ORIGINAL ARTICLE

Dental X–Ray Images for Automated Detection of Caries Classes Using Deep Learning Techniques

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Abstract

Purpose: Dental caries can emerge anywhere in the mouth, particularly in the interior of the cheeks and the gums. Some of the indications are patches on the inner lining of the mouth, along with bleeding, toothache, numbness, and an unusual red and white staining. Hence, it is important to predict the presence of a cavity at an early stage. The currently available manual method is inefficient and hence we provide an advanced method by using the deep learning concepts.

Materials and Methods: In this work, different types of algorithms such as Res Net, Deeper Google Net, and mini VGG Net are to be used to predict the class of cavity at an early stage.

Results: A comparison between the accuracy of three different algorithms is given in this paper. Thus, by using efficient deep learning algorithms, it will be able to predict the presence of the cavity and the class of the cavity at an early stage and take the necessary steps to overcome it.

Conclusion: In this work, a comparison between three different algorithms is given and proved that the efficient algorithm is the inception algorithm among the other algorithms that achieves an accuracy of about 98%, which is suitable for use in hospitals.

Keywords: Algorithm; Caries; Deeper Google Net; Mini VGG Net Res Net.

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1. Introduction

Dental caries, sugar-driven tooth decay, is a common health issue that leads to oral pain and tooth loss with considerable economic and quality-of-life burdens. It continues to be a major public oral threat among all age groups despite significant advancements in the dental healthcare of the population in the world [1]. The facultative anaerobic bacteria, Mutants Streptococci (MS), was found to be the chief causative agent of dental caries. It aggregates on the dental surface breaking down the sugars giving rise to an acidic environment. This leads to the demineralization of the tooth enamel thereby forming dental caries [2]. The tooth, bacteria causing dental plaque (Streptococcus Mutants), and the eating habits that deposit sugar in the teeth are the key factors contributing to dental caries [3]. According to the report by the American Dental Association, dental caries can be classified as normal, initial, moderate, or extensive based on the lesion extent detected in the patients [4]. Patients with dental caries suffer not only from toothache and difficulty in chewing food but also have trouble communicating with others due to discolorations and missing of the tooth [5]. If the dental caries is allowed to progress without proper treatment, it may be life-threatening. It results in odontogenic infections such as Sepsi and Ludwig angina. There is also a chance for deep neck abscesses as reported in a study for 49.1% of cases [6]. The earlier the spotting of initial tooth decay, the lesser the burden of invasive treatment and dental healthcare costs. Dentists utilize a diagnostic tool, oral panoramic radiographs (X-rays), for the earlier diagnosis of dental caries. It plays a central role in the detection of masked dental structures, cavities, and malignant or benign masses that cannot be explored under visual checkup. Adequate decalcification of tooth structures allows examining dental caries using radiography [7, 8]. In most cases, Dental X-rays are performed yearly. However, they can be more frequent depending on the severity of a dental problem or treatment [9, 10]. In the last few years, with the rapid progress of artificial intelligence, researchers have analyzed deep learning with Convolutional Neural Network (CNN) to extract a promising variety of medical images to greatly alleviate the burden of clinical doctors in dental healthcare. CNN algorithm is a fully connected network and requires little pre-processing which is a major advantage of CNN [11]. The utilization of deep learning for the diagnosis of dental issues has shown greatly improved clinical outcomes [12]. Deep learning (computer software) is a sub-group of machine learning that imitates the neural networks in a brain. Deep learning has its name from the usage of deep neural networks [13]. The first deep learning model was initiated in [14] for semantic segmentation. The SegNet model that offers improvements through the adoption of asymmetric auto-encoder architecture [15] follows this. The U-Net model is another model that takes inspiration from auto-encoders but introduces skip connections between corresponding layers in the encoding and decoding path, thereby leading to further betterments in accuracy [16]. Some other oral diseases are also diagnosed and treated using machine learning techniques along with imaging techniques. Inflammations on gingival surfaces were detected using intraoral fluorescence imaging [17] and plaque classification used quantitative light-induced fluorescence imaging [18]. These software measures allow the diagnosing of products, processes, and projects, and also check whether there is an unexpected deviation of the values of measures or they are within the expected norm [19]. Efforts were made in recent years to develop a computerized dental X-ray image analysis system for clinical usage like image segmentation, anatomical landmark identification, diagnosis, and treatment [20-23].

2. Materials and Methods

The X-ray images of the dental cavity of different classes and normal dental X-ray images are collected and pre-processed to reduce the size of images so that they can be directly trained and tested. Around 150 images have been utilized for the work. The data has been collected from Kaggle. Figure 1 represents a sample image of dental X-rays with the classes of caries.

The software used is python-anaconda power shell prompt.

One Filter Module: VGG16 architecture

The VGG network was established to classify CT slices, which can avoid the failure of CT slice segmentation without MS [24].

Two Filter Module: ResNet architecture

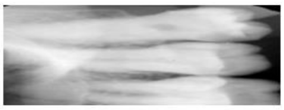
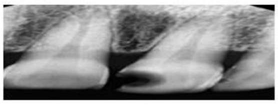
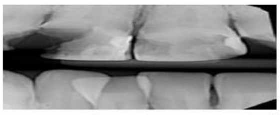
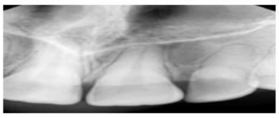
S.No	SAMPLE IMAGES	CLASS
i		NORMAL
ii		CLASS 1
iii		CLASS 2
iv		CLASS 3
v		CLASS 4

Figure 1. Images of Classes of dental caries

Following the victory of AlexNet [25] at the ILSVRC2012 classification contest, deep Residual Network [26] was found to be the most cutting edge in the computer vision/deep learning community in the last few years.

Inception Module: Deeper GoogleNet

The main purpose of the GoogLeNet model is to employ a number of smaller convolution kernels to restrict the number of neurons and parameters, and it wins the championship in the challenge of Imagenet 2014 [27, 28].

3. Results

Comparison of images is done with the help of three architectures (VGG Net, Deeper Googlenet, and Resnet 50). Results are compared using accuracy, recall, precision, and F measures values for all the normal and classes of the cavity. The validation accuracy is found running for 20 epochs, respectively and increased gradually to find the state of accuracy. Classification is done using the 3 architectures. We have compared VGGNet, ResNet 50, and Deeper Googlenet and classified to which category the dental caries class belongs to. In this work, the dental cavity is determined by using three different algorithms and gives a comparison with achieving the maximum efficient accuracy with the inception module. Initially, the anaconda navigator is started which is used to perform all the required execution of the work. As the execution is completed, the accuracy is been plotted for the training obtained which is around 67%.

The graphs plotted for the number of epochs used can be seen in Figures 2, 3, and 4, which are a comparison between the accuracy of the model trained and the loss of the model. Tables 1, 2, and 3 depict the parameter values obtained after the images of different classes are tested using the VGG Net, Res Net, and Deeper Googlenet.

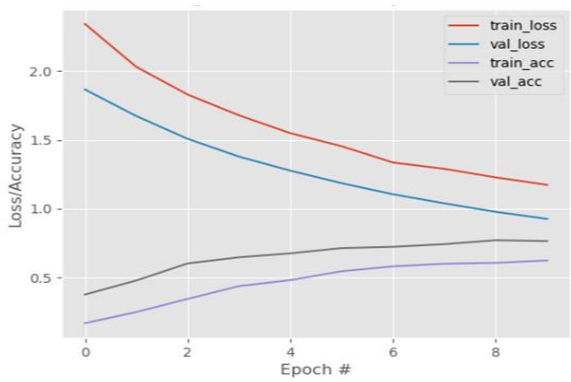


Figure 2. Graphical Output of Single Filter Graph Architecture

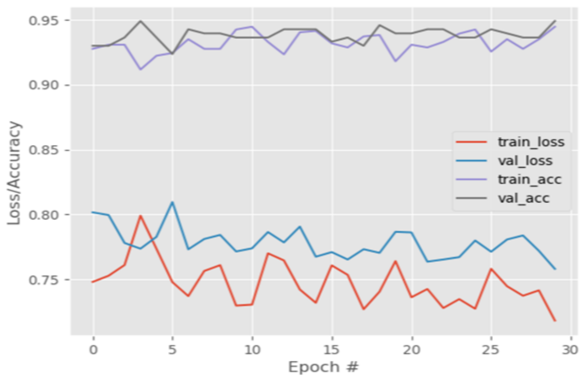


Figure 3. Graphical Output of Two Filter Architecture

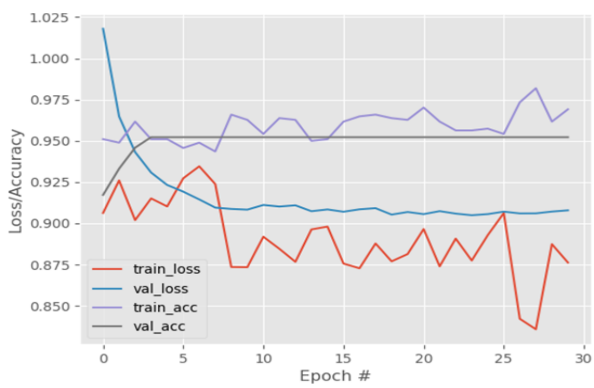


Figure 4. Graphical Output of Inception Module Architecture

Table 1. Single filter output

Class of Dental Caries	Precision	Recall	F1-Score	Support
1	0.50	0.02	0.05	41
2	0.34	1.00	0.50	32
3	1.00	0.86	0.92	35
4	1.00	0.96	0.98	24
Normal	0.62	0.29	0.40	34

Table 2. Two filter output

Class of Dental Caries	Precision	Recall	F1-Score	Support
1	1.00	1.00	1.00	41
2	0.94	1.00	0.97	32
3	1.00	0.77	0.87	35
4	0.67	1.00	0.80	24
Normal	1.00	0.82	0.90	34

Table 3. Inception Module Output

Class of Dental Caries	Precision	Recall	F1-Score	Support
1	1.00	0.90	0.95	41
2	1.00	1.00	1.00	32
3	1.00	1.00	1.00	35
4	1.00	1.00	1.00	24
Normal	0.89	1.00	0.94	34

Table 4 represents a comparison of the three algorithms in terms of accuracy.

4. Conclusion

This work gives a comparative analysis between 3 different types of architectures in deep learning and analyzes which algorithm serves the best in automated detection of the class of cavity. Different types of classification algorithms are applied to the dataset containing the X-ray images of teeth and their efficiency is studied. The performance of classification was validated based on accuracy, precision, and recall, and the F-score gave better accuracy in deeper Google net than the other networks. The accuracy value for deeper google Net was calculated as 98%. The accuracy value for Resnet 50 was calculated as 92%. The accuracy value for VGGnet was calculated as 52%. Hence, the classification method compared with Deeper Google Net provided higher accuracy than VGGnet and Resnet 50. The proposed method helps even the junior doctors to treat the patient in the absence of the senior doctor since everything is generated automatically. Only a few are fully automatic among the methods that are proposed, the manual dependent on X-ray results could lead to time delay, which can be avoided if the following is incorporated. The proposed system helps to automatically differentiate between the types of cavity from the normal, future it can be improved to analyze the depth of the cavity and segment the cavity region, which will be more useful in the treatment. A few more sectors of artificial intelligence can also be incorporated along with the proposed system to increase the standard of the proposed system [29].

Table 4. Comparison of Output

Total No. Of Epochs	Architecture	Accuracy	
		F1-Score	Support
20	VGGNET	0.58	166
	RESNET	0.92	166
	DEEPERGOOGLENET	0.98	166

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