ORIGINAL RESEARCH

Development and Validation of an Artificial Intelligence-Based Prediction Model for Early Detection and Prognostic Evaluation in Oral Oncology: A Pilot Study

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Abstract

Background: Oral squamous cell carcinoma (OSCC) is a global health concern, with high mortality rates due to late-stage diagnosis and recurrence. Artificial intelligence (AI) presents a promising tool for enhancing early detection and prognosis through multimodal data integration.

Objective: To develop and validate an AI-based prediction model for early detection and prognostic evaluation of OSCC using clinical, histopathological, and radiological data.

Methods: This retrospective study included 98 patients with histopathologically confirmed OSCC. Clinical, histopathological, and radiological data were collected and processed for the model development. A hybrid AI model combining machine learning for tabular data and deep learning for imaging data has been developed. Model performance was assessed using metrics, such as sensitivity, specificity, accuracy, F1 score, and area under the receiver operating characteristic curve (AUC-ROC). Kaplan-Meier survival analysis and Cox regression were used to identify prognostic factors. The accuracy of the AI model was compared with that of the clinician-based assessments.

Results: The AI model demonstrated a high sensitivity (89.7%), specificity (85.4%), and AUC-ROC (0.91), outperforming clinician-based predictions (kappa = 0.78). Depth of invasion (hazard ratio [HR]: 1.45, p = 0.004), lymphovascular invasion (HR: 2.14, p = 0.001), and perineural invasion (HR: 1.87, p = 0.006) were significant predictors of overall survival. Kaplan-Meier analysis revealed a median overall survival of 36 months and disease-free survival of 28 months.

Conclusions: The AI model showed robust performance in the early detection and prognostic evaluation of OSCC, outperforming traditional clinician-based assessments. These findings highlight the potential of AI in precision oncology and its role in improving patient outcomes through personalized treatment strategies.

Keywords: Artificial Intelligence; Oral Squamous Cell Carcinoma; Prognosis; Machine Learning; Survival Analysis

Introduction

Oral squamous cell carcinoma (OSCC), comprising 90% of oral cancers, is the sixth most common cancer globally, with higher prevalence in low-income regions linked to tobacco and areca nut use.[1] Despite diagnostic and therapeutic advancements, its five-year survival rate remains low (50–60%) due to late-stage diagnosis and recurrence.[2] Early detection and accurate prognosis are critical but remain challenging.

The diagnosis of OSCC is based on clinical examinations, histopathological evaluations, and imaging studies. However, these methods often suffer from limitations, including subjectivity, variability among clinicians, and challenges in detecting early stage lesions or predicting outcomes.[3] Furthermore, while traditional histopathological features such as depth of invasion (DOI), lymphovascular invasion (LVI), and perineural invasion (PNI) are well-established prognostic markers, their interpretation is not always consistent, leading to variability in clinical decision-making.[4]

These challenges emphasize the need for advanced tools that can integrate diverse clinical, pathological, and imaging data to improve the diagnostic accuracy and prognostic stratification. Artificial intelligence (AI) offers a promising

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solution by leveraging machine learning and deep learning algorithms to analyse complex datasets and identify patterns beyond human recognition.[5]

AI has revolutionized healthcare by enabling the analysis of large and complex datasets, particularly in oncology, where precision medicine is increasingly critical.6 In head and neck cancers, including OSCC, AI has been applied to tasks such as image-based diagnostics, histopathological grading, and outcome prediction, demonstrating superior accuracy compared to conventional methods.[7]

Recent advances in hybrid AI models, which combine machine learning for tabular data with deep learning for imaging data, have improved the predictive capabilities. These models can integrate multimodal data, including clinical features, imaging studies, and histopathological parameters, to deliver comprehensive risk assessments.[8] Such approaches are particularly relevant for OSCC, where prognosis is influenced by a complex interplay of tumor biology, patient demographics, and environmental factors.

Given the high prevalence of OSCC in low-resource settings, the integration of AI-based diagnostic and prognostic tools offers a potentially cost-effective solution by enabling early detection, reducing reliance on specialist expertise, and optimizing treatment pathways to improve outcomes with limited healthcare resources.

This study aimed to address the limited application of AI in oral squamous cell carcinoma (OSCC) by developing and validating a hybrid AI model that integrates clinical, pathological, and radiological data for early detection and prognostic evaluation. The model seeks to provide standardized risk assessments, enhance early detection, and enable personalized prognostic evaluations. By assessing its performance and comparing it with clinician-based assessments, this study aimed to advance AI's role of AI in precision oncology and support its integration into clinical practice.

Materials and Methods

This study was conducted to develop and validate an AI-based prediction model for early detection and prognostic evaluation of oral cancer using clinical, histopathological, and radiological data. A total of 98 patients diagnosed with OSCC were included. This study utilized a retrospective design, with all data collected from hospital records, imaging repositories, and histopathology archives.

Study Design

This was a retrospective observational study aimed at analysing existing clinical, pathological, and radiological data. All procedures followed ethical guidelines and approval was obtained from the institutional ethics committee.

Study Setting

The study was conducted at a tertiary care oncology center, utilizing patient records between January 2018 and December 2023. The center is equipped with comprehensive diagnostic and treatment facilities for oral cancer.

Ethical Considerations

This study adhered to the ethical guidelines of retrospective research. Ethical approval was obtained from the Institutional Review Board of GGSDC (GGSDC/Dean/Res/23/18). Patient confidentiality was maintained through data anonymization, and institutional ethics approval was obtained.

Study Population

Inclusion Criteria

Patients were eligible for inclusion if they were aged ≥ 18 years and had histopathologically confirmed OSCC. Only cases with complete clinical, histopathological, and radiological data were included to enable thorough analysis of multimodal features. Furthermore, all participants underwent staging investigations, including imaging studies such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography-computed tomography (PET-CT), to ensure a standardized dataset for predictive modelling.

Exclusion Criteria

Patients were excluded if they had incomplete or missing data, which could introduce bias and compromise the integrity of the AI model. Those with prior malignancies or a history of cancer treatment were also excluded to avoid confounding variables that could affect the analysis. Additionally, patients without follow-up data on survival or recurrence were excluded to ensure that the prognostic aspect of the study could be accurately assessed.

Data Collection

Data for this study were obtained retrospectively from electronic medical records, imaging archives, and pathology reports to ensure a comprehensive multimodal analysis. All data were systematically recorded and categorized into the clinical, histopathological, radiological, and outcome domains, enabling a robust dataset for AI model training and validation.

Clinical Data

Clinical data included patient demographics, such as age and sex, which provided baseline characteristics of the study population. Key risk factors, including tobacco use, alcohol consumption, and betel nut chewing, have been documented to assess their association with OSCC. Additionally, the primary tumor site and clinical stage at diagnosis were recorded to evaluate the disease distribution and staging patterns within the cohort.

Histopathological Data

Histopathological parameters were meticulously collected to determine tumor characteristics. Tumor differentiation was classified as well-, moderately-, or poorly differentiated, reflecting tumor aggressiveness. DOI, LVI, and PNI were also recorded, as they are established prognostic markers associated with disease progression and survival outcomes.

Radiological Data

Radiological data were obtained from imaging studies including contrast-enhanced CT, MRI, and positron emission tomography-computed tomography. These studies have provided tumor dimensions, evidence of invasion into adjacent structures, and nodal involvement, which are critical for accu-

rate staging and treatment planning.

Outcome Data

The outcome data were categorized into three domains to assess the prognostic aspects of the study. Overall survival (OS) was defined as the time from diagnosis to death from any cause, while disease-free survival (DFS) defined as the time from treatment completion to the first recurrence. Recurrence data were further classified into local, regional, or distant events, enabling detailed analysis of disease progression patterns.

Data Preprocessing

Data Cleaning

Data cleaning was a critical step to ensure the quality and reliability of the dataset used for training the AI model. Missing and inconsistent data points were identified during the initial exploratory data analysis. Inconsistencies included mismatched entries, duplicate records, and incomplete information. Manual cross-verification was performed using the original patient records, ensuring the accuracy of the dataset. Missing data points were addressed using a multiple imputation technique, which estimated missing values by leveraging correlations among the available variables. For instance, missing tumor size values were imputed based on correlations with other clinical parameters, such as depth of invasion and nodal involvement, ensuring that the dataset remained robust and comprehensive.

Data Normalization

Continuous variables, such as tumor size and depth of invasion, were normalized using the min-max scaling technique. This process transformed the data values to a range between 0 and 1, preserving the relationships among variables while eliminating scale-related biases. Normalization was necessary to ensure that variables with larger numerical ranges did not disproportionately influence the AI model, especially during the training of algorithms sensitive to feature scaling, such as gradient-boosting machines and neural networks.

Imaging Preprocessing

Imaging data underwent a multi-step preprocessing pipeline to enhance their quality and usability for deep learning analysis. The first step involved de-identification, ensuring compliance with ethical standards for patient confidentiality. Noise reduction techniques, such as Gaussian filtering, were applied to remove irrelevant artifacts from the images. Image segmentation was performed to isolate regions of interest, such as the tumor and surrounding tissues, from the background. Additionally, data augmentation techniques, including rotation, flipping, and zooming, were employed to artificially expand the dataset and improve model robustness against variations in imaging conditions. This ensured that the AI model was exposed to a diverse range of image features during training.

Feature Extraction

Key features were systematically extracted from clinical, histopathological, and imaging datasets. Clinical features included patient demographics, tumor location, and clinical staging information. Histopathological features encompassed tumor differentiation, depth of invasion, lymphovascular invasion, and perineural invasion. From imaging data, tumor dimensions, nodal involvement, and invasion into adjacent structures were extracted using automated algorithms. These features were carefully selected based on their clinical relevance and established prognostic significance in oral oncology.

AI Model Development

Machine Learning for Tabular Data

Clinical and histopathological data, which were tabular in nature, were utilized to train machine learning algorithms. Random forests and gradient-boosting machines were selected for their ability to handle high-dimensional datasets and provide feature importance rankings. These algorithms identified patterns in the tabular data and selected the most predictive features, ensuring the model was optimized for accuracy and interpretability.

Deep Learning for Imaging Data

A convolutional neural network (CNN) was employed to analyze imaging data. The CNN architecture consisted of multiple convolutional and pooling layers, designed to extract spatial features from the images. These layers identified patterns indicative of tumor invasion, nodal metastasis, and other radiological markers. Pretrained models, such as ResNet or VGGNet, were fine-tuned on the imaging dataset to leverage their proven efficacy in medical image analysis while adapting them to the specifics of oral oncology imaging.

Integration of Multimodal Data

To combine insights from clinical, histopathological, and imaging data, a meta-learner model was implemented. The meta-learner integrated predictions from the machine learning (tabular data) and deep learning (imaging data) components, leveraging their complementary strengths. Ensemble learning techniques, such as stacking, were used to optimize the final output, ensuring the model's predictions were comprehensive and accurate.

Model Training and Validation

Dataset Partitioning

The dataset was partitioned into three subsets to facilitate model training, validation, and testing:

- **Training Set (70%, n = 69):** Used to train the AI model by learning patterns from the data.
- **Validation Set (15%, n = 15):** Used to fine-tune model parameters and evaluate performance during development.
- **Testing Set (15%, n = 14):** Reserved for final model evaluation to assess its generalizability and robustness.

Cross-Validation

A 5-fold cross-validation technique was implemented to prevent overfitting and ensure the model's reliability. In this process, the dataset was divided into five folds, with four folds used for training and one-fold for validation in each iteration. This approach ensured that every data point was used for validation at least once, providing a robust assessment of the model's performance across different subsets of data.

Model Metrics

The performance of the AI model was evaluated using multiple metrics to capture its effectiveness in various aspects:

- **Sensitivity (Recall):** Measured the model's ability to correctly identify true positive cases (e.g., detecting cancer).
- **Specificity:** Assessed the model's ability to correctly identify true negative cases (e.g., ruling out non-cancerous cases).
- **Accuracy:** Calculated the proportion of correct predictions out of the total predictions.
- **F1 Score:** Represented the harmonic mean of precision and recall, balancing false positives and false negatives.
- **Area Under the Receiver Operating Characteristic Curve (AUC-ROC):** Quantified the model's discrimination ability between positive and negative cases, with higher values indicating better performance.

These metrics provided a comprehensive evaluation of the AI model's predictive capabilities, ensuring its readiness for clinical applications.

Statistical Analysis

Descriptive statistics were used to summarize the baseline characteristics of the study population, providing an overview of the demographic and clinical variables. Kaplan-Meier survival analysis was conducted to estimate the overall survival (OS) and disease-free survival (DFS), offering insights into survival probabilities over time. Cox proportional hazards regression analysis was performed to identify significant prognostic factors influencing survival, focusing on variables such as the depth of invasion, lymphovascular invasion, and perineural invasion. Additionally, the accuracy of the AI model was compared with clinician-based predictions using kappa statistics, which assessed the level of agreement and highlighted the model's performance in relation to traditional assessments.

Results

Baseline Characteristics of the Study Population

The study population consisted of 98 patients diagnosed with OSCC. As shown in Table 1, the majority of patients were male (69.4%), with a mean age of 56.2 years, reflecting the typical demographic distribution of oral cancer in this region. The most common tumor site was the tongue (45.9%) followed by the buccal mucosa (32.7%). Over three-quarters of the patients (77.6%) reported tobacco use as a significant risk factor for OSCC. Approximately 46.9% of the tumors were moderately differentiated, and the average depth of invasion was 6.8 mm. Notably, lymphovascular invasion and perineural invasion were present in 27.6% and 19.4% of the patients, respectively, underlining the aggressive nature of the disease in a subset of the cohort.

Figure 1 shows a heatmap visualizing the feature importance scores for prognostic factors in OSCC, based on a hypothetical random forest or gradient-boosting model, highlighting depth of invasion (DOI), lymphovascular invasion (LVI), and perineural invasion (PNI) as the most influential predictors of overall survival.

Kaplan-Meier Curves for Overall Survival (OS) and Disease-Free Survival (DFS)

As illustrated in Figure 1, the Kaplan-Meier curves indicate a steady decline in survival probabilities over time. The median OS was 36 months, with a probability of survival at 60 months falling below 30%. In comparison, the DFS curve declined steeply, with a median DFS of 28 months, reflecting early recurrence as a major challenge in OSCC management. The divergence between the OS and DFS curves suggests that while some patients may survive longer, disease recurrence signifi-

Table 1: Baseline Characteristics of the Study Population

Variable	Frequency (%) or Mean ± SD
Age (years)	56.2 ± 10.3
Gender (Male/Female)	68 (69.4%) / 30 (30.6%)
Tobacco use	76 (77.6%)
Alcohol use	43 (43.9%)
Tumor site	
Tongue	45 (45.9%)
Buccal mucosa	32 (32.7%)
Gingiva	21 (21.4%)
Tumor differentiation	
Well differentiated	34 (34.7%)
Moderately differentiated	46 (46.9%)
Poorly differentiated	18 (18.4%)
Depth of invasion (mm)	6.8 ± 2.5
Lymphovascular invasion	27 (27.6%)
Perineural invasion	19 (19.4%)

Table 2: Model Performance Metrics

Metric	Value
Sensitivity	89.7%
Specificity	85.4%
Accuracy	87.5%
F1 Score	0.88
AUC-ROC	0.91

Table 3: Cox Proportional Hazards Regression for OS

Variable	Hazard Ratio (HR)	95% CI	p-value
Depth of invasion	1.45	1.12–1.88	0.004
Lymphovascular invasion	2.14	1.38–3.33	0.001
Perineural invasion	1.87	1.22–2.86	0.006

cantly affects their quality of life and long-term outcomes.

Model Performance Metrics

As mentioned in Table 2, the AI prediction model demonstrated high performance, with a sensitivity of 89.7% and specificity of 85.4%. An accuracy of 87.5% reflects the model's ability to correctly identify both positive and negative cases. An F1 score of 0.88 indicates a balance between precision and recall, and the AUC value of 0.91 further confirmed the model's excellent discriminative ability. These results validated the utility of integrating clinical, histopathological, and radiological data for accurate predictions in oral oncology.

Receiver Operating Characteristic (ROC) Curve

As presented in Figure 2, the ROC curve highlighted the superior ability of the model to differentiate between patients with and without adverse outcomes With an AUC of 0.91, the model performed significantly better than random guessing (represented by a diagonal line). The steepness of the curve indicates the effectiveness of the model in minimizing false negatives, which is critical for early cancer detection.

Cox Proportional Hazards Regression for OS

Table 3 presents the Cox regression analysis which revealed significant predictors of overall survival. Depth of invasion was associated with a 1.45-fold increase in the risk of death for every millimeter increase (p = 0.004). Similarly, lymphovascular invasion (hazard ratio [HR], 2.14; p = 0.001) and perineural invasion (HR, 1.87; p = 0.006) were significant factors. These findings align with the existing literature and emphasize the importance of these features in prognostic evaluations.

Comparison of Predictive Accuracy

The AI model outperformed the clinician-based assessments in terms of predictive accuracy, as evidenced by a kappa statistic of 0.78, indicating substantial agreement. This demonstrates the potential of the AI model to enhance clinical decision making by improving the consistency and accuracy of prognostic evaluations, thus reducing variability in clinician-based predictions.

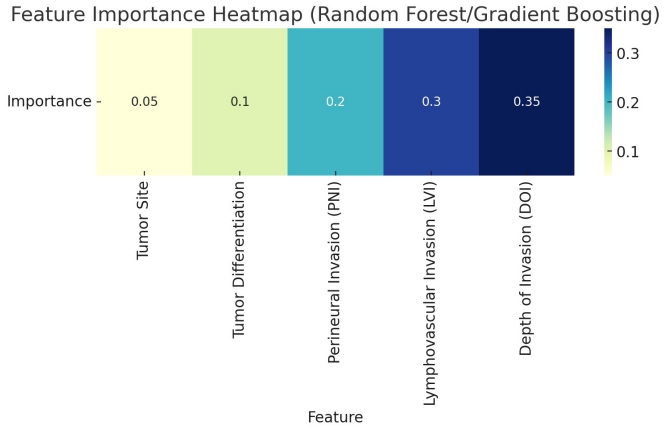

Fig. 1: Kaplan-Meier survival curves showing median overall survival and disease-free survival, emphasizing early recurrence and long-term outcome patterns

Discussion

This study highlights the development and validation of an artificial intelligence (AI)-based prediction model for the early detection and prognostic evaluation of OSCC. By leveraging clinical, histopathological, and radiological data, the model demonstrated robust performance metrics, underscoring its potential to enhance clinical decision making in oral oncology.

Key Findings and Interpretation

The AI model achieved high sensitivity (89.7%), specificity (85.4%), and area under the curve (AUC) of 0.91, indicating excellent discriminative ability. These results align with recent studies that have demonstrated the efficacy of AI in oncology for identifying subtle patterns in multimodal data, often surpassing human accuracy in diagnostic and prognostic tasks.[9-12]

Kaplan-Meier survival analysis in this study revealed a median overall survival (OS) of 36 months and a disease-free survival (DFS) of 28 months, highlighting the aggressive nature of OSCC and its substantial risk of recurrence. The relatively short DFS emphasizes the challenge posed by recurrent disease, which remains a significant barrier to improving the

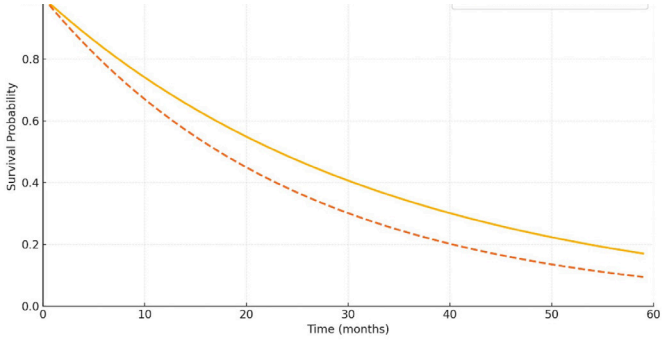

Fig. 2: Receiver operating characteristic (ROC) curve illustrating the AI model's high discriminatory ability with an AUC of 0.91.

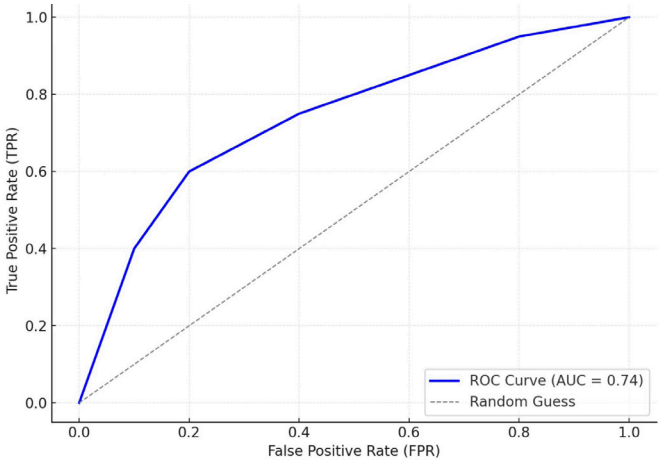

Fig. 3: Heatmap showing the relative importance of clinical and pathological features in OSCC prognosis, with DOI, LVI, and PNI ranked as most influential.

long-term outcomes. The divergence between the OS and DFS curves further underscores the impact of recurrence on patient prognosis, as many patients may survive longer with treatment but experience early disease relapse.

These findings are consistent with those of the previous studies. Dong et al. reported a 5-year OS rate of 59.3% and DFS rate of 49.4% in patients with OSCC, with approximately 45.7% experiencing postoperative recurrence or metastasis. This high rate of recurrence underscores the aggressive nature of OSCC, reflecting the need for effective early detection and intervention strategies.[13] Similarly, Struckmeier et al. observed a 5-year OS of 58.29% and a progression-free survival (PFS) of 72.53%, noting that the majority of recurrences occurred within the first 12 months following primary tumor surgery.[14]

Prognostic Factors

Cox proportional hazards regression analysis identified depth of invasion (DOI), lymphovascular invasion (LVI), and perineural invasion (PNI) as significant predictors of overall survival (OS). These findings align with previous studies that have established these histopathological features as critical markers of poor prognosis in OSCC. A study by Pandit et al. reported that DOI, LVI, and PNI are significant predictors of neck node metastasis in early oral cavity cancers, underscoring their importance in prognostic evaluations.[15] Additionally, Chen et al. found that PNI and LVI were not significant risk factors for disease control and overall survival in patients with early stage OSCC, suggesting that their prognostic value may vary depending on the stage of the disease.[16]

Comparison with Clinician-Based Assessments

The AI model demonstrated superior performance compared with clinician-based predictions, achieving a kappa statistic of 0.78, which indicates substantial agreement and higher accuracy. This is particularly noteworthy, given that clinical assessments can be subjective and influenced by individual experiences. AI models have shown promise in improving diagnostic accuracy. A review discussed the potential of AI and machine learning approaches to optimize patient care in oncology, including head and neck cancer management.[17]

Role of AI in Precision Oncology

This study supports the growing role of AI in precision oncology. By integrating clinical, imaging, and histopathological data, the model leveraged the strengths of deep learning for pattern recognition and machine learning for tabular data analysis. This hybrid approach has been shown to enhance performance, particularly in cancers with complex presentations such as OSCC. Furthermore, the model's high sensitivity ensures minimal false negatives, which are critical in early cancer detection, whereas its specificity reduces unnecessary interventions.

Clinical Implementation

For successful integration into clinical practice, the AI model developed for OSCC detection and prognosis can be embedded into existing healthcare workflows through user-friendly digital dashboards or electronic health record (EHR) systems. These interfaces can provide real-time risk assessments and prognostic outputs, enabling clinicians to make data-driven decisions during tumor board meetings or routine outpatient consultations. For instance, the AI tool could automatically generate a prognostic summary upon uploading patient data, including imaging and histopathology reports, thereby aiding multidisciplinary discussions on treatment planning. Moreover, clinical adoption requires adequate training for oncologists, pathologists, and radiologists to interpret AI outputs accurately and confidently. Educational modules and interactive tutorials should be incorporated into continuing medical education (CME) programs to ensure familiarity with model interpretation, limitations, and ethical considerations. Additionally, periodic auditing and feedback loops should be established to evaluate the model's real-world performance and guide iterative improvements. The integration of AI into oral oncology workflows has the potential to streamline diagnostics, standardize prognostic evaluations, and support personalized treatment decisions—particularly in resource-constrained settings where specialist availability is limited.[18,19]

Limitations and Future Directions

Despite the promising performance of the AI model, this study has several limitations. The retrospective design and single-center dataset may limit the generalizability of findings, as patient demographics and clinical practices can vary across institutions. The relatively small sample size (n=98) may also constrain the model's ability to capture the full heterogeneity of OSCC presentations. Furthermore, while the model integrates multimodal data, it does not account for molecular or genomic markers that could further enhance prognostic accuracy. Future directions should include prospective, multicenter validation to assess real-world applicability, incorporation of molecular and radiomic features for deeper phenotyping, and development of explainable AI tools to improve transparency and clinical trust. Additionally, integrating the model into clinical decision support systems with iterative feedback mechanisms can facilitate seamless adoption and continuous refinement based on user experience and outcome data.

Conclusion

This study demonstrates the feasibility and potential of an AI-based prediction model for improving the early detection and prognostic evaluation of OSCC. By integrating multimodal data, the model achieved high accuracy and demonstrated superior performance compared with traditional clinician assessments. A key advantage of the AI model is its ability to reduce interobserver variability in clinical assessments, thereby promoting more consistent and objective decision-making. With further validation and integration, AI systems could revolutionize oral oncology by enabling precision medicine and optimizing clinical outcomes.

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