Artificial Intelligence in the Diagnosis of Oral Diseases

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Today, artificial intelligence (AI) has been suggested useful in disease diagnosis, predicting prognosis, or developing patient-specific treatment strategies. Particularly, AI can assist dentists in making time-sensitive critical decisions. It can remove the human element of error in decision-making, providing a superior and uniform quality of health care while reducing the stress load on the dentists.

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1. Dental Caries

Dental caries is the most prevalent disease across the globe. Early diagnosis is key in decreasing caries-related indisposition in patients. Caries diagnosis is exceedingly based on visual cues and radiographic data. This visual data can be a form of input dataset for machine learning (ML). Devito et al. (2008) evaluated the efficiency of a multi-layer perceptron neural network in diagnosing proximal caries in bitewing radiographs and concluded that the diagnostic improvement was 39.4% [1]. Lee et al. (2018) used 3000 periapical radiographs to evaluate the efficacy of deep convolutional neural networks to identify dental caries. High accuracy of 89%, 88%, and 82% was observed in the premolar, molar, and both the premolar-molar regions [2]. Hung et al. (2019) conducted a study with the test and training set comprised of data obtained from the National Health and Nutrition Examination Survey. Supervised learning methods were used to classify the data based on the presence or absence of root caries. Among the various ML methods used in their study, the support vector machine (SVM) showed the best performance in identifying root caries [3].

Similarly, the clinical imaging data from various sources have been used in AI models for diagnosing dental caries with excellent results. In 2019, a study examined the use of convolutional neural networks (CNN) to identify dental caries in near-infrared transillumination images. CNN increased the speed and accuracy of caries detection [4]. Cantu et al. (2020) used bitewing radiographs to assess the performance of a deep learning (DL) network in detecting carious lesions. A total of 3686 radiographs were used, out of which 3293 were used for training while 252 were used as test data. The deep neural network showed higher accuracy compared to dentists and can be used to detect initial caries lesions on bitewing radiographs [5] Park et al. (2021) tested ML prediction models for the detection of early childhood caries compared to traditional regression models. Data of 4195 children (1–5 yrs) were obtained from the Korea National Health and Nutrition Examination survey (2007–2018) and analyzed. ML-based prediction models were able to detect ECC, predict high-risk groups, and suggest treatment, similar to traditional prediction models [6].

2. Tooth Fracture

The third most common reason for tooth loss is traumatized or cracked teeth. Early detection and treatment can save a cracked tooth and help retain it. However, cracked teeth often present with discontinuous symptoms, making their detection problematic. Conventional techniques, such as CBCT and intraoral radiographs, have low sensitivity and clarity. Paniagua et al. (2018) developed a novel method capable of detecting, quantifying, and localizing cracked teeth using high-resolution CBCT scans with steerable wavelets and machine learning methods. The performance of ML models was tested using Hr-CBCT scans of healthy teeth with simulated cracks. ML models showed high specificity and sensitivity [7]. Fukuda et al. (2020) used CNN to detect vertical root fractures using 300 panoramic radiographs with 330 vertically fractured teeth with visible fracture lines. Moreover, 80% of the data was used for training while 20% was used as a test data set. Results suggest that CNN can be used as a diagnostic tool for the detection of vertical root fractures [8].

3. Periodontal Diseases

Periodontal disease affects more than a billion people globally, destroying alveolar bone and leading to tooth loss. Early diagnosis of periodontal disease using AI can improve the dental status of the patient and improve their overall health and quality of life. Ozden et al. (2015) examined the use of a support vector machine (SVM), decision tree (DT), and ANN to identify and classify periodontal disease. Data from a total of 150 patients were used, 100 as training data and 50 as test data. The three systems classified the data into six types of periodontal conditions. SVM and DT were more accurate as diagnostic support tools compared to ANN [9]. Nakano et al. (2018) used deep learning (DL) to detect oral malodor from microbiota. A total of 90 patients, 45 patients with weak or no malodor, and 45 patients with marked malodor were selected using organoleptic tests and gas chromatography. Gene analysis of the amplified 16s rRNA from the patient's saliva was carried out. DL was used to classify the samples into malodor and healthy breath. DL showed a predictive accuracy of 97% compared to SVM, which showed 79% [10]. ANN has been used to predict the occurrence of recurrent aphthous ulcers. Gender, serum B12, hemoglobin, serum ferritin, folate levels, candida count in saliva, tooth brushing frequency, the number of fruits and vegetables consumed daily, were related to the occurrence of ulcers [11] Danks et al. (2021) used a deep neural network to measure periodontal bone loss with the help of periapical radiographs. Periapical radiographs of single, double, and triple rooted teeth obtained from 63 patients were used. First, the DNN was trained to detect dental landmarks on the radiographs, and then the periodontal bone loss was measured using these landmarks by the DNN model. The system achieved a total percentage of correct key points of 89.9%. The system showed promising results, which can be further improved upon by experimentation and cross-validation with extended data sets [12] Similarly, a DL model was used to detect and measure periodontal bone loss from panoramic images, which was then used for staging periodontitis. The performance of the DL model was compared to that of three oral radiologists. The staging was done according to the new classification of periodontal and peri-implant disease and conditions [13]. A total of 340 panoramic radiographs were used out of which 90% were used for training while 10% were used for testing. Data augmentation was carried out to increase the data by 64%. The DL model had high accuracy and excellent reliability, suggesting that it can be used for the automatic diagnosis of periodontal disease and as a routine surveillance tool [14].

4. Maxillary Sinus Diseases

The maxillary sinuses are structures that are commonly visualized using extraoral radiographs. Automated identification of the sinuses and detection of any pathology in them by AI can lead to a manifold decrease in misdiagnoses. AI can be used as a tool to assist inexperienced dentists. Murata et al. (2018) evaluated the performance of a DL system in diagnosing maxillary sinusitis using panoramic radiographs. The AI performance was compared to that of two radiologists and two residents. The diagnostic performance of the system was similar to that of the radiologists. However, the AI was superior to dental residents [15]. Kim et al. (2019) used radiographs of the maxillary sinus in Water's view to evaluate the diagnostic performance of the DL system. AI showed a statistically significant improved sensitivity and specificity to radiologists [16]. Mucosal thickening and mucosal retention cysts are often missed by radiologists. Kuwana et al. (2021) used OPG to detect and classify lesions in the maxillary sinus using a DL object detection technique. Detection of the normal maxillary sinus and inflamed maxillary sinus showed 100% sensitivity, whereas the detection sensitivity of mucosal retention cysts was 98% and 89% in the two test data sets that were used. This DL model can be reliably used in a clinical setup [17]. A recent study proposed a CNN model to assist radiologists. The CNN model is capable of detecting and segmenting mucosal thickening and mucosal retention cysts of the maxillary sinus using CBCT images. A total of 890 maxillary sinuses from 445 patients were used in the study. Low dose images were used for training and testing, while full-dose images were used as test data sets. The CNN model performed effectively in both dosage images with no significant difference [18].

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