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Advancement and Application of Deep Learning on Detection of Peri-Implantitis, a Narrative Review

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Abstract

AI is expanding and thriving quickly across every sector. It can acquire knowledge from handling tasks and human expertise that usually necessitate human-like intelligence. It has also been utilized in dentistry and medicine. Peri-implantitis is a pathological phenomenon observed in tissues surrounding dental implants, marked by inflammation in the peri-implant mucosa and continuous depletion of supporting bone. Recently, developments in advanced implant dentistry, imaging methods and digital transformation have come together to introduce novel dental implantology procedures. For the detection of peri-implant disorders, particularly peri-implantitis, AI employing 2D radiographs can increase patient care in implant dentistry. This narrative review will describe the role of Al in dentistry and medicine, specifically in the detection of peri-implantitis.

Keywords: Deep learning; Peri-implantitis, Artificial intelligence, Image processing.

1. INTRODUCTION

The beginning of the fourth industrial revolution resulted in a new digital epoch where Artificial Intelligence (AI) plays a remarkable and vital role. With an escalating proliferation of electronic devices supporting human life extensively, the data documented by these devices allows convenient examination and utilization of the data originating from those electronic devices via AI. AI is expanding and thriving quickly across every sector. It can acquire knowledge from handling tasks and human expertise that usually necessitate human-like intelligence. Al has discovered applications in various industry sectors, such as smart cities, financial assessment, automobile robots, etc. In addition, it has been utilized in dentistry and medicine, for instance, dental and medical imaging diagnostics, drug discovery, decision aid, digital and precision medicine, hospital supervision, virtual assistants and wearable technology [1].

In numerous instances, artificial intelligence can be recognized as an essential tool to aid clinicians and dentists in decreasing their workload. Apart from diagnosing diseases utilizing a sole information source geared towards a particular illness, Al can attain intelligence from numerous information resources (multi-modal data) to diagnose or detect beyond human abilities. For instance, advancements in artificial intelligence have facilitated the detection and classification of mandibular fractures in panoramic radiography, significantly improving diagnostic accuracy and treatment planning in maxillofacial injuries [2]. Hence, the Al can detect not only ocular ailments, including diabetic retinopathy, using fundus images but also cardiac disease. It appears that AI-driven image analysis is adequate and firm. All of these depend on the swift growth (as a product) of computing potential (hardware), extensive database (input data) and algorithmic research. Based on these considerations, there are substantial opportunities for using AI in the medical and dental field.

Several studies regarding AI applications in dentistry are currently in progress or have already been used in areas including treatment outcome prediction, decision-making, disease prognosis and diagnosis [3–8]. By investigating the role of deep learning in dental and medical contexts, this narrative review seeks to offer an understanding of the possible impact of AI-based methods for detecting peri-implantitis.

1.1 Definition of Artificial Intelligence

The phrase “artificial intelligence” (AI) originated in the 1950s and pertains to developing machines that can execute actions commonly performed by humans. Machine learning (ML) constitutes a subset of AI involving algorithms that perceive the inherent statistical configuration and patterns in data, enabling anticipations of unseen data. A commonly utilized type of ML model is a neural network (NN), which surpasses conventional ML algorithms, especially when dealing with complex data patterns such as language and imagery.

The significant components of NNs are artificial neuron, which represents a mathematical non-linear model derived from the human neuron. By concatenating and assembling artificial neurons and establishing links between those layers utilizing mathematical techniques, a network is constructed to resolve a particular task such as image classification (e.g., a radiographic image displaying a decayed or deteriorated tooth: no or yes).

The phrase “deep learning” signifies deep NN frameworks. These are specifically beneficial for intricate data formats, including imagery, as they can represent an image and its hierarchical attributes, such as macroscopic patterns, shapes, edges and corners. Deep or multi-layered NNs are considered universal approximation systems [9, 10]. In the presence of a series of mathematical constraints, NNs can associate any input and approximate (for instance, an X-ray image displaying a decayed tooth) to a designated output (for example, “decayed tooth”). With sufficient data and substantial computational resources accessible, these kinds of NNs can be instructed to encapsulate the complex statistical patterns within the provided dataset.

Throughout the training process, data points and their associated labels (for classification task) or numeric outcomes (for regression task) are systematically transmitted via NN. Therefore, the connections linking the neurons, also called model weights, are continually optimized to decrease the prediction error (the contrast between predicted and actual outcome). A well-trained NN can anticipate the result of novel data by transmitting the unexplored data point utilizing the network.

Over the last 70 years, AI has been considered both a menace and a chance. In that period, several setbacks happened, commonly called ”AI-winters,” when the prospects in Al technology were unmet by the actual results. Currently, the confidence is higher than previously experienced; the past decade was noted by exceptional breakthroughs in the domain of ML and, into a broader scope, AI. For example, the textual outcome of advanced natural language models turned so compelling that readers cannot differentiate between artificially generated or human-written texts. Face recognition evolved so capable that the ability of technology to impact lawmakers’ civil liberties inspired activists and watchdog groups to act. Ultimately, AI technologies advanced from being an illusion to becoming real; discussions related to effects on healthcare, society, politics and economics are unfolding in several disciplines and fields. Dentistry should be a component of them [11].

1.2 Definition of Peri-Implantitis

Peri-implantitis is a pathological phenomenon observed in tissues surrounding dental implants, marked by inflammation in the peri-implant mucosa and continuous depletion of supporting bone [12, 13].

In the clinical context, the inflammation of soft tissue is identified through probing (BOP or bleeding gums), whereas continuous depletion of bone is detected on radiographic images. Literature on peri-implantitis needs threshold values and case definitions to discriminate:

1) disease and health, and
2) peri-implantitis and mucositis. It is vital to note that, despite substantial variation in the approach peri-implantitis is characterized in different studies, [14] the definition of the condition remains..

1.3 Applications of Deep Learning in the Field of Medicine and Dentistry

Over the past few years, there have been significant strides in deep and machine learning, resulting in their growing integration into various consumer-oriented technologies like web search engines, cameras, and smartphones. Concurrently, healthcare digitalization, such as the generation of digitalized healthcare data, including imagery and records, has enabled the growing implementation of deep and machine learning in dentistry and medicine [15, 16]. Below are some studies that highlight the application of deep learning in medicine and dentistry.

Casalegno et al. (2019) proposed a deep-learning model for diagnosing caries in TI images (near-infrared transillumination). Their CNN (convolutional neural network) attained a notable mean intersection-over-union of approximately 72.7% on a task of 5-class segmentation, comprising specific IOU scores of 49.0% and 49.5% for occlusal and proximal carious lesions. During simplified studies, high accuracy was demonstrated by the model, consisting of the area under the ROC curve (receiver operating characteristic) values of 85.6% and 83.6% for proximal and occlusal lesions. This investigation highlights the capability of deep learning to enhance the accuracy of caries detection remarkably, advantageous for both patient and dental practitioner outcomes [17].

Celik (2023), in their study, explored the use of deep learning technology to automatically detect periapical lesions in panoramic dental radiographs. The dataset included 454 entities from 357 PRs, diligently pre-processed and tagged to ensure optimal analysis. Several deep learning options were examined, with RetinaNet as the most effective method. Outcomes highlighted the capability of deep learning in effectively recognizing periapical lesions, highlighting the impact of deep understanding in progressing dental healthcare for both healthcare systems and clinicians [18].

Another study conducted by Yuma Miki et al. (2017) Applied deep learning, particularly a DCNN (deep convolutional neural network) model, to expedite the classification of teeth in cone-beam computed tomography (CT) images. They attained an accuracy of approximately 88.8% in classifying different types of teeth. The performance of DCNN was enhanced by 5% with the aid of data augmentation, highlighting the possibility of further enhancement. This investigation displays how deep learning, even without meticulous tooth segmentation, can expedite dental charting and fortify forensic identification methodologies, pointing toward the utility of artificial intelligence in dentistry [19].

In a study, Brosch et al. (2013) introduced a new method for examining 3D brain images employing deep learning. In contrast to traditional approaches, it doesn't depend on predetermined similarity measures or linear manifold arrangements. Instead, it uses DBNs, also called deep belief networks, previously regarded as computationally challenging for interpreting 3D images. This investigation offers a practical DBN training approach, allowing the assessment of brain high-resolution brain volumes. This study demonstrates that DBNs can detect low-dimensional brain volume patterns associated with demographic and medical attributes. This method shows potential for understanding anatomical differences in medical images [20].

Alipanahi et al. [21] suggested DeepBind, a deep framework utilizing CNNs to estimate RNA- and DNA-binding proteins. In the presented investigation, DeepBind exhibited the capability to retrieve novel and recognized sequence patterns, quantify the impact of sequence adjustments and detect functional SNVs (functional single nucleotide variations). Zhou and Troyanskaya [22] utilized CNNs to anticipate chromatin marks based on DNA sequence. Correspondingly, Kelley et al. [23] established Basset as an accessible platform to expect DNase I hypersensitivity involving several cell types and evaluating the impact of SNVs on the accessibility of chromatin.

Hammerla et al. [24] assessed RNNs and CNNs with LSTM to anticipate the gait freezing in individuals with Parkinson's disease (PD). Freezing is considered a prevalent motor issue in PD, where impacted persons encounter to initiate actions like walking. Results derived from accelerometer data from areas above the knee, above the ankle, and the trunk of around ten individuals indicated that RNNs provided the best outcomes, with a markedly substantial improvement compared to other models, such as CNNs.

2. DISCUSSION

Advanced dentistry is dedicated to utilizing advanced therapeutic approaches to increase the durability of teeth. Nevertheless, tooth loss still occurs due to various factors, including periodontal disease—an alternative for tooth replacement dental implants [25]. However, patients encounter different complications, such as peri-implantitis. Below is a detailed discussion of AI in implant dentistry and the role of 2D radiographs in detecting bone loss and peri-implantitis.

2.1 Step-by-Step Processing of an Image by a CNN

1. **Input image**
    - The image is fed into the CNN. Typically, the image has three color channels (Red, Green, Blue) and dimensions (height x width).
2. **Preprocessing**
    - Resizing: The image is resized to a fixed dimension required by the CNN (e.g., 224x224 pixels).
    - Normalization: Pixel values are normalized, usually by dividing by 255 to bring them in the range [0, 1].
3. **Convolutional layer (Conv Layer)**

- Convolution Operation: The image is convolved with a set of filters (kernels). Each filter slides over the image, performing element-wise multiplication and summing the results to produce a feature map.
- Activation Function (ReLU): A Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity. ReLU replaces negative values with zero and keeps positive values unchanged.

4. **Pooling layer (Downsampling)**
    - Max Pooling: A pooling operation, typically max pooling, reduces the spatial dimensions of the feature map. It retains the most important information by taking the maximum value from a defined window (e.g., 2x2) and sliding it across the feature map.
5. **Stacking layers**
    - Multiple convolutional and pooling layers are stacked. Each convolutional layer learns increasingly complex features (edges, textures, shapes, etc.), while pooling layers progressively reduce the spatial dimensions.
6. **Flattening**
    - After several convolutional and pooling layers, the 2D feature maps are flattened into a 1D vector. This vector represents the learned features and is fed into the fully connected layers.
7. **Fully connected layer (Dense Layer)**
    - Dense Layer: The flattened vector is passed through one or more fully connected layers. Each layer performs a weighted sum of the inputs followed by an activation function, typically ReLU.
    - Activation Function (ReLU): Again, a ReLU activation function introduces non-linearity.
8. **Output layer**
    - Softmax Activation: For classification tasks, the final fully connected layer uses a softmax activation function. This function converts the output into a probability distribution over the classes.
    - Sigmoid Activation: For binary classification tasks, a sigmoid activation function is used to output a probability between 0 and 1.
9. **Prediction**
    - The output layer provides the final class probabilities. The class with the highest probability is selected as the prediction.

2.2 Advancement of AI in the Field of Implant Dentistry

Recent developments in advanced implant dentistry, imaging methods and digital transformation have come together to introduce a novel dental implantology procedure: guided implant dentistry or CAI (Computer-assisted implant dentistry). Through the utilization of this innovative approach, a digitally produced guide is employed during surgical processes. The virtual placement is transferred to the dental patient as a drilling template, facilitating the establishment of implant depth and slope. Specifically, implant insertion can be performed without the surgical guide template (merely via pre-clinical virtual analysis of implant placement) or via a fully guided method (utilizing the 3D printed template that originates from the virtual implant position during the surgical procedure).

While designing the digital guide, implants are positioned without contradicting the basic principle of advanced implantology, which states that the prosthetic design determines the implant's position and, thus, the surgical process. The significant benefit of using a surgical template is to enhance the accuracy of implant insertion and to decrease trauma, pain, swelling and surgery time for patients. Conclusively, it leads to a diminished healing time for patients [26]. Considering the problematic angles and the limited visibility during dental surgery, inserting implants accurately without a template can result in clinicians mistakenly cutting patients' gum or positioning implants, leading to different oral health issues and millions of dollars utilized on processing insurance claims. Due to this reason, digital-guided dental implant surgery has witnessed growing use in recent years, supporting both reliable patient care and consistent implant position [27, 28].

2.3 Explanation of Peri-Implantitis

Peri-implantis can associated with uneven distribution of chewing force on the peri-implant tissues, thus resulting in inflammatory processes, destabilization of the artificial supports and infection of peri-implant tissues [29]. Dental implant failure is often correlated with failure in osseointegration. An implant is regarded as a failure if it is mobile, lost or displays significant bone loss surpassing 1.0 mm during the first year and exceeding 0.2 mm annually. Peri-implantitis can lead to bone recession encircling the implant, ultimately leading to implant removal. The preferred outcome of peri-implantitis therapy is rejuvenating the compromised implant's supporting soft and hard tissues [30].

Bacterial infections are regarded as the predominant factor behind implant failure. The microbial flora linked to peri-implantitis and periodontitis exhibit resemblances [31]. The microorganisms frequently associated with implant failure are the Gram-negative anaerobic bacteria, such as Fusobacterium nucleatum, Porphyromonas gingivalis, Bacteroides forsythus, Prevotella nigrescens, Prevotella intermedia and Treponema denticola [31, 32]. Peri-implant tissue is a vital biological defense against factors leading to peri-implant disorders. Bacterial infections can lead to swift bone degeneration if this defense is compromised. Excessive mechanical pressure, suboptimal dental implant design, and corrosion resulting from a non-noble metal framework linked to a titanium dental implant are crucial elements in the development and onset of peri-implantitis. Other etiological features include radiation, corticoid therapy, chemotherapy, diabetes mellitus, smoking and osteoporosis (due to increased osteoclasts).

The given symptoms and signs are usual for peri-implantitis lesions: radiographic evidence of crystal bone vertical destruction. The defect typically exhibits a saucer shape, and the apical segment of the fixture displays osseointegration; vertical bone loss occurs concurrently with peri-implant pocket formation, bleeding on probing potential peri-implant tissue swelling, and hyperplasia. Pain is considered an atypical characteristic; if it exists, it's usually correlated with infection. Peri-implantitis diagnosis requires distinguishing it from peri-implant mucositis, early problems in attaining tissue integration, and issues lacking inflammation. The diagnostic techniques for evaluating peri-implantitis include suppuration, peri-implant radiography, rigorous plastic probe examination, clinical indices, microbiology and bleeding on probing (BOP) [33, 34].

3. DETECTION OF PERI-IMPLANTITIS AND BONE LOSS USING 2D RADIOGRAPHICAL IMAGES

Recently, a range of extra-oral and intraoral techniques has been accessible to aid in evaluating periodontal patients. Typically utilized two-dimensional (2D) modalities consist of panoramic, periapical and bitewing radiography. These techniques are applicable as they are easily obtained, economical, and yield high-resolution images [35]. Danks et al. observed that the AI-based periapical radiographic imaging technique can detect landmarks and periodontal bone loss [36].

The modern periapical radiographic technique is recommended. Panoramic radiographs (PRs) also can detect peri-implantitis. A study observed that a CNN can diagnose peri-implant marginal bone loss on 2D periapical radiographic images with preciseness comparable to that of a dental professional. This season suggests that CNN and 2D periapical radiographic images are beneficial in detecting peri-implantitis [37, 38].

A reference position that serves as a threshold for a sound bone level must exist in order to quantify the degree of bone loss. The use of a baseline radiograph is advised following physiologic remodeling, which is typically at the time of prosthesis installation unless immediate loading is carried out, in order to assess the changes in the level of the crestal bone, according to the 7th and 8th European Workshop on Periodontology [39, 40]. Nevertheless, a baseline radiograph is frequently unavailable in clinical settings. Such scenarios were covered in earlier research. When there is no prior radiograph, a vertical distance of 2 mm from the predicted marginal bone level is advised as a criterion, according to the agreement of the 8th European Workshop on Periodontology [39].

Cha et al. demonstrated that the Mask R-CNN model's capacity to assess the degree of bone loss on radiographs for diagnosing peri-implantitis has advanced to the expert level following fine-tuning using a machine learning technique and 708 periapical radiographic images, based on transfer learning. Thus, dentists can receive assistance in detecting and classifying peri-implantitis by using the automated technique based on this model [41].

4. LIMITATION

In this narrative review evaluating the use of deep learning in detecting peri-implantitis, it is essential to recognize specific constraints inherent in this task. While AI displays substantial prospects in the dental and medical fields, such as implant dentistry, several restrictions require consideration:

1. The dynamic evolution of Al and its uses requires acceptance of possible improvements beyond the scope of this review.
2. Peri-implantitis may not be fully acquired using 2D radiographs, restricting the comprehensiveness of the evaluation.
3. The need for studies on peri-implantitis and 2D radiographs can hinder the widespread use of this technique. There are needs for larger datasets with much more images to better train the algorithms.
4. Because the boundaries of the bones surrounding implants are frequently ambiguous and because three-dimensional bone levels must be realized from a two-dimensional image, clinical settings and determining the peri-implant marginal bone level on radiographs are difficult and by themselves are not sufficient to determine, much less predict, peri-implant bone loss or future implant failure. When it comes to seeing craters, furcation flaws, and bone deformities, CBCT is seen to be an advantageous technique. If machine learning can use CBCT data along with other radiographs to detect peri-implant, then CBCT will have greater use. However, compared to a 2D picture like a periapical imaging, a CBCT will require a lot more radiation.
5. The beginning of peri-implantitis is another barrier to peri-implant diagnosis. The following conditions must be met in order to diagnose peri-implantitis: bleeding and/or suppuration on light probing. deeper pocket probe penetration than in earlier tests. bone loss in excess of the crestal bone level alterations brought on by the early remodeling of the bone. Machine learning is able to forecast the beginning of peri-implantitis more accurately than detection techniques.

5. CONCLUSION

In summary, this review focuses on the potential of deep learning for peri-implantitis diagnosis in implant dentistry. Although promising, it's essential to acknowledge limitations, Including the evolving state of artificial intelligence and the necessity for detailed data sources. Nevertheless, using AI for early detection employing 2D radiographs displays an exciting potential to increase patient care in implant dentistry. Embracing advanced technologies and encouraging collaborations between dental professionals and AI experts can be crucial to realizing this capability in clinical applications.

References

[1] Stevenson A. Oxford Dictionary of English. Oxford University Press. 2010.

[2] Yari A, Fasih P, Hosseini Hooshiar MH, Goodarzi A, Fattahi SF. Detection and Classification of Mandibular Fractures in Panoramic Radiography Using Artificial Intelligence. Dento Maxillo Facial Rad. 2024:twae018.

[3] Khanagar SB, Al-ehaideb A, Maganur PC, Vishwanathaiah S, Patil S, et al. Developments, Application, and Performance of Artificial Intelligence in Dentistry – A Systematic Review. J Dent Sci. 2021;16:508-522.

[4] Khanagar SB, Al-Ehaideb A, Vishwanathaiah S, Maganur PC, Patil S, et al. Scope and Performance of Artificial Intelligence Technology in Orthodontic Diagnosis, Treatment Planning, and Clinical Decision-Making—a Systematic Review. J Dent Sci. 2021;16:482-492.

[5] Mahmood H, Shaban M, Indave BI, Santos-Silva AR, Rajpoot N, et al . Use of Artificial Intelligence in Diagnosis of Head and Neck Precancerous and Cancerous Lesions: A Systematic Review. Oral Oncol. 2020;110:104885.

[6] Farook TH, Jamayet NB, Abdullah JY, Alam MK. Machine Learning and Intelligent Diagnostics in Dental and Orofacial Pain Management: A Systematic Review. Pain Res Manag. 2021;2021:6659133.

[7] AbuSalim S, Zakaria N, Islam MR, Kumar G, Mokhtar N, et al . Analysis of Deep Learning Techniques for Dental Informatics: A Systematic Literature Review. Healthcare . 2022;10:1892.

[8] Yari A, Fasih P, Goodarzi A, Nouralishahi A, Nikeghbal D. The Effect of Augmented Reality Book on the Proficiency of Local Anesthesia Administration of the Inferior Alveolar Nerve. J Dent Educ. 2024:1-9.

[9] Israni ST, Verghese A. Humanizing Artificial Intelligence. JAMA. 2019;321:29-30.

[10] Dashti M, Londono J, Ghasemi S, Moghaddasi N. How Much Can We Rely on Artificial Intelligence Chatbots Such as the ChatGPT Software Program to Assist With Scientific Writing? J Prosthet Dent. 2023;S0022-3913:00371-003722

[11] Dashti M, Ghasemi S, Khurshid Z. Role of Artificial Intelligence in Oral Diagnosis and Dental Treatment. Eur J Gen Dent. 2023;12:135-137.

[12] Lang NP, Berglundh T. Periimplant Diseases: Where Are We Now?–Consensus of the Seventh European Workshop on Periodontology. J Clin Periodontol. 2011;11:178-181.

[13] Lindhe J, Meyle J. Group D of European Workshop on Periodontology. Peri-Implant Diseases: Consensus Report of the Sixth European Workshop on Periodontology. J Clin Periodontol. 2008;35:282-285.

[14] Tomasi C, Derks J. Clinical Research of Peri-Implant Diseases—Quality of Reporting, Case Definitions and Methods to Study Incidence, Prevalence and Risk Factors of Peri-Implant Diseases. J Clin Periodontol. 2012;39:207-223.

[15] Mohammad-Rahimi H, Rokhshad R, Bencharit S, Krois J, Schwendicke F. Deep Learning: A Primer for Dentists and Dental Researchers. J Dent. 2023;130:104430.

[16] Londono J, Ghasemi S, Hussain Shah A, Fahimipour A, Ghadimi N, et al. Evaluation of Deep Learning and Convolutional Neural Network Algorithms Accuracy for Detecting and Predicting Anatomical Landmarks on 2D Lateral Cephalometric Images: A Systematic Review and Meta-Analysis. Saudi Dent J. 2023;35:487-497.

[17] Casalegno F, Newton T, Daher R, Abdelaziz M, Lodi-Rizzini A, et al. Caries Detection With Near-Infrared Transillumination Using Deep Learning. J Dent Res. 2019;98:1227-1233.

[18] Çelik B, Savaştaer EF, Kaya HI, Çelik ME. The Role of Deep Learning for Periapical Lesion Detection on Panoramic Radiographs. Dento Maxillo Facial Rad. 2023;52:20230118.

[19] Miki Y, Muramatsu C, Hayashi T, Zhou X, Hara T, et al. Classification of Teeth in Cone-Beam CT Using Deep Convolutional Neural Network. Comput Biol Med. 2017;80:24-29.

[20] Brosch, T. Manifold Learning of Brain Mris by Deep Learning. Medical Image Computing and Computer-Assisted Intervention: Miccai ... International Conference on Medical Image Computing and Computer-Assisted Intervention.2013;16:633-640.

[21] Alipanahi B, Delong A, Weirauch MT, Frey BJ. Predicting the Sequence Specificities of Dna-And Rna-Binding Proteins by Deep Learning. Nat Biotechnol. 2015;33:831-838.

[22] Zhou J, Troyanskaya OG. Predicting Effects of Noncoding Variants With Deep Learning-Based Sequence Model. Nat Methods. 2015;12:931-934.

[23] Kelley DR, Snoek J, Rinn JL. Basset: Learning the Regulatory Code of the Accessible Genome With Deep Convolutional Neural Networks. Genome Res. 2016;26:990-999.

[24] Hammerla NY, Halloran S, Ploetz T. Deep, convolutional, and recurrent models for human activity recognition using wearables. 2016. ArXiv preprint: https://arxiv.org/pdf/1604.08880

[25] Mauer RG, Shadrav A, Dashti M. Predictability of Dental Implants. In: Stevens, M.R., Ghasemi, S., Tabrizi, R. (eds) Innovative Perspectives in Oral and Maxillofacial Surgery. Springer, Cham. 2021:35-45.

[26] Da Silva Salomão GV, Chun EP, Panegaci RD, Santos FT. Analysis of Digital Workflow in Implantology. Case Rep Dent. 2021;2021:6655908.

[27] Tallarico M, Scrascia R, Annucci M, Meloni SM, Lumbau AI, et al. Errors in Implant Positioning Due to Lack of Planning: A Clinical Case Report of New Prosthetic Materials and Solutions. Materials. 2020;13:1883.

[28] Mauer RG, Shadrav A, Dashti M. Static Surgical Guides and Dynamic Navigation in Implant Surgery. In: Parhiz SA, James JN, Ghasemi S, Amirzade-Iranaq MH, Editors. Navigation in Oral and Maxillofacial Surgery. Cham: Springer. 2022.135-150.

[29] Georgiev T. Method of Treatment of Periimplantitis. JIMAB Annu Proceeding.2009.

[30] Smiler D, Soltan M. The Bone-Grafting Decision Tree: A Systematic Methodology for Achieving New Bone. Implant Dent. 2006;15:122-128.

[31] Heydenrijk K, Meijer HJ, van der Reijden WA, Raghoebar GM, Vissink A, et al . Microbiota Around Root-Form Endosseous Implants: A Review of the Literature. Int J Oral Maxillofac Implants. 2002;17:829-838.

[32] Shibli JA, Martins MC, Lotufo RF, Marcantonio E, Jr. Microbiologic and Radiographic Analysis of Ligature-Induced Peri-Implantitis With Different Dental Implant Surfaces. Int J Oral Maxillofac Implants. 2003;18:383-390.

[33] Kazemifard S, Dashti M. Molecular and Cellular Basis of Bone. In: Stevens, M.R., Ghasemi, S., Tabrizi, R. (eds) Innovative Perspectives in Oral and Maxillofacial Surgery. Springer, Cham. 2021.7–10 https://doi.org/10.1007/978-3-030-75750-2_2

[34] Prathapachandran J, Suresh N. Management of Peri-Implantitis. Dent Res J. 2012;9:516-521.

[35] Bagis N, Kolsuz ME, Kursun S, Orhan K. Comparison of Intraoral Radiography and Cone-Beam Computed Tomography for the Detection of Periodontal Defects: An in Vitro Study. BMC Oral Health. 2015;15:64.

[36] Danks RP, Bano S, Orishko A, Tan HJ, Moreno Sancho F, D'Aiuto F et al. Automating Periodontal Bone Loss Measurement via Dental Landmark Localisation. Int J Comput Assist Rad Surg. 2021;16:1189-1199.

[37] Ramanauskaite A, Juodzbalys G. Diagnostic Principles of Peri-Implantitis: A Systematic Review and Guidelines for Peri-Implantitis Diagnosis Proposal. J Oral Maxillofac Res. 2016;7:e8.

[38] Cha JY, Yoon HI, Yeo IS, Huh KH, Han JS. Peri-Implant Bone Loss Measurement Using a Region-Based Convolutional Neural Network on Dental Periapical Radiographs. J Clin Med. 2021;10:1009.

[39] Sanz M, Chapple IL, Working Group 4 of the VIII European Workshop on Periodontology. Clinical Research on Peri-Implant Diseases: Consensus Report of Working Group 4.J Clin Periodontol;2012;39;Suppl 12:202-206.

[40] Lang NP, Berglundh T, Working Group 4 of Seventh European Workshop on Periodontology. Periimplant Diseases: Where Are We Now?–Consensus of the Seventh European Workshop on Periodontology. J Clin Periodontol;. 2011;11:178-181.

[41] Cha JY, Yoon HI, Yeo IS, Huh KH, Han JS. Peri-Implant Bone Loss Measurement Using a Region-Based Convolutional Neural Network on Dental Periapical Radiographs. J Clin Med. 2021;10:1009.