Artificial Intelligence-Assisted Discrimination of Oral Cancerous Lesions

Subjects: Dentistry, Oral Surgery & Medicine
Contributor: Ji-Sun Kim, Byung Guk Kim, Se Hwan Hwang

Early detection of oral cancer is important to increase the survival rate and reduce morbidity. For the past few years, the early detection of oral cancer using artificial intelligence (AI) technology based on autofluorescence imaging, photographic imaging, and optical coherence tomography imaging has been an important research area.

Keywords: mouth neoplasms ; imaging ; optical image ; precancerous conditions

1. Introduction

Oral cancer accounts for 4% of all malignancies and is the most common type of head and neck cancer [1]. The diagnosis of oral cancer is often delayed, resulting in a poor prognosis. It has been reported that early diagnosis increases the 5-year survival rate to 83%, but if a diagnosis is delayed and metastasis occurs, the survival rate drops to less than 30% [2]. Therefore, there is an urgent need for early and accurate detection of oral lesions and for distinguishing precancerous and cancerous tissues from normal tissues.

The conventional screening method for oral cancer is visual examination and palpation of the oral cavity. However, the accuracy of this method is highly dependent on the subjective judgment of the clinician. Diagnostic methods such as toluidine blue staining, autofluorescence, optical coherence tomography (OCT), and photographic imaging were useful as adjunctive methods for oral cancer screening [3][4][5][6].

Over the past decade, studies have increasingly showed that artificial intelligence (AI) technology is consistent with or even superior to human experts in identifying abnormal lesions in additional images of various organs [7][8][9][10][11]. These results give the hope for the potential of AI in the screening of oral cancer. However, large-scale statistical approaches to diagnostic power for using oral imaging with AI are lacking.

2. Efficacy of Artificial Intelligence-Assisted Discrimination of Oral Cancerous Lesions

Oral cancer is a malignant disease with high disease-related morbidity and mortality due to its advanced loco-regional status at diagnosis. Early detection of oral cancer is the most effective means to increase the survival rate and reduce morbidity, but a significant number of patients experience delays between noticing the first symptoms and receiving a diagnosis from a clinician [12]. In clinical practice, a conventional visual examination is not a strong predictor of oral cancer diagnosis, and a quantitatively validated diagnostic method is needed [13]. Radiographic imaging, such as magnetic resonance imaging and computed tomography, can help determine the size and extent of oral cancer before treatment, but these techniques are not sensitive enough to distinguish precancerous lesions. Accordingly, various adjunct clinical imaging techniques such as autofluorescence and OCT have been used [14].

AI has been introduced in various industries, including healthcare, to increase efficiency and reduce costs, and the performance of AI models is improving day by day [15]. For the past few years, the early detection of oral cancer using AI technology based on autofluorescence imaging, photographic imaging, and OCT imaging has been an important research area. Diagnostic values including sensitivity and specificity data were comprehensively confirmed in various studies that performed AI analysis of images. The diagnostic sensitivity of oral cancer analyzed by AI was as high as 0.92, and the analysis including precancerous lesions was slightly lower than the diagnostic sensitivity for cancer, but this also exceeded 90%. In subgroup analysis, there was no statistically significant difference in the diagnostic rate according to each image tool. In particular, the sensitivity of OCT to all precancerous lesions was found to be very high at 0.94.

Autofluorescence images are created using the characteristic that autofluorescence naturally occurring from collagen, elastin, and other endogenous fluorophores such as nicotinamide adenine dinucleotide in mucosal tissues by blue light or ultraviolet light is expressed differently in cancerous lesions [16][17]. It has been noted that autofluorescence images have a low diagnostic rate when used in oral cancer screening. Most of the previous clinical studies on autofluorescence-obtained images used differences in spectral fluorescence signals between normal and diseased tissues. Recently, time-resolved autofluorescence measurements using the characteristics of different fluorescence lifetimes of endogenous fluorophores have been used to solve the problem of broadly overlapping spectra of fluorophores, improving image accuracy [18]. Using various AI algorithms for advanced autofluorescence images, the diagnostic sensitivity of precancerous and cancerous lesions was reported to be as high as 94% [19]. As confirmed in the study, AI diagnosis sensitivity using autofluorescence images was confirmed to be 85% in all precancerous lesions. It showed relatively low diagnostic accuracy when compared to other imaging tools. However, autofluorescence imaging is of sufficient value as an adjunct diagnostic tool. Efforts are also being made to improve the diagnostic accuracy for oral cancer by using AI to analyze images obtained using other tools along with the autofluorescence image [20].

The photographic image is a fast and convenient method with high accessibility compared to other adjunct methods. However, there is a disadvantage in that the image quality varies greatly depending on the camera, lighting, and resolution used while obtaining the image. Unlike external skin lesions, the oral cavity is surrounded by a complex, three-dimensional structure including the lips, teeth, and buccal mucosa, which may decrease the image accuracy [6]. In a recent study introducing a smartphone-based device, it was reported that the problem of the image itself was solved through a probe that can easily access the inside of the mouth and increasing images pixel [21]. Image diagnosis using a smartphone is very accessible in the current era of billions of phone subscribers worldwide, and in particular, it is expected that accurate and efficient screening will be possible by diagnosing a vast number of these images with AI. According to the analysis, AI-aided diagnosis from photographic images was confirmed to have a diagnostic sensitivity of over 91% for precancerous and cancerous lesions.

OCT is a medical technology that images tissues using the difference in physical properties between the reference light path and the sample light path reflected after interaction in the tissue [22]. OCT is non-invasive and uses infrared light, unlike other radiology tests that use X-rays. It is also a good diagnostic method that allows real-time image verification. Since its introduction in 1991 [23], OCT has been developed to provide high-resolution images at a faster speed and has played an important role in the biomedical field. In an AI analysis study of OCT images published by Yang et al., it was reported that the sensitivity and specificity of oral cancer diagnosis was 98% or more [24]. OCT images were found to be the most accurate diagnostic test, with sensitivity of 94% in AI diagnosis compared to other image tools (sensitivity of autofluorescence and photographic images of 89% and 91%, respectively). Therefore, AI diagnosis using OCT images is considered to be of sufficient value as a screening method for oral lesions. Each image tool included in the study has its own pros and cons to be considered when using it in actual clinical practice. In addition, accessibility of equipment or systems that can be performed on patients in actual outpatient treatment will be an important factor.

Based on the results, AI analysis of images in cancer diagnosis is thought to be helpful in making fast decisions regarding further examination and treatment. The accuracy of discriminating between precancerous lesions and normal tissues showed a high sensitivity of over 90%, showing good accuracy as a screening method. Although the question of whether AI can replace experts still exists, it is expected that oral cancer diagnosis using AI will sufficiently improve mortality and morbidity due to disease in low- and middle-income countries with poor health care systems. Acquisition of large-scale image datasets to improve AI analysis accuracy will be a clinically important key.

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