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Application of artificial intelligence in early warning, diagnosis and precise treatment of head and neck tumors (Review)

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Abstract. Head and neck tumors face challenges in clinical practice such as difficulty in early warning, delayed diagnosis, and insufficient individualized treatment due to their complex anatomical structure and insidious early symptoms. In recent years, the rapid development of artificial intelligence (AI) technology in the medical field has brought new opportunities for the diagnosis and treatment of head and neck tumors. With its powerful data processing and pattern recognition capabilities, it provides new ideas for solving problems related to early cancer diagnosis, planning optimal treatment strategies, and predicting patient survival likelihood. However, the clinical translation of AI models still faces bottlenecks such as data standardization, model generalization, and ethical compliance. In the future, it is necessary to build a multi-center collaboration platform and develop interpretable algorithms to promote the deep integration of AI technology and clinical practice. The present review analyzes and summarizes the latest progress of AI in head and neck malignant tumors and explores its application and development prospects in cancer research and clinical practice.

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Abbreviations: AI, artificial intelligence; ML, machine learning; DL, deep learning; CNN, convolutional neural network; RF, random forest; DT, decision tree; NPC, nasopharyngeal carcinoma; NBI, narrow band imaging; WLI, white light imaging; AUC, area under curve; AUROC, area under the receiver operating characteristic curve; ICD, immunogenic cell death; XAI, explainable AI; HNSCC, squamous cell carcinoma of the head and neck; OS, overall survival; circRNA, circular RNA

Key words: AI, head and neck malignant tumors, clinical decision making, precision treatment

Contents

1. Introduction
2. Diagnosis
3. Treatment and prognosis
4 Explainable AI (XAI)
5. Current restrictions
6. Prospect
7. Conclusion

1. Introduction

Head and neck malignant tumors refer to all malignant tumors extending from the base of the skull to above the clavicle and anterior to the cervical spine, including malignant tumors in the soft tissues of the head and face, ears, nose, pharynx, larynx, oral cavity, salivary glands, soft tissues of the neck and thyroid gland. They generally exclude intracranial, cervical and intraocular tumors. The incidence rate of these tumors accounts for ~5% of all systemic malignant tumors, posing a serious threat to human health (1). Early diagnosis and precision treatment of cancer play a crucial role in improving patients' prognosis and quality of life. For decades, researchers have collected vast amounts of clinical data in various forms to tackle cancer. However, it is difficult for individual clinicians to handle such a massive dataset. With the development of artificial intelligence (AI), this problem is gradually being solved. As an important subfield of AI, machine learning (ML), which can autonomously learn, analyze, and process big data, and deep learning (DL), as an important branch of ML, have become popular tools for medical researchers. Various learning techniques, including Convolutional Neural Network (CNN), Support Vector Machine, Bayesian Network, Random Forest (RF) and Decision Tree (DT), have been widely applied in cancer research to develop predictive models for effective and accurate decision-making (Figs. 1 and 2) (2,3).

With the rapid development of AI technology, clinical research is entering a new stage of intelligence and data-driven at an unprecedented speed. In the current era of increasingly complex medical practices and diverse disease spectrum changes, the deep integration of traditional statistical methods, medical experience and emerging technologies is gradually building a research paradigm centered on precision medicine. A group of scholars at the forefront of interdisciplinary research are exploring how AI can be efficiently applied to disease diagnosis, prediction and individualized treatment pathways, providing scientific support for achieving precision medicine.

AI-based medical imaging has emerged as a powerful tool. By integrating multi-omics data such as radiomics, electronic medical records and pathology, it constructs risk stratification models that can identify high-risk populations and assist clinicians in early screening. Leveraging its advantages of being non-invasive, cost-effective and rapid, it significantly optimizes the cancer diagnosis and monitoring processes (4-6). AI in medical radiotherapy can automate manual tasks, enhance safety measures, optimize adaptive treatment, and improve processes such as image segmentation, generating synthetic CT scans, automatic planning, and motion tracking, thereby enhancing the efficiency and quality of the treatment process (7,8). AI can extract imaging features that were previously unresolvable from medical imaging and categorize them into clinical 'phenotypes'. Positron emission tomography-computed tomography and single photon emission computed tomography have been widely used in the detection and staging of cancer lesions, aiding in improved prediction of prognosis and detection of adverse events (9). Introducing AI into the pathological images of tissue samples can reveal structural features in histological images that are unobservable to the human eye, efficiently diagnose disease types, and generate corresponding biomarker profiles (10). Current research on AI-assisted clinical diagnosis and treatment not only focuses on enhancing the performance of the model itself but also strives to develop interpretability to ensure the credibility of the decision-making process.

As individuals' emphasis on health increases, clinicians' work becomes increasingly busy. The use of AI to assist doctors in diagnosis and treatment can not only improve clinical efficiency but also reduce errors. AI has shown great potential in the medical field. In the present review, focus is addressed on the application of AI in early warning, early diagnosis and precision treatment of head and neck tumors.

2. Diagnosis

Nasopharyngeal carcinoma (NPC) and malignant tumors of the pharynx often lack specific manifestations in the early clinical stages. Early diagnosis of patients relies on the detection of lesions through endoscopy. Therefore, it is particularly important for endoscopists to observe the morphological characteristics of the mass through endoscopy and make preliminary judgments. However, it is challenging for the human eye to distinguish between mucosal inflammation, cysts and early-stage tumors under endoscopy. Junior doctors need extensive training to develop the ability to identify the microvascular characteristics of tumors. For endoscopists with limited training and experience, the diagnostic accuracy and consistency for early NPC and malignant throat tumors are not ideal. Therefore, developing a computer-aided diagnostic system to assist doctors in diagnosis is of great significance (Table I) (11-14).

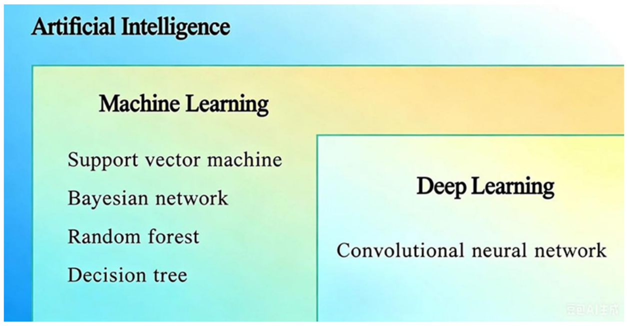

Figure 1. Artificial intelligence concept map.

The classical ML model shows unique value in the task of small amount of data. Li *et al* (15) constructed a ML model for early staging and detection of laryngeal cancer using only 378 optical coherence tomography images of 12 patients. The intraoperative sensitivity of 84.21% was obtained, which can assist in diagnosing whether the vocal cord leukoplakia further progressed to vocal cord cancer, and clarify the direction for subsequent treatment (15). ML models such as DT and RF rely on artificial precise cutting features (such as shape and texture), which endows the model with high transparency and interpretability, and is helpful for clinical understanding of model logic. However, it also brings inherent limitations. Manually defining features requires a lot of time, has high requirements for operators, and it is difficult to exhaust lesion features by manual definition.

With the ability of automatically extracting multi-level features, DL has achieved excellent performance in large sample endoscopic image analysis and has become the preferred technology for AI models. Sampieri *et al* (16) trained a DL model based on 3,933 laryngeal cancer images of 557 patients to demarcate the laryngeal cancer boundary under laryngoscope, and its accuracy is equivalent to that of human physicians. Tie *et al* (17) developed a vocal cord leukoplakia diagnosis model using 7,057 images of 426 patients, which significantly improved the area under curve (AUC) and accuracy of laryngologists. The DL model can automatically learn image features and avoid manual features, so it can surpass the traditional learning model in tasks with clear standards and sufficient data. Narrow band imaging (NBI) further amplifies this advantage, which enhances the display of mucosal blood vessels and fine structures through specific narrow-band spectra, providing high-quality input for DL. Tamashiro *et al* (18) developed a CNN diagnosis system based on NBI to detect all cancer lesions in 1,912 validation images in the detection of pharyngeal malignant tumors. The sensitivity of NBI images is as high as 85.6%, markedly higher than 70.1% of white light imaging (WLI) images, which also confirms the advantages of NBI in cancer screening (18).

In the field of endoscopic NPC recognition, several studies have developed an AI model based on static nasal endoscopic images, which has proved its feasibility and recognition performance (19-22). However, these models lack the ability of real-time dynamic detection, which is not conducive to rapid diagnosis and guidance of biopsy. In recent years, researchers began to focus on the real-time detection of NPC in nasal endoscopic video. He *et al* (23) developed an NPC detection

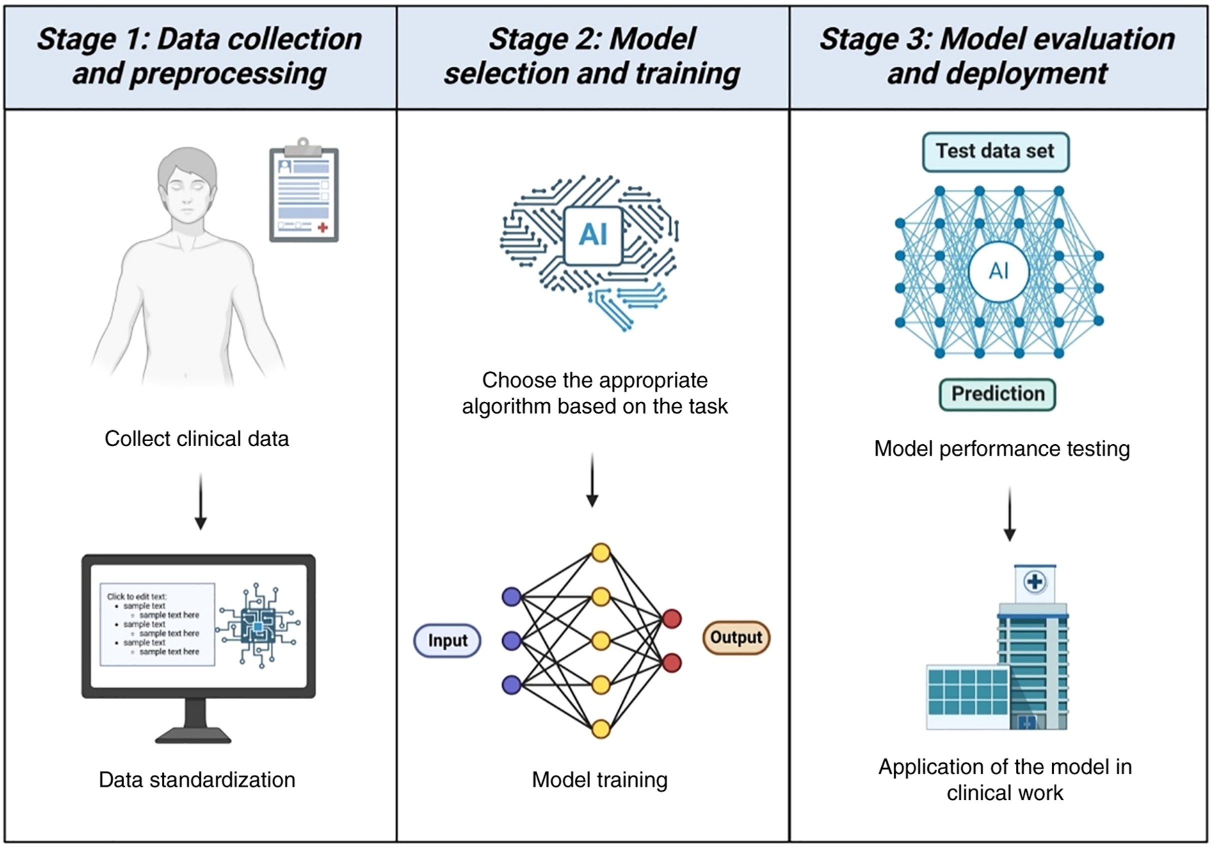

Figure 2. AI model construction. AI, artificial intelligence.

model based on DL using the 'you only look once' network. The model shows excellent performance and stability in the test. The accuracy, recall, average precision mean and F1 score of the internal test set are 0.977, 0.943, 0.977 and 0.960, respectively, and those of the external test set are 0.825, 0.743, 0.814 and 0.780 (23). Xu *et al* (24) developed a DL model for NPC diagnosis using nasal endoscopic imaging omics, which integrates a large number of static images and videos. The model shows high accuracy, sensitivity and specificity in the real environment, which is superior to the existing models that mainly rely on biopsy, MRI and CT images. The AUC in the two hospital datasets is 0.981 and 0.937, respectively (24). The NPC SDNet multimodal real-time nasal endoscopy new DL neural network model built by He *et al* (25) allows feature extraction, segmentation and lesion feature description simultaneously in the process of image processing. The diagnostic accuracy of NPC SDNet is 94.0%, and it processes 1,000 frames per min, which is better than the accuracy of clinicians of different professional levels (68.9-88.2%), proving that it can help clinicians improve the diagnostic accuracy of NPC (25).

In other application scenarios of head and neck tumors such as imaging and pathology, the advantages of the DL model are also reflected. The DL model thynet developed by Peng *et al* (26) was used to identify benign and malignant nodules by thyroid ultrasound, with an area under the receiver operating characteristic curve of 0.922, which was significantly higher than that of 0.839 for radiologists. After assisting decision-making, the unnecessary puncture proportion was reduced, and the missed diagnosis rate was slightly reduced. Its advantage was that deep features such as echo texture and boundary morphology were stably extracted from massive pixels, avoiding the fatigue and bias of human eye perception (26). Fine needle aspiration for thyroid nodules with high suspicion of malignancy is essential for appropriate therapeutic intervention, but there are still a small number of samples that produce uncertain cytological results (27). The thyroid patch-oriented WSI ensemble recognition (thyropowe) AI-assisted model developed by Wang *et al* (28) using whole slide images can improve the specificity of primary cytopathologists in diagnosing thyroid cancer from 0.887 to 0.993, and the accuracy from 0.877 to 0.948. This system is helpful for rapid and accurate cellular diagnosis of thyroid nodules, thus enhancing the diagnostic ability of cytopathologists, and is a potential solution to alleviate the problem of insufficient cytopathologists (28). These studies once again show the outstanding advantages of DL in image global feature learning.

However, the black box characteristic of DL makes its decision-making process difficult to disassemble, and the model performance is highly dependent on large-scale and high-quality annotation data, which is prone to over fitting problems. When the imaging conditions change, the generalization ability of the model may be significantly attenuated.

By fusing the complementary information of different modes, multimodal learning effectively overcomes the upper performance limit of single-mode model. The laryngopharyngeal AI diagnostic system developed by Li *et al* (29) integrates laryngoscope white light and NBI images at the same time. The accuracy rate of the multimodal model reaches 0.94,

Table I. Application of artificial intelligence in otolaryngology.

First author/s, year	Model task	Data source	Algorithm	Model performance	(Refs.)
Li *et al*, 2025	Early classification and detection of vocal cord leukoplakia	378 optical coherence tomography images from 12 patients	Random Forest	Accuracy=92.59%, Recall=93.25%	(15)
Sampieri *et al*, 2024	Real-time delineation of laryngeal cancer boundaries	3,933 images of laryngeal cancer from 557 patients	Deep Learning	Dice Similarity Coefficient=0.83, Accuracy=0.97	(16)
Tie *et al*, 2024	Early diagnosis of vocal cord cancer	7,057 laryngoscope images from 426 patients	Deep Learning	Accuracy=0.879, sensitivity=0.882, specificity=0.875, AUC=0.936	(17)
Tamashiro *et al*, 2020	Pharyngeal cancer detection	5,403 laryngoscope images of 202 cases of superficial pharyngeal cancer and 45 cases of advanced pharyngeal cancer	Deep Learning	AUC=0.8, NBI sensitivity=85.6%, WLI sensitivity=70.1%	(18)
Li *et al*, 2018	Detection of nasopharyngeal malignant tumors	28,966 nasopharyngeal endoscopy images of 7951 patients	Deep Learning	Accuracy=88.7%, sensitivity=91.3%, specificity=83.1%, AUC=0.938	(21)
Xu *et al*, 2022	Identify NPC and non-cancerous diseases	4,783 nasopharyngeal endoscopy images from 671 patients	Deep Learning	S-DCNN (Siamese deep CNN): Accuracy=95.7%, sensitivity=97.0%, specificity=94.3%, AUC=0.985	(22)
He *et al*, 2023	Real-time detection of NPC during nasopharyngeal endoscopy	2,429 video frames of nasopharyngeal endoscopy from 690 patients	Deep Learning	Precision=0.825, Recall=0.743, Mean Average Precision=0.814	(23)
Xu *et al*, 2024	Accurate diagnosis of NPC	12,087 nasopharyngeal endoscopic images and 309 videos from 1108 patients	Deep Learning	Fujian image dataset: Accuracy=0.956, Sensitivity=0.948, Specificity=0.963, AUC=0.981 Fujian video dataset: Accuracy=0.906, Sensitivity=0.847, Specificity=0.934, AUC=0.953 Jiangxi image dataset: accuracy=0.880, sensitivity=0.931, specificity=0.827, AUC=0.937	(24)
He *et al*, 2025	Real-time AI-assisted detection and segmentation	There are a total of 8,816 frames of nasal endoscopy videos from 707 patients	Deep Learning	NBI: Accuracy=95.8%, Accuracy=93.1%, Recall=96.0%, Specificity=97.2%, AUC=0.998 and 0.977 WLI: Accuracy=95.0%, Accuracy=93.5%, Recall=97.2%, Specificity=93.5%, AUC=0.977 and 0.970	(25)

Table I. Continued.

First author/s, year	Model task	Data source	Algorithm	Model performance	(Refs.)
Peng *et al*, 2021	Assist in the diagnosis and management of thyroid nodules	22,354 ultrasound images from 111,114 patients	Deep Learning	Accuracy=0.877, AUROC=0.922, NPV=0.97, PPV=0.95	(26)
Wang *et al*, 2024	Pathological diagnosis of thyroid cells	11,254 full-slide images from 4037 patients	Deep Learning	Accuracy=0.707, Average AUROC=0.936	(28)
Li *et al*, 2023	Real-time detection of throat cancer	31,543 NBI and WLI images from 2,382 patients	Deep Learning	Multimodal: Accuracy=0.956, Sensitivity=0.948, Specificity=0.964, PPV=0.965, NPV=0.946 Single-modality WLI: Accuracy=0.948, Sensitivity=0.885, Specificity=0.988, PPV=0.978, NPV=0.932 Single-modality NBI: Accuracy=0.935, Sensitivity=0.978, Specificity=0.798, PPV=0.94, NPV=0.917	(29)
Kwon *et al*, 2025	Diagnosing early-stage glottic cancer using laryngeal imaging and voice analysis	Pusan National University Hospital dataset	DT, CNN	The accuracy of the laryngeal image model is 87.88%; the accuracy of the speech DT is 89.06%; and the accuracy of the combined learning of the two is 95.31%	(30)
Kim *et al*, 2024	Diagnosing laryngeal diseases based on voice	From January 2015 to December 2022, the voices of male patients who underwent voice assessments and had voice changes within three weeks	SVM, gradient boosting tree, artificial neural network, CNN	SVM: Accuracy=0.6828, Precision=0.6451 Recall=0.6905 Gradient Boosting Tree: Accuracy=0.7152, Precision=0.6790, Recall=0.6769 Artificial neural network: Accuracy=0.6407, Precision=0.6577, Recall=0.5192 CNN: Accuracy=0.7530, Precision=0.7515, Recall=0.7264	(32)

NPC, nasopharyngeal carcinoma; SVM, support vector machine; CNN, convolutional neural network; WLI, white light imaging; PPV, positive predictive value; NBI, narrow band imaging; NPV, negative predictive value; DT, Decision Tree; AUROC, area under the receiver operating characteristic curve; AUC, area under curve.

which is better than using either mode alone, and is equivalent to that of expert laryngologists (29). Kwon *et al* (30) further introduced acoustic mode, fused laryngeal image and voice DT results, and the classification accuracy increased from 87.88 and 89.06% of single mode to 95.31%, reflecting the performance breakthrough brought by multiple modal information complementation. Nowadays, an increasing number of otolaryngologists have tried to combine voice analysis and endoscopic technology with AI (31,32). The mechanism advantage of multimodal fusion is that it enhances the robustness and generalization ability of the model, and different modes provide complementary evidence, so that the system can understand complex lesions from multiple dimensions. However, this strategy also brings new challenges. Multimodal input requires higher standardization of data acquisition, equipment compatibility and consistency of inspection process, which increases the complexity of the system. When introducing voice and other modes that are easily disturbed by age, sex, vocalization habits and environmental noise, the problem of feature stability and cross mechanism generalization must be solved to ensure the reliable application of the model.

3. Treatment and prognosis

In clinical treatment, AI models are applied in the formulation of personalized treatment strategies for various cancers. For instance, by integrating data from imaging, histopathology, clinical information and other sources, AI can predict a patient's treatment response, thereby guiding the implementation of systemic treatment or translational therapy, improving efficacy and saving resources.

The treatment for Squamous Cell Carcinoma of the Head and Neck (HNSCC) primarily involves surgery, supplemented by radiotherapy and chemotherapy. The comprehensive treatment of malignant tumors requires the rational and planned application of existing methods based on the patient's physical condition, tumor pathological type, extent of invasion and tendency, in order to significantly improve the cure rate (33). Postoperative chemoradiotherapy is the standard treatment for cancer with positive resection margins or extracapsular extension, but the benefits of chemotherapy for patients with other intermediate-risk characteristics remain unclear. To predict patients with intermediate-risk HNSCC who may benefit from chemoradiotherapy, Howard *et al* (34) trained three ML survival models: DeepSurv, neural multitask logistic regression and random survival forests. From the National Cancer Database of the United States, 33,527 patients who underwent radical surgery and adjuvant chemoradiotherapy or radiotherapy alone were retrospectively selected. The median follow-up time was 43.2 months, and there was no significant difference in the prognostic accuracy among the three models. Treatment was administered according to the recommendations of the ML model, and the survival rate was significantly improved in all models. The hazard ratio was 0.79 for DeepSurv, 0.83 for neural multitask logistic regression, and 0.90 for random survival forest model. Among the three models, no survival benefit of chemotherapy was observed in patients recommended to receive radiotherapy alone, indicating that these models identified a subgroup of patients who only needed radiotherapy alone (34). Based on clinical data such as MRI, tumor TN staging, histological subtypes and plasma EBV DNA levels, Zhang *et al* (35) developed a DL model to assess distant metastasis-free survival in locally advanced NPC and explored the value of additional chemotherapy for different risk groups on the basis of concurrent chemoradiotherapy. By combining clinical variables with prognostic significance for distant metastasis-free survival with coefficients weighted through logistic regression analysis, the researchers established a prediction model for distant metastasis-free survival. Patients were divided into high-risk and low-risk groups based on the median risk score. Subgroup survival analysis was conducted on patients who received concurrent chemoradiotherapy alone and those who received additional chemotherapy plus concurrent chemoradiotherapy in different risk groups. The distant metastasis-free survival period of patients in the high-risk group was significantly shorter than that of patients in the low-risk group. In the low-risk group, patients who received concurrent chemoradiotherapy alone had a longer distant metastasis-free survival period than those who received additional chemotherapy plus concurrent chemoradiotherapy. However, in the high-risk group, there was no significant difference between patients who received concurrent chemoradiotherapy alone and those who received additional chemotherapy plus concurrent chemoradiotherapy (35).

Radiotherapy is the primary treatment method for non-metastatic NPC. Among radiation therapy techniques, intensity-modulated radiotherapy (IMRT) is the most widely used, offering improved 5-year local regional control and overall survival with low toxic side effects. However, its efficacy in locally advanced NPC is unsatisfactory (36-38). Hu *et al* (39) utilized ML algorithms to construct a prognostic model for patients with stage III-IV advanced NPC after their initial IMRT. A total of 427 patients were included, with an average follow-up period of 7.16 years. Three algorithms, namely logistic regression, DT and RF, were employed. Among them, RF demonstrated the best predictive performance, identifying six most significant predictors as Epstein-Barr virus DNA, aspartate aminotransferase, body mass index, age, blood glucose level and alanine aminotransferase (39). Radiation-induced temporal lobe injury is a severe sequela of radiotherapy in patients with NPC, having a significant adverse impact on their quality of life, physical and emotional functioning, and even survival. Although the use of IMRT in NPC has reduced the incidence of radiotherapy-related complications, some patients still report such events (40-42). Wen *et al* (43) retrospectively analyzed data from 8,194 patients with NPC who received IMRT and developed a predictive model incorporating dosimetric and clinical variables. D0.5cc (the dose delivered to 0.5 cm^3 of the temporal lobe) was the most predictive dose-related feature, with the highest AUC of 0.799. D0.5cc65.06 Gy was the tolerable dose for the temporal lobe and reducing D0.5cc could reduce the risk of temporal lobe damage, especially in elderly patients with advanced disease.

The application of AI in precision oncology enables the analysis of tumor genomic data, aiding in the design of innovative clinical trials and the development of personalized combination therapy strategies tailored to individual biomarker characteristics (44,45). Circular RNA (circRNA) is involved in various biological processes and plays a crucial role in disease diagnosis, treatment and prognosis. Wang *et al* (46) proposed a computational model based on collaborative learning using circRNA multi-view functional annotation to predict potential circRNA disease associations, which demonstrates favorable performance in predicting candidate disease-related circRNAs. Miao *et al* (47) established a tumor drug sensitivity prediction model to assist doctors in designing personalized tumor treatment plans, including targeted drugs and non-specific chemotherapy drugs. The model was tested on 87 molecular targeted drugs and non-specific chemotherapy drugs, and the results showed that the method could effectively predict tumor drug sensitivity, with an average sensitivity of 0.98 and specificity of 0.97 (47).

Immunogenic cell death (ICD) is a type of regulatory cell death capable of activating adaptive immune responses, capable of reshaping the tumor immune microenvironment (TIME) by emitting danger signals or damage-associated molecular patterns. Wang *et al* (48) established and validated a prognostic model for HNSCC related to ICD, identifying two subtypes associated with ICD through consensus clustering. The high ICD subtype is associated with favorable clinical outcomes, abundant immune cell infiltration, and high activity of immune response signals. This stratification has important clinical implications for predicting the prognosis of patients with HNSCC and for immunotherapy (48). Kim *et al* (49) developed a high-throughput immunogenic cell death inducer screening system utilizing real-time image analysis based on AI. This system screens for ICD inducers by identifying the typical morphology of dead cells that undergo ICD. In a blinded test, it efficiently identified three ICD inducers, which were then verified through analyses of cell death type, DAMP release, and immune activation. This system significantly reduces the time and resources required for screening and can also detect subtle morphological differences that are difficult to detect manually (49). Patients with cancer with different prognoses often exhibit differences in their TIME and response to immune checkpoint inhibitors (ICIs). Cao *et al* (50) constructed and validated a prognostic combined cell death index model consisting of 16 genes by combining ICD and necroptosis characteristics. This model can predict the response to ICIs in esophageal squamous cell carcinoma (ESCC). They found that HOOK1 can induce necroptosis in ESCC cells and inhibit their proliferation and migration, while CUL4A exhibits the opposite effect. Immunoprecipitation experiments and data from ESCC patients support the view that HOOK1 and CUL4A may act as tumor suppressors and oncogenes, respectively (50).

The application of AI in the medical field has taken healthcare a significant step towards individualization and precision. AI assists doctors in formulating chemotherapy and radiotherapy plans, enabling patients with cancer to achieve maximum therapeutic effects with minimal side effects. AI helps in the search for potential biomarkers and targets, making immunotherapy more accessible to a wider range of patients with cancer. AI-enhanced healthcare will become the mainstream direction of future medical care.

4. Explainable AI (XAI)

Although AI is highly useful in cancer diagnosis and prognostic prediction, it lacks the necessary accountability, transparency and reliability in decision-making for cancer diagnosis and prognosis, rendering it difficult to be applied clinically. Therefore, it is necessary to develop intelligent models that can explain their predictions, so that clinicians can use them reliably.

Kausar (51) developed a model based on ML and XAI to predict the survival of patients with HNSCC using microRNA (miRNA) sequences and clinical datasets. ML models were developed using RF, Cox Regression, Lasso Regression, Elastic Regression and Gradient Boosting to predict the survival risk of patients with HNSCC. Dysregulated miRNAs can lead to cancer metastasis and can be used to predict patient survival. Based on this, an XGBoost model based on XAI was developed to explain the prediction results by displaying specific miRNAs involved in the survival of patients with HNSCC. Experiments showed that the important miRNAs identified by the interpretable model for predicting the survival of patients with HNSCC were consistent with the prognostic-related miRNAs reported in biological studies, demonstrating the reliability of the ML model for predicting the survival of patients with HNSCC, which can be used by clinicians for treatment decisions (51).

Researchers in the field of medical image analysis are increasingly using XAI to explain the results of their algorithms. Dörrich *et al* (52) developed an interpretable CNN for evaluating histopathology of head and neck cancer. Initially, a CNN model was trained to classify tumor and non-tumor tissues. Then, XAI techniques were applied to explore the important features that contributed to the CNN model's decision-making. The interpretable AI method demonstrated that the CNN model's decisions relied on features consistent with the opinions of pathology experts. This confirmed that the CNN model could predict head and neck cancer with high accuracy and had promising prospects in assisting pathologists in evaluating cancer slides (52).

Multiple research reports have confirmed that the introduction of XAI helps to enhance the transparency and reliability of models, bridging the gap between algorithm output and clinical trust. However, the explanation is only an approximation of the model's decision-making process and is not completely faithful to the original model, thus inevitably reducing its accuracy on the primary task. Another issue is how to evaluate whether XAI technology can provide favorable explanations (53).

5. Current restrictions

The use of AI has brought numerous conveniences to the medical industry. However, the adoption of AI solutions and their implementation in healthcare are still in their infancy. Although numerous models have shown favorable generalization in clinical testing, it is still difficult to effectively implement them in clinical work. This situation is partly due to the fact that the impact of AI in healthcare is mostly preclinical research, which takes place in artificial simulation environments, making it difficult to infer the actual effectiveness of models in real-world clinical settings (54,55). On the other hand, patients tend to trust treatment decisions led by doctors (56).

ML and DL models require large datasets to accurately classify or predict different tasks. Due to the non-interchangeability of healthcare systems across regions, obtaining sufficient data often requires collaboration among multiple large hospitals, which creates a barrier for building models with more complex and precise algorithms. Overfitting is also a problem that must be addressed in model development. The model may learn the relationship between patient variables and unrelated outcomes, such as specific pixels or textures. Therefore, the algorithm may work well in the training dataset, but it may provide inaccurate results when predicting future outcomes. In addition, the incidence rate of some diseases varies significantly across different age groups and sexes. The incidence rate of HNSCC is higher in male than in female patients. In diagnostic and treatment decision-making experiments related to HNSCC, male patients usually account for a higher proportion. The bias caused by the imbalance in sex ratio cannot be effectively evaluated, and even traditional AI algorithms may amplify this potential bias, resulting in inconsistent accuracy of model results across different populations (57,58).

What's worse, the reliability of AI is often broadly described based on its working principle, which cannot directly prove the accuracy of its output results. In clinical application scenarios, the input data is complex and multidimensional, making it more difficult to interpret the visual output results of AI. There is no way of knowing whether the model has captured effective information fragments, or whether the importance weights assigned by the model to different data are reasonable. For example, the authors once built a multimodal diagnosis model for early vocal cord cancer, using voice and laryngoscope images as input information. In experiments, the accuracy of disease diagnosis using single-modality data was not consistent, and it was not possible to determine the weight allocation of the two-modality data when the multimodal model performed diagnostic tasks. Researchers analyze the decision-making behavior of AI by probing the input and output or approximating its decision logic, but this cannot fully capture the behavior of the underlying model, and the performance of model interpretation is rarely tested. Currently, there is no unified evaluation metric in the field of interpretable AI. This means that the interpreted model decisions may be correct or incorrect, and similarly, the interpretation may also be correct or incorrect (59).

Ethics has been a topic that has plagued AI since its inception. Although existing guidelines for the implementation and use of AI ethics draw on principles such as autonomy, non-maleficence, beneficence and justice from medical ethics, and emphasize transparency, interpretability, accountability and fairness, they do not provide a clear definition of AI ethics (60). At the current stage, the public has various concerns about the application of AI in the medical field. How to clearly define the responsible parties in case patients adopt AI decision-making schemes and adverse medical outcomes occur? Is there any unauthorized commercial use or leakage of patients' clinical data? All these issues require us to continuously improve relevant laws and regulations and enhance regulatory technology, so that in the future, precision medicine can strike a balance between new AI technologies and humanistic care, efficiency improvement and risk control (61).

6. Prospect

In recent years, the great potential of AI has greatly increased the related research in otolaryngology head and neck surgery. In the clinical diagnosis and treatment of Otolaryngology Head and neck surgery, imaging examination has irreplaceable core value. The application of AI technology in this field is increasingly in-depth. From the early auxiliary recognition of static laryngoscope and nasal endoscope images, it is gradually expanded to the real-time analysis of dynamic laryngoscope and video nasal endoscope, and then to a multimodal joint analysis framework that integrates images, clinical texts and physiological signals. With the continuous innovation of algorithm architecture and training strategy, the diagnosis efficiency of AI system has been significantly improved, the missed detection rate has been effectively controlled, and its adaptability to complex clinical scenarios has been continuously enhanced. This technology iteration process not only effectively optimized the existing workflow but also showed broad prospects for clinical transformation.

At the molecular biology level, AI can efficiently screen tumor related markers, predict key inhibitory targets, and evaluate the prognosis and recurrence risk of patients based on multi-omics data, while providing intelligent screening and verification path for the development of new antitumor drugs. In the clinical treatment, the AI assisted decision system can optimize the radiotherapy and chemotherapy scheme of Otolaryngology Head and neck, accurately regulate the drug dose, significantly reduce the toxic and side effects while improving the curative effect, especially help to avoid unnecessary damage to brain tissue caused by head irradiation, and improve the quality of life of patients. The application of AI runs through the whole chain from molecular typing, efficacy prediction to scheme optimization and risk control, showing the strong trend of continuous iteration and multi-field integration of AI in the diagnosis and treatment of Otolaryngology Head and neck tumors. Its clinical application has broad prospects and is expected.

Medical AI still faces significant challenges from construction to clinical transformation, among which the-black box-problem is particularly critical. The black box makes the algorithm decision-making process lack the necessary transparency, and it is difficult for users to understand its reasoning basis and internal logic. Current research frontiers and future directions mainly include developing more sophisticated explanation methods to mitigate the negative correlation between model performance and interpretability. Research also encompasses establishing unified interpretability evaluation metrics and enhancing the inherent interpretability of complex models such as deep learning, with the goal of achieving interpretability and traceability at each execution step. By increasing the transparency of technology, we can enhance people's trust in AI.

To ensure the safe and reliable operation of AI systems, the focus should be on rigorous and thorough verification procedures. The only effective way to prove the decisions made by AI systems is through thorough, careful and meticulous safety and verification work. Instead of requiring complex AI systems to provide partial explanations, thorough and rigorous verification of these systems should be advocated for, among as numerous different groups as possible, to maximize the guarantee that marginalized groups are not disproportionately affected by any specific system.

In terms of ethical challenges, academic disciplines and governments have made concerted efforts to develop ethical guidelines for the implementation and use of AI, clarifying the future development path of AI. In 2021, UNESCO issued the 'Recommendation on the Ethics of AI', which is the world's first normative framework specifically for AI ethics. A total of 193 member states have officially adopted this ethical framework. China also introduced the 'Ethical Norms for New-Generation AI' in the same year, aiming to integrate ethics into the entire life cycle of AI and provide ethical guidance for individuals, legal entities, and other relevant institutions engaged in AI-related activities. The IEEE Global Initiative provides a platform for multi-stakeholders and the public from related scientific and engineering fields to exchange ideas, reach broad consensus on pressing ethical and social issues, as well as candidate recommendations for the development and implementation of these technologies, and explore how to establish ethical and socially compliant applications for intelligent and autonomous systems and technologies, aligning them with established values and ethical principles, while prioritizing human welfare in specific cultural contexts (https://standards.ieee.org/wp-content/uploads/import/documents/other/ead_v2.pdf).

7. Conclusion

In the present review, the roles of multiple ML and DL models in the diagnosis, treatment and prognosis of head and neck malignancies were specifically described. AI models have been applied in various fields such as clinical decision-making, precision treatment, molecular mechanisms and targeted drug development, indicating that the application of AI in medicine is rapidly advancing. The integration of AI technology into healthcare heralds a new era of medical innovation. AI can help improve clinical efficiency, reduce healthcare costs, and advance clinical research. Automation technology can achieve or surpass the performance of expert physicians in certain diagnostic or research tasks in a shorter time. Healthcare systems and professionals can recognize and harness the potential of AI technology, ensuring that responsibility and ethics are combined to benefit patients.

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Availability of data and materials

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Authors' contributions

SYQ wrote the major part of the manuscript. DY and HZ revised and reviewed the manuscript. All authors read and approved the final version of the manuscript. Data authentication is not applicable.

Ethics approval and consent to participate

Not applicable.

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Not applicable.

Competing interests

The authors declare that they have no competing interests.

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