Artificial Intelligence and Machine Learning in Periodontics

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Abstract: Artificial intelligence, machine learning, and deep learning are evolving modern technologies in the field of periodontics. This science uses the machine – learning algorithm and computer software to aid in diagnostics in medical and dental fields. This field encompasses anything from coaching to medical diagnostics, and it encompasses all that machine and deep learning can accomplish. Artificial intelligence is revolutionizing dentistry in all areas, including data collecting, algorithms creation for orthodontic operations, radiographic data, 3D scan, CBCT, and CAD CAM systems for restorative and prosthetic functions. In the next years, the field of technology development, with its many applications, will change the face of periodontology.

Index Terms: Artificial intelligence; Machine learning, deep learning, laser, periodontitis, convoluted neural network, Autofluorescence

I. INTRODUCTION:

Periodontal infections are a class of inflammatory diseases caused by bacteria populating the teeth and infecting the soft tissues around them. The pathogens impede the health of the gingival tissue, bone, cementum and periodontal ligament. Periodontal diseases are of two phases, gingivitis and periodontitis, depending on the two stages of the disease. Only the soft gum tissue is affected in gingivitis, which is the first stage of periodontal disease. This condition is still reversible at this point. It can, however, lead to periodontitis if not treated. Periodontitis is the advanced stage of gum disease. The gums, bone, and other supporting tissues have been irreparably harmed. The disease may require substantial therapy at this point, or teeth may need to be removed [1]. The etiology of this diseases are plaque and dental calculus evoking immune and inflammatory reactions causing loss of periodontal health. It is necessary to diagnose these diseases in early stages so that a professional intervention can down regulate the ongoing damage and simultaneously restore health. The diagnosis of periodontal disease is summation of parameters from visual inspection, manual probing, radiographic interpretation, additionally with value added biomarker assays.

Various technological advancements have occurred in diagnosing these diseases overcoming the limitations of traditional methods. The encroachment of scientific advancements into medical field made the invisible entities into a visible and treatable one. These advancements ranged from automated plaque detection to neural network based bone loss detection, providing data acquisition software to aiding in diagnosis of diseases using the same data.

Tooth plaque is a biofilm formed by a diverse community of microorganisms on dental surfaces that is embedded in an extracellular matrix made up of polymers from both the host and the microbiota. Plaque plays a key role in the emergence and progression periodontal disease[2].The traditional method of plaque detection is by using disclosing methods which reported to have staining and allergic reactions to some extent and had limited visibility. Recent advanced technologies are able to detect plaque even through photographic and various methods.

DenTiUS

DenTiUS began as a stand-alone application for quantifying dental plaque, complete with modules for managing patients and experiments for a single user. By uploading plaque photos and developing and processing experiments, physicians and researchers could join up, register, manage patients, and engage with DenTiUS Plaque. The goal was to make DenTiUS Plaque an automated decision support system that could assist experts in analyzing and quantifying macroscopically visible dental plaque on teeth. Duplicating, processing, removing, and trimming the linked photos are all possible with this software. DenTiUS Plaque uses a unique algorithm to detect and quantify dental plaque levels using UV images. This method first identifies the dental region, then segments and quantifies visible plaque by assessing the difference between the green and blue channels, and then displays plaque that is not perceived to the naked eye[3]. DenTiUS Plaque software enables for the automatic, consistent, and accurate assessment of dental plaque levels, as well as information on area, intensity, and growth pattern. This software is excellent for quantifying tooth plaque levels, according to dentistry specialists. As a result, its use is the therapeutic setting for analyzing plaque evolution patterns associated with various dental diseases, as well as evaluating the effectiveness of various oral hygiene measures, can be beneficial[4].

Optical Coherence Tomography:

OCT is a non-invasive high-resolution imaging tool that utilizes backscattered light from tissue to construct depth- resolved cross-sectional pictures with an axial resolution of 2 to 10 microns. The textural examination of the pictures recorded by OCT analysis revealed that inflammatory conditions created low intensity images as compared to healthy regions. In comparison to traditional imaging modalities, dental OCT has shown encouraging results with enhanced spatial resolutions[5]. This would be a pragmatic tool in assessing plaque distribution. Hand held probe based OCT operated on healthy and gingivitis subjects revealed low intensity of plaque distribution in gingivitis subjects. The distribution of the dental plaque after one-week use of the oral hygiene products was compared, showing the capability of OCT as a longitudinal tracking tool[6]. Gingival soft tissue analysis through OCT in non-alcoholic fatty liver disease revealed NAFLD may be an aggravating factor for the inflammation of periodontal disease[7].

Digital Imaging:

Plaque identification became considerably more illustrative and patient-educational thanks to digital imaging. Images of teeth rinsed with 1% methylene blue were acquired and analyzed with optimas image analysis software for red, green, and blue [RGB space] as well as hue, saturation, and intensity values [HIS values] analysis. Finally, the identified plaque is depicted in a vivid red color. This technology allowed researchers to compare the performance of different cleaning techniques, pinpoint the precise location of plaque, track the efficacy of anti- plaque agents, and compare manual and powered tooth brushing[8]. The success rate for classifying pixels as plaque or non-plaque using digital imaging was 87.3 percent based on saturation and intensity, and 98.7 percent based on hue and intensity, according to the discriminant analysis.

Fluorescence

The enhanced method of fluorescein revealing and digital plaque picture analysis was developed in response to a desire to improve the sensitivity of plaque identification. The method is based on fluorescein adherence to plaque followed by computerized measurement of the fluorescent component. Fluorescein [FDandC yellow No. 8] is a UV fluorescent dye that has been shown to penetrate plaque and reveal it. The idea behind employing a fluorescent dye is that it will reveal plaque that is a distinct color [yellow green] from the surrounding dark oral hard and soft tissues when exposed to long wave UV light. In this method, digital image techniques may be used to analyze photographs of the teeth, and the amount of plaque can be properly assessed. This approach can be used to measure denture hygiene and study patient hygiene habits. Because the fluorescein approach is more sensitive, it can examine fewer levels of plaque and find minor differences between treatments[9].

Fluorescence spectroscopy for plaque screening, which uses a 405 nm excitation light, is a robust and efficient way to monitor dental health, identifying three bacteria based on spectral intensity ratios [510/635 and 500/635 nm] with 99 percent sensitivity and specificity. UV radiation was used to irradiate the endogenous fluorophores, which then emitted visible light. The Stokes shift is the energy difference between the absorption wavelength and the fluorescence wavelength. Dental plaque can be detected using this fluorescent feature. The red glow was discovered in a biofilm and was thought to be caused by porphyrins made by bacterial metabolites. Dental caries, oral malodor, and dental plaque have all been detected using red fluorescence[10]. The use of various fluorescent dyes in a single gel is a simpler method for quantifying various sets of proteins or peptides as multiple bacterial- and host-derived mediators [e.g., collagen-degrading enzymes, elastase-like enzymes, etc.] produced in saliva and gingival crevicular fluid in periodontitis can be used as diagnostic markers for detection of periodontitis[11]

Hyperspectral Microscopy

To capture the fluorescence spectra of microorganisms, the hyperspectral microscopy system [HMS][12] was created. A microscope system and a hyperspectral imaging system [HIS] make up the majority of the HMS. An inverted microscope, a CCD camera, and two emission light sources, including a halogen and a mercury source, make up the microscopy system. An eyepiece is included, as well as picture output ports on the left and right sides of the observation glass. The HIS is attached to the left-side output port, while the CCD is connected to the right- side output port. In the experiment, a halogen source was employed to provide excitation lights in various bands. The excitation band was determined based on the provided excitation filter. The excitation light is reflected by the dichromatic mirror and then passed through the objective lens [OBL] to irradiate a sample. After being irradiated, the sample is stimulated and creates fluorescence. The emission filter and the OBL are where the fluorescence travels. The beams splitter 1 splits the fluorescence into two halves. The CCD or eyepiece receives one component, while the HIS receives the other. A relay lens, a stepping motor, a spectrometer, and an electron- multiplying charge-coupled device [EMCCD] camera comprise the HIS. To convey images from one side to the other, the relay lens is made up of numerous symmetrical lenses. The image is inverted laterally and vertically. To regulate the location of the relay lens, the stepping motor controls the coil current and magnetizes the opposing rotor at a specific angle. It has the advantage of being able to rotate precisely. By moving the relay lens, the system scans the target, allowing the target to be measured without changing the target or the system. The splitting system splits the light into spectra ranging from 400 to 1000 nanometers. It encompasses all visible light as well as a portion of ultraviolet and near-infrared radiation. The electrical gain function of the EMCCD allows the charge to multiply through the gain register and enhance the weak signal, making it easier to gather weak fluorescence signals and identify organisms[13]. This method helped in calculus detection where experimental results showed that the diagnostic model's accuracy, sensitivity, and specificity for identifying four different caries stages and calculus were 98.6%, 98.4%, and 99.6%, respectively[14].

Convoluted Neural Network

Deep learning-based plaque detection is gaining prominence these days. The dental plaque detection model was created with a standard neural network [CNN] framework and fine-tuned with realistic images utilizing transfer learning techniques. Genuine teeth were photographed, then re-photographed with a revealing chemical. The tooth areas were marked and resized using the LabelMe software. Before the computer program was utilized to perform the disclosing procedure, LabelMe was used to mark the plaque locations on the revealing photographs, and the marked regions were transferred to photos of the teeth. From these photographs, the AI model was able to learn the characteristics of dental plaques.

When compared to an experienced dentist, this AI model was able to detect dental plaque on the major teeth at clinically acceptable levels. This discovery signifies that similar AI technologies could be utilized to assist children in improving their oral health[15]. Studies on this technology revealed that the diagnostic accuracy for classifying normal versus disease was 73.0%, and 59% for the classification of the levels of severity of the bone loss and this deep CNN algorithm [VGG-16] was useful to detect alveolar bone loss in periapical radiographs, and has a satisfactory ability to detect the severity of bone loss in teeth[16]

The Fiber-Optic Endoscopy

Only one device, Perioscopy [Perioscopy Inc., Oakland, CA, USA], employs the fiber-optic endoscopy-based technology for calculus detection. Perioscopy is a small periodontal endoscope that is introduced into the periodontal pocket for sub gingival root surface viewing at magnifications of 24–48x. A 10,000-pixel fiber optic bundle with a 1mm diameter, several illumination fibers, a light source, an irrigation system, and a liquid crystal display monitor make up this system. The sub gingival root surface, tooth structure, and residual calculus may all be seen in real time with this automated method. The magnified images can also be viewed in real time on a display, and images and films can be saved in computer files. Furthermore, during instrumentation, this endoscope-based approach may aid in recognizing and finding residual calculus spots [17,18]. Perioscopy was also used as adjunct to non-surgical periodontal therapy which provided a slight benefit to the outcomes of non-surgical therapy particularly at deeper probing depths[19].

Spectro-Optical Technology Based System

The only tool that uses spectro-optical technology to detect calculus is DetecTar [Dentsply Professional, York, PA, USA]. This automated system is made up of a light-emitting diode, an optical fiber, a computer, and this device, which comes in the form of a portable cordless hand piece with a curved periodontal probe with millimeter markings to measure pocket depths. Because of absorption, reflection, and diffraction, red light shined on the sub gingival calculus produces a particular spectral signature. The spectrum signals are detected by an optical fiber and converted to an electrical signal, which is then analyzed by a computer system. The sub gingival root surface can be scanned tactilely and without pressure using this device. The operator receives the information via audio and visible indications as soon as calculus is detected[20].

Auto fluorescence Based System

The fluorophores emitted by dental calculus and carious lesions are found in oral bacteria and their metabolites, such as porphyrins, metalloporphyrins, and other chromatophores[21]. Calculus can be identified by irradiating it with light of a specific wavelength, which causes it to emit fluorescent light.Based on this auto luminescent characteristic of calculus, a revolutionary diagnostic gadget, the Diagnodent [KaVo, Biberach, Germany], has been developed. The equipment was created to identify cavities in the first place. Later, the method was refined to enable for the detection of calculus. Diagnodent can measure a wide range of fluorescence intensities, which are subsequently converted and shown on a digital display as relative calculus-detection values ranging from 0- 99. This technology also allowed early detection of dental biofilm plaque, and its meticulous removal has been directly responsible for the prevention of this disease[22].

Laser Technology Based System [key laser]

Because of its capacity to ablate both soft and hard tissue without creating major thermal adverse effects, the Er: YAG laser has long been considered the most promising for periodontal therapy. The automated system uses a 655-nm InGaAs diode laser for calculus identification and a 2940-nm Er: YAG laser for calculus removal. The Er: YAG laser is triggered when the diode laser's threshold value exceeds 0-99. As soon as the reading goes below the threshold value, the treatment laser switches off. This Key laser 3 mechanism aids in the elimination of calculus and decreases the negative effects associated with Er: YAG laser [23,24]. Diode Lasers are being used as photo disinfectants also, recently 30secs irradiation of diode laser with 1W power killed Aggregatibacter actinomycetemcomitans in vitro[25].

Deep CNN to Diagnose Bone Loss

A unique hybrid architecture has been presented to identify and categorize periodontal bone loss in each individual tooth automatically. The framework employs a hybrid of deep learning architecture and classical CAD processing for detection. On panoramic radiographs, deep learning was utilized to detect the radiographic bone level [or the CEJ level] as a basic structure for the entire jaw. The next step was to combine the tooth long-axis with the periodontal bone and CEJ levels in a percentage rate study of radiographic bone loss. Periodontal bone loss was classified using the percentage rate method. On panoramic radiographs, the suggested method can aid dental professionals in diagnosing and monitoring periodontitis in a systematic and exact manner. As a result, it has the potential to significantly improve dental practitioners' performance in terms of diagnosing and treating periodontitis[26]. CAD is projected to become a more useful and efficient diagnostic tool when more high-quality image datasets are accumulated and new algorithms are applied [27].

CNN with Momentum Optimization

The CNN model is made up of five convolution layers, five pooling layers, one fully connected layer, and one output layer. Input data is the information extracted from an actual image by data processing processes. To discover features in the convolution layer, convolution and rectified linear unit [ReLU] techniques are utilized. Pooling layer can be done in two ways: max-pooling and average-pooling. A 2x2 window reduces the entire image to 1/4 size in Max-pooling, while a 7x7 window reduces the data to 1x1x512 size in Average-pooling. A linear transformation is performed by the Fully-connected layer. The softmax approach is employed in the output layer to estimate the final output value as a categorical distribution, and a computation procedure is performed to make the sum equal to 1. ReLU is used in the hidden layer, softmax is used in the output layer, and cross-entropy is used in the loss function. This CNN Model Structure also included a momentum optimization strategy to speed up the development of neural networks. Because the past gradient values are recorded using exponentially weighted averages, the momentum optimization technique provides for faster and more stable optimization[28].

Machine Learning Classifier [CNN Method]

An auto encoder framework is used with convolutional layers in the deep learning network architecture. Convolutional layers, maximum pooling layers, up sampling, rectified linear unit, and final sigmoid activation make up the network. The goal of the architecture is to figure out how to transfer the input image to the ground- truth gingival inflammation segmentation. To avoid gradient vanishing and speed up learning, residual connections have been used. The classifier uses a single channel binary picture of size 640480 as the ground truth and color-augmented RGB images with dimensions of 640480 pixels as input. The classifier was trained using adaptive gradient descent with momentum and the loss function was dice loss. A single NVIDIA GeForce GTX Titan X GPU was used to train the classifier, which was developed in Tensor Flow. An initial learning rate of 1 106 was employed with a batch size of 32. Every 500 repetitions, the learning rate dropped by a factor of five. 5000 iterations of training were completed. A color-augmented intraoral image is sent into the trained classifier, which produces pixel-by-pixel segmentation. This automated method can employ intraoral pictures at point-of- care settings to detect gingival inflammation early in patients, helping to prevent severe periodontal disease and tooth loss[29,30].

Fractal Analysis

Fractal analysis is a technique for assessing bone trabeculation quantitatively. This technique recognizes complex structural patterns in trabecular bone and uses a measure termed fractal dimension [FD] to quantify the bone's complexity. The intricacy of the alveolar bone structure surrounding the teeth is demonstrated by the calculated FD in the periapical radiograph. The box-counting method is most commonly utilized for binary images such as periapical radiography among the known methods for computing FD. FD is a measure of the number of boxes required to cover the trabecular pattern in this method. A higher FD indicates a more complex trabecular pattern.

The radiographs' DICOM files were transferred to ImageJ for fractal analysis. The apical ROI was chosen as the largest rectangle extending horizontally from the mesial of the mandibular first molar to the most posterior molar or the posterior border of the image and vertically from the molar apexes to the inferior border of the image or the inferior alveolar canal in each radiograph. Rectangles stretching from the alveolar crest to the line connecting the apex of the first molar and its surrounding teeth were chosen as proximal ROIs in the mesial and distal areas. Using the "Clear Outside" tool, selected ROIs were removed out of the original image. To minimize noise, the generated regions were duplicated and a "Gaussian Blur" filter with a sigma of 10 was used to the second image. After that, the filtered image was subtracted from the original image, and a black and white image was created using the "Make Binary" tool. The mean intensity was set to 128 [8-bit picture], and the FD was calculated using the "Fractal Box Count" tool. This approach can be used to assess bone changes in patients with mild to severe periodontitis[31,32]. This technology would effectively detect trabecular microarchitectural differences in patients with aggressive periodontitis compared to periodontally healthy individuals. This technique might be useful in predicting the susceptibility of patients to periodontal disease[33].

Encoder-Decoder Neural Network

This is a neural network based method that would generate implants with much more precision. The implant body was designed with all parameters like radius, neck width, number of healing chambers, height of threads and others. Then the data was converted into matrix with a pixel size of 0.05mm. This data was passed through pooling layers and design was obtained[34]

Multilayer perceptron ANN

This neural network algorithm was able to classify periodontitis by immune response profile to aggressive periodontitis [AgP] or chronic periodontitis [CP] class with accuracy rates of 90%-98%.ANNs can be employed for accurate diagnosis of AgP or CP by using relatively simple and conveniently obtained parameters, like leukocyte counts in peripheral blood

Conclusion

Introduction of tech-advancements like AI, machine learning and convoluted neural networks will improve the precision of diagnosis and will remain as helpful tools for early detection of diseases/etiological factors. They also play a major role in patient compliance and also for professional communication of parameters avoiding bias.

S.no	Author	Year	Result
1.	Jungeun won	2020	OCT has a strong potential to display and assess dental plaque and gingiva in a clinical setting
2.	Surlin	2021	OCT analysis revealed that Non Alcoholic Fatty Liver Disease may be an aggravating factor for the inflammation of periodontal disease.
3.	Shweta bali	2022	Multiple bacterial- and host-derived mediators [e.g., collagen-degrading enzymes, elastase-like enzymes, etc.] produced in saliva and gingival crevicular fluid in periodontitis can be used as diagnostic markers for the condition detected through fluorescence technology
4.	Wang	2023	Detection of spectral, textural and color characteristics of calculus
5.	Alotaibi	2022	CNN technology had the diagnostic accuracy for classifying normal versus disease was 73.0%, and 59% for the classification of the levels of severity of the bone loss
6.	Naicker	2021	perioscope provided a slight benefit to the outcomes of non-surgical therapy particularly at deeper probing depths.
7.	Krause	2021	Diagnodent allowed minute detection of calculus flecks
8.	Joseph	2022	Light induced fluorescence allowed a quality detection of plaque and can be used as a diagnostic tool
9.	Martu	2023	1W diode laser eradicated Aggregatibacter actinomycetemcomitans in vitro
10.	Korkmaz	2022	Fractal analysis effectively detected trabecular microarchitectural differences in patients with aggressive periodontitis compared to periodontally healthy individuals. This technique might be useful in predicting the susceptibility of patients to periodontal disease.

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