Review Article

ARTIFICIAL INTELLIGENCE IN ORAL PATHOLOGY PRACTICE– AN OVERVIEW

Nagjyothi Kariamal[1], Punnya Vaijanath Angadi[1]*

[1] *Department of Oral Pathology and Microbiology, V.K. Institute of Dental Sciences, KLE Academy of Higher Education and Research (KAHER), Belgaum-590010, Karnataka, India. punnya_angadi@rediffmail.com*

https://doi.org/10.51847/AQAJtO9N1U

ABSTRACT

Despite more recent medical achievements and a significant amount of information on various diseases, it is impossible to anticipate disease diagnosis and progress accurately. The advent of artificial intelligence (AI) has opened up many new possibilities for healthcare improvement and has ushered in a new era of increased exactitude in pathology. Artificial intelligence (AI) can be helpful in the diagnosis of diseases, in making prognostications, or in creating patient-specific treatment plans. AI can help pathologists in particular when they need to make important judgements quickly. It can eliminate human mistake from the judgement process, resulting in improved and standardised health care while diminishing the strain on the doctor. Pathologists are going to employ AI to find specific imaging indicators connected to disease processes in order to improve early diagnosis, ascertain prognosis, and select the treatments that are most likely to be successful. In the upcoming years, this trend is frequently anticipated to continue and change the pathology landscape. Given the ageing population and rising patient volume, as well as the fact that there is a dearth of pathologists globally, this is especially crucial. Even though AI models have been effective, it has taken a while for them to be translated from research to clinical use. AI and pathologists working together can produce outcomes that are superior to what humans are capable of in terms of accuracy, consistency, timeliness, and utility. This review presents the components, emerging techniques and applications of AI in oral pathology.

Key words: Artificial intelligence, Pathology, Digital pathology, Oral pathology.

Introduction

The amalgamation of artificial intelligence (AI) in healthcare will be the biggest revolution in medicine and pathology, right at the center of this development. The earliest change evidenced over the years includes the large reliance on digital pathology, which is becoming a progressively more imperative technological requisite in laboratory settings in most countries. Pathologists can now manage digital data owing to advances in computer resources, faster networks, and more affordable storage. Slide photos can now be shared for telepathology and clinical use with greater simplicity and versatility than in previous years [1, 2]. However, the growth evidenced in pathology has not extended to oral pathology, with digital pathology still in its infancy here.

Digital pathology involves the creation of virtual slides using Whole-slide scanners, and these digitized whole-slide images are analyzed using computer methods. The whole slide scanners came into existence more than two decades earlier. Still, the origins of the digitalization of pathology date back to 1960, when Prewitt and Mendelsohn established a system that scanned the microscopic images of a conventional blood smear preparation and converted these images based on their optical density values into various spatial relationships, which allowed categorization of different cells present in the image [3-5].

McCarthy *et al*. first adopted the phrase "artificial intelligence" (A.I.) in the 1950s to refer to computer science, where machine-based techniques are used to simulate what a rational person would do in a certain circumstance, such as making a prediction [6-8].

Artificial intelligence (AI) has been cited as being helpful in the diagnosis of diseases, in making prognostications, or in creating patient-specific treatment plans. AI can help pathologists, particularly when they need to make important judgments quickly. It can eliminate human mistakes from the judgment process, resulting in improved and standardized health care while diminishing the strain on the doctor [9]. This review outlines the components, recent applications, and advancements of artificial intelligence in digital oral pathology.

Units of artificial intelligence

Machine learning

Any Pathology AI (Artificial Intelligence) system must have machine learning, which enables a task to be learned from data (without being directly designed). Machine learning techniques ' primary goal is creating a model that may be used for categorization, prediction, approximation, or any other similar activity.

ML techniques fall into two categories: supervised learning and unsupervised learning. In supervised learning, the input data are approximated or matched to the intended output using a labeled training data set. Unsupervised learning techniques don't give out labeled samples or know the results after completing the learning. It is up to the training instances or model to identify the groups or characteristics in the incoming data. Semi-supervised learning combines supervised and unsupervised learning, is another class of ML techniques that has seen extensive use. To build a precise learning model, it integrates labeled and unlabelled data. This type of learning is typically employed if there are more unidentified datasets than identified [10, 11].

Deep learning
Deep learning, which is accurately referred to as a subfield of machine learning, is thought to be the most recent evolution of machine learning. All of the preceding machine learning applications can be achieved with deep understanding. Still, it also has more sophisticated capabilities, decision-making abilities, and the ability to handle big datasets. Convolutional, pooling and fully linked layers make up CNN compositions. The convolutional layer's main function is recognizing patterns, lines, and other features like edges. Convolutional layers in each of CNN's hidden layers convolve the input array with weight-parameterized convolution cores. The cores provide numerous feature images and enable success in various vision tasks, including segmentation and classification [12, 13].

Artificial intelligence in oral pathology workflow
In routine clinical practice, pathologists make histological diagnoses by analyzing the slide for its morphological features, semi-quantifying the relevant components, and visually recognizing the pathology. However, this histopathological analysis has inherent subjectivity, and considerable differences may be observed in visual perception and judgment among individual oral pathologists, leading to variation and lack of standardization in diagnosing wide-ranging lesions. Further, this problem is intensified by the emergence of non-invasive and minimally invasive biopsies, which are presently in trend that reduce the size and quality of samples received. The introduction of numerous immunohistochemical markers and genomics components for diagnosing various lesions adds to the dilemma due to the lack of uniform reporting guidelines. Thus, A.I.-based approaches, thought to be more robust and reproducible, may serve as a foundation for assuaging these challenges faced by pathologists [1, 2]. Some applications for improving the workflow include quality control and quality assurance, improving the pathology workstream, triaging cases into high/low priority, and automated requests for additional investigations. This may lead to faster processing times and reduced errors during specimen handling, thus enhancing the efficiency of the services.

Artificial intelligence in clinical oral pathology
AI can be integrated with clinical data, patient demography, and histopathological and genetic data that can efficiently and accurately diagnose. Therefore, it is imperative to adopt a more encompassing approach with input from A.I. researchers, pathologists, and other participants like oncologists and surgeons while training the algorithms [14, 15].

An effective screening test that can be applied in primary care settings is needed to improve the effectiveness of secondary or tertiary care referrals. This should distinguish the commonly encountered benign lesions without any malignant potential and potentially malignant oral lesions (PMOLs) at "risk" for becoming cancerous or those with a heightened risk for cancer progression [16].

A minimally invasive brush cytology sample has been developed to analyze cell specimens using the Point-of-Care Oral Cytology Tool. The cell suspension obtained is subjected to a sophisticated image recognition program and pattern recognition techniques aided by cutting-edge statistical techniques, enabling the concurrent quantitative measurement of cell morphologic information and the appearance of molecular biomarkers of malignant potential in an automated manner. This advanced procedure produces cytology findings quickly instead of the typical histopathology preparation of slides that may take days, making it appropriate for screening. This test will allow dental professionals and primary care dentists to avoid the need for numerous referrals and appointments before acquiring an assessment of the molecular risk of PMOL, which is likely to affect the management of the disease significantly [16].

The Mobile Mouth Screening Anywhere (MeMoSA) app, developed by Kingston University of UK and University of Malay scientists, takes pictures of the mouth for expert remote interpretation. Following the training of a Deep learning algorithm that can distinguish between photos with and without oral cancer symptoms in dozens of images, the app has included the algorithm. The implementation of Artificial intelligence into MeMoSA, according to Professor Dr. Sok Ching Cheong of Cancer Research Malaysia, offers huge potential in assuring that the measures allow for timely identification in areas that show high prevalence of this disease [17-19].

Artificial intelligence in oral histopathology
A.I. has been demonstrated to increase agreement among pathologists in a variety of contexts, including the evaluation of certain subjective features like nuclear and cellular pleomorphism in the cells and degree of dysplasia, amount of cellularity, and assessment of mitotic figures, grading of

tumors infiltrating lymphocytes, and assessment of proliferation using Ki-67 levels [14].

Das *et al*. presented a two-stage method for computing oral histology images using a 12-layered deep convolution neural network (CNN) that separates component levels in the primary and secondary stages. From these isolated keratin areas, developed random forests of the Gabor filter are employed to locate the keratin pearls. When utilizing these random forest classifiers to recognize keratin pearls, detection accuracy was reported to be 96.88 percent overall [17, 20].

A Convolutional neural network-operated automatic computer-aided hyperspectral image detection method was used to classify OSCC by Jeyaraj and Nadar. OSCC vs. benign lesions image classification accuracy for this system was 91 percent overall, and OSCC vs. normal tissue image classification accuracy was 95 percent overall [17, 21].

Only a few research have examined oral squamous cell carcinoma digital histopathologic images for machine learning techniques. A computer-assisted histomorphometry classifier based on nuclear morphology was developed by Lu *et al*. (2017). By using a digitized tissue microarray to analyze 2mm sections of OSCC (115), an ML classifier was able to identify cases at high and moderate risk for disease-specific survival with an AUC (0.72). This study yielded a low specificity (71%) and sensitivity (62%), but it demonstrated the potential of analyzing even small amounts of tissue [21, 22].

Using AI-based techniques on potentially malignant oral disorders offers tremendous potential to improve OSCC early detection. Shamim *et al*. 2019 trained deep-learning convolutional networks for classification tasks using an annotated information base of clinical and histopathological photos of potentially malignant and benign tongue lesions. In this investigation, their model was able to differentiate between potentially malignant and benign tongue lesions with a mean classification accuracy of 0.98 [21, 23].

Artificial intelligence in prognosis in oral pathology

Many studies have been conducted about prognostic systems for anticipating the survival of patients and local recurrence in OSCC patients in order to improve the prognostication of oral cancer [21, 24-27].

These models examined huge information repositories of Oral cancer patients using AI-based methods. Still, the scope of the data analysis was restricted to demography, clinical correlation, or genetic data. In 2013, Chang *et al*. created an OSCC prognostication model that included genomic data of p53 and p63 outcomes from IHC slides and clinicopathologic material. Their model, which used machine learning techniques, produced an AUC (0.90) in the prognosis of OSCC depending on the presentation, marker(P63), and alcoholic intake [21, 28].

Shabana *et al*. (2019) created a special Deep-learning method to measure cancer infiltrating lymphocytes utilizing whole slide images of oral Squamous cell carcinoma. They reached an efficiency of ninety-six percent.

Eventually, all morphological traits detected individually by pathologists should be combined into a single classification system to describe the type and behavior of tumors. These may offer crucial directions for patient care and targeted therapy heading in the future [21].

Limitations and challenges in adoption of AI in oral pathology

Adopting AI image models in everyday oral pathology practice has taken longer than anticipated despite their preliminary success in pathology and other medicinal areas. The 'black box' nature of these models, which makes it difficult to comprehend why the algorithm generates certain estimates, is probably one of the main causes of this issue. Algorithm developers are attempting to incorporate feedback from the algorithms' customers to boost the acceptance of A.I. applications for regular use. Although the expansion of the pathologic sector in A.I. to include cancer severity evaluation and prognosis prediction is intriguing, a significant amount of data is still required to create A.I. that may be used in various healthcare settings. It is still necessary to assess the medical relevance of integrating A.I. technologies into the histopathological practice and its impact on the outcomes, as well as their pricing system [14, 29-32].

Further, the perception that A.I. may replace the pathologists lingers in many minds. However, this notion is not particularly true since the final say will always be with the pathologist. However, AI can assist in enhancing the accuracy and speed of diagnosis in heavy workflow conditions where the pathologist may get overwhelmed by the sheer amount of work, leading to inadvertent errors.

Conclusion

The creation and application of Automated tools, such as image-based algorithms that are utilized in pathology, has increased significantly, and it is anticipated that they will soon rule the area of oral pathology, too. AI and pathologists working together can produce outcomes that are superior to what humans are capable of in terms of accuracy, consistency, timeliness, and utility. Artificial intelligence applications will also enable more sophisticated diagnostics, allowing developers and healthcare practitioners to exchange expertise and employ automated systems to evaluate and offer insightful contributions that could eventually result in a more thorough pathology diagnosis. The future of precision oncology will benefit from this combination, which has the potential to produce personalized care plans.

Acknowledgments: None

Conflict of interest: None

Financial support: None

Ethics statement: None

References

1. Niazi MKK, Parwani AV, Gurcan MN. Digital pathology and artificial intelligence. Lancet Oncol. 2019;20(5):e253-e61.
2. Farahani N, Parwani AV, Pantanowitz L. Whole slide imaging in pathology: advantages, limitations, and emerging perspectives. Pathol Lab Med Int. 2015;7:23-33.
3. Prewitt JM. Intelligent microscopes: recent and near-future advances. InRecent and Future Developments in Medical Imaging II 1979 Dec 26 (Vol. 206, pp. 206-219). SPIE.
4. Prewitt JMS. Parametric and nonparametric recognition by computer: an application to leukocyte image processing. Adv Comput. 1972;12:285-414.
5. Prewitt JM, Mendelsohn ML. The analysis of cell images. Ann N Y Acad Sci. 1966;128(3):1035-53.
6. McCarthy J, Minsky ML, Rochester N, Shannon CE. A proposal for the Dartmouth summer research project on artificial intelligence. AI Mag. 2006;27(4):12-6.
7. McCarthy JJ, Minsky ML, Rochester N. Artificial intelligence. Research Laboratory of Electronics (RLE) at the Massachusetts Institute of Technology (MIT); 1960. Available from: https://dspace.mit.edu/handle/ 1721.1/52263 (1959).
8. Bera K, Schalper KA, Rimm DL, Velcheti V, Madabhushi A. Artificial intelligence in digital pathology - new tools for diagnosis and precision oncology. Nat Rev Clin Oncol. 2019;16(11):703-15.
9. Patil S, Albogami S, Hosmani J, Mujoo S, Kamil MA, Mansour MA, et al. Artificial Intelligence in the Diagnosis of Oral Diseases: Applications and Pitfalls. Diagnostics (Basel). 2022;12(5):1029-32.
10. Kourou K, Exarchos TP, Exarchos KP, Karamouzis MV, Fotiadis DI. Machine learning applications in cancer prognosis and prediction. Comput Struct Biotechnol J. 2014;13:8-17.
11. Pang-Ning T, Steinbach M, Kumar V. Introduction to data mining; 2006. 2nd Edition, Web book: https://www-users.cse.umn.edu/~kumar001/dmbook/index.php
12. Jiang Y, Yang M, Wang S, Li X, Sun Y. Emerging role of deep learning-based artificial intelligence in tumor pathology. Cancer Commun (Lond). 2020;40(4):154-66.
13. Choi RY, Coyner AS, Kalpathy-Cramer J, Chiang MF, Campbell JP. Introduction to Machine Learning, Neural Networks, and Deep Learning. Transl Vis Sci Technol. 2020;9(2):14. doi:10.1167/tvst.9.2.14
14. Rakha EA, Toss M, Shiino S, Gamble P, Jaroensri R, Mermel CH, et al. Current and future applications of artificial intelligence in pathology: a clinical perspective. J Clin Pathol. 2021;74(7):409-14.
15. Ali HR, Dariush A, Provenzano E, Bardwell H, Abraham JE, Iddawela M, et al. Computational pathology of pre-treatment biopsies identifies lymphocyte density as a predictor of response to neoadjuvant chemotherapy in breast cancer. Breast Cancer Res. 2016;18(1):21.
16. McRae MP, Modak SS, Simmons GW, Trochesset DA, Kerr AR, Thornhill MH, et al Point-of-care oral cytology tool for the screening and assessment of potentially malignant oral lesions. Cancer Cytopathol. 2020;128(3):207-20.
17. Krishna AB, Tanveer A, Bhagirath PV, Gannepalli A. Role of artificial intelligence in diagnostic oral pathology-A modern approach. J Oral Maxillofac Pathol. 2020;24(1):152-6.
18. Park A. Researchers Training AI Mobile App to Detect Early Signs of Oral Cancer. Available from: https://oralcancernews.org/wp/researchers training ai mobile app to detect early signs of oral cancer/. [Last accessed on 2022 Sep 30].
19. Can Artificial Intelligence Spot Warning Signs of Oral Cancer? Kingston University Experts Develop System for Mobile Phone App in New Study. Available from: https://www.kingston.ac.uk/news/ article/2201/04 jun 2019 can artificial intelligence spotwarning signs of oral cancer kingston universityexperts develop system for/. [Last accessed on 2022 Sep 30].
20. Das DK, Bose S, Maiti AK, Mitra B, Mukherjee G, Dutta PK. Automatic identification of clinically relevant regions from oral tissue histological images for oral squamous cell carcinoma diagnosis. Tissue Cell. 2018;53:111-9.
21. Sultan AS, Elgharib MA, Tavares T, Jessri M, Basile JR. The use of artificial intelligence, machine learning and deep learning in oncologic histopathology. J Oral Pathol Med. 2020;49(9):849-56.
22. Lu C, Lewis JS, Dupont WD, Plummer WD, Janowczyk A, Madabhushi A. An oral cavity squamous cell carcinoma quantitative histomorphometric-based image classifier of nuclear morphology can risk stratify patients for disease-specific survival. Mod Pathol. 2017;30(12):1655-65.
23. Shamim M, Syed S, Shiblee M, Usman M, Ali S. Automated detection of oral precancerous tongue lesions using deep learning for early diagnosis of oral cavity cancer. Comput J. 2022;65(1):91-104.
24. Karadaghy OA, Shew M, New J, Bur AM. Development and Assessment of a Machine Learning Model to Help Predict Survival Among Patients With Oral Squamous Cell Carcinoma. JAMA Otolaryngol Head Neck Surg. 2019;145(12):1115-20. doi:10.1001/jamaoto.2019.0981
25. Bur AM, Holcomb A, Goodwin S, Woodroof J, Karadaghy O, Shnayder Y, et al. Machine learning to predict occult nodal metastasis in early oral squamous cell carcinoma. Oral Oncol. 2019;92(2):20-5.

26. Alabi RO, Elmusrati M, Sawazaki-Calone I, Kowalski LP, Haglund C, Coletta RD, et al. Machine learning application for prediction of locoregional recurrences in early oral tongue cancer: a Web-based prognostic tool. Virchows Arch. 2019;475(4):489-97.
27. Arora A, Husain N, Bansal A, Neyaz A, Jaiswal R, Jain K, et al. Development of a New Outcome Prediction Model in Early-stage Squamous Cell Carcinoma of the Oral Cavity Based on Histopathologic Parameters With Multivariate Analysis: The Aditi-Nuzhat Lymph-node Prediction Score (ANLPS) System. Am J Surg Pathol. 2017;41(7):950-60.
28. Chang SW, Abdul-Kareem S, Merican AF, Zain RB. Oral cancer prognosis based on clinicopathologic and genomic markers using a hybrid of feature selection and machine learning methods. BMC Bioinform. 2013;14(1):170-4.
29. Benitez JM, Castro JL, Requena I. Are artificial neural networks black boxes? IEEE Trans Neural Netw. 1997;8(5):1156-64.
30. Hartman DJ, Pantanowitz L, McHugh JS, Piccoli AL, OLeary MJ, Lauro GR. Enterprise implementation of digital pathology: feasibility, challenges, and opportunities. J Digit Imaging. 2017;30:555-60.
31. Madabhushi A, Lee G. Image analysis and machine learning in digital pathology: challenges and opportunities. Med Image Anal. 2016;33:170-5.
32. Tizhoosh HR, Pantanowitz L, Intelligence A. Artificial intelligence and digital pathology: challenges and opportunities. J Pathol Inform. 2018;9(1):38-9.