Review Article

A narrative review on machine learning in diagnosis and prognosis prediction for tongue squamous cell carcinoma

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Background: Tongue squamous cell carcinoma (TSCC) is the most common subtype of oral cavity squamous cell carcinoma (OCSCC), and it also has the worst prognosis. It is crucial to find an effective way to solve the challenges in diagnosis and prognosis prediction for TSCC. Machine learning (ML) has been widely used in medical research and has shown good performance. It can be used for feature extraction, feature selection, model construction, etc. Radiomics and deep learning (DL), the new components of ML, have also been utilized to explore the relationship between image features and diseases. The current study aimed to highlight the importance of ML as a potential method for addressing the challenges in diagnosis and prognosis prediction of TSCC by reviewing studies on ML in TSCC.

Methods: The studies on ML in TSCC in PubMed, Scopus, Web of Science, and China National Knowledge Infrastructure published between the dates of inception of these databases and April 30, 2022, were reviewed.

Key Content and Findings: ML (including radiomics and DL) which was used in diagnosis and prognosis prediction for TSCC, has shown promising performance.

Conclusions: Despite its limitations, ML is still a potential approach that can help to deal with the challenges in diagnosis and prognosis prediction for TSCC. Nevertheless, more efforts are needed to enhance the usefulness of ML in this field.

Keywords: Machine learning (ML); tongue squamous cell carcinoma (TSCC); diagnosis; prognosis prediction

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Introduction

Oral cavity squamous cell carcinoma (OCSCC) is one of the most common cancers worldwide, with a 5-year survival rate of less than 60% (1,2). The most common subtype of OCSCC is tongue squamous cell carcinoma (TSCC), which has the worst prognosis. Recently, an increasing incidence of TSCC among young people has been observed (2,3). Challenges in diagnosis and prognosis prediction for TSCC,

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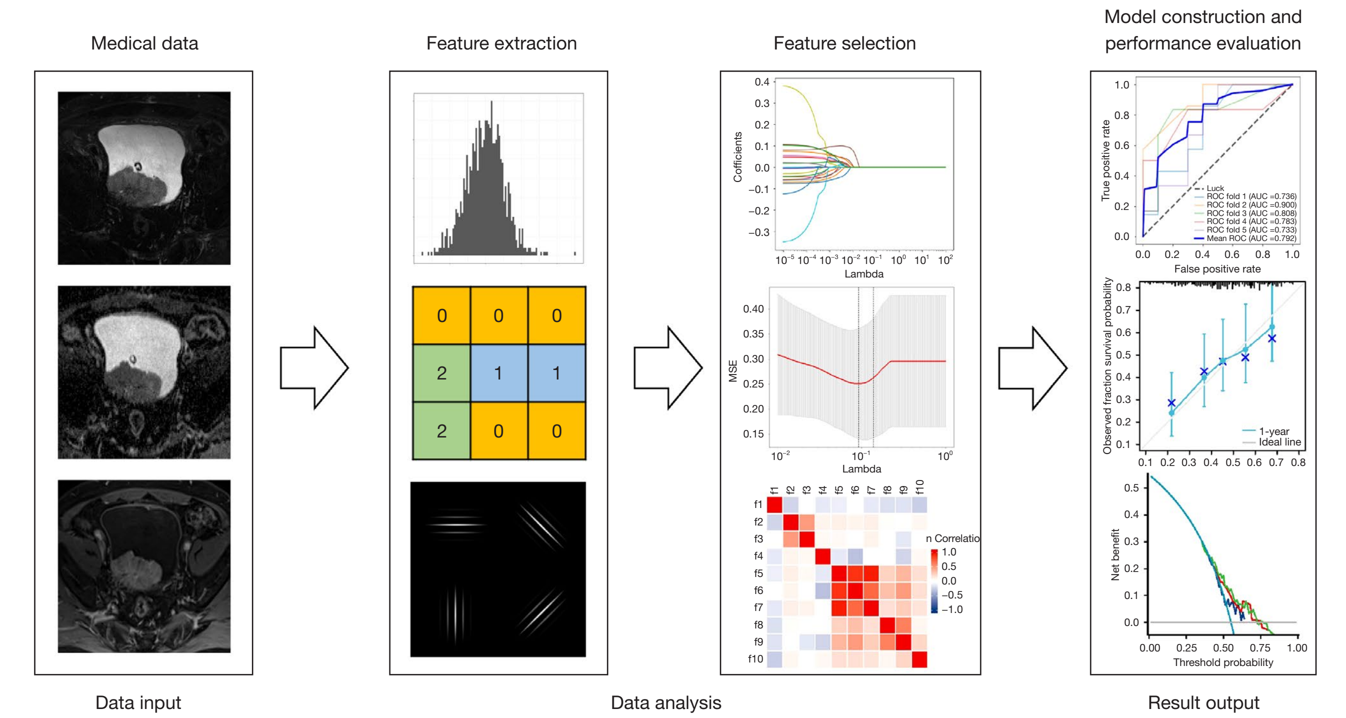

Figure 1 The machine learning protocol. MSE, mean square error.

such as developing effective strategies for early diagnosis and evaluating the risk of postoperative recurrence, still exist, but reliable approaches to solve these problems are elusive (4-6).

Machine learning (ML) is a technique that involves learning from input data, analyzing data, and outputting the result, which can be used for feature extraction, feature selection, model construction, etc. The ML protocol is shown in *Figure 1*. ML has been widely used for medical research and has shown excellent performance in multiple aspects, such as diagnosis, efficacy evaluation, and prognosis prediction (7-10).

Radiomics and deep learning (DL), which fall under ML, have developed rapidly. Radiomics extracts numerous features, such as first-order and texture features, from the region of interest (ROI) on medical images while DL can extract deep features (11,12). The features extracted by radiomics and DL, which are invisible to the naked eye, can be analyzed to determine their relationship with diseases (13,14). The utilization of radiomics and DL enables a more accurate and more objective method for medical research and clinical decision (15,16).

In this paper, studies on ML in TSCC were reviewed to highlight that ML may be a potential approach to solve the challenges regarding diagnosis and prognosis prediction for TSCC. We present the following article in accordance with the Narrative Review reporting checklist (available at https://tcr.amegroups.com/article/view/10.21037/tcr-22-1669/rc).

Methods

Literature searches were performed on May 3, 2022 and July 18, 2022 in PubMed, Scopus, Web of Science, and China National Knowledge Infrastructure databases. Papers in English or Chinese, published between the dates of inception of these databases and April 30, 2022, were included. The keyword "tongue cancer" or "tongue squamous cell carcinoma" was used together with either "machine learning", "radiomics" or "deep learning". The search results were screened by two reviewers independently through titles and abstracts to select the eligible studies. A summary of the search strategy and the search flow are shown in *Table 1* and *Figure 2* respectively. After the exclusion of duplicates, irrelevant papers, and papers involving other oral lesions, 24 papers were finally included in the review. Among the papers included, 21 focused on diagnosis and 3 focused on prognosis prediction. There was

Table 1 Summary of the search strategy

Items	Specification
Date of search	May 3, 2022 and July 18, 2022
Databases and other sources searched	PubMed, Scopus, Web of Science and China National Knowledge Infrastructure
Search terms used	"tongue cancer" or "tongue squamous cell carcinoma" with either "machine learning", "radiomics" or "deep learning"
Timeframe	From inception to April 30, 2022
Inclusion and exclusion criteria	Papers in English or Chinese were included
Selection process	Two reviewers screened the search results independently through titles and abstracts to select the eligible ones

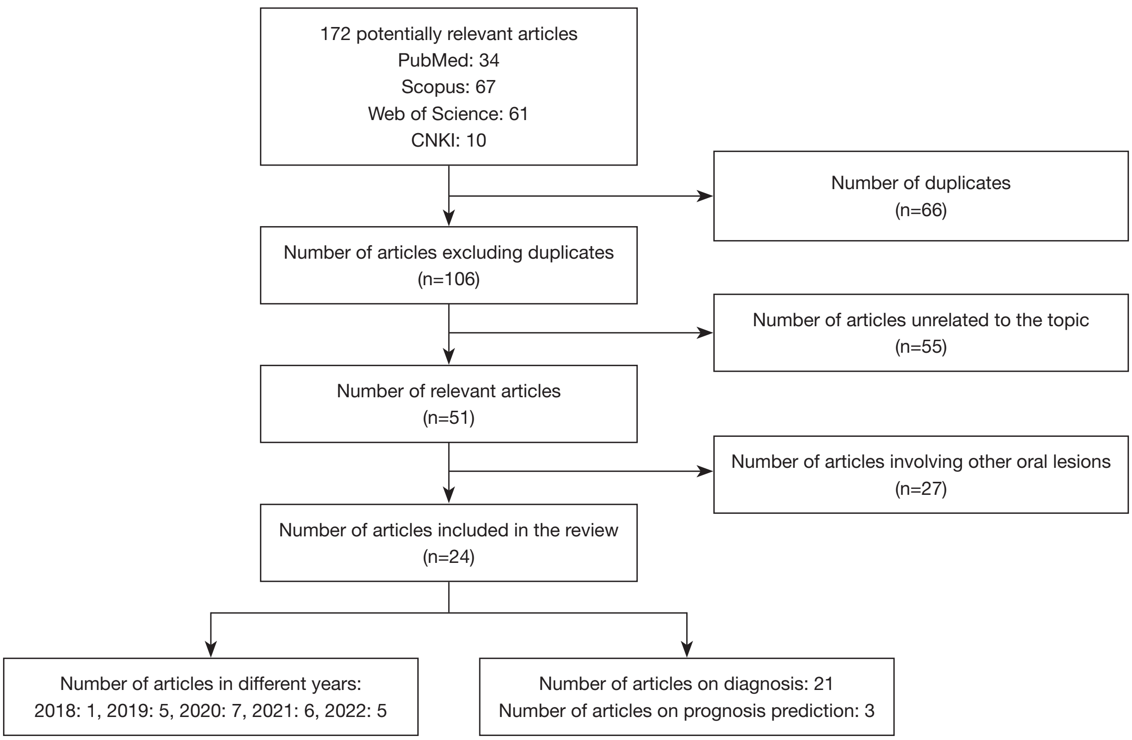

Figure 2 The search flow and the classification of included papers. CNKI, China National Knowledge Infrastructure.

only 1 article regarding ML in TSCC in 2018, whereas the number of articles concerning ML in TSCC published per year has reached or exceeded 5 since 2019.

Applications of ML in TSCC

Diagnosis

The conventional screening methods for OCSCC are inspection and palpation. A biopsy is needed to confirm the diagnosis of suspicious lesions (17). However, the result relies largely on the experience of the clinician. Even for experienced clinicians, the result of the biopsy may not represent the whole lesion due to the heterogeneity within the tumor. Additionally, this approach is invasive and expensive (18,19). Thus, it is necessary to develop a noninvasive and reliable diagnostic method.

Lu *et al.* (19) used hyperspectral imaging (HSI), autofluorescence imaging, and vital-dye fluorescence imaging combined with a variety of ML algorithms for tongue neoplasia detection in mouse models. The area under the curve (AUC), sensitivity, and specificity of the HSI in tongues *in vivo* were 0.84, 78%, and 78% respectively, and those in tongues *ex vivo* were 0.86, 79%, and 79% respectively. Due to its non-invasiveness, less dependence on the experience of the clinician and contrast agent, and good performance *in vivo* and *ex vivo*, HSI was considered a potential method to detect tongue neoplasia. Manni *et al.* (20) successfully built a support vector machine (SVM) model based on patient HSI data to detect TSCC, with an AUC of 0.92. Several researchers have constructed DL models based on HSI data, which showed good performance in distinguishing TSCC from normal tissue (21-23). The results supported the point that HSI augmented with ML may have notable potential as a supportive tool for clinicians.

Yu *et al.* (24) used convolutional neural network (CNN), linear discriminate analysis, and SVM to analyze the Raman spectrum data of tongue specimens to discriminate between TSCC and normal tissue. The sensitivity, specificity, precision, and accuracy of the CNN model were 99.31%, 94.40%, 94.70%, and 96.90%, respectively, which were superior to those of other models. Yan *et al.* (25,26) found that the CNN model combined with Raman spectroscopy had great potential as a useful tool for the intraoperative evaluation of the resection margins of TSCC. Xia *et al.* (27) combined CNN and SVM to develop a model for TSCC detection, whose AUC reached 0.99. Ding *et al.* (28) used the residual network, a type of CNN, to construct a diverse spectral band-based model, which could also distinguish TSCC from normal tissue. CNN was also used to analyze clinical images of tongues for the early detection of TSCC, which showed promising performance (29). These studies indicated that the CNN model can be applied for the evaluation of resection margins during surgery to reduce the possibility of reoperation due to insufficient resection.

Yu *et al.* (30) constructed magnetic resonance (MR) imaging-based radiomics models with good performance in predicting the degree of pathological differentiation in TSCC. Committeri *et al.* (31) successfully built an ML model combining radiomics features and clinical parameters to predict tumor grading, with an accuracy of 0.82. These results confirmed the superiority of radiomics in pathologic diagnosis.

Regional lymph node metastasis is considered one of the most important prognostic factors (32). Accurate detection of lymph node metastasis in TSCC can help to select the appropriate treatment strategy. To predict late cervical metastasis in early TSCC, Ariji *et al.* (33) developed a DL model based on intraoral Doppler ultrasound images, with an AUC of 0.883. Several studies were also conducted to predict lymph node metastasis in early-stage TSCC. Ren *et al.* (34) found that T2 weighted imaging radiomics signature was an independent predictor of occult lymph node metastasis. Shan *et al.* (35) used clinicopathologic features to construct four ML models, which showed better performance than the depth of invasion (DOI), neutrophil-to-lymphocyte ratio, and tumor budding. Yuan *et al.* (36) extracted texture features from MR images and constructed six ML models, among which the Naïve Bayes model achieved the best performance. Kubo *et al.* (37) used radiomics features of lymph nodes to construct ML models for predicting occult cervical lymph node metastasis. Zhong *et al.* (38) built artificial neural network (ANN) models incorporating computed tomography radiomics of the primary tumor with traditional lymph node evaluation to detect cervical lymph node metastasis. Both studies showed promising results. Kudoh *et al.* (39) also found that the model based on positron emission tomography radiomics features performed well in predicting cervical lymph node metastasis in TSCC. Wang *et al.* (40) showed that models based on MR radiomics signature from the primary tumor with 10 mm peritumoral extensions and clinicopathological characteristics had the highest AUC of 0.995 in the training cohort and 0.872 in the testing cohort. These satisfactory results have revealed the promising prospect of ML.

Prognosis prediction

Surgical resection is the primary treatment for TSCC, but the postoperative recurrence rate cannot be ignored. In a multicenter international study, 27.8% of the patients with early-stage TSCC experienced recurrence, which indicated that patients with a high risk of recurrence may require early intervention to improve prognosis (4). Therefore, the assessment of the risk of recurrence has an important impact on the treatment strategy for TSCC.

Almangush *et al.* (4) showed that patients with TSCC whose DOI exceeded 4 mm had a higher risk of local recurrence. Alabi *et al.* (41) compared four ML models with a DOI-based model and found that all the ML models performed significantly better than the DOI-based one. In another research, they constructed two ANN models to estimate the risk of locoregional recurrence in early-stage TSCC based on several parameters of 311 early-stage

TSCC patients. The parameters included T stage, WHO histologic grade, DOI, tumor budding, and perineural invasion. The accuracy of the ANN model was 92.7%, which was higher than that of the logistic regression model. The study also indicated that the number of tumor buds and DOI were the most important prognostic factors (42). Another study suggested that ML models could provide a more accurate prediction of overall survival in patients with TSCC compared to a nomogram (43). The excellent performance of the ML models has shown their potential to assist clinical decisions.

Discussion and summary

As the most common type of OCSCC, TSCC is malignant and has a high recurrence rate. The difficulties in diagnosis and prognosis prediction for TSCC still need to be addressed. In recent years, ML has been applied to the analysis of TSCC medical data and performed well in various aspects, such as early detection and recurrence risk evaluation. Despite promising results, ML has its limitations, such as the bias caused by differences in image quality due to various scanners with different parameters, time consumption caused by manual ROI delineation, and the difficulty in explaining the biological significance of radiomics features (44-46). Although some measures have been employed to solve these problems, such as image normalization to standardize image quality, semi-automatic or automatic ROI delineation, and radiogenomics which focuses on the relationship between imaging phenotypes and genomics (47-49), the challenges are still notable. Therefore, more efforts are required to improve ML to make it more helpful for diagnosis and prognosis prediction in TSCC.

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Footnote

Reporting Checklist: The authors have completed the Narrative Review reporting checklist. Available at https://tcr.amegroups.com/article/view/10.21037/tcr-22-1669/rc

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Conflicts of Interest: All authors have completed the ICMJE uniform disclosure form (available at https://tcr.amegroups.com/article/view/10.21037/tcr-22-1669/coif). The authors have no conflicts of interest to declare.

Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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