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Original Research Paper

Dentistry

THE NEW ERA OF DENTISTRY: MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

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ABSTRACT Innovative computer techniques are now being utilized not only in academic research but also in commercial dental practice, revolutionizing various areas of dentistry. This digitalization trend is driven by the increasing demands for treatment and diagnosis in the field. Accurate diagnosis is crucial in dentistry, whether it be in orthodontics, maxillofacial surgery, periodontics, or prosthetics, as it forms the basis for creating effective treatment plans and restoring patients' oral health. While a specialist's expertise plays a vital role in diagnosis and treatment planning, it is susceptible to the inherent risks of human error, given the multifactorial nature of dental conditions. Consequently, there is growing interest in leveraging multi-parametric pattern recognition methods, including statistics, machine learning, and artificial intelligence (AI), to enhance clinical decision-making. The introduction of clinical decision support systems (CDSS) and genetic algorithms (GAs) in dental research and clinical practice holds great promise for both healthcare professionals and patients. Extensive work has been undertaken to develop CDSS in dentistry, and this article reviews the latest advancements in this field.

KEYWORDS : Dentistry, Clinical Decision Support System, Machine learning, Artificial intelligence.

INTRODUCTION

Digitalization in dentistry has experienced significant growth over the past decade or two. Particularly in developing countries facing a shortage of medical and dental professionals, there is a growing need for technology, particularly artificial intelligence (AI) software, to bridge the gap. Implementing AI can lead to reduced costs, time requirements, reliance on human expertise, and instances of medical errors. Within oral health care, computational methods like artificial intelligence and machine learning have emerged to address diagnostic and prognostic challenges [1]. Machine learning, a subset of artificial intelligence, utilizes data-driven approaches to develop models that require fewer decisions by the modeler compared to traditional techniques [2]. This capacity to develop prediction models and analyze complex, non-linear, and high-dimensional data has made machine learning widely accepted [3]. It can be efficiently applied in healthcare for disease diagnosis, medical image analysis, big data collection, research and clinical trials, management of health records, and disease outbreak prediction [4]. As the demand for new prognostication systems utilizing machine learning is expected to rise, it is crucial to critically evaluate these emerging methods. In the field of dental science, machine learning finds diverse applications depending on specific needs. These range from addressing dental emergencies and providing differential diagnosis for oral pain to interpreting radiographic images, analyzing facial growth in orthodontics, and planning personalized prosthetics. Despite the recognized demand for clinical decision support systems (CDSS), their production has been limited and slow. Challenges in programming development, cost, skepticism about their value and feasibility, and a lack of formal evaluation have contributed to this situation.

Application Of Machine Learning In Dentistry:

1. Orthodontics:

1. A. Need of an extraction during treatment: The diagnosis of extractions using neural network (NN) machine learning methods has shown promise in the field of dentistry. Neural networks are computational models inspired by the human brain that can learn patterns and make predictions based on input data. The algorithms may identify patterns and make accurate predictions regarding the need for extractions, the complexity of the extraction procedure, and potential complications. These algorithms have the potential to improve the accuracy of diagnosis, reduce errors, and enhance treatment planning for extractions.[5] The computational formulation of orthodontic tooth-extraction decisions involves the application of computational methods, such as machine learning algorithms, to aid in the decision-making process related to tooth extraction in orthodontic treatment. These methods utilize patient-specific data, including dental records, cephalometric radiographs, and 3D imaging, to develop models that can assist orthodontists in determining the need for tooth extraction and the optimal teeth to extract. Machine learning algorithms can analyze a wide range of factors, including dental crowding, tooth size discrepancies, skeletal relationships, and soft tissue profiles, to predict the potential outcomes of different tooth-extraction scenarios. Through computational formulation, orthodontists can benefit from a more objective and evidence-based approach to tooth-extraction decision-making. This approach can enhance treatment outcomes, reduce the risk of complications, and optimize treatment efficiency by helping orthodontists make informed decisions regarding tooth extraction in alignment with individual patient needs. [6]

1. B. For prediction of size of un-erupted canine and pre-molars: The design and implementation of a hybrid Genetic Algorithm (GA) and Artificial Neural Network (ANN) system can be utilized to predict the sizes of un-erupted canines and premolars in orthodontic treatment planning. This hybrid approach combines the optimization capabilities of GA with the pattern recognition and learning abilities of ANN. By leveraging the optimization capabilities of GA and the learning capabilities of ANN, this system may improve orthodontic outcomes. [7]

1. C. Cephalometric analysis: Cephalometric analysis is commonly used in orthodontics and maxillofacial surgery to assess craniofacial structures and aid in treatment planning. However, the interpretation of cephalometric radiographs can be complex and subjective, leading to potential diagnostic uncertainties. [8] A paraconsistent ANN is a type of neural network that can handle inconsistent or contradictory information, which is often encountered in cephalometric analysis due to anatomical variations and measurement errors. [9] It enhances the diagnostic process by reducing subjective biases and increasing the objectivity of assessments. [10]

1. D. For predicting mandibular morphology: The mandible morphology plays a crucial role in determining the skeletal relationship between the upper and lower jaws, and accurate prediction of its shape. It can aid in guiding orthodontic interventions. [11] Automated learning techniques, such as machine learning and artificial intelligence algorithms, provides insights into the extent of mandibular growth and can guide decisions regarding the use of orthodontic appliances, surgical interventions, or other treatment modalities. [12]This can lead to improved treatment outcomes by aligning the treatment plan with the patient's specific skeletal class and mandibular characteristics. [13]This saves valuable time for orthodontists, allowing them to focus on other aspects of patient care. Additionally, it can reduce the cost associated with complex manual assessments and provide a more efficient workflow.

2. Conservative Dentistry And Prosthodontics:

2. A. Dental restoration: Modeling the longevity of dental restorations using a Case-Based Reasoning (CBR) system offers a promising approach. [14] A CBR system considers the specific characteristics of each dental restoration case, including patient factors (e.g., age, oral health status), restoration materials used, treatment techniques, and follow-up data. [15] The system can identify patterns and trends that contribute success and failure of the restorations. The CBR system can assist dentists in treatment planning by providing insights into the expected lifespan of different restoration options. [16]

2. B. Colour matching in restoration/ Prosthesis: The prediction in computer color matching of dentistry using a combination of Genetic Algorithm (GA) and Backpropagation to achieve accurate color matching in dental restorations. [17] It enhances the precision and reliability of color predictions, assisting clinicians in achieving desirable and consistent color outcomes for dental restorations. [18]

2. C. Fabrication of Removable partial denture: An ontology-driven, case-based clinical decision support model for removable partial denture (RPD) design utilizes ontologies and case-based reasoning to provide support and guidance in the process of designing RPDs. [19] It facilitates the design process, enhances decision-making, and promotes consistency and best practices in RPD treatment. [20]

2.D.Teeth whitening procedure: A decision support system for predicting color change after tooth whitening is provide guidance and predictions regarding the expected color change in teeth following a whitening procedure. By this system, dental professionals can make more informed treatment decisions and communicate realistic expectations to patients. This enhances patient satisfaction with the whitening outcomes. [21]

3. Periodontology:

3. A. Diagnosis of periodontal disease: Diagnosing periodontal diseases using classification algorithms can be a valuable approach in dental practice. These algorithms analyze patient data and help in the identification and classification of different types and stages of periodontal diseases. The program introduced a groundbreaking diagnostic tool for periodontal diseases, providing substantial support with exceptional accuracy. This innovative approach has opened up new avenues in the field of identifying and classifying periodontal diseases. [22]

3. B. Diagnosis of aggressive periodontitis with immunologic parameters: Artificial Neural Networks (ANNs) have emerged as a promising method for diagnosing aggressive periodontitis, particularly when trained using immunologic parameters. Aggressive periodontitis is a severe form of periodontal disease characterized by rapid progression and destruction of the periodontal tissues. By incorporating immunologic parameters, which include various biomarkers and immune response indicators, ANNs can effectively capture the complex relationships between these parameters and the diagnosis of aggressive periodontitis. [23]

3. C. Diagnosis of malodor micro flora: Supervised machine learning-based classification of oral malodor using microbiota in saliva samples has emerged as a promising approach. Oral malodor, commonly known as bad breath, is often caused by the imbalance of microbial communities in the oral cavity. By leveraging the power of machine learning algorithms, it becomes possible to analyze the microbiota composition in saliva samples and accurately classify individuals based on their oral malodor status. [24]

4. Prediction of aphthous ulcer occurrence and recurrence: Recurrent aphthous ulceration, also known as recurrent aphthous stomatitis or canker sores, is a common oral condition characterized by the recurrence of painful ulcers in the oral mucosa. The utilization of GA-optimized Neural Networks (NNs) holds promise in predicting recurrent aphthous ulceration, patient's medical history, lifestyle factors, genetic markers and more precise prediction of ulceration risk for each individual. [25]

5. Diagnosis of temporomandibular disorders (TMD): TMD refers to a group of disorders affecting the temporomandibular joint and associated muscles, causing pain and dysfunction in the jaw area. Bayesian Belief Network (BBN) analysis has shown promise in determining the progression of Temporomandibular Disorders (TMD) using Magnetic Resonance Imaging (MRI) data. By applying BBN analysis to MRI findings, it becomes possible to assess the likelihood and severity of TMD progression. [26] The use of Artificial Neural Networks (ANNs) has been explored in differentiating subgroups of Temporomandibular Internal Derangements (TMD-ID). TMD-ID refers to a group of disorders affecting the temporomandibular joint (TMJ) that involve structural abnormalities or dysfunction of the TMJ's internal structures. ANNs can be employed to classify and differentiate between different subgroups of TMD-ID based on various clinical and imaging parameters. [27]

6. Dental surgery:

6. A. Detection of vertical root fracture [VRF]: High-resolution and well-annotated dental radiographs or cone beam computed tomography (CBCT) scans are necessary to diagnose the vertical toot fracture. For the detection of VRF in CBCT, Artificial Neural Networks(ANN) can be useful. Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), can be employed to extract and learn complex patterns like root morphology, texture patterns, change in density and other developmental anomalies in dental images. [28]

6. B. Decision making in dental treatment: A Computerized Decision Support System (CDSS) for dental treatment is a valuable tool that aids dental professionals in making informed and evidence-based decisions regarding patient care. It incorporates clinical guidelines, scientific research, and patient-specific data to provide recommendations and assistance throughout the treatment process. [29]

6. C. Dental implant: A Computerized Decision Support System (CDSS) can help in the development of personalized treatment plans for dental implant placement. CDSS can assist in the design and fabrication of surgical guides for precise implant placement. It uses advanced imaging techniques, such as cone beam computed tomography (CBCT), to generate 3D virtual models of the patient's jaw. These models are used to plan and simulate implant placement, ensuring optimal positioning and angulation. A CDSS can recommend suitable implant systems and components. It takes into account factors like implant size, design, surface characteristics, and material composition, ensuring compatibility and long-term success. CDSS can assess the patient's risk factors and potential complications associated with dental implant treatment. It considers factors such as systemic health, oral hygiene, bone quality, and parafunctional habits to evaluate the patient's suitability for implant placement. It can provide recommendations to mitigate risks and optimize treatment outcomes. A CDSS can assist in the design of implant-supported restorations. It considers factors such as occlusion, esthetics, and functional requirements to recommend appropriate prosthetic designs, including crown or bridge materials, implant-abutment connections, and restoration types (e.g., screw-retained or cement-retained). CDSS can provide guidance on the sequencing and timing of dental implant treatment in complex cases. It considers factors such as extractions, bone grafting procedures, and orthodontic treatment, ensuring a comprehensive and well-planned treatment approach. CDSS can enhance patient education by providing visual aids, explanatory materials, and personalized treatment plans. It helps patients understand the implant treatment process, potential outcomes, and post-operative care requirements. This improves patient engagement and satisfaction. CDSS can assist in documenting treatment plans, procedures, and outcomes. It aids in maintaining comprehensive patient records and facilitates long-term follow-up and monitoring of implant success and maintenance requirements. [30]

7. Oral Cancer: The prognosis of oral cancer can be improved by incorporating clinic-pathologic and genomic markers and utilizing a hybrid approach that combines feature selection techniques with machine learning methods. By leveraging relevant features and employing advanced computational algorithms, this approach can help predict the prognosis and outcomes of oral cancer patients more accurately. [31] Hyper nasality is a condition characterized by excessive nasal resonance during speech production, which can occur as a result of structural changes or functional impairments following cancer treatment. Artificial Neural Network (ANN) analysis can be utilized to assess hyper nasality in patients who have undergone treatment for oral or oropharyngeal cancer. By leveraging ANNs, which are computational models inspired by the human brain's neural networks, it is possible to develop predictive models for hyper nasality assessment.[32] Fuzzy Logic(FL) models can generate risk assessments and provide recommendations for further investigation, preventive measures, or referral to specialists. [33]

8. Diagnostic Aid for Oral Pathology: Machine learning algorithms have shown promise as diagnostic aids in the field of oral pathology. By analyzing various data inputs including clinical features, radiographic images, and histopathological findings, these algorithms can help clinicians in the accurate and efficient diagnosis of oral diseases. [34]The algorithms can learn patterns and correlations from large datasets, enabling them to provide valuable insights and support to healthcare professionals in making timely and precise diagnostic decisions. [35]

CONCLUSION:

Machine learning algorithms in dentistry should be developed and validated using robust and diverse datasets, and the results should always be interpreted by dental professionals. Machine learning algorithms are supportive tools that enhance the capabilities of dentists, but they do not replace the expertise and judgment of human practitioners. As technology continues to evolve and more data becomes available, the scope of machine learning in dentistry is expected to expand further. However, it is crucial to ensure ethical considerations, data privacy, and validation of machine learning algorithms in real-world dental practice to ensure their safe and effective use. Collaboration between dental professionals, researchers, and data scientists will be essential to harness the full potential of machine learning in dentistry.

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