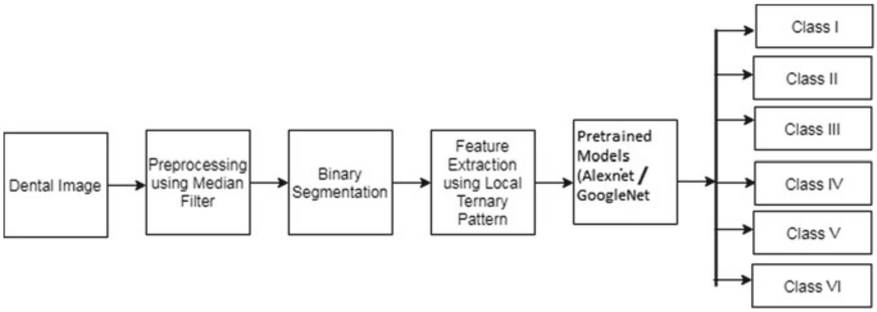

Fig. 2. Proposed architecture for G.V Black classification

3.1 Preprocessing

The acquired images are preprocessed using median filtering. This step removes unwanted noise from the image. Figure 5 shows the result of the dental images after applying median filtering. Binary segmentation is used for segmenting the images into different segments. Figure 6 shows the result of the dental images after applying binary segmentation.

3.2 Feature Extraction

The features are extracted using local ternary pattern(LTP) [9]. The neighbor pixel value were encoded into three values (−1,0,1) instead of (0,1). The upper LTP and lower LTP was obtained. Then, the local ternary pattern was determined which is the concatenation of upper LTP and lower LTP. The advantages of LTP is its robustness to noise and more accurate. The principal component analysis (PCA) [10] is a tool that reduces the data into fewer dimension while retaining most of the information.

3.3 Convolutional Neural Network for Image Classification

A convolutional neural network (CNN) is a multilayer neural network [11]. CNN is one of the most popular algorithms for deep learning, a type of machine learning in which a model learns to perform classification tasks directly from image, video, text or sound. The most common use of convolutional neural networks is finding patterns in images to recognize objects, faces and scenes. We propose the use of two convolutional neural networks for Dental image classification. AlexNet and GoogleNet are used for the classification of images into six classes. AlexNet architecture was proposed by Hinton et al. [12]. The AlexNet architecture consists of five convolutional layers, two fully connected layers and one softmax layer. Rectified Linear unit follows each convolution layer. The last layer is the softmax layer which is fully connected to six output classes with help of softmax function. The dropout rate employed is 50%. The preprocessed input image is of size 227 × 227 pixels. 1500 images were used out of which 1200 images were used for training and 300 images were used for testing. Figure 3 shows the architecture of AlexNet architecture. Table 1 describes the various layers (in sequence) with the kernel, kernel size, stride and padding in detail for AlexNet architecture

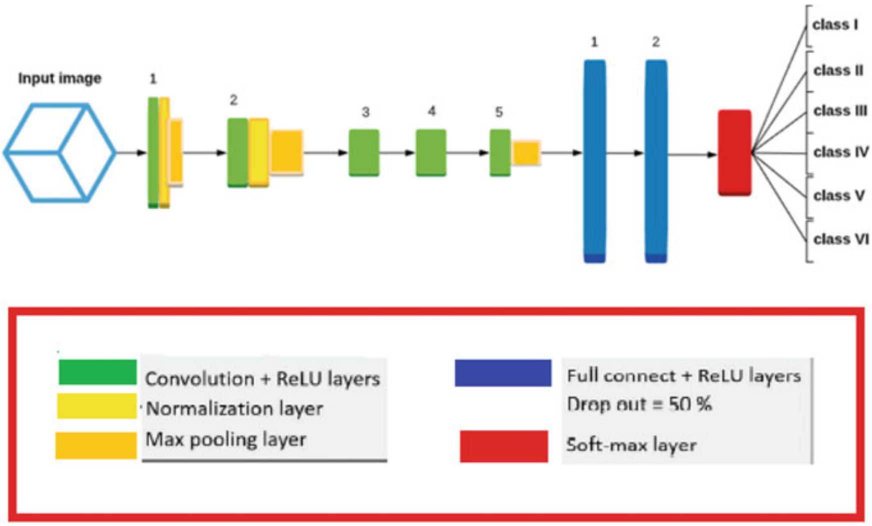

Fig. 3. Architecture of AlexNet architecture

GoogleNet is a convolutional neural network proposed by Google [13]. Figure 4 describes the GoogleNet architecture. It has 22 layers deep architecture. It uses the combination of various inception modules that uses some pooling, convolutional and some concatenation operations. The inception module is the heart of the GoogleNet architecture. The architecture consists of simple convolutional layers followed by many blocks of inception modules and a layer of maxpooling which affects the spatial dimension. Each inception module contains two convolutional layers [14]. The average pooling layer at the end is connected to the fully connected layer with six neurons that classify into six G.V Black classes. Table 2 describes the Google Net architecture's various layers, input, kernel size, stride and padding in detail.

4 Results

A pertained deep convolution network was used to classify the dental images into G.V Black classes. A total of 1500 periapical images were used for the study of classifying dental images into various classes (class I–Class VI) based on G.V Black classification. Out of 1500 images, 1200 images (80%) were used to train the model and 300 images (20%) was used as testing dataset. First, the dental images were preprocessed using median filtering. Figure 5 shows the result of the periapical dental image after applying median filtering to remove the unwanted noise in the image. After removing the noise, the images were segmented. Figure 6 shows the segmented image. After segmentation, the features are extracted from the images based on local Ternary pattern (LTP) and were further reduced using Principal Component Analysis (PCA). The pretrained models used are AlexNet architecture and GoogleNet architecture. Table 3 shows the confusion matrix of classifying the dental images into six classes using AlexNet architecture. Table 4 shows the confusion matrix for classifying the dental images into six classes using GoogleNet

Table 1. Detailed description of AlexNet architecture

Layer's name	Input image size	Output image size	No. of filter	Filter size	Stride	Padding
Convolution + ReLU + Normalization	227 × 227	55 × 55 × 96	96	11 × 11	4	0
Pooling	55 × 55 × 96	27 × 27 × 96		3 × 3	2	0
Convolution + ReLU + Normalization	27 × 27 × 96	27 × 27 × 256	256	5 × 5	1	2
Pooling	27 × 27 × 256	13 × 13 × 256		3 × 3	2	0
Convolution + ReLU	13 × 13 × 256	13 × 13 × 384	384	3 × 3	1	1
Convolution + ReLU	13 × 13 × 384	13 × 13 × 384	384	3 × 3	1	1
Convolution + ReLU	13 × 13 × 384	13 × 13 × 256	256	3 × 3	1	1
Pooling	13 × 13 × 256	6 × 6 × 256		3 × 3	2	0
Fully Connected + Relu + Dropout			4096			
Fully Connected + Relu + Dropout			4096			
Softmax			6			

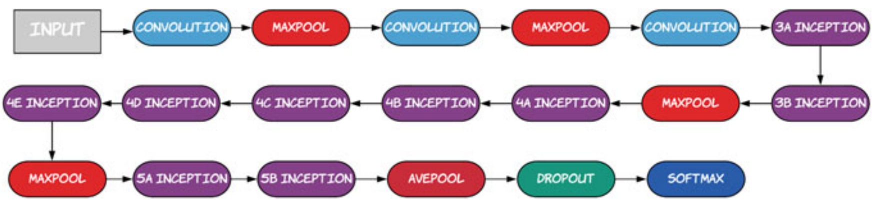

Fig. 4. GoogleNet architecture for G.V.Black classification

architecture. The performance of both the models are compared in Table 5 with AlexNet architecture showing the accuracy of 93%, sensitivity of 90% and specificity of 92%

Table 2. Detailed description of GoogleNet architecture.

Layers	Input image size	Output image size	No. of filter	Filter size	Stride	Padding
Convolution	227 × 22 × 7	112 × 112 × 64	64	7 × 7	2	1
Pooling	112 × 112 × 64	56 × 56 ×× 64		3 × 3	2	1
Convolution	56 × 56 × 64	56 × 56 × 192	192	3 × 3	1	1
Pooling	56 × 56 × 192	28 × 28 × 192		3 × 3	2	1
Inception 3a	28 × 28 × 192	28 × 28 ×× 256	256			
Inception 3b	28 × 28 × 256	28 × 28 × 480	480			
Pooling	28 × 28 × 480	14 × 14 × 480		3 × 3	2	1
Inception4a	14 × 14 × 480	14 × 14 × 512	512			
Inception4b	14 × 14 × 512	14 × 14 × 512				
Inception4c	14 × 14 × 512	14 × 14 × 512				
Inception4d	14 × 14 × 512	14 × 14 × 528				
Inception4e	14 × 14 × 528	14 × 14 × 832				
Pooling	14 × 14 × 832	7 × 7 × 832		3 × 3	2	1
Inception 5a	14 × 14 × 832	7 × 7 × 832				
Inception 5b	14 × 14 × 832	7 × 7 × 1024				
Avepool	7 × 7 × 1024	1 ×× 1 × 1024				
Dropout	1 × 1 × 1024	1 × 1 × 1024				
Softmax	1 × 1 × 1024		6			

and GoogleNet architecture with accuracy of 94%, sensitivity of 91% and specificity of 93%. The performance of the proposed approach is also compared with the G.V Black classification proposed by Prerna et al. [8] in Table 5.

Fig. 5. Dental images after filtering

Fig. 6. Dental image after segmentation

Table 3. Confusion matrix for AlexNet architecture.

	Class1	Class II	Class III	Class IV	Class V	Class VI
Class I	47	4	0	0	0	0
Class II	1	48	1	0	0	0
Class III	0	0	46	2	2	0
Class IV	0	0	5	43	2	0
Class V	0	0	3	0	47	0
Class VI	0	0	0	0	2	48

5 Conclusion

The proposed technique was used to classify 1500 dental periapical images into various classes based on G.V Black classification model (Class I–Class VI). Features are extracted using Local Ternary Pattern and after feature reduction, the features are subjected using various classifiers. The pertained model used are AlexNet architecture and

Table 4. Confusion matrix for GoogleNet architecture.

	Class1	Class II	Class III	Class IV	Class V	Class VI
Class I	49	1	0	0	0	0
Class II	2	47	1	0	0	0
Class III	0	0	45	0	5	0
Class IV	0	1	2	42	3	0
Class V	0	0	1	0	49	0
Class VI	0	0	0	0	0	50

Table 5. Performance of Pretrained Models (AlexNet and GoogleNet) and Adaboost Classifier

	Accuracy (%)	Sensitivity (%)	Specificity (%)
AlexNet	93	90	92
GoogleNet	94	91	93
Adaboost	92	90	90

GoogleNet architecture with a classification accuracy of 93% and 94%. The proposed algorithm can be used by the dentist to classify the dental images based on the type of caries.

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