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Review Article

Assistance of Artificial Intelligence in the Early Detection of Oral Cancer is Transforming Diagnosis Methods

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Abstract

The early diagnosis of cancer is pivotal for effective clinical management and Artificial Intelligence (AI) shows promise in enhancing the diagnostic process. This study aimed to advance the understanding of AI's application in the early diagnosis of oral cancer. A comprehensive literature search focused on non-invasive early diagnosis of oral cancer using AI during screening. Previous studies primarily focused on image-based detection methods (including optical imaging, enhancement technology, and cytology) aided by AI models. These studies exhibited heterogeneity, with each employing different algorithms, potentially leading to training data biases and limited comparative data for AI interpretation. While AI shows promise for accurately predicting oral cancer development, several methodological challenges must be addressed alongside AI advancements to enable widespread integration into population-based detection protocols..

Keywords: Oral Cancer; Artificial Intelligence; Screening; Early Diagnosis; Machine Learning; Deep Learning

Abbreviations

AI: Artificial Intelligence; HPV: Human Papillomavirus; OPMD: Potentially Malignant Oral Disorders; ML: Machine Learning; DL: Deep Learning; NNs: Neural Networks; ANNs: Artificial Neural Networks; OSCC: Oral Squamous Cell Carcinoma; CT: Computed Tomography; MRI: Magnetic Resonance Imaging; CNN: Convolutional Neural Networks; OSF: Oral Submucosal Fibrosis; NBI: Narrow-Band Imaging

Introduction

Oral cancer exhibits one of the lowest survival rates among cancers globally, and despite recent therapeutic advancements, only slight improvements have been observed. The World Health Organization Global Cancer Observatory-GLOBOCAN data in 2020 reported 377,713 newly diagnosed lip and oral cancer cases, comprising 264,211 men and 113,502 women. The mortality rate stood at 177,757, with 125,022 men and 52,735 women succumbing to the death [1,2]. Numerous cases of oral and oropharyngeal cancers have been identified during the late stages of disease progression, leading to unnecessary suffering and death [3]. Hence, early detection of lesions is crucial to enhance the likelihood of successful treatment. Late-detected cancers or those with challenging access routes are associated with lower survival rates, increased treatment complexities, and higher medical expenses [4,5].

An enhanced disease understanding, risk factors, and symptoms could positively influence the diagnosis by enabling the identification of potential malignancy signs that might have been overlooked or insufficiently evaluated [4-6]. Subsequently, diligent control measures are necessitated for well-established risk factors for oropharyngeal cancers such as smoking, alcohol abuse, and human papillomavirus (HPV) infection [7].

Recent technological advancements have resulted in significant transformations in the healthcare sector. The advent of digital medicine is anticipated to reshape the practices of healthcare professionals via enhanced engagement with innovative information and communication technologies [8,9]. Artificial Intelligence (AI) assists the decision-making process by enabling rapid analysis and interpretation of vast amounts of data within seconds. Innovations in digital technology are advantageous for healthcare professionals, healthcare systems, and patients equally [10]. AI has led to notable progress in the field of oncology. This study conducted a review to explore usefulness of AI combined with non-invasive techniques for the early diagnosis of oral cancer and it proposes avenues for future investigation in this field.

Early diagnosis vs late diagnosis

PPotentially malignant oral disorders (OPMD) are characterized by any abnormalities in the oral mucosa with a statistically increased risk of developing oral cancer. There are pathologies which classified as OPMD such as: oral leukoplakia, erythroplakia, proliferative verrucous leukoplakia, oral lichen planus, oral submucosal fibrosis, oral lichen planus, actinic keratosis, oral lichenoid lesions, palatal lesions in reverse smokers, oral lupus erythematosus, dyskeratosis congenita, epidermolysis bullosa, oral lichenoid lesions, and oral chronic graft-versus-host disease [11]. Identifying lesions with the potential for malignant transformation is crucial. Screening of the oral cavity lesions by visual tools has been widely acknowledged as a reliable, safe, and accurate method for identifying oral lesions [12]. Currently, the diagnosis relies on a comprehensive clinical examination, typically integrated into routine medical consultations. This approach offers excellent discrimination capability and can be efficiently performed in the clinic with minimal time [4,12]. Several studies have assessed the efficacy of autofluorescence in population-screening initiatives and advocated its use as a supplementary tool with conventional oral examinations for evaluating OPMD. However, oral biopsy remains the gold standard diagnostic method for all cases [13,14]. Delayed oral cancer diagnosis arises from the multifaceted interplay of various interconnected factors. As such, several authors have outlined four key issues necessitating remedial efforts: (a) delayed detection of symptoms, (b) interventions focusing on specific risk groups, (c) late seeking of medical care, and (d) inadequate knowledge of oral cancer [6,15].

Digital medicine and AI

AI is beginning to provide significant difference through enhancing diagnostic accuracy in specific medical domains, providing substantial assistance across all facets of the oncological workflow, from screening to patient treatment [10,16]. Additionally, it encompasses the software's ability to mimic human cognitive functions. Machine learning (ML), a subset of AI, focuses on integrating algorithms for addressing various problems, such as data classification or regression. It is an emerging field for researchers aiming to convert large datasets into actionable clinical decision-making knowledge. ML algorithms operate without explicit programming, autonomously adapt to data patterns and can be categorized according to the learning type as follows [17]:

- Supervised learning: Utilizes labeled data with a known external standard, referred to as "ground truth," for training.
- Unsupervised learning: Unlabeled data are analyzed to uncover the underlying structures and patterns.
- Reinforcement learning: Involves software actions receiving positive or negative reinforcement in dynamic environments.

Supervised learning is the most commonly employed form, while unsupervised learning requires extensive datasets and often presents complex interpretations. Implementing reinforcement learning in health sciences presents challenges because of its trial-and-error nature, which is primarily applied in domains such as robotics, telecommunications, and game theory [17,18].

The utilization of ML has expanded in recent years due to technological progress, enhancing digitalization of patient data, particularly via electronic medical records and image files, notably in Radiology and Pathology. A considerable trend is the increased adoption of radiomics, which is a computational tool for aiding diagnosis and primarily involves conversion of imaging data to identify subtle features. These emerging imaging characteristics have diagnostic, prognostic, and therapeutic potential [8-10,16-18].

Deep learning (DL), which can be regarded as a subset of ML, represents the latest advancement ML with operations that are intricate, facilitating decision-making and handling vast datasets efficiently [17,19].

Recent studies highlight a set of ML algorithms known as neural networks (NNs), garnering significant attention. NNs consist of intricate models comprising nodes or neurons organized into deep networks with multiple layers. The use of NNs with this architecture is referred to as DL, which facilitates the abstraction of input data at a high level and demonstrates exceptional performance across various tasks, ranging from image analysis to personalized drug design [17].

Teledentistry in diagnosis of OPMD and oral cancer

Teledentistry, facilitated by mobile phones, connects primary healthcare providers, dentists, and specialists in oral medicine or cancer. A recent study emphasized the potential of AI to reduce delays in oral cancer diagnosis, particularly via telemedicine in low-resource settings [20]. Identifying OPMD lesions showed 100% agreement between oral disease explorers and specialists at cancer centers when the explorers were dentists. However, this agreement dropped to a predictive value of 45% when the explorers were frontline health workers [21]. Young dentists showed lower ability than oral cancer experts for precisely identifying lesions, classifying it, or deciding to refer patients, with rates of 70% and 81%, in turn [22]. Integrating fluorescence techniques or enhanced camera technology for improving image quality and streamline processing represents an improvement in mobile phone database design. With this type of light, categorizing of images taken using mobile phones, categorized through a specialist of oral oncology, and subsequently classified using the VSG- convolutional neural networks (CNN)-M model, produces better results compared to both the VGG-CNN-S and VSG-CNN models [23] and exhibits a sensitivity of 85% [24,25]. Incorporating annotations of demographic and risk factors into the categorization led to lower sensitivities for the need to refer to both low- and high-risk OPMD or cancer (43% and 56%, respectively) [26]. Nevertheless, these resources provide significant advantages, particularly in high-incidence oral cancer settings with limited healthcare resources, reducing unnecessary referrals and shortening distances between patients and specialists [27,28]. Additionally, the use of artificial neural networks (ANNs) has been proposed to support inaccessible cytological diagnosis of malignancies and high-grade OPMDs [27], thereby mitigating challenges linked with photographic images [26].

Various studies have utilized clinical photographs to demonstrate the ease of automatically differentiating lesions suspected to correspond with oral squamous cell carcinoma (OSCC) using an algorithm. This provides practitioners, including non-specialists, with a practical, noninvasive, and cost-effective tool for OSCC detection, thereby improving oral cancer prognosis. In dermatology, AI contributs in diagnosing precancerous lesions and carcinomas, for instance: basal cell carcinoma and melanoma. The accuracy and AUC of methods for extracting texture features for diagnosing melanomas are 98.35% and 0.81, respectively [29-31]. However, variability in photographic images poses a challenge in identifying oral cancers or potentially malignant disorders (OPMDs), which is more complex than classifying skin lesions due to potential interference from oral structures such as teeth, mucosa, tongue, lips, and palate.

AI in the discrimination of OPMD and oral cancer

When discriminating between OPMD and oral cancer, photographic images demonstrate high accuracy in distinguishing OSCC from benign lesions (94% accuracy) and normal tissue (88.7% internal validation) [32]. The specificity for OPMD was higher for solar cheilosis (96%) compared to oral lichen planus (81%) [33,34]. Jurczyszyn *et al.* reached valuable results for diagnosing leukoplakia by using a larger number of textural characteristics, leading to higher sensitivity (100% vs. 57%) and specificity (97% vs. 74%) [34,35]. Although recent advancements in deep-learning techniques for medical-image interpretation, a large data volume is required to achieve the desired diagnostic performance. Unlike computed tomography or magnetic resonance imaging, oral photography is not warranted prior to treatment [10,36]. Consequently, compiling a substantial number of photographs for comparative studies is challenging. Improvements in study outcomes are attributed to the mixture of deep CNN and texture filters, for example: Gabor, co-occurrence matrix, sunlight matrix, or various grey-level matrices.

Using of light-based detection improve the AI reading

WWhen considering luminescence usage, such as xenon light, to enhance registries, more favorable outcomes have been observed in the binary differentiation of images between normal and pathological states, or between healthy tissue and cancerous lesions, compared with distinguishing benign and premalignant lesions [37]. The accuracy was notably poor in the latter scenario. Additionally, this method proves effectiveness for expecting progression of precancerous lesions to cancer [38], identifying oral submucosal fibrosis [32], and diagnosing leukoplakia [39].

A recent review highlighted the identification of vascular alterations in the chorion and submucosal capillary loop microvascular architecture through narrow-band imaging (NBI), offer greater reliability than white-light imaging in diagnosing premalignant oral lesions and oral cancer [40]. Additionally, AI-assisted segmentation of NBI videos has been conducted for diagnosing oropharyngeal cancer [41], oral precancer, and cancer [42]. In a recent publication, Paderno., *et al*. reported a Dice similarity coefficient of 0.6559 for the segmentation of videoendoscopic images using fully convoluted neural networks [42]. Although not evaluated in the present study, NBI appears to be a favorable tool for diagnosing oral cancer.

Biopsy helps in AI reading

While fluorescence can serve as a supplementary tool for oral examination in the diagnosis of oral precancer and cancer [43], it should not replace biopsy [44]. The latest Cochrane review reaffirmed this stance, underscoring that none of the supplementary tests, such as vital staining, light-based detection, oral cytology, and oral spectroscopy, are capable of substituting for biopsy in diagnosing oral cancer [45].

Another aspect to consider is whether exfoliative cytology delivers valuable data for screening patients at risk for oral malignancy. Support vector machine-based classification can assist with decision-making through the use of liquid-based exfoliative cytology or exfoliative cytology samples for identifying oral leukoplakia and oral squamous cell carcinomas with high sensitivity and specificity. Furthermore, exfoliative cytology is appropriate for early diagnosis of lesions in smokers [46] and for observing malignant transformation of lesions [47]. Hence, these factors should be measured during the initial screening of smokers.

Demographic variables helps in AI reading

The final question addressed attributes or variables that could be utilized to screen patients at risk of developing oral cancer, considering both the number of attributes and type of variables. It has been emphasized that it is crucial to minimize the number of variables in the algorithm to achieve better accuracy [48]. Regarding variable type, Rosma et al. reported AUCs of 0.724 and 0.713 for classification by clinicians and fuzzy classification in drinkers, respectively. Moreover, the AUCs for classification in patients who drank and chewed tobacco were 0.78 and 0.76, in turn [49]. Mohd et al. reported an accuracy of 94.76% upon analyzing 14 attributes, including histopathological parameters and clinical factors such as sex, ethnicity, site, size, and presence of painful or painless ulceration lasting >14 days [48]. Due to limited number of published articles, further studies are necessitated to evaluate the demographic parameters and toxicity habits that are highly relevant to patient selection in screening programs.

The confusion matrix serves as an evaluation framework for supervised DL algorithms. Despite most studies in the present review assessed the sensitivity, specificity, and accuracy, other metrics were available for validating CNN process. Future studies should adhere to the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis criteria [50], and Standard Protocol Items: Recommendations for Interventional Trials—Artificial Intelligence guide. This approach guarantees methodological consistency and facilitates proper interpretation of results [51].

Limitations

The investigated articles exhibit several limitations:

- Few studies involved small sample sizes with less than 30 patients, particularly in the context of DL.
- Some studies obtained images from the Internet or conducted external validation using images from a select few representative journals in oral and maxillofacial surgery.

- Certain studies considered images of the contralateral side of the lesion or individuals with toxic habits representing healthy tissue, which may not accurately reflect true healthy tissue.
- Not all studies validated clinical diagnoses with biopsy findings.
- Due to the emerging nature of the topic, there is a limitation imposed due to the timeframe of searching for publications.

Knowledge gaps exist due to insufficient available evidence for validating diagnostic tools or DL for diagnosing specific precancerous lesions. Limited data have been provided in only a few studies analyzing oral leukoplakia, actinic cheilosis, oral lichen planus, and oral submucous fibrosis.

Conclusion

In conclusion, AI is poised to revolutionize studies for early detection of oral cancer, thereby enhancing clinical practice and offering remarkable opportunities for task automation through complex pattern detection. Interdisciplinary research is essential for facilitating the incorporation of such techniques, and corresponding advancements may pave the way for future studies.

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Conflict of Interest

The authors declare no conflict of interest.

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