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DENTAL CARIES GRADE CLASSIFICATION BASED ON IMPROVED VERY DEEP CONVOLUTIONAL NEURAL NETWORK

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Abstract

Dental Caries is one of the major oral diseases that can be seen increasing among adults as well as in children. It is a progressive bacterial infection that can cause tooth loss if left untreated. Early detection and proper treatment of this disease can prevent loss of tooth.Many Artificial Intelligence (AI) based works have been caried out for early detection of dental caries but achieving a good accuracy is still a challenge. This work aims to develop a model that can classify the three classes of the dental caries namely enamel caries, dentin caries and pulpitis. The proposed design is a fine-tuned model based on the VGG16 model emulating deep learning-based classification of dentin caries. The dataset of Radio Visio Graphy (RVG) images which comprises of infected tooth is collected and labelled for this purpose. The proposed model is also compared with the fully train VGG16 and Bi-Long Short-Term Memory (Bi-LSTM) coupled with the transfer learning. The performance of these models is evaluated based on the Accuracy, Precision, Recall and F1 Score. Based on the evaluation metrics, it has been observed that the proposed method is able to achieve highest accuracy as compared to the fully train VGG16 and Bi-LSTM coupled with the transfer learning. The proposed model shows an overall accuracy of 97.87% with minimal loss. It's performance has also been compared with state of the art models with similar settings to verify its performance upper hand. The proposed model's performance suggests it can be proved to be beneficial in dental caries classification which can act as secondary opinion for the healthcare expert dealing with this disease

Keywords: Dental Caries, Artificial Intelligence, RVG images, Deep Learning

INTRODUCTION

Dentists have long considered dental caries is commonly occurring disease, with early lesions present in the majority of the population worldwide. The global oral health data bank conducted a recent survey that found the prevalence of dental caries varies between 49% and 83% regardless of age [1]. Out of the dental disease, dental caries is one of the most ancient diseases that is seen in humans since 3000 BC (Before Christ) [2]. Based on the recent studies, it has been found that the progressive dental caries which is left untreated can be the root cause of permanent dentition. Caries in the mouth occurs when the calcified tissue of the teeth becomes infected. There are several factors that contribute to caries, includes improper dental hygiene, frequent snacking, presence of bacteria in mouth, consumption of sugary drinks [3]. The primary cause of caries is bacteria converting sugar as well as carbohydrates present in the edible items to acid, that consequently causes the minerals residing inside enamel to dissolve and then results in damage of the teeth. Inflammation, tooth loss and pain are some common symptoms of caries [4]. There are still concerns over dental caries in developing countries like India. Additionally, the disease has spread deep into regions with very limited resources and facilities for treatment, mostly in the dental area. Another major concern is that people lack proper knowledge of adverse effects of intake of more carbohydrates. Therefore, detection of dental caries at an early stage is vital task for the tele dentistry dental healthcare system with the use of dental images and feeding them in classification model for predicting the caries stages for better treatment [5].

In order to determine the extent of dental caries, various techniques are used, including visual-tactile methods, radiography, chemometric methods incorporating caries that detects dyes, and recently Fiberoptic Illumination (FOTI), Digital Fiberoptic illumination (DIFOTI) and lastly Electric Caries Monitor (ECM) [6 – 10]. The most conventional method used by dentists are visual tactical method that makes clinical judgement by making observation of the infected tooth by dental mouth mirror. Several radiographic techniques are effective for detecting caries radiographically, including an Intraoral Periapical Radiograph (IPR), a Bitewing Radiograph (BR) for Occluso-Proximal Caries (OPC), and RVG, which measures the amount of noise and hardness of the carious tooth [11, 12]. There are several dyes that can be used as chemical methods to stain the collagenous part of the tooth to depict the caries infected tooth and uninfected tooth.

Based on the histological extent of lesion the dental caries or according to the affected tissue of the tooth, the classes of caries can be classified as follows-

Enamel Caries: Also known as smooth surface caries. This class of caries is mainly caused due to formation of plaque on the surface of enamel of the tooth. This is the early stage of caries that can be seen beneath the area of dental plaque which is characterized by decalcification or white spots. Detection of enamel caries at an early stage and early restoration proves as a good prognosis [13].

Dentin Caries: The caries starts spreading naturally leading to involvement of dentinal tubules of the tooth. These dentinal tubules pave the path for microorganisms to reach the pulp [14]. Patient suffering from this class of caries have high sensitivity in the infected tooth, feel soreness to cold, hot as well as sweet substances. If left untreated, the infection may lead to pulp causing much severity of the disease.

Pulpitis: This kind of caries affects the root of the tooth causing severe pain and even leads to tooth loss. The pulp tissue is destroyed by the entry of microorganisms [15]. This causes inflammation of the infected tooth and is generally treated by root canal therapy.

The RVG images shown depicts the different classes of dental caries.

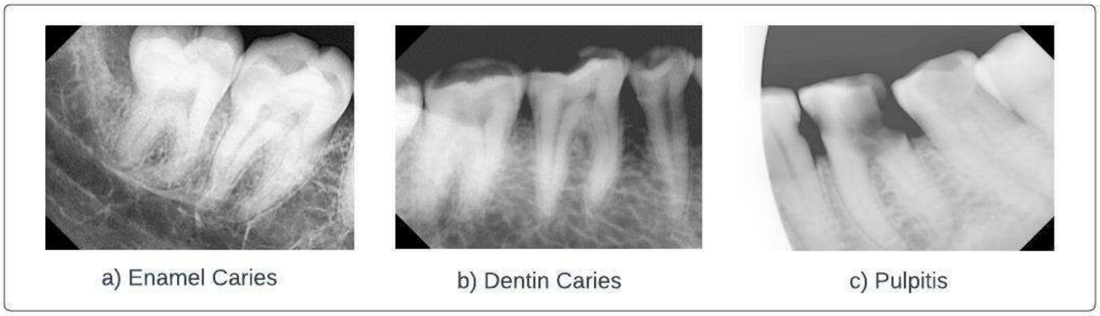

Fig 1: Classes of Dental Caries a) Enamel Caries b) Dentin Caries c) Pulpitis

LITERATURE SURVEY

Now a days, medical misdiagnosis can be seen widely spreading and many people are directly or indirectly suffering from this. There is a huge rise misdiagnosis of disease which is an outcome of less précised medical analysis as well as inefficiency in caring of drugs. Therefore, the advanced technologies which includes machine learning for various dataset training-based analysis is used as one of the efficient solutions to overcome misdiagnosis and the power of neural network as well as CNN is widely accepted as one of the solutions which has greatly improved the analysis of dental diseases [16].

Caries detection of 2417 Intraoral Images was performed based on AI algorithms CNN that achieved an accuracy of 92.5% on test images [17]. Detection of apical lesions were performed on panoramic dental radiographs consisting of about 2001 image segments of particular infected tooth that is manually cropped. The detected of the apical lesions was implemented using 7-layer deep convolutional neural network. The system was able to achieve a sensitivity rate of 0.65 and specificity rate of 0.87 [18]. About 800 dental bitewing radiographs are taken for training and 200 dental bitewing radiographs are taken for testing in order to diagnosis interproximal caries. The detection was done using YOLO (You only look once) that is CNN based model and it gave an overall accuracy of 94.59% [19]. Deep CNN was implemented to build up a Computer Assisted Detection (CAD) system to predict periodontally compromised tooth using periapical radiographic images. The CAD system was able to predict the periodontally compromised tooth with an accuracy of 81% for premolars and 76.7% for molars [20]. For diagnosis of dental caries, a total number for 105 dental X ray images are considered. Morphological operations like Laplacian Filtering are applied and classified using back propagation neural networks. This diagnostic system gave an accuracy of about 97.1% and false positive rate of about 2.8% [21].

Oral Squamous Cell Carcinoma (OSCC) is considered as higher mortality cancer caused in oral epithelium. For detection of OSCC at an early stage, 7894 Confocal Laser Endomicroscopy (CLE) was collected and applied deep learning approach. The proposed method outperformed giving an accuracy of 88.3%, specificity 90% and sensitivity of 86.6% [22]. Dental restorations are detected and classified using AI based algorithm. A total number of 83 anonymized panoramic Xray images consisting of 738 restorations are considered for the study. The overall accuracy for detecting restorations is 93.6% [23]. Proper treatment is most vital part in case of orthognathic surgery. This depends mainly on two factors diagnosis and treatment planning.

For this work, 316 samples of patients of different age groups are taken that consists of 160 samples with planned surgical treatment and 156 samples with non-surgical treatment. The AI based model succeeded to show an accuracy of 96% for decision support for surgical and non-surgical treatment and 91% for suggesting detailed diagnosis for surgical ones [24]. Segmentation of dental caries is performed utilizing motion filtering along with Back propagation Neural Networks. Around 120 periapical dental Xray images are used for the study that yielded an accuracy of about 98% [25]. This work focuses on detecting and diagnosing dental caries with various deep learning algorithms [26]. A total number of 844 dental radiographs are used for the purpose of accurate diagnosis of dental caries through deep learning algorithms such as VGG19, ResNet18 and Inception V3. The ResNet18 is seen to outperform than the rest two algorithms by achieving an accuracy of 82% [27].

METHODOLOGY

This work focuses on developing a classification model that is able to classify the different grades of Caries viz. Enamel Caries, Dentin Caries, Pulp Caries or Pulpitis by utilization of the deep learning technique. The framework of the purposed classification for dental caries consists of data collection, data augmentation and classification models as shown in Fig 1:

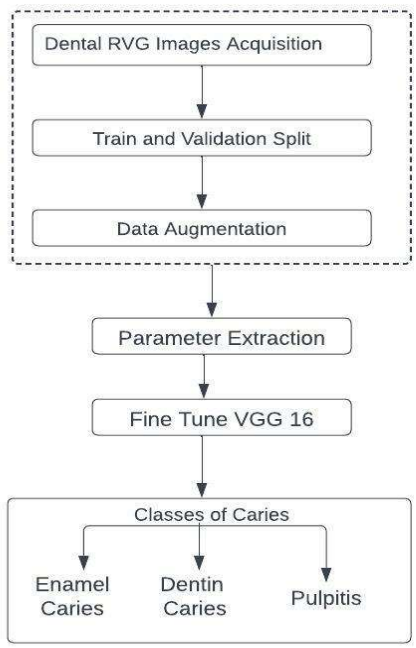

Fig 2: Proposed Methodology

Dental RVG Images Acquisition: The first step is collection of Dental RVG images. For this purpose, the dataset collected from School of Dental Science, Sharda University. These RVG images includes images of the patients of ages above 18 years excluding their personal information like name, sex or any other clinical information. A total number of 550 dental periapical RVG image is collected of the people from age range 18-70 years. The patient's personal information like name, address, gender, phone number is not collected due to privacy concern. Periapical Xray images are generally used anterior as well as posterior tooth. These Xray mainly focuses on the specific infected tooth. A periapical dental image shows both the chewing surface and the root tip of the tooth along with the surrounding bone. The images collected are in the 'JPEG' format.

Training and Validation Split: The data collected is used as diagnostic data sample for the classification model. For this, it further classified into three classes of caries i.e., enamel caries, dentin caries and pulp caries with the help of dentist and radiologists. The performance of the Machine Learning (ML) models basically depends on the training and validation data. For evaluation of the generality of the trained model, the dataset is randomly split to two sets training set and validation set in the ratio 80:20. The training set serves as an input for the model in which the model is trained on by adjusting the weights of the network. The validation set is for evaluating the performance of the model and calculating the error rate. This validation set yields the model's accuracy based on which it will tune its parameters.

The model would be trained as $x = [\, x^{(1)}, x^{(2)}, \ldots\ldots.., x^{(m)}]$, where x is the input image and m is the number of training images of the model with dimensions 224*224*3.

Table 1: Criteria to select in order to train and validate the Model

Type	**No. of Dental RVG Images**	**%**
Training	**2334**	80
Validation	**584**	20
Total	**2918**	100

Data Augmentation: The performance of supervised Deep Learning models primarily reliant on the quantity as well as diversity of the training dataset. In most cases, insufficient data can result as a challenge for good accuracy. The concept behind data augmentation technique is to use the existing data points to generate new ones that can artificially increase the size of the dataset during the training process. Apart from this, data augmentation techniques also deal with imbalanced class problem in classification. The ImageDataGenerator first processes a batch of input images into a series of random translations, rotations, etc. to generate new set of transformed images. Data augmentation can be represented as.

Table 2: Parameters to Augment Image

Parameters to Augment Image	**Values**
Width_shift_range	0.2
Height_shift_range	0.2
Rotation range	15
Rescale	1./255
Shear range	0.2
Zoom range	0.2

Horizontal Flip	True
Fill mode	Nearest
Brightness range	0.5, 1.5

Fine Tune VGG16: Convolutional Neural Networks (CNN) serves as a backbone for image classification. Visual Geometry Group (VGG)16 based on CCN architecture is used for this classification purpose. Until today, it is known as one of the most outstanding vision model architectures. The output of the model is represented as

$$Y= [y^{(1)}, y^{(2)}, y^{(3)}] \quad (1)$$

where $y^{(1)}, y^{(2)}, y^{(3)}$ represents the three classes of the caries.

MODEL ARCHITECTURE

A number of applications use deep learning, including image classification and object tracking. Convolutional Neural Networks (CNN) are one of the most widely used method in deep learning. In general, pretrained models prove to be efficient for better initialization as well as convergence incase the dataset is comparatively smaller. VGG16 architecture is a simple as well as widely used pretrained CNN model. Its network design is fundamentally characterized by the depth of its connections. The architecture of VGG16 is portrayed in the figure below. It comprises of five convolutional blocks and each block further consist of multiple convolutional layers as well as max pooling layer along with activation function ReLu. There are only 3 * 3 filters with stride and pad set to 1, together with 2 × 2 maxpooling layers with stride set to 2.

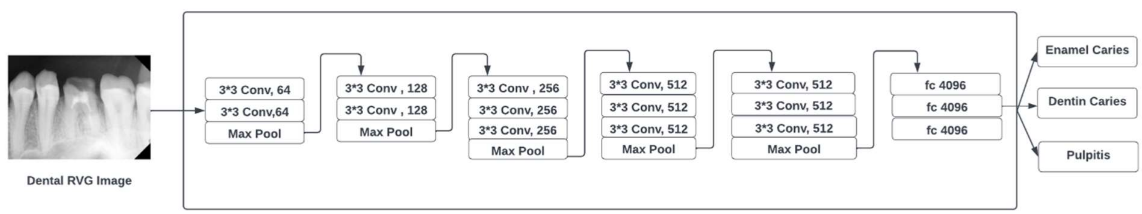

Fig 3: Proposed Architecture for Classification of Caries

Convolutional Layer: Convolutional Layer is the key element of the network. An independent set of filters together forms the convolutional layer of the model. These filters slide over the input image and generates a feature map based on the image properties. In order to combine features from the local domain of an input, CNN uses convolutions. The features are seen as filters and each filter exactly matches with the features that is to be extracted from the images for classification.

Mathematically, it can be calculated as

Feature Map G [m, n] = (x * h) [m, n]

$$= \sum_j \sum_k h[j,k]\, x\,[m-j, n-k] \quad (2)$$

where x is the input image and k is the kernel, m and n are the rows and columns of the resultant matrix.

Pooling Layer: This layer is generally placed in between two convolutional layers. Initially, pooling was used to make CNN layers less prone to distortion. For example, the Scale Invariant Feature Transform (SIFT) descriptor uses a 4*4 grid to pool the data. It allows features to move in relation to each other even small distortions are present. This layer is responsible for applying pooling operation i.e., reduction of the image size while conserving the vital characteristics of the image. It also degrades the number of parameters of the network and calculations that leads to improvement in efficiency and prevents over learning.

Fully Connected (FC) Layer: The FC layer applies linear combination to the input vector to generate new output feature vector. This feature vector captures the information which is important to the input vector. It can be also utilized as an encoded vector. While training the model, this feature vector evaluates the loss and also helps in training the network. The local features of an image such as edges, blobs, shapes, etc. are stored in the convolutional layers. In each convolutional layer, there are many filters that represents at least one local feature. The information stored in fully connected layer comprises aggregated information of all the convolutional layers.

The proposed model is enhanced by changing three specified parameters that are batch normalization, drop out and dense layer of VGG16. As a part of transfer learning, the layers of the base model are freeze expect the batch normalization layer so that the weights of the network is don't go under further modification. Thus, for preventing the model from overfitting, a drop out value is set to 0.4. Batch normalization is used which acts as a regularizer that normalizes the input of the layers. An extra dense layer is added to the model. The activation function ReLU is used. ReLU stands for Rectified Linear Unit which is basically used for adding non-linearity to the network.

Mathematically, ReLu is represented as $\text{ReLu}(x) = \begin{cases} 0 \; if \; x < 0 \\ x \; if \; x \geq 0 \end{cases}$ (3)

The model summary of the proposed model is shown below.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dense (Dense)	(None, 1024)	525312
dropout (Dropout)	(None, 1024)	0
batch_normalization(Batch)	(None, 1024)	4096
dense_1 (Dense)	(None, 3)	3075

Total params: 15,247,171

Trainable params: 15,245,123

Non-trainable params: 2,048

RESULTS

The experimental environment for classification of dental caries is performed over a standard Workstation having dual Nvidia GeForce GTX 2070 graphical processing unit (GPU) support. The experiments were carried out taking Python 3.7.6 including TensorFlow 2.1.0 and Keras 2.2.4. A total number of 2918 images are taken for this classification out of which 80 percent is for training and 20 percent is for validation of the system. The performance of the proposed system is evaluated by the following parameters like accuracy, recall, precision, F1 score. The evaluation parameters mainly depend on the confusion matrix also known as error matrix or contingency table. This confusion matrix consists of four terms, namely, True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN). The evaluation of the proposed model was performed on 584 validation RVG images in which the performance metrics such as Precision, Sensitivity, Accuracy and F1 Score is calculated.

The mathematical equations of the proposed model are defined:

Precision= $\frac{TP}{TP+FP}$ (4)

Recall = $\frac{TP}{TP+F}$

(5)

Accuracy= $\frac{TP+F}{TP+TN+FP+FN}$ (6)

F1 score = $\frac{2*Precision*Recall}{Precision+Recall}$ (7)

Precision Equation (4) defines the ability of the classification model to identify the data points that are relevant. This can also be termed as the ratio between the TP and all the positive (i.e., TP+FP)

Recall Equation (5) measures the ability of the classification model to predict the positive classes in the dataset.

Accuracy Equation (6) determines the efficiency of the classification model in case of identifying the patterns and the relationship among the variables in the trained dataset.

F1 Score Equation (7) is one of the vital performance metrics that is basically the harmonic mean of the precision value and the recall value.

The table 3 shows the resulting performance metrics of the proposed method i.e., fine tune VGG16 and fully train VGG16 for dental caries and Bi-LSTM coupled with VGG16.

Table 3: Comparison of performance metrics of fine tune VGG16 and fully train VGG16

Performance Metrics					
Architecture	Classes of Caries	Precision	Recall	F1 Score	Accuracy
Fully Train VGG16	Enamel Caries	0.33	0.28	0.30	77.50 %
	Dentin Caries	0.35	0.38	0.36	

[2014]	Pulpitis	0.25	0.28	0.26	
Bi-LSTM coupled with VGG 16 [2021] [26]	Enamel Caries	0.54	0.43	0.32	87.4%
	Dentin Caries	0.28	0.45	0.39	
	Pulpitis	0.28	0.42	0.43	
Fine Tune VGG16 [proposed]	Enamel Caries	0.91	0.65	0.71	97.87%
	Dentin Caries	0.70	0.95	0.67	
	Pulpitis	0.92	0.65	0.69	

The graph shows the training accuracy and the validation accuracy of both fully train and fine tune models. The model is trained for 20 epochs. The fully train model shows an accuracy of 77.50% with high loss rate of 0.5557. The Bi-LSTM coupled with VGG16 when applied on the dental RVG images shows and accuracy of 87.45% with maximum loss of 13%. Whereas, the proposed fine tune model is able to achieve a satisfactory validation accuracy of 97.87% on collected dataset. The validation loss of the model is almost 0.0325.

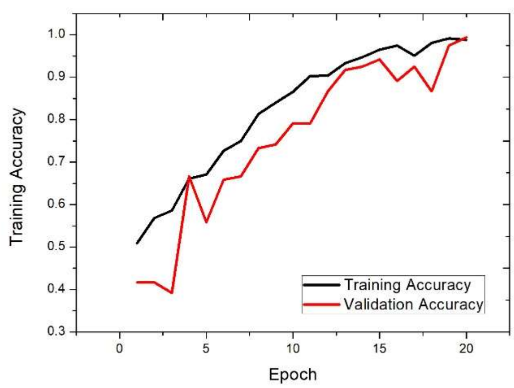

Fig 4: Training Accuracy vs Validation Accuracy

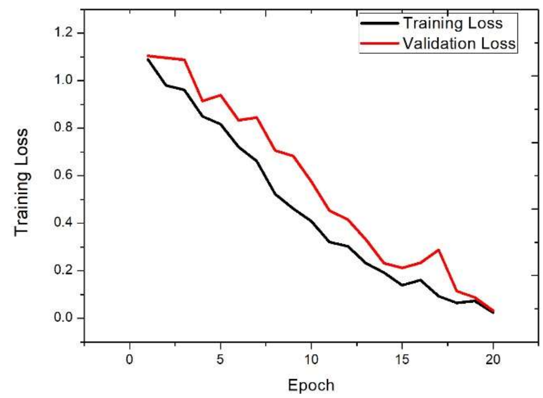

Fig 5: Training Loss vs Validation Loss

Deep Learning models tend to show over fitting issue in case of small dataset. Drop out can be a regularization method to solve this issue. The table below shows the value change in dropout and its affect in performance of the model.

Table 4 : Dropout Value and Accuracy

Drop out Value	**Accuracy**
0.2	88.75%
0.3	87.50%
0.4	97.87%
0.5	93.87%
0.6	92.66%
0.7	93.12%
0.8	91.25%

CONCLUSION

The AI modalities that is able to recognize patterns in photos as well as videos such as the ML, deep learning, computer vision algorithms and Natural Language Processing (NLP) plays a crucial role in the field of dentistry. This work developed a classification model for classification of three classes of dental caries i.e., Enamel caries, Dentin caries, Pulpitis. The proposed model is also compared with the fully train VGG16 model and Bi-LSTM coupled with VGG16. The proposed approach yields an accuracy of 97.87% with a minimal loss of 0.0325 for 20 epochs that shows the best performance as compared to the fully train model. The findings of the proposed model prove promising and it can stand as a second opinion for dentist and radiologist to detect the accurate class of caries for proper treatment. However, the adequate data is required for achieving more stability and precise results. In the coming years, AI will be a superior technology that will rule the dental domain for detecting other oral diseases combinedly from big dataset. Using AI in dentistry, smart dental health care monitoring of patient and various research innovations can be established.

REFERENCES

1. Grischke, J., Johannsmeier, L., Eich, L., Griga, L., Haddadin, S. (2020). Dentronics: Towards robotics and artificial intelligence in Dentistry. Dental Materials, 36(6), 765–778. https://doi.org/10.1016/j.dental.2020.03.021.

2. Qiu, W., Zhou, Y., Li, Z., Huang, T., Xiao, Y., Cheng, L., Peng, X., Zhang, L.,Ren, B. (2020). Application of antibiotics/antimicrobial agents on dental caries. BioMed Research International, 2020, 1–11. https://doi.org/10.1155/2020/5658212 .

3. Giri, D. D. (2022). Artificial Intelligence - future trend in oral diagnosis and radiology. International Journal of Current Science Research and Review, 05(09). https://doi.org/10.47191/ijcsrr/v5-i9-18.

4. Nyvad, B.,Takahashi, N. (2020). Integrated hypothesis of dental caries and periodontal diseases. Journal of Oral Microbiology, 12(1), 1710953. https://doi.org/10.1080/20002297.2019.1710953.

5. Whelton, H., Spencer, A., Do, L.,Rugg-Gunn, A. (2019). Fluoride Revolution and Dental Caries: Evolution of Policies for Global Use. Journal of Dental Research, 98(8), 837–846. https://doi.org/10.1177/0022034519843495.

6. Kaur, P., Vyas, M.,Verma, S. (2022). Dental caries: A review on etiology, therapeutic approaches, novel formulations, and marketed preparations. ECS Transactions, 107(1), 8035–8048. https://doi.org/10.1149/10701.8035ecst.

7. Basri, K. N., Yazid, F., Megat Abdul Wahab, R., Mohd Zain, M. N., Md Yusof, Z.,Zoolfakar, A. S. (2022). Chemometrics analysis for the detection of dental caries via UV absorption spectroscopy. Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 266, 120464. https://doi.org/10.1016/j.saa.2021.120464.

8. Hogan, R., Pretty, I. A., Ellwood, R. P. (2019). Fibre-optic transillumination: Foti. Detection and Assessment of Dental Caries, 139–150. https://doi.org/10.1007/978-3-030-16967-1_14.

9. Marmaneu-Menero, A., Iranzo-Cortés, J. E., Almerich-Torres, T., Ortolá-Síscar, J. C., Montiel-Company, J. M.,Almerich-Silla, J. M. (2020). Diagnostic validity of digital imaging fiber-optic transillumination (DIFOTI) and near-infrared light transillumination (NILT) for caries in Dentine. Journal of Clinical Medicine, 9(2), 420. https://doi.org/10.3390/jcm9020420.

10. Talwar, M., Borzabadi-Farahani, A., Lynch, E., Borsboom, P.,Ruben, J. (2019). Remineralization of demineralized enamel and dentine using 3 dentifrices—an invitro study. Dentistry Journal, 7(3), 91. https://doi.org/10.3390/dj7030091.

11. Endres, M. G., Hillen, F., Salloumis, M., Sedaghat, A. R., Niehues, S. M., Quatela, O., Hanken, H., Smeets, R., Beck-Broichsitter, B., Rendenbach, C., Lakhani, K., Heiland, M., Gaudin, R. A. (2020). Development of a Deep Learning Algorithm for Periapical Disease Detection in Dental Radiographs. Diagnostics, 10(6), 430. https://doi.org/10.3390/diagnostics10060430.

12. Talpur, S., Azim, F., Rashid, M., Syed, S. A., Talpur, B. A.,Khan, S. J. (2022). Uses of different machine learning algorithms for diagnosis of dental caries. Journal of Healthcare Engineering, 2022, 1–13. https://doi.org/10.1155/2022/5032435.

13. Macey, R., Walsh, T., Riley, P., Glenny, A.-M., Worthington, H. V., Malley, L., Clarkson,J. E.,Ricketts, D. (2021). Visual or visual-tactile examination to detect and inform the diagnosis of enamel caries. Cochrane Database of Systematic Reviews, 2021(12). https://doi.org/10.1002/14651858.cd014546.

14. Ossowska, A., Kusiak, A.,Świetlik, D. (2022). Artificial Intelligence in dentistry—narrative review. International Journal of Environmental Research and Public Health, 19(6), 3449. https://doi.org/10.3390/ijerph19063449.

15. Bjørndal, L., Simon, S., Tomson, P. L.,Duncan, H. F. (2019). Management of deep caries and the exposed pulp. International Endodontic Journal, 52(7), 949–973. https://doi.org/10.1111/iej.13128.

16. Schwendicke, F., Golla, T., Dreher, M.,Krois, J. (2019). Convolutional Neural Networks for Dental Image Diagnostics: A scoping review. Journal of Dentistry, 91, 103226. https://doi.org/10.1016/j.jdent.2019.103226.

17. Kühnisch, J., Meyer, O., Hesenius, M., Hickel, R.,Gruhn, V. (2021). Caries detection on intraoral images using artificial intelligence. Journal of Dental Research, 101(2), 158–165. https://doi.org/10.1177/00220345211032524.

18. Ekert, T., Krois, J., Meinhold, L., Elhennawy, K., Emara, R., Glla, T.,Schwendicke, F. (2019). Deep learning for the radiographic detection of apical lesions. Journal of Endodontics, 45(7). https://doi.org/10.1016/j.joen.2019.03.016.

19. Bayraktar, Y., Ayan, E. Diagnosis of interproximal caries lesions with deep convolutional neural network in digital bitewing radiographs. Clin Oral Invest 26, 623–632 (2022). https://doi.org/10.1007/s00784-021-04040-1.

20. Lee, J.-H., Kim, D.-hyung, Jeong, S.-N., Choi, S.-H. (2018). Diagnosis and prediction of periodontally compromised teeth using a deep learning-based convolutional neural network algorithm. Journal of Periodontal Implant Science, 48(2), 114. https://doi.org/10.5051/jpis.2018.48.2.114.

21. Geetha, V., Aprameya, K. S.,Hinduja, D. M. (2020). Dental caries diagnosis in digital radiographs using back-propagation neural network. Health Information Science and Systems, 8(1). https://doi.org/10.1007/s13755-019-0096-y.

22. Aubreville, M., Knipfer, C., Oetter, N., Jaremenko, C., Rodner, E., Denzler, J., Bohr, C., Neumann, H., Stelzle, F. Maier, A. (2017). Automatic classification of cancerous tissue in laserendomicroscopy images of the oral cavity using Deep Learning. Scientific Reports, 7(1). https://doi.org/10.1038/s41598-017-12320-8.

23. Abdalla-Aslan, R., Yeshua, T., Kabla, D., Leichter, I.,Nadler, C. (2020). An artificial intelligence system using machine-learning for automatic detection and classification of dental restorations in panoramic radiography. Oral Surgery, Oral Medicine, Oral Pathology and Oral Radiology, 130(5), 593–602. https://doi.org/10.1016/j.oooo.2020.05.012.

24. Artificial intelligent model with neural network machine learning for the diagnosis of orthognathic surgery. (2020). Journal of Craniofacial Surgery, 31(4), 1156. https://doi.org/10.1097/scs.0000000000006531.

25. Rad, A. E., Rahim, M. S., Kolivand, H.,Norouzi, A. (2018). Automatic Computer-aided caries detection from dental x-ray images using intelligent level set. Multimedia Tools and Applications, 77(21), 28843–28862. https://doi.org/10.1007/s11042-018-6035-0.

26. Musri, N., Christie, B., Ichwan, S. J., & Cahyanto, A. (2021). Deep learning convolutional neural network algorithms for the early detection and diagnosis of dental caries on periapical radiographs: A systematic review. *Imaging Science in Dentistry*, *51*(3), 237. https://doi.org/10.5624/isd.20210074.

27. Zheng, L., Wang, H., Mei, L., Chen, Q., Zhang, Y.,Zhang, H. (2021). Artificial Intelligence in Digital Cariology: A new tool for the diagnosis of deep caries and pulpitis using convolutional neural networks. Annals of Translational Medicine, 9(9), 763–763. https://doi.org/10.21037/atm-21-119.